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A household-scale life cycle assessment model for understanding the food-energy-water nexus

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The household is an important locus of decision-making regarding food, energy, and water (FEW) consumption. Changes in household FEW consumption behaviors can lead to significant reductions in environmental impacts, but it can be difficult for consumers to compare the relative impacts of their consumption quantitatively, or to recognize the indirect impacts of their household consumption patterns. We describe two novel tools designed to address this problem: A hybrid life cycle assessment (LCA) framework to translate household consumption of food, energy, and water into key environmental impacts including greenhouse gas emissions, energy use, and water use; and a novel software application called *HomeTracker* that implements the framework by collecting household FEW data and providing environmental impact feedback to households. We explore the question: *How can a life cycle assessment-based software application facilitate collection and translation of household consumption data to meaningful environmental impact metrics?* A case study in Lake County, Illinois is presented to illustrate use of the *HomeTracker* application. Output data describing environmental impacts attributable to household FEW consumption in the study area are shown in order to illustrate key features and trends observed in the case study population. The framework and its associated output data can be used to support experimental research at the household scale, allowing for examination of what users purchase and consume over an extended period of time as well as increased understanding of household behavior trends and environmental impacts, and as future work.

KEYWORDS

environmental life cycle assessment, food-energy-water (FEW) nexus, resource management, household consumption, web application development, household monitoring

1 Introduction

The interdependencies of food, energy, and water (FEW) resources, known collectively as the FEW nexus, require careful planning and management of each resource to avoid unintended consequences in the other sectors. Pressure on these resources is rising due to global population growth, increases in *per capita* consumption, changes in dietary preferences to include more animal products, and a changing climate (Flammini et al., 2014; Scanlon et al., 2017). Globally,

household consumption accounts for more than 70% of total greenhouse gas (GHG) emissions (Hertwich and Peters 2009; Wilson et al., 2013) and approximately 80% of total freshwater use (Ivanova et al., 2016). In the United States, over 80% of GHG emissions have been attributed to consumption at the household level (Jones and Kammen 2011). Thus, there is an opportunity to reduce water use and greenhouse gas impacts globally and domestically through changes in household consumption behavior, and an understanding of current behavior trends, motivations, and barriers to change can help identify effective interventions.

Everyday household consumption of food, energy, and water has both direct and indirect resource use and environmental impacts that need to be accounted for. For example, the average water footprint of an individual person's diet varies between approximately 158,500 and 475,000 gallons (600 and 1,800 m³) per year, depending on what type of food is consumed (Hoekstra and Chapagain 2008; D'Odorico et al., 2018). This water footprint includes both "green water" (rainwater used by crops) and "blue water" (water withdrawals for irrigation) (Falkenmark and Rockström 2006). The average GHG emissions from a person's diet is estimated at 4.7 kg CO₂ eq. per day (Heller et al., 2018). Similarly, electricity generation requires significant volumes of freshwater use and emits greenhouse gases into the atmosphere. Over 40% of United States energy is consumed for household and commercial purposes (Chini et al., 2016). While the industry average water use for electricity generation has been cited as 25 gallons per kWh, the water use intensity of electricity generation varies by orders of magnitude depending on fuel mix, prime mover of generation, cooling technology, and emissions controls (Sovacool and Sovacool 2009; Grubert and Sanders 2018).

Multiple studies have investigated the environmental impacts, including GHG emissions and water use, of dietary choices and maintaining a healthy diet (e.g., Heller and Keoleian 2015; Tom et al., 2016; Hallström et al., 2017). Agricultural activities have negative impacts on the environment through emission of GHGs (Chandio et al., 2020; Chandio et al., 2021; Alavijeh et al., 2022), intensive use of fertilizers and pesticides (e.g., Kross et al., 2022), withdrawal and consumption of freshwater resources (D'Odorico et al., 2018), land use change (e.g., Hunter et al., 2017), and degradation of biodiversity (Yang et al., 2018). The agricultural sector accounts for approximately 70% of global water withdrawals (Marston et al., 2018). In addition, the environmental impact of food consumption at the household level has been quantified and related to sociodemographic characteristics such as race, income, and education level (Boehm et al., 2018). Other studies have related food consumption, and in particular the obesity epidemic, with energy use and environmental degradation (Koengkan and Fuinhas 2021; Koengkan and Fuinhas, 2022). Kanyama et al. (2021) assessed the GHG emission impacts of shifting expenditures on food and holidays, along with furnishings.

Several studies have quantified the environmental impacts of household consumption at global, national, or regional levels. For example, Ivanova et al. (2016) used the EXIOBASE 2.2 multiregional input-output (MRIO) database (Wood et al., 2013) to analyze global supply chains and trace the origin of products consumed by households, quantifying the impacts of consumption in terms of global GHG emissions and total land, material, and water use. Steen-Olsen et al. (2016) combined use of the EXIOBASE 2 MRIO database with a national consumer expenditure survey to assess the GHG footprint of Norwegian

household consumption. Kok et al. (2006) compared different methods for quantifying the energy requirements of household consumption, including input-output analysis based on national accounts, input-output analysis using household expenditure data, and a hybrid analysis combining input-output modeling with process modeling. They obtained similar results from the three methods for a case study of households in the Netherlands but noted that the hybrid analysis enables identifying options for more sustainable consumption. Jones and Kammen (2011) quantified carbon footprints of typical U.S. households in 28 cities for a range of household sizes, as well as GHG and financial savings from a set of potential mitigation actions across household types. Chini et al. (2016) evaluated the relationship between water and energy in U.S. household appliances and fixtures and identified opportunities for reducing direct and indirect water and energy use through a cost abatement analysis.

In addition to these large-scale studies, a number of studies have developed tools for tracking consumption and measuring the impacts of individual households. For example, Benders et al. (2006) describe a web-based tool that provides participants with feedback on their energy use and personalized options for energy conservation. Indirect energy use was estimated using a hybrid approach combining input-output analysis with process analysis. The tool was tested with a sample of 300 households in the Netherlands, resulting in a reduction of about 8.5% in direct energy use compared to a control group, though the reduction in indirect energy use was not statistically significant. Using the same analysis program, Abrahamse et al. (2007) developed other web-based tools to encourage households to reduce direct and indirect energy use. Using a combination of tailored information, goal setting, and feedback, they examined whether this combination of interventions would result in changes in direct and indirect energy use, energy-related behaviors, and knowledge. Households exposed to the combination of interventions reduced their direct energy use by about 5%, but as in Benders et al. (2006), changes in indirect energy use were not significant. Jones and Kammen (2011) incorporated their carbon footprint model in an open-access online tool that can be used to inform behavior change at the household level. Another online tool, called EcoRunner, was developed by Frostell et al. (2015) to calculate the direct and indirect environmental loads of purchase decisions by households in Sweden. Use of EcoRunner was demonstrated using average expenditure values to analyze energy use, global warming potential, and nitrogen oxide emissions. Related to these studies are a number of "living lab" experiments, i.e., collaborative work with households to change practices and behaviors, particularly focusing on energy conservation (e.g., Korsnes et al., 2018; Sovacool et al., 2020; Sahakian et al., 2021).

Our work builds on these previous studies to focus on the FEW nexus at the household scale. Specifically, we have developed a web-based software application called *HomeTracker* for measuring the direct and indirect energy use, water use, and GHG emissions of household food purchases, water use, and energy consumption. While many of the existing studies use datasets that represent either an average level of consumption or a snapshot of consumption behavior, *HomeTracker* captures FEW consumption in participating households over an extended period of time to allow for trends to be assessed. *HomeTracker* provides timely feedback on the life-cycle impacts of FEW consumption, potentially affecting conservation behavior and short-term decision making.

Design and development of the *HomeTracker* application, participant FEW data collection procedures, and environmental impact factors and norming used in the model are summarized in the methods section. (Additional details are provided in [Supplementary Information](#).) Data is then presented to demonstrate how *HomeTracker* is used in a multidisciplinary study. Finally, limitations of the tool and future work are discussed.

2 Materials and methods

2.1 *HomeTracker* software development

The Food-Energy-Water Conscious (FEWCON) project focuses on the environmental impacts of household food, energy, and water consumption and potential interventions for reducing those impacts ([Watkins et al., 2019](#)). A major component of the project is a study conducted from February 2020 to August 2021 among 174 household participants in Lake County, Illinois, an area selected to be representative of United States suburban populations. The *HomeTracker* application was developed to provide a common portal for participants in the study.

Through *HomeTracker*, study participants enter their grocery and restaurant receipt purchases, monthly water bills, monthly natural gas bills, and monthly electricity bills. Environmental impacts, including greenhouse gas emissions and water use, are calculated from this consumption, and feedback is provided to participants in a visual interface highlighting the environmental impact of their household consumption. A key component of *HomeTracker* is a novel food, energy, and water consumption-based life cycle assessment (LCA) model quantifying direct and indirect environmental impacts from households. The hybrid LCA model, based on input-output and processed-based methods, is implemented in the software to compute environmental impact metrics from consumption input. In addition to collecting utility and food data *via HomeTracker*, the study also included a series of surveys to capture socio-economic and demographic information, as well as beliefs, attitudes and self-reported behaviors related to food, energy, and water consumption.

As the central communication medium for participants in the FEW consumption study, the *HomeTracker* system has a number of key system requirements. The primary behavioral (functional) requirements are continuous collection of consumption data and accurate reporting of household consumption *via* intervention messages. Equally important are the following non-behavioral requirements: minimization of participant burden, maintenance of privacy, and clarity of the consumption input interface and the intervention messaging.

The foundation for the *HomeTracker* application is Grails, an open-source Java-based framework that uses the Apache Groovy programming language. An Apache Tomcat server hosted at Michigan Technological University provides Java Database Connectivity between the application and the MariaDB relational database management system. Implementing *HomeTracker* as a web application allows household participants to access the service through any device that supports a standard web browser. Since Grails is the application framework used in Michigan Technological University's User Interface Design and Implementation course, students can easily transition from that course into a *HomeTracker* development role. The W3.CSS (cascading style sheet) framework provides a responsive

interface layout that adapts to the type of device being used (e.g., laptop, tablet, smartphone).

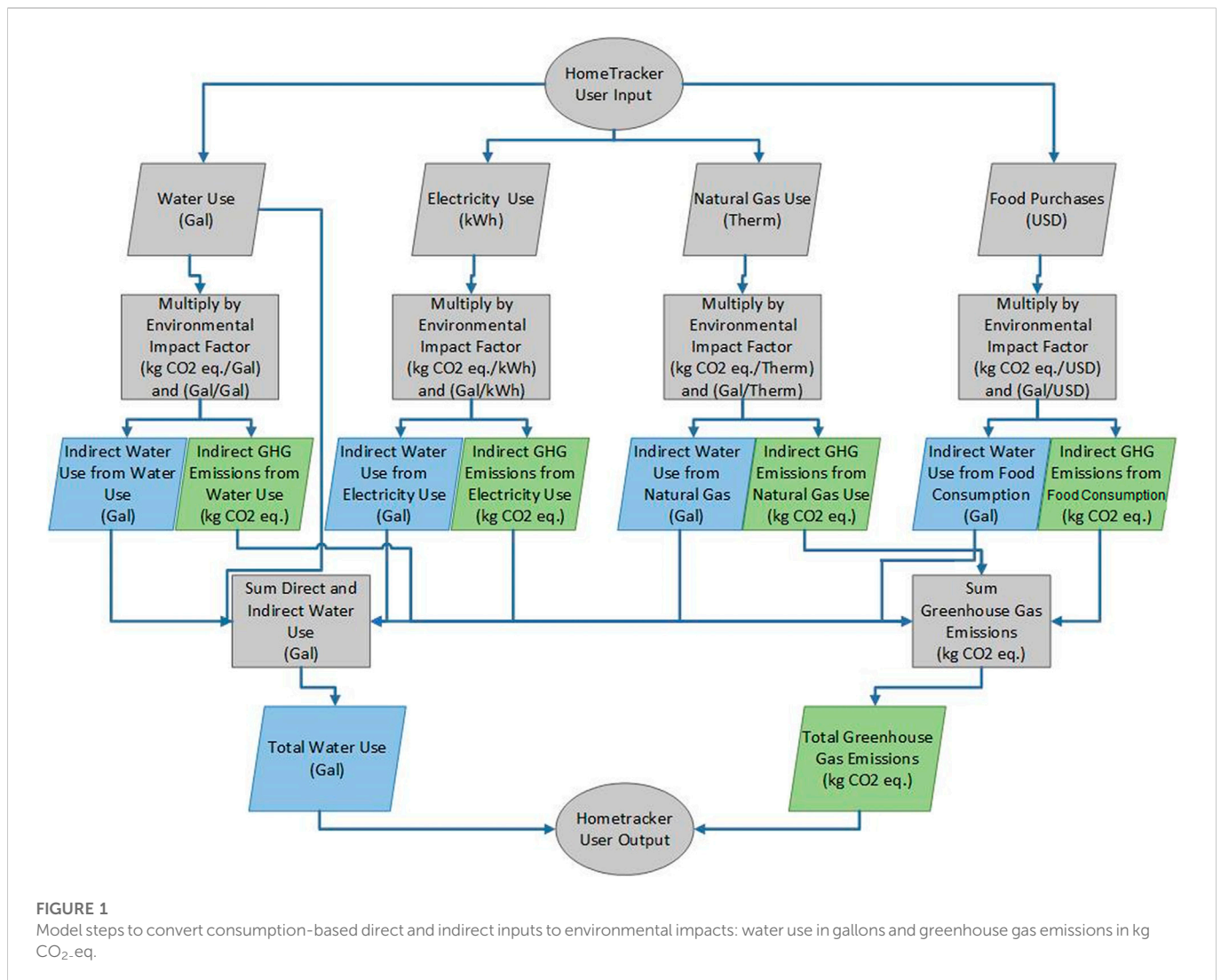
Development of *HomeTracker* began in summer 2018; student developers at Michigan Technological University worked iteratively with members of the project team in designing and implementing the app, according to the needs and expectations of the project scientists. In spring 2019, students at Michigan Technological University and Rutgers University provided initial user testing, followed by a pilot test with household volunteers from the Rutgers community. User feedback from this testing drove changes to the interface design, along with development of the *HomeTracker* User Guide, in summer 2019. A second round of user testing was conducted among FEWCON project staff and a small group of volunteers in Lake County, evaluating the revised interface and checking that the *HomeTracker* application and the User Guide were compatible. *HomeTracker* was deployed and made available to study participants in February 2020.

2.2 Data collection

Consumption data collected by *HomeTracker* include electricity use, natural gas use, water use, and food purchases. Food data collection is the most onerous from the household perspective and was thus limited to three two-week periods during the study period, as opposed to continuous monthly collection of energy and water data. *HomeTracker* collects consumption data through a variety of automated and manual methods. In addition to these quantitative data, households were asked to respond to a series of surveys and invited to provide reflective statements on their consumption behavior through open-ended survey questions and a journaling feature in *HomeTracker*.

In designing the data acquisition processes, automation was favored for easing the burden on household participants, but only if the underlying technology was robust and came at minimal risk to accuracy of the data. We initially explored the use of in-house sensor devices (e.g., Smappee, Sense) that household owners can install on the metering equipment in their houses. Many of these devices offer application programming interfaces (APIs) that allow third parties to access data collected by the devices, but they also require some non-trivial work attaching physical sensors to metering equipment. After some experience installing a few such devices in local houses, it became clear that the risk of faulty installation and the cost of installing and maintaining hundreds of individual monitors made this option infeasible.

An alternative automated means of collecting electricity consumption data that avoids the costs and inaccuracies of in-house installation was identified. The study area's local service provider, Commonwealth Edison (ComEd), partners with a company called UtilityAPI to provide electricity billing data, for consumers who authorize it, to third-party applications. UtilityAPI stores up-to-date versions of these data on its own secure servers so that apps like *HomeTracker* can access them as needed. In addition, subscribing to the UtilityAPI service provides access to a rich set of additional historical billing data for authorizing consumers. Household participants must authorize UtilityAPI to access their ComEd billing data. Completing the authorization form creates secure credentials that *HomeTracker* then uses to access data through UtilityAPI.



Unlike electricity, the utilities supplying natural gas and water vary within the study area. The smaller-scale authorities providing these utilities, particularly the local municipalities in charge of water supply, do not have the resources to provide third-party data access. While there are home-installed sensors (e.g., Sense, Pecan Street) that provide monitoring, most of these products were not available during the development of *HomeTracker*, and risk and cost concerns over installation and maintenance made this option infeasible. Participants instead entered their gas and water billing data manually in *HomeTracker* using the standard billing statements they receive at regular intervals.

Food data collection occurred during several specified two-week periods in the study. During these periods, household participants were asked to upload all purchases, both food at home (i.e., food purchased with the intent of preparing it at home) and food away from home (i.e., food prepared and purchased outside the home). Participants distinguished between full service restaurants, defined as food establishments that provide not only preparation but also service of the food and limited service restaurants, defined as establishments like delicatessens or cafeterias that prepare but do not serve the food. For food at home, the itemized breakdown of the purchases allows for greater detail and more nuanced analysis. In

entering these purchases into *HomeTracker*, participants were asked to provide details for each item purchased. If the purchase included a receipt, the household participant uploaded images of the receipt and provided an item-by-item description of the purchase. Later, student workers consulted the receipt images and participant descriptions of the line items to determine the food category and confirm price information. For a purchase without receipt images (e.g., farmer's market, forgotten or lost receipt), household participants provided descriptions and prices of the line items.

2.3 Environmental impact factors

HomeTracker uses a LCA approach to quantify direct and indirect environmental impacts of household consumption of food, energy, and water resources. Life cycle assessment is used to assess the potential environmental impact of a product, process or service using four key steps: i) Goal definition and scoping, ii) Inventory analysis, iii) Impact assessment, and iv) Interpretation of results (Curran 2008). The framework for this LCA-based environmental impact model starts with input of direct household resource consumption values. These resources include water use in gallons

TABLE 1 Summary of environmental impact factors for indirect resource consumption (1 Gal = 0.003785 m³).

Environmental impact	Indirect contributor	Factor	Units	Scale	References
Water Use	Water	3.01	Gal/Gal	National	Wernet et al. (2016)
	Electricity	See Table 2	Gal/kWh	Regional	U.S. EIA (2019b)
	Natural Gas	0.46	Gal/Therm	National	Ali and Kumar (2016) and U.S. EIA (2019c)
	Food	See Figure 2	Gal/USD	National	Yang et al. (2017b)
Greenhouse Gas Emissions	Water	0.0044	kg CO ₂ eq./Gal	National	Wernet et al. (2016)
	Electricity	0.643	kg CO ₂ eq./kWh	Midwest	U.S. EPA (2018)
	Natural Gas	8.05	kg CO ₂ eq./Therm	Midwest	Wernet et al. (2016)
	Food	See Figure 2	kg CO ₂ eq./USD	National	Yang et al. (2017b)

*Gal, Gallon; kWh, Kilowatt-Hour; Therm, Therm; USD, US Dollar; kg CO₂ eq, Kilograms of Carbon Dioxide Equivalent.

(gal), electricity use in kilowatt hours (kWh), natural gas use in therms (therm), and food purchases in U.S. dollars (USD). Environmental impact factors are applied to determine the direct and indirect environmental impact due to the use or consumption of each resource. The direct and indirect environmental impacts are then summed to output total water withdrawal in gallons and total greenhouse gas emissions in kilograms of carbon dioxide equivalents (kg CO₂ eq). Figure 1 summarizes the steps in calculating direct and indirect environmental impacts. The environmental impact factors used in these calculations are summarized in Table 1. Sample calculations are shown in Supplementary Information.

2.3.1 Water use factors

It is important to clearly define water use when quantifying it to avoid ambiguity and inconsistency (Grubert, Rogers, and Sanders 2020). Water use in this study refers to water withdrawn from its original source (i.e., blue water). Water use per therm of natural gas was estimated from a study which developed life cycle water use factors for different stages of conventional and shale gas life cycles, combined with Energy Information Administration data on the current proportion of each gas source currently in use in the U.S. (Ali and Kumar 2016; U.S. EIA, 2019c). Water use per gallon of water used at the household is a cumulative estimate that includes both direct water use and indirect water use embedded in all of the materials and energy required to treat and deliver water to the home, as well as all of the unit operations involved in treating water after it leaves the household in a standard municipal wastewater treatment system. Life cycle inventory data for upstream water treatment and delivery, as well as downstream wastewater treatment, comes from the Ecoinvent database (Wernet et al., 2016). Water use factors for food purchases are described in Section 2.3.3, and water use factors for electricity are described in Section 2.3.4.

2.3.2 Greenhouse gas emissions factors

Greenhouse gas emissions per gallon of water used in the household are also estimated from Ecoinvent, and are analyzed with the Intergovernmental Panel on Climate Change 2013 GWP 100a method, which is an impact assessment method that expresses emissions impacts of climate-active greenhouse gas emissions in kg CO₂-eq. (Wernet et al., 2016). Greenhouse gas emissions per kilowatt hour (kWh) of electricity generated were estimated by combining U.S.

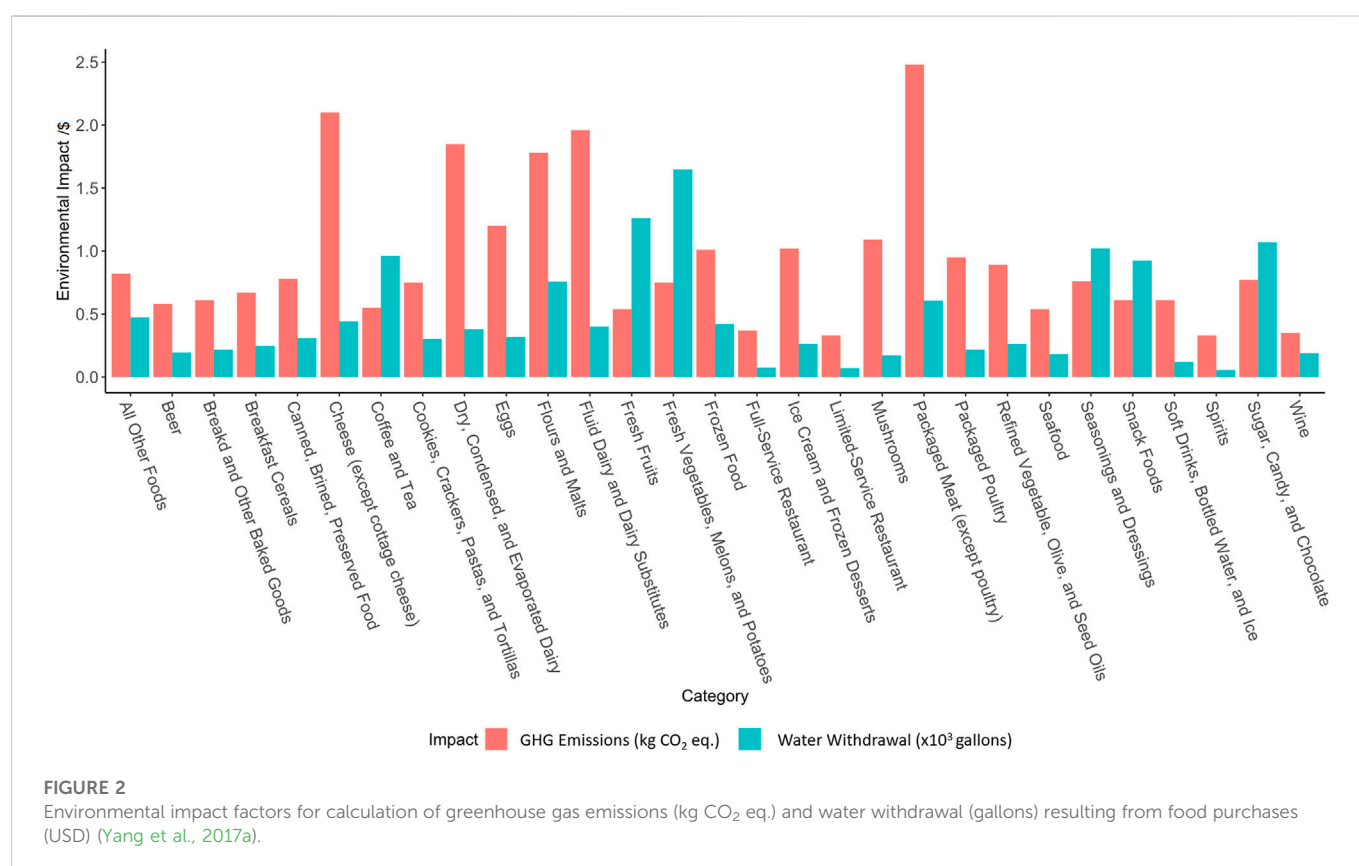
TABLE 2 Monthly water withdrawal intensities for PJM.

Month	Water withdrawal intensity (Gal/MWh)
January	10,569
February	9,621
March	9,850
April	11,910
May	12,505
June	12,312
July	11,972
August	11,926
September	11,894
October	12,219
November	11,218
December	11,288

EPA eGRID data on average emissions per kWh for power plant emissions in the RFC West subregion, combined with the average grid composition in the region and the upstream emissions impacts for fuel production for each relevant fuel type from Ecoinvent (U.S. EPA 2018). Greenhouse gas emissions per therm of natural gas were estimated by combining combustion emissions per therm of natural gas with Ecoinvent data on upstream natural gas processing and transmission. Greenhouse gas emissions factors for food purchases are described in Section 2.3.4.

2.3.3 Water use intensity for electricity generation

The Pennsylvania-New Jersey-Maryland Interconnection (PJM) is a Regional Transmission Organization (RTO) that administers the grid for the region in which our study area lies. The water use intensity of electricity generation for the entire fuel mix in PJM was calculated at a monthly resolution for 2019 to best represent the FEWCON study area. The United States Energy Information reports monthly thermoelectric cooling water data at the generator level for power plants in the United States in Form EIA-923 (U.S. EIA 2019a). This form was cross-indexed with Form EIA-860 (U.S. EIA 2019b) to determine which plants are connected to the PJM grid. Since Form



EIA-923 only reports on thermoelectric generators, electricity generation data from PJM was used to determine how much electricity generation was attributed to hydroelectric, solar, and wind generation (PJM 2019). Total water withdrawal and total generation were aggregated by month. The total water withdrawal (gallons) in month i , W_i , is calculated from the total electricity generation (MWh) in month i , G_i , and the average monthly water withdrawal intensity (gallons/MWh) for month i , (AWF_i) using Eq. 1.

$$W_i = G_i \cdot AWF_i \quad (1)$$

Monthly water withdrawal intensity values (AWF_i) for PJM are shown in Table 2.

2.3.4 USEEIO v.1.1

The United States Environmentally Extended Input-Output Model (USEEIO v.1.1) is a United States-specific environmentally extended input-output model that can be used to quantify environmental impacts of production and consumption in 389 industry sectors. Environmental data allows for quantification of impacts related to land cover, water, energy use, mineral use, greenhouse gas emissions, air pollutants, nutrients, and toxics. This model was selected for use in this research task as it is useful in performing streamlined life cycle assessment. Environmental impact is quantified per U.S. Dollar (USD) spent, allowing for simple calculation of environmental impact based on purchase data submitted by participants through the *HomeTracker* interface. The environmental impacts, specifically water use and greenhouse gas emissions, can be calculated for 29 detailed categories of food-related spending. Greenhouse gas emissions are estimated using the 2013 greenhouse gas inventory as compiled by the U.S.

Environmental Protection Agency while water withdrawals were determined for irrigation of crops, watering of livestock, cooling water in thermoelectric power generation, mining operations, and other commercial and industrial purposes using multiple data sources as outlined in the USEEIO Model Details (Yang et al., 2017a).

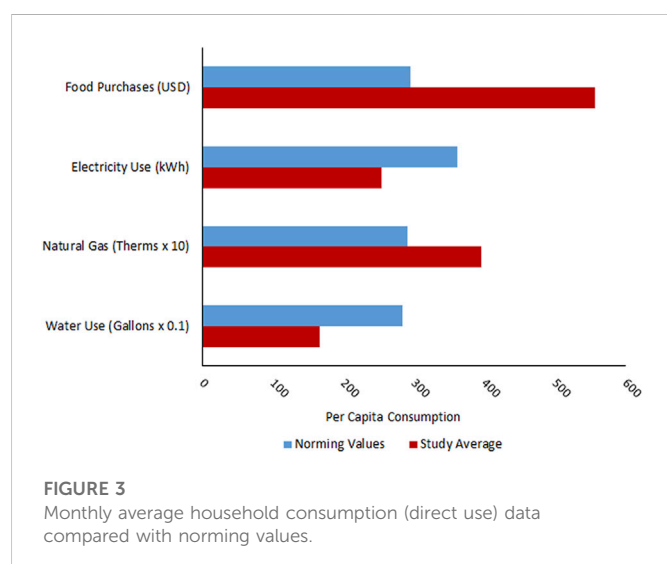
Figure 2 represents the environmental impact factors for calculation of GHG emissions and water withdrawal resulting from food consumption. Packaged meat and dairy have the highest greenhouse gas emissions per dollar spent, while fresh fruits, breakfast cereals, and seafood have notably lower greenhouse gas emissions per dollar spent. Fresh vegetables, melons, and potatoes require the most water per dollar spent. Other water-intensive categories include fresh fruits; sugar, candy and chocolate; snack foods; coffee and tea; and seasonings and dressings. Less water-intensive categories include mushrooms, breakfast cereal, and seafood. Full-service and limited-service restaurant impacts are relatively low for both GHG emissions and water withdrawal per dollar spent compared to other food categories, due to the increase in price of goods purchased at a restaurant rather than at a market, effectively increasing the denominator in the “impact per dollar spent” factor.

2.4 Norming values

Table 3 shows the average household consumption values that are displayed as norming feedback to participants in the FEWCON study. According to Steg and Vlek (2009), descriptive norms “refer to the extent to which behaviour is supposed to be commonly approved or disapproved of.” These values were selected to be as representative as

TABLE 3 Summary of average consumption values for household norming feedback.

Consumption category	Monthly average	Units	Scale	References
Water Use	6,254	Gal	Lake County	USGS (2018)
Electricity Use	796	kWh	Midwest	U.S. EIA (2018)
Natural Gas Use	64	Therm	Midwest	U.S. EIA (2018)
Food Purchases	658	USD	National	U.S. BLS (2018)



possible of Lake County, IL. The average volume of water for domestic water use in Lake County is 6,254 gallons per household per month. This data comes from the United States Geological Survey (USGS) Water Resources National Water Information System for Lake County, IL (USGS 2018). The average monthly household electricity use and natural gas use is 796 kWh and 64 therms, respectively. These values are from the 2018 Residential Energy Consumption Survey (RECS) Report and are based on annual averages for the Midwest United States. This data is representative of the year 2015. The average dollar amount spent on food at home and food away from home is 658 USD and comes from the U.S. Bureau of Labor Statistics 2018 Consumer Expenditure Survey: Table 1,400 (BLS 2018). The average water withdrawal and GHG emissions footprints for food are calculated based on the average dollar amount spent using the United States Environmentally Extended Input Output model (Yang et al., 2017b).

3 Results and discussion

This section presents consumption data and associated environmental impact data for 130 households in Lake County, IL using the *HomeTracker* application. We show how household consumption and environmental impact data can be analyzed and summarized to identify opportunities for behavior change and reduced environmental impact. Data is analyzed by evaluating temporal trends, trends by household size and income range, and general averages for the entire study group. These trends and observations are summarized in Figures 3–10.

Figure 3 shows average household consumption data for all participating households collected via *HomeTracker* in 2020 compared with the norming values (Table 3). On average, households participating in the study consumed less electricity and natural gas, but used more water and spent more on food than the norming values. These results may be indicative of the study sample, which on average had household incomes above the median income for the county. Additionally, 79 households reported having children, while 51 households reported having no children. This consumption data can be assessed for individual households, and paired with survey responses to identify specific causes of above or below average household consumption behavior as future work.

HomeTracker food data entry distinguishes between food consumed at home and food consumed away from home. Figure 4 shows average monthly household food consumption both at the home and out of the home for 2020. Notable differences in the style of food consumption can be observed in the households enrolled within the study. While most households spent more in the “Food at Home” category compared to “Food Away From Home,” this proportion varied considerably across households. Total household spending on food was also quite variable, which can be attributed in part to the short duration of our food data collection, as well as the variability between households in size, income, and consumption patterns. Disruptions due to the COVID-19 pandemic may also have contributed to high variability in food purchasing patterns, such as households stocking large quantities of food.

Figure 5 shows a summary of direct water and energy use in 130 households over the course of the study. Impacts of the COVID-19 crisis are not apparent in this aggregated data, and variability is consistent with typical seasonal patterns. For example, natural gas use occurs primarily in the winter for heating, while electricity use increases in the summer due to the use of air conditioning, consistent with heating and cooling degree-day data for the county (Figure 6, NOAA, 2022). Another expected pattern is the increase in water use during the growing season, when outdoor water use occurs. Outdoor water use is expected to be inversely proportional to rainfall, and this relationship is observed in the water use data. Specifically, the spring of 2020 was wetter than average (16.7 inches of rainfall in March–May), followed by near-average rainfall in the summer; whereas the spring of 2021 was very dry (just 3.4 inches of rain in March–May), followed by a wet June (4.7 inches of rain) (NOAA, 2022).

Figures 7, 8 show the variation in contributions to environmental impacts from FEW consumption categories, along with decreases in *per capita* impacts associated with larger household sizes. Food purchases represent by far the largest contribution to total (blue) water use, and they are also the largest contributor to GHG emissions, with natural gas use and electricity contributing significantly to GHG emissions as well. Direct water use in the home is small compared to

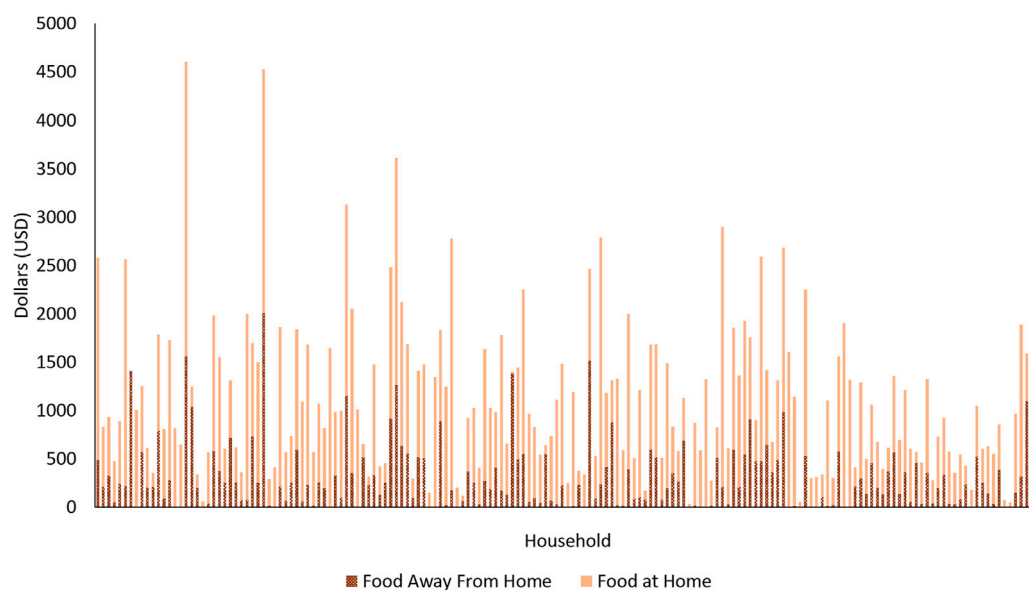


FIGURE 4

Average monthly total food spending for 130 sample households categorized as amount (USD) spent on food consumed away from home (FAFH) and amount spent on food consumed at the home (FAH) in 2020.

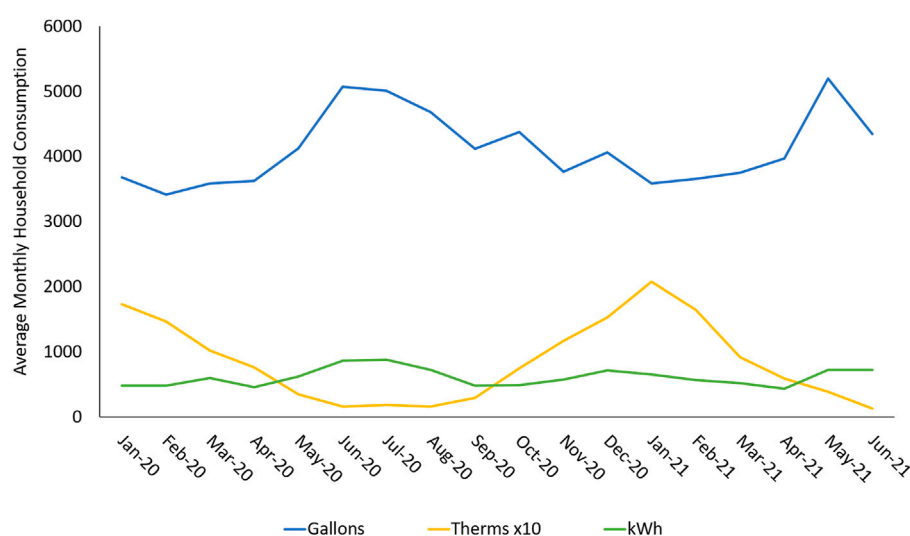


FIGURE 5

Monthly time series data showing average household direct water use (gallons), electricity use (kWh), and natural gas use (therms) over the study period for 130 households. Average household size is 3.2 people.

indirect water use, and water use makes an insignificant contribution to GHG emissions. The average person in the United States uses 82 gallons per day (Dieter et al., 2018), and in our study the average direct water use was just 42 gallons per person per day. However, the average indirect water use was 755 gallons per person per day. Thirty-seven households did not report household size and were excluded from this analysis.

Figures 9, 10 show how consumption and environmental impacts vary with household income. There are increasing trends in all FEW

consumption categories as household income rises, with the greatest increase seen in food purchases. Households in the highest income category spend more than five times the amount on food than do households in the lowest category. This results in sharply rising trends in environmental impacts with increasing income, as the highest-income households have approximately four times the total water use and GHG emissions attributable to the household FEW consumption. Eighteen households did not report their household income and were excluded from this analysis.

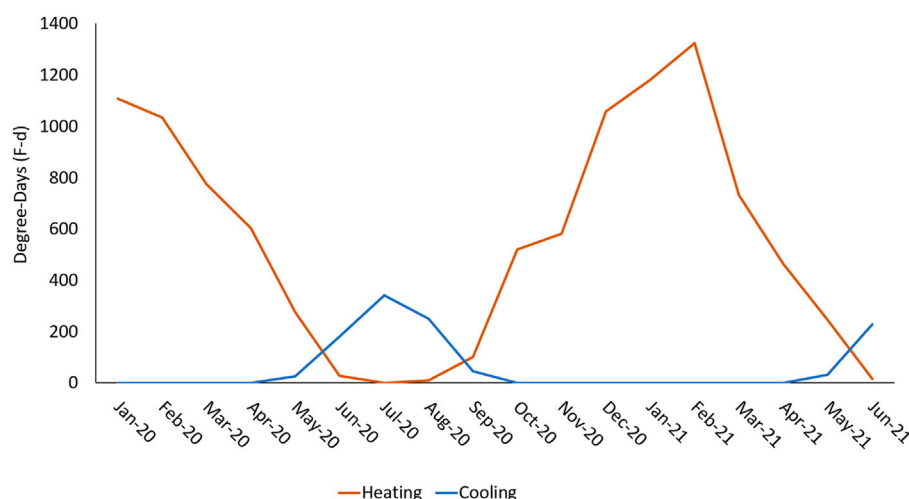


FIGURE 6

Monthly heating and cooling degree-days in Lake County, IL during the study period (NOAA, 2022).

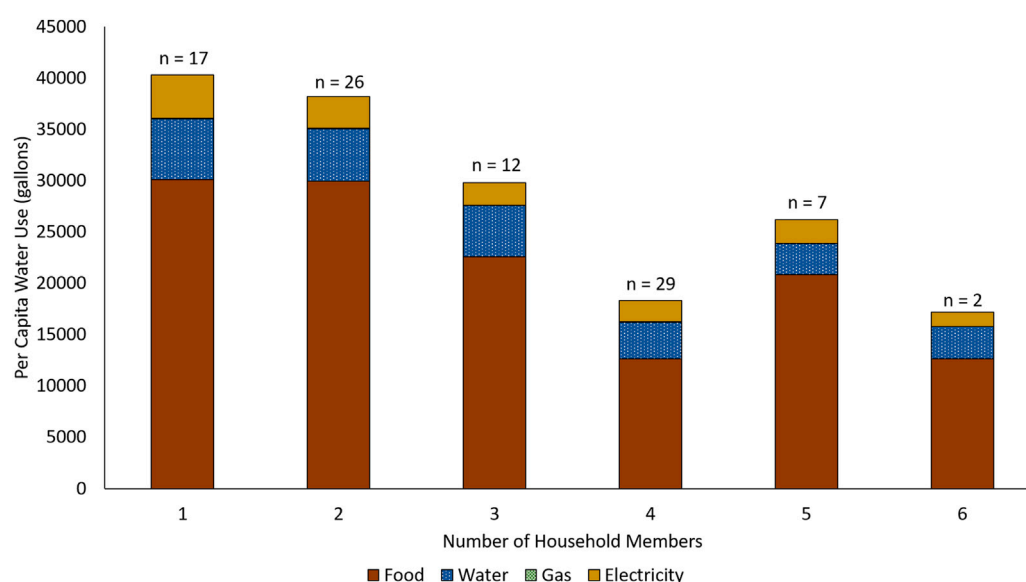


FIGURE 7

Average monthly total (direct + indirect) water use by FEW consumption category and household size in 2020.

4 Future work

While the analyses herein focus on the aggregated data for all participating households, future work will investigate how demographics, attitudes, and behaviors affect consumption patterns of individual households. The impacts of intervention messages, sent periodically by *HomeTracker* in the closing months of the study, will also be analyzed. The messages were both graphical and textual in form, reporting household consumption and the associated environmental impacts and comparing them to the norming values. Example textual messages are shown in Table 4. This feedback from *HomeTracker* can help identify targeted messages

that will inform households of their consumption patterns and identify mitigation strategies to reduce environmental loads.

There are also a number of methodological and data limitations in our study that could be addressed in future work. First, data collection and analysis focused on food, water, and energy consumption within the home and did not include transportation or other expenditures such as clothing, appliances, furniture, and other goods, as in other household metabolism studies (e.g., Frostell et al., 2015; Vita et al., 2021). This was mainly due to a desire to focus on the FEW nexus and limit the administrative burden placed on study participants. *HomeTracker* could be extended to account for other activities and household expenditures in the future using various life cycle inventory

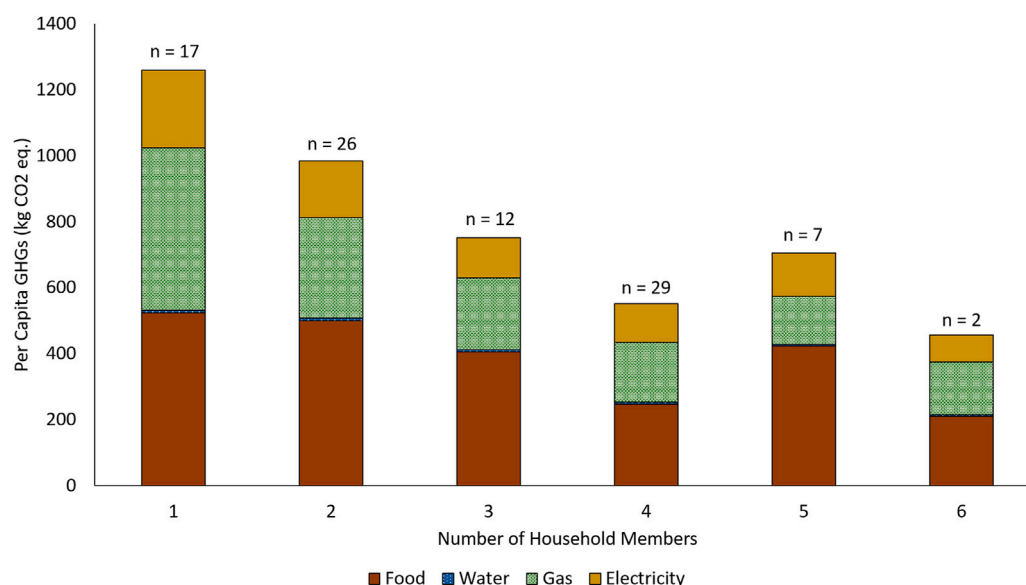


FIGURE 8

Average monthly greenhouse gas emissions by FEW consumption category and household size in 2020.

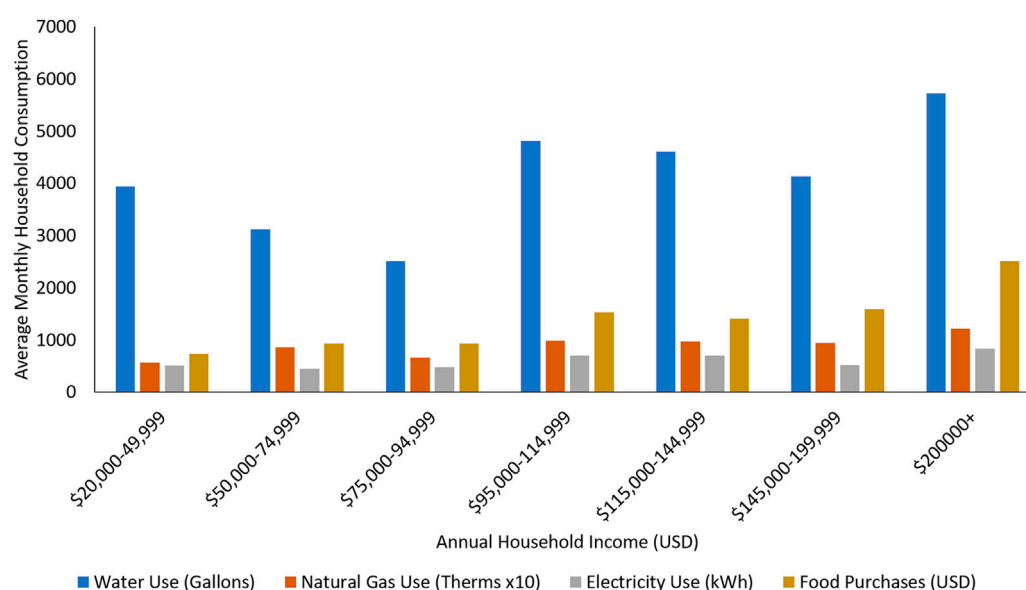


FIGURE 9

Direct FEW consumption (water use, natural gas use, electricity use, and food purchases) by household income range.

databases, including USEEIO, Ecoinvent, and the U.S. Life Cycle Inventory Database.

Second, USEEIO v1.1 (Yang et al., 2017a) has some important limitations for ecological footprint analysis. One limitation is that USEEIO considers only water withdrawals and consumptive use of withdrawals (i.e., blue water use) and does not account for rainwater used by crops (i.e., green water use). This can lead to an underestimation of the terrestrial and aquatic ecosystem impacts of food production, as well as an inability to compare results directly with those of other water footprint studies. Another limitation of USEEIO

v1.1 is that it is based on the value of commodities at the point of manufacture (producer's price) rather than at the point of sale (purchaser's price). Since distribution and retail margins may be considerable, this leads to a systematic overestimation of environmental impacts in our study based on food purchase data. While this may have some effect on household behavior changes (e.g., participants overestimate the relative impact of changing their diet compared to adjusting their thermostat), this is not expected to have a significant impact on observed household behavior since norming values were derived consistently. In future work, the most recent

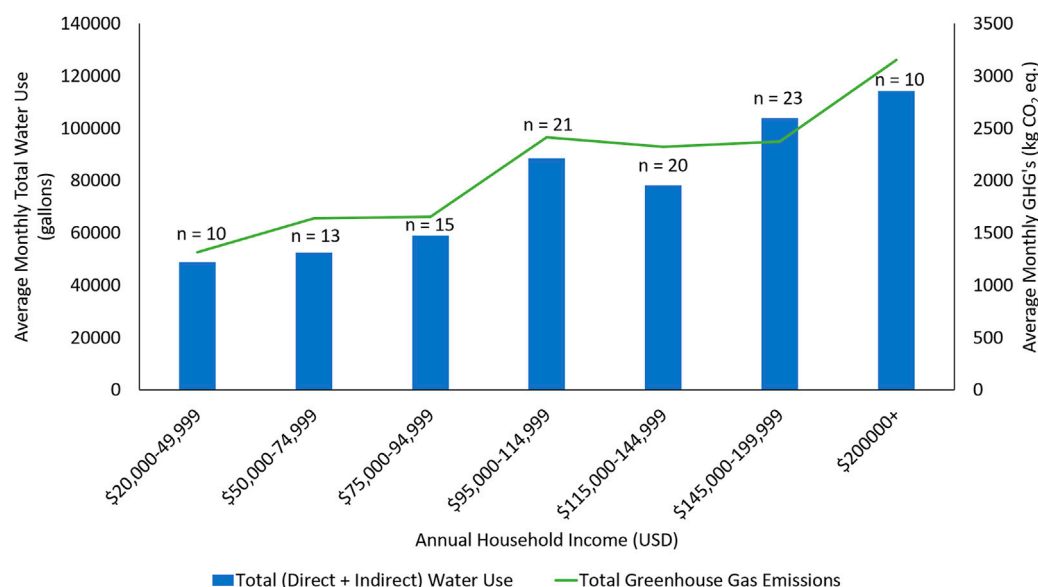


FIGURE 10

Total (direct and indirect) water use and total GHG emissions by household income range.

TABLE 4 Sample intervention message feedback to participants.

Message	Feedback
Message 1	Changing your old incandescent light bulbs to newer light emitting diodes (LEDs) can reduce your household GHG emissions from electricity use by 1,000 lb per year (5%) and reduce your household water footprint by over 16,000 gallons per year (2%).
Message 2	Switching your household to a renewable energy option at your electric utility could reduce your household GHG emissions by over 10,500 lb per year (43%) and reduce your household water footprint by over 230,000 gallons (27%).
Message 3	Lowering your thermostat by 5° in the winter can reduce your household GHG emissions by 740 lb per year (4%); and for homes with A/C, raising your thermostat by 5° in the summer can reduce your household GHG emissions by an additional 630 lb per year (3%).

version of USEEIO will be used, and USEEIO v.2 accounts for the value added per commodity between point of manufacture and point of sale (Ingwersen et al., 2022).

5 Conclusion

This paper explores how a life cycle assessment-based software application can facilitate collection and translation of household food, energy, and water consumption data to meaningful environmental impacts. Specifically, the *HomeTracker* software tool supports quantification of the environmental impact values for household consumption in a typical U.S. suburban area, allowing for examination of what consumers actually purchase and consume over an extended period of time. The *HomeTracker* was implemented in an intervention study with a data collection period running from February 2020 through June 2021. The study included three two-week food collection periods, continuous electricity monitoring, bi-monthly water data input, and monthly natural gas input. Households also received messaging and took surveys throughout the study. Across all households in the study, seasonal and weather-dependent trends in water, electricity, and natural gas use are apparent, as are significant trends in *per capita* food, energy, and

water consumption with household size and income. Impacts of the COVID-19 pandemic are not apparent in the aggregated data.

Future research using *HomeTracker* consumption and environmental impact data will investigate the specific attitudes and behaviors that affect consumption levels, as well as attempt to better understand consumption impacts of the COVID-19 pandemic, in individual households. Future work may also include expansion of the environmental impact factors to improve spatial and temporal resolution, in areas with sufficient data availability. It may also include expansion of the geographic coverage of environmental impact factors to allow users across the United States, or globe, to benefit from use of the *HomeTracker* without modifying the source code. In addition, as sensor and automation technology become more robust and affordable, *HomeTracker* can be modified to reduce the burden of data entry on users.

Ultimately, we think it is valuable to provide more detailed information to stakeholders, on both the consumption side and the production side of FEWS, regarding the direct and indirect consequences of our current FEWS system metabolism on multiple scales. On the consumption side, a more informed set of choices at the household scale might lead people to make different choices about the amount and type of FEWS services to consume in order to lower their household impacts. At a policy level, the results of this study could

inform policy analyses of environmental labeling and information schemes, as well as the setting of nationally determined contributions to emissions reduction targets. While it is hard to predict the ultimate effects household behavior change may have on the production of FEW services, the impacts could lead to, for instance, a shifting of power production to a different grid mix when baseload power needs are lower, postponement of energy and water infrastructure investments, as conservation offsets projected increases in demand; or a shift in the market share of comparable FEW products with markedly different environmental impacts, such as the rise in popularity of plant-based dairy and meat alternatives.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by the Institutional Review Board of Michigan Technological University. The patients/participants provided their written informed consent to participate in this study.

Author contributions

JD: Methodology, data generation, data curation, visualization, investigation, writing—original draft, writing—review and editing. CW: Conceptualization, methodology, software, data generation, writing—original draft, writing—review and editing. DW: Conceptualization, investigation, writing—review and editing, funding. RH: Methodology, data generation, visualization, writing—review and editing. YY: Methodology, data generation. DH: Methodology, data curation, writing—review and editing. SA: Data generation, data curation, investigation, writing—review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenvs.2023.1059301/full#supplementary-material>

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