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Comparing life cycle environmental impacts of food access and consumption pre- and during COVID 19 in New York State's Capital Region

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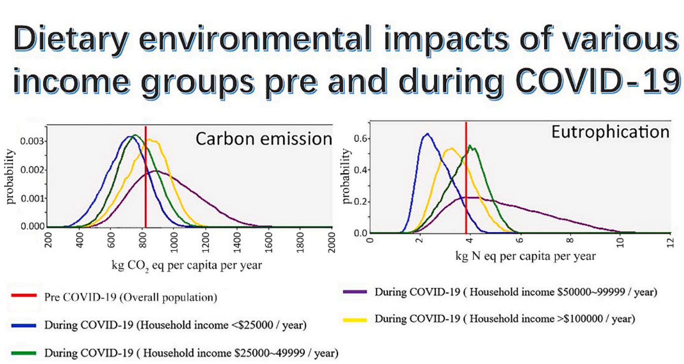
HIGHLIGHTS

- The life cycle global warming potential and cumulative energy demand, of dietary consumption, decreased during COVID-19
- The life cycle eutrophication of dietary consumption slightly increased during COVID-19
- The lowest-income group had the lowest dietary environmental impacts during COVID-19
- The second highest-income group had the highest dietary environmental impacts during COVID-19

GRAPHICAL ABSTRACT



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ABSTRACT

The COVID-19 pandemic has significantly influenced household food shopping, food consumption, and food waste generation. However, the dietary environmental impacts for different income groups during COVID-19 remain unknown. To analyze dietary environmental impacts for various income groups, a process-based life cycle assessment (LCA) was conducted based on two electronic food access surveys implemented in the New York State's Capital Region during the COVID-19 pandemic and public and proprietary databases. We found that life cycle global warming potential, cumulative energy demand, acidification potential, and water resource depletion of per capital food consumption in the studied area tended to be lower during COVID-19 than pre-COVID-19. In contrast, life cycle eutrophication during COVID-19 was slightly higher than pre-COVID-19. The environmental impacts occurring at the food production stage were higher than those at the local transportation and waste disposal stages. The lowest income group had the lowest dietary environmental impacts due to their lowest food

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consumption of all the food categories. The second-highest income group had the highest dietary environmental impacts, since they consumed the most red meat which has a high impact intensity. This is the first study to our knowledge to investigate the differences in dietary environmental impacts among income groups during COVID-19.

1. Introduction

Food production and consumption exert environmental pressure. Household food consumption accounts for about 1/3 of households' life cycle greenhouse gas emissions and energy use (Jungbluth et al., 2011). Food production accounts for 70 % of global freshwater withdrawals and 78 % of global ocean and freshwater eutrophication (FAO, 2011; Poore and Nemecek, 2018). Different food types have distinct environmental impacts (Jungbluth et al., 2011; Notarnicola et al., 2017). For example, meat (beef, pork, and poultry) and dairy products (cheese, milk and butter) have about 14–40 times higher greenhouse gas emissions than fruit and vegetable (Notarnicola et al., 2017; Ritchie and Roser, 2020). In addition, compared to other food categories, the production of red meat, dairy, and seafood exhibits higher impact intensity for acidification and eutrophication potential (Poore and Nemecek, 2018).

COVID-19 exacerbated food insecurity for many and changed food access and consumption behaviors, particularly during the early stage of COVID-19. Numerous studies found that food insecurity among households increased during COVID-19 compared to prior to COVID-19 (Adams et al., 2020; Chenarides et al., 2021; Kakaei et al., 2022; Niles et al., 2020). Meanwhile, COVID-19 has impacted food access and consumption for nearly one-third of Americans (Whetstone, 2021). Ben Hassen et al. (2022) found that people consumed more fruits and vegetables based on their questionnaire, and reduced food waste during COVID-19 due to not purchasing excessive food. Ammar et al. (2020) confirmed that people increased their consumption of unhealthy food, eating out of control, and snacking between meals due to eating out of anxiety or boredom. As of March to April 2020, household expenditures were found to be significantly reduced because of reduced frequencies of dining outside of the home, although the households increased online grocery shopping (Ellison et al., 2021). All of the above changes may lead to changes in dietary environmental impacts due to the difference in the emissions from food production and transportation.

Life cycle assessment (LCA) is a systematic approach for assessing the environmental effects of a product, process, or activity throughout its life cycle or lifetime (Roy et al., 2009). Numerous LCAs have been widely applied to assessing the environmental impacts of food production and consumption (Cucurachi et al., 2019; Roy et al., 2009; J. H. Schmidt et al., 2014). These LCA studies are valuable for quantifying the environmental impacts of food systems and can suggest effective strategies capable of reducing the negative environmental effects of food systems (Cucurachi et al., 2019; Roy et al., 2009; J. H. Schmidt et al., 2014). An LCA of food access and consumption during COVID-19 is essential in comprehending the environmental implications of food access and consumption during such crises.

To the best of our knowledge, there are only two LCA studies that have been conducted on food access and consumption during COVID-19 (Batlle-Bayer et al., 2020; Yao, 2022). Batlle-Bayer et al. (2020) reported a 30 %–36 % increase in diet-related global warming potential, blue water footprint, and land use in Spain between March and April 2020. In contrast, Yao (2022) observed reductions in food consumption-related impacts, including greenhouse gas emissions and energy use, at the U. S. national level in 2020.

While previous studies have made valuable contributions, there are still some limitations that need to be addressed. One such limitation is the dietary environmental impacts of New York State (NYS) during COVID-19 has not been studied yet. Due to the COVID-19 pandemic, NYS issued Executive Order No. 202 in March 2020 to declare a state disaster emergency for the entire state (State of New York, 2020). As NYS residents were among the most affected during the early spread of the pandemic, resulting in significant changes to their food provisioning and consumption behaviors (Babbitt et al., 2021), may subsequently lead to changes in dietary environmental impacts. Even if the early stage of COVID-19 is a short period, environmental impacts often have long-term consequences. For example, global warming is primarily associated with total cumulative carbon emission (Gillett, 2023; Matthews et al., 2012). Since NYS Capital Region has over 0.9 million population (United States Census Bureau, 2022a), the magnitude of total dietary environmental impacts can be very considerable. The New York Legislature passed the Climate Leadership and Community Protection Act in 2019, which aims for State-wide carbon neutrality by 2050 (Senate Bill S6599, 2019). Nevertheless, COVID-19 may greatly affect this progress due to limited resources for tackling environmental protection during the pandemic. However, no study has yet conducted an LCA on dietary environmental impacts during COVID-19 in the NYS Capital Region.

The other limitation of previous research is the lack of studies on the differences in dietary environmental impacts among income groups during COVID-19. New York State has implemented several policies aimed at enhancing nutritional access for its low-income residents (Billings, 2023; DiNapoli, 2023; Nestle, 2019), particularly given that 14.3 % of the population lives below the poverty line (United States Census Bureau, 2022b). Concurrently, the New York State Environmental Quality Review Act [SEQRA] (2018) requires all state and local government agencies to equally exam environmental impacts with social and economic considerations during discretionary decision-making. To support these policies, it is imperative to understand the dietary environmental impacts across different income groups. To the best of our knowledge, there are only three studies explored food access and consumption related environmental impacts for different income groups. Bozeman et al. (2019) investigated the impacts of food consumption across three demographic groups in the US by integrating socioeconomic status with pertinent LCA findings. Bozeman et al. (2019) discovered that the environmental impact/dollar spent on food for low-income households is greater than for high-income households. Jones and Kammen (2011) used consumption-based life cycle accounting techniques to measure the carbon footprints of typical US households across 12 income brackets. Differently, Jones and Kammen (2011) found that there were little differences in food-related carbon footprints between low- and high-income households. In addition, Rose et al. (2019) investigated the greenhouse gas emission from US adults' diet selections and found that when divided the demographics groups by income, they did not reveal significant differences in dietary greenhouse gas emission. Considering low-income groups are more likely to face to the challenges of food access (Flores and Amiri, 2019; United States Department of Agriculture, 2022a), COVID-19's effects on dietary environmental impacts among the NYS income groups can be different. Still, there is a knowledge gap as no LCA has been conducted for food access and consumption across income groups during the early stage of COVID-19 pandemic.

To address the aforementioned knowledge gaps, our goals are: (1) to estimate the dietary environmental impacts in NYS during COVID-19; (2) to identify the dietary environmental impacts among different income groups during COVID-19.

2. Methods

We performed a process-based LCA to compare the life cycle impacts of food consumption, transportation, and waste disposal during COVID-19 for different income groups. According to the International Organization for Standardization guidelines (Iso.org, 2010), the LCA framework includes 4 stages: (1) goal and scope definition, (2) life cycle inventory analysis, (3) life cycle impact assessment, and (4) life cycle interpretation. Each stage of the LCA study is described below.

2.1. Goal and scope definition

The scope of this LCA study considers food production, transportation for obtaining food, and food waste disposal, as shown in Fig. 1. The system boundary includes background processes and foreground processes. The background processes include food production, raw materials, energy, and infrastructure. The foreground processes include food consumption, food waste disposal, and associated transportation (i.e. transportation for obtaining food). Both background and foreground processes have environmental emissions to air, water, and soil compartments. The functional unit sets a reference for comparing the environmental impacts of food consumption pre- and during COVID-19, and for different income groups. In this study, we use yearly food consumption (kg) of 1 person as the functional unit (FU). This choice aligns seamlessly with the datasets ([dataset] USDA Economic Research Service, 2019) employed in our research, allows a straightforward comparison of food consumption patterns before and during COVID-19, and enables the dietary environmental impacts both before and during COVID-19. Furthermore, this functional unit effectively captures per capita dietary environmental impacts, thereby illustrating variations across individuals within different income levels.

In this study, we selected the 5-month period from October 2020 to February 2021 as the studied period, that was the early stage of COVID-19 when the food supply chains were disturbed (Vyas et al., 2021). The studied region is the 11-county Capital Region in NYS. The pre-COVID period is delineated as the calendar year 2019, chosen as it represents the most recent year preceding the onset of the COVID-19 pandemic. To the best of our knowledge, no data exists regarding the food consumption pattern of the NYS Capital region pre-COVID-19. However, Morrison et al. (2011) discovered only minor differences exist between the average food consumption estimates of regional and national datasets, and discrepancies between national and regional food consumption may arise when average ages of regional populations significantly differ from the national average. Given that the NYS Capital region has a similar median age (40.9 ± 0.4) to the U.S. (39 ± 0.1) (United States Census Bureau, 2022c, 2022a), we assume comparable per capita food consumption between the NYS Capital region and the U.S. nationwide pre-COVID-19. Hence, we opt to utilize food consumption data at the national level in 2019 as a benchmark for comparing food consumption in the NYS Capital region during COVID-19. This approach allows us to illustrate potential shifts in food consumption patterns amid the pandemic.

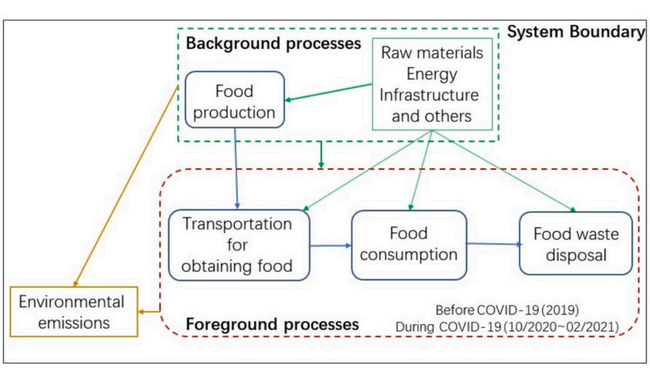

Fig. 1. System boundary for LCA of food production, transportation, and waste disposal pre- and during COVID-19. The system boundary includes both background and foreground processes.

2.2. Life cycle inventory (LCI) analysis

The foreground datasets are composed of three parts: (1) Transportation for obtaining food; (2) Food consumption, including food intake and the food finally be wasted; and (3) Disposal of wasted food. The data on individual-level food access and consumption during COVID-19 was obtained from two online self-administered food access surveys implemented in the NYS Capital Region. One of these two surveys, UAlbany COVID Food Access Survey, with a sample size of 595, was administered from October 10, 2020 to January 31, 2021 (Feingold et al., 2021). The other survey, UAlbany COVID Food Access Minority Health Disparities (MHD) Survey, with a sample size of 454, was performed from January 5 to February 7, 2021 (Feingold et al., 2021). The background datasets were obtained from the Ecoinvent v3.10 database and individual literature. Ecoinvent v3.10 is one of the largest and most comprehensive LCI databases based on ISO 14040 and 14044. This study incorporates additional literature values to augment the life cycle inventory of agricultural production. Table 1 summarized the data sources for the life cycle inventory.

2.2.1. LCI for transportation for obtaining food

To assess transportation for obtaining food pre-COVID-19, we utilize data on the changes in in-store grocery shopping frequency during COVID-19, the travel distances to local stores during COVID-19, and associated transportation modes. The local stores in the study include grocery stores, supermarkets, large bulk stores, convenience stores, corner stores, bodegas, ethnic markets, and specialty stores. The transportation modes include bus or public transportation, personal vehicle, ride from friend/family/neighbor, taxi or Lyft/Uber, walk or bike.

To calculate the travel distance (km/capita/year) to local stores pre-COVID-19 (S_p), we use the formula:

$$S_p = \frac{S_l}{1-p} \tag{1}$$

Within Eq. (1), p represents the reduction of in-store grocery shopping frequency during COVID-19 (%); S_l represents the travel distance (km) to local stores during COVID-19 (km/capita/year). To calculate the environmental releases of food shopping by each transportation mode pre-COVID-19 ($R_{t,p}$), we use the formula:

$$R_{t,p} = S_p \times T_p \times I_T \tag{2}$$

T_p is the intensity of a transportation mode usage (%) pre-COVID-19, and I_T is the life cycle impact intensity of a transportation mode usage. S_l, p, and T_p are gathered from the two food access surveys (Feingold et al., 2021). I_T is obtained from the Ecoinvent v3.10 database.

For assessing transportation for obtaining food during COVID-19, we use the travel distance to local stores and associated transportation modes. To calculate the environmental releases of food shopping by each transportation mode during COVID-19 ($R_{t,d}$), we use the formula:

$$R_{t,d} = S_l \times T_d \times I_T \tag{3}$$

Within Eq. (3), T_d is the intensity of a transportation mode used (%) during COVID-19 and gathered from the two food access surveys (Feingold et al., 2021).

2.2.2. LCI for production of food and food waste disposal

For food intake pre-COVID-19, we directly used food intake datasets from the USDA Food Availability (Per Capita) Data System, which reflect loss-adjusted food availability ([dataset] USDA Economic Research Service, 2019). The data collected by the USDA offer valuable insights into dietary trends by providing an independent measure of food supplies available for consumption in various outlets (United States Department of Agriculture, 2022b). The data provide good estimates of

Table 1
Data sources for LCI.

Parameters or processes		Data source	Reference
Background datasets (Life cycle impact intensities of food production, I_f)	Life cycle impact intensities of food production (if not specified)	Ecoinvent v3.10	Wernet et al. (2016)
	Life cycle impact intensities of pork production	Individual literature	Basset-Mens et al. (2007); Garcia-Launay et al. (2014)
	Life cycle impact intensities of lamb production	Individual literature	Geß et al. (2020)
	Life cycle impact intensities of fish production	Ecoinvent v3.10 and individual literature	Abdou et al. (2020); Wernet et al. (2016)
	Life cycle impact intensities of ice cream production	Individual literature	Konstantas et al. (2019)
	Life cycle impact intensities of hazelnut production	Individual literature	Sabzevari et al. (2015)
	Life cycle impact intensities of pistachios production	Individual literature	Bartzas & Komnitsas (2017)
	Life cycle impact intensities of milk	Ecoinvent v3.10 and individual literature	Baldini et al. (2017); Wernet et al. (2016)
	Life cycle impact intensities of beef production	Ecoinvent v3.10 and individual literature	de Vries et al. (2015); Poore and Nemecek (2018); Wernet et al. (2016)
Foreground datasets	Per capita food intake pre-COVID-19 in terms of kg/capita/year (M_p, M_v, M_m); vegetable or fruit intake rate (C_v) pre-COVID-19 in cups/capita/day, for conversion factors calculation	USDA Food Availability (Per Capita) Data System	[dataset] USDA Economic Research Service (2019)
	Per capita dairy, red meat, seafood, grain, and nut intake rate (T_m) in terms of times/day, for conversion factors calculation.	National Health and Nutrition Examination Survey (NHANES) Data Documentation	Centers for Disease Control and Prevention (CDC) (2005-2006, 2009-2010, 2017-2018)
	Per capita food intake rate during COVID-19 (M_d)	UAlbany COVID Food Access Survey and UAlbany COVID Food Access MHD Survey	Feingold et al. (2021)
	Per capita food waste pre-COVID-19 (W_h, N_p)	EPA 2018 Wasted Food Report, United State Census Bureau Quick Facts	U.S. Environmental Protection Agency (EPA) (2018)
	The percentages of people who reported wasting more food (r_m); the percentages of people who reported wasting less food (r_l); the percentage reduction (r) in food waste rate during COVID-19	UAlbany COVID Food Access Survey and UAlbany COVID Food Access MHD Survey individual literature	Feingold et al. (2021) Cosgrove et al. (2021)
	Life cycle intensity of landfilling (I_w)	Ecoinvent v3.10	Wernet et al. (2016)
	The reduction of in-store grocery shopping frequency during COVID-19 (p), the food shopping kilometers to local stores during COVID-19 (S_l), the intensity of transportation modes used pre- (T_p) and during COVID-19 (T_d)	UAlbany COVID Food Access Survey and UAlbany COVID Food Access MHD Survey	Feingold et al. (2021)
	Life cycle impact intensity of a transportation mode usage (I_t)	Ecoinvent v3.10	Wernet et al. (2016)

per capita availability of basic commodities and allow for testing hypotheses on the impact of government and general sources of diet and health information on consumer food choices (United States Department of Agriculture, 2022b). Based on the USDA data and our food access surveys, we included the following food categories: vegetable, fruit, dairy, red meat, seafood, grains, and nuts. The unit of food intake of each food category (M_p) pre-COVID-19 is kg/capita/year. The specific food species included in each category are listed in Table S1.

To estimate food intake during COVID-19, we use reported food intake rates from two food access surveys (Feingold et al., 2021). In these surveys, vegetable and fruit intake rates were measured in cups/capita/day, while all the other food categories were measured in times/capita/day. To facilitate comparison with fruit or vegetable intake in pre-COVID-19, we convert intake rates of each food categories to kg/capita/year (M_y) using the following eq:

$$M_y = M_d \times f \tag{4}$$

Within Eq. (4), M_d is food intake rate in terms of cups/capita/day or times/capita/day. M_d is obtained from the two food access surveys (Feingold et al., 2021). f is the conversion factor. The conversion factors for each food category are calculated individually. For example, the conversion factor (f_v) to convert vegetable intake rates from cups/capita/day to kg/capita/year is calculated as:

$$f_v = \frac{M_v}{C_v} \tag{5}$$

Within Eq. (5), M_v is the vegetable intake rate in kg/capita/year, and C_v is the vegetable intake rate in cups/capita/day. Both M_v and C_v are retrieved from the USDA Food Availability (Per Capita) Data System ([dataset] USDA Economic Research Service, 2019). Similarly, we calculate the conversion factor for fruit. For another example, the conversion factor (f_m) to convert the red meat intake rate from times/capita/day to kg/capita/year is calculated as:

$$f_m = \frac{M_m}{T_m} \tag{6}$$

Within Eq. (6), M_m represents the red meat intake rate in terms of kg/capita/year, and T_m represents the red meat intake rate in terms of times/capita/day. We obtained M_m from the USDA Food Availability (Per Capita) Data System ([dataset] USDA Economic Research Service, 2019) and T_m from the National Health and Nutrition Examination Survey (NHANES) Data Documentation (Centers for Disease Control and Prevention (CDC), 2006, 2010, 2018). NHANES stands as a distinctive program aimed at evaluating the health and nutritional conditions of adults and children across the United States, blending interviews with physical examinations (Centers for Disease Control and Prevention, 2023). This survey scrutinizes a nationally representative sample of approximately 5000 individuals each year (Centers for Disease Control and Prevention, 2023). We apply the same method to calculate the conversion factors for dairy, seafood, grain, and nut intake rates from times/capita/day to kg/capita/year. All the conversion factors are listed in Table S2(A) and (B).

To estimate food waste amount (ΣW_p, kg/capita/year) during pre-COVID-19, we use the formula:

$$\sum W_p = \frac{W_h}{N_p} \tag{7}$$

With Eq. (7), W_h represents household food waste (153.3 kg/household/year) obtained from the Environmental Protection Agency (EPA) 2018 Wasted Food Report (United States Environmental Protection Agency, 2018). N_p represents the number of persons per household (2.60 persons/household), obtained from the United State Census Bureau (United States Census Bureau, 2022d). In the NYS Capital Region, the primary waste treatment method is landfill (III Winners Circle, 2014). The environmental releases of landfilling food waste pre-COVID-19 ($R_{w,p}$) are calculated as:

$$R_{w,p} = \Sigma W_p \times I_w \tag{8}$$

Within Eq. (8), I_w represents the life cycle impact intensity of landfilling, obtained from the Ecoinvent v3.10 database. The food waste rate pre-COVID-19 (r_p) can be calculated as:

$$r_p = \frac{\Sigma W_p}{\Sigma W_p + \Sigma M_p} \tag{9}$$

Within Eq. (9), ΣM_p represents the total intake of all the food categories pre-COVID-19 (kg/capita/year).

For assessing food waste rate during COVID-19, we retrieve the percentages of people who reported wasting more food (r_m) and the percentages of people who reported wasting less food (r_l) from the two food access surveys (Feingold et al., 2021). We denote the percentage reduction (r) in food waste rate as a variable depending on the difference between r_l and r_m, and the ration is x:

$$r = x \times (r_l - r_m) \tag{10}$$

According to Cosgrove et al. (2021)'s study, when $r_l = 50.8\ \%$ and $r_m = 26.5\ \%$, the median percent of household food waste was cut in half ($r = 50\ \%$). We then estimate $x = \frac{50\%}{50.8\% - 26.5\%} = 2.06$, thus,

$$r = 2.06 \times (r_l - r_m) \tag{11}$$

Using this information, we calculate the food waste rate during COVID-19 (r_d) as:

$$r_d = r_p \times (1 - r), \tag{12}$$

or:

$$r_d = \frac{\Sigma W_d}{\Sigma W_d + \Sigma M_y} \tag{13}$$

Within Eq. (13), ΣM_y represents the total intake of all the food categories during COVID-19 (kg/capita/year).

And then the food waste amount (ΣW_d, kg/capita/year) during COVID-19 can be calculated from Eq. (13) as:

$$\Sigma W_d = \frac{\Sigma M_y \times r_d}{1 - r_d} \tag{14}$$

The environmental releases of landfilling food waste during COVID-19 ($R_{w,d}$) are calculated as:

$$R_{w,d} = \Sigma W_d \times I_w \tag{15}$$

For pre-COVID-19, we assume that the waste rate of each category (W_p, kg/capita/year) is proportional to its eaten amount, and then it can be calculated as:

$$W_p = \frac{M_p \times r_p}{1 - r_p} \tag{16}$$

The environmental releases of production for each food category ($R_{f,p}$) pre-COVID-19 is calculated as:

$$R_{f,p} = (M_p + W_p) \times I_f \tag{17}$$

Within Eq. (17), I_f is the median value of the life cycle impact intensity for producing the food category. The life cycle impact intensity for each food species within that food category was obtained from Ecoinvent v3.10 and individual literature.

Similarly, for during COVID-19, the food waste amount of each category (W_d, kg/capita/year) is calculated as:

$$W_d = \frac{M_d \times r_d}{1 - r_d} \tag{18}$$

The environmental releases of production for each food category ($R_{f,d}$) during COVID-19 in the is calculated as:

$$R_{f,d} = (M_y + W_d) \times I_f \tag{19}$$

The total dietary environment releases pre-COVID-19 (R_p), in terms of per capita per year, is calculated as:

$$R_p = \Sigma R_{f,p} + \Sigma R_{t,p} + R_{w,p} \tag{20}$$

Within Eq. (20), $\Sigma R_{f,p}$ signifies the combined environmental emissions resulting from the production of all food categories pre-COVID-19; while$\Sigma R_{t,p}$ denotes the cumulative environmental emissions associated with all transportation modes for food shopping pre-COVID-19.

The total dietary environment releases during COVID-19 (R_d), in terms of per capita per year, is calculated as:

$$R_d = \Sigma R_{f,d} + \Sigma R_{t,d} + R_{w,d} \tag{21}$$

Within Eq. (21), $\Sigma R_{f,d}$ represents the cumulative environmental releases from the production of all the food categories during COVID-19; $\Sigma R_{t,d}$ represents the cumulative environmental releases of all the transportation modes for food shopping during COVID-19.

2.3. Life cycle impact analysis

The life cycle impacts are determined based on the summation of the life cycle emission inventories multiplied by corresponding characterization factors (CF) for each life cycle impact category (Lee et al., 2020; Romeiko et al., 2020). CFs for the global warming potentials (GWP) for a time frame of 20 years were provided by the Intergovernmental Panel on Climate Change (IPCC 2021) (Masson-Delmotte et al., 2021). GWPs offer a standardized unit of measurement, enabling analysts to aggregate emissions estimates across various gases (e.g., for compiling a national GHG inventory). This standardization also facilitates policymakers in comparing opportunities for emissions reduction across different sectors and gases (United States Environmental Protection Agency, 2023). The unit for dietary GWP is kg CO_2 eq per capita per year. CFs of the cumulative energy demand (CED) are quantified by the CED impact assessment method (Frischknecht et al., 2015). The CED of a product represents direct and indirect energy use throughout the complete life cycle (Huijbregts et al., 2006). CED has been one of the key indicators being addressed since the very first LCA studies (Frischknecht et al., 2015). The unit for dietary CED is MJ per capita per year. CFs of the acidification potential (AP) and eutrophication potential (EP) are supplied by the Tool for the Reduction and Assessment of Chemical and other environmental Impacts (TRACI 2.1) (Bare, 2014). TRACI, developed by the EPA, is capable of estimating CFs in North America. AP is connected to acid deposition of acidifying contaminants on soil, groundwater, surface waters, biological organisms, and ecosystems (Dincer and Bicer, 2018). The unit for dietary AP is mole of H^+ eq per capita per year. Eutrophication signifies the accumulation of surplus nutrients, like nitrogen and phosphorus, in a water body. This accumulation may foster excessive plant growth, such as harmful algal blooms, leading to a depletion of dissolved oxygen, and occasionally, the generation of cyanotoxins (Niblick et al., 2018). The unit for dietary EP is kg N eq per capita per year. The water resource depletion was quantified by the International Reference Life Cycle Data System (ILCD 2.0 2018 midpoint) (Sala et al., 2012). The water footprint is an environmental indicator that measures the volume of fresh water used throughout the entire production chain of a consumer item or service, as suggested by the Water Footprint Network and the recent ISO14046 (Vanham and Bidoglio, 2013). The unit for dietary water resource depletion is m^3 water per capita per year. Previous literature have utilized the same assessment methods to derive CFs for GWP, CED, AP, EP, and water resource depletion (Egilmez and Park, 2015; Grabarczyk and Grabarczyk, 2022; Lee et al., 2020; McAuliffe et al., 2023; Romeiko, 2019; Romeiko et al., 2020; Xue and Landis, 2010). Table 2 outlines the tools for calculating the life cycle impacts and corresponding impacts.

2.4. Life cycle impact interpretation

2.4.1. Stage contribution

The environmental impacts of each stage (food production, transportation for obtaining food, food waste disposal) are identified to determine the stage contribution. The results are summarized in Sections 3.1 and 3.2.

2.4.2. Differences among income groups

The differences in environmental impacts among income groups are compared. The population is divided into 4 income groups by their annual household income: (1) Lowest income group: annual household income less than \$25,000; (2) Second-lowest income group: annual household income from \$25,000 to \$49,999; (3) Second-highest income group: annual household income from \$50,000 to \$99,999; (4) Highest income group: annual household income is \$100,000 or more. The delineation of these income categories is based on a twofold criterion. Firstly, it ensures that no category is disproportionately small or large, maintaining a balanced distribution. Secondly, it approximates the federal poverty guidelines, with the lowest income category (less than \$25,000) closely aligning with the 2023 federal poverty line (Office of the Assistant Secretary for Planning and Evaluation, 2023) for a household of three (\$24,860). Notably, households in the second-highest income group (\$50,000 - \$99,999) are unlikely to fall below the poverty line, except in cases where the household size is 8 or more, a highly improbable scenario within the survey sample (Feingold et al., 2021).

2.4.3. Variability of dietary environmental impacts of different income groups

Based on the results of food access surveys, the food choices and consumption vary at individual level (Table S3), consequently may lead to various dietary environmental impacts. To assess the variability of dietary environmental impacts caused by various food consumption, Monte Carlo (MC) simulation is applied to this study. MC simulation is a type of simulation that relies on repeated random sampling and statistical analysis to compute the variability of results (Romeiko, 2019). MC simulation is performed on the environmental impacts of each income group and stages of food production and transportation for obtaining food. The tested input food intake parameters include intake of vegetables, fruits, red meat, seafood, dairy, nuts, and grains (Table S8). The tested input transportation parameters include the total travel distances of food shopping by each transportation mode (Table S9). As showing in Figs. S1 and S2, the food intake and transportation parameters fit triangular distributions. The sampling approach is Latin hypercube sampling (LHS), which is a type of stratified MC that divides the range of each component for partition sampling region into a specific manner (Atangana, 2018). The iterations are set to 100,000 to ensure enough confidence.

Table 2
Life cycle impact assessment in this study.

Impact category	Methodology	Unit	Reference
GWP	IPCC2021	kg CO_2-eq/kg	Masson-Delmotte et al. (2021)
CED	Cumulative energy demand	MJ/kg	Frischknecht et al. (2015)
Acidification	TRACI 2.1	Moles of H^+-eq/kg	Bare (2014)
Eutrophication	TRACI 2.1	kg N-eq/kg	Bare (2014)
Water resource depletion	ILCD 2.02018 midpoint	m^3 water/kg	Sala et al. (2012)

2.4.4. Sensitivity analysis

The sensitivity analysis aims to elucidate the relative impacts of input parameters on overall environmental outcomes, shedding light on data uncertainty and guiding future data collection efforts. By employing the one-at-a-time technique for sensitivity assessment (Romeiko, 2019), each parameter was individually perturbed while keeping others constant. This method facilitates the calculation of sensitivity ranges for individual parameters, providing insights into their influence on life cycle impact results. The tested input parameters encompassed per capita intake rates for each food category, totaling seven parameters for each environmental impact category. The sensitivity analysis is carried out the with a $\pm$ 10 % change (Kim et al., 2020) of food intake rates derived from the UAlbany COVID Food Access Survey and the UAlbany COVID Food Access MHD Survey. The specific parameters subjected to sensitivity analysis are detailed in Table S4.

3. Results

3.1. Comparing of total dietary environmental impacts during COVID-19 to pre-COVID-19

Total dietary environmental impacts during the early COVID-19 period (October 2020-February 2021) were significantly lower than pre-COVID-19 (calendar year 2019) for GWP, CED, and AP categories. In comparison, the median value of the total dietary GWP, CED, and AP (in terms of per capita per year) during COVID-19 was respectively 10 % (79.2 kg CO_2 eq.), 20 % (1713.6 MJ eq.), and 25 % (60 mol of H^+ eq.) lower than pre-COVID-19 (Fig. 2A, B, C). The lower consumption of red meat, dairy, and grain, and lower personal vehicle usage for food shopping during COVID-19 caused these differences. Specifically, the median consumption of red meat, dairy, and grains were respectively 43 %, 6 %, and 13 % lower than pre-COVID-19. In terms of transportation, personal vehicle usage during COVID-19 was also 38 % lower than pre-COVID-19 (Table S5). Before the pandemic, the production of red meat and dairy were major contributors (16–44 %) to total dietary GWP, CED, and AP. In addition, personal vehicle usage for food shopping also significantly contributed (15–19 %) to dietary GWP and CED. Grain production contributed 22 % to total dietary CED. This shows the smaller food production and transportation-related emissions resulted in lower total dietary GWP, CED, and AP during COVID-19.

The median value of total water resource depletion during COVID-19 was 6 % lower compared to pre-COVID-19 (Fig. 2E). The main contributors to total dietary water resource depletion pre-COVID-19 were the production of grains (29 %), fruit (24 %), vegetables (17 %), and dairy (14 %). Although median consumption of fruit was 31 % higher than pre-COVID-19, consumption of grain, vegetables, and dairy was lower during COVID-19. The decrease in water resource depletion associated with grains, dairy, and vegetables consumption during

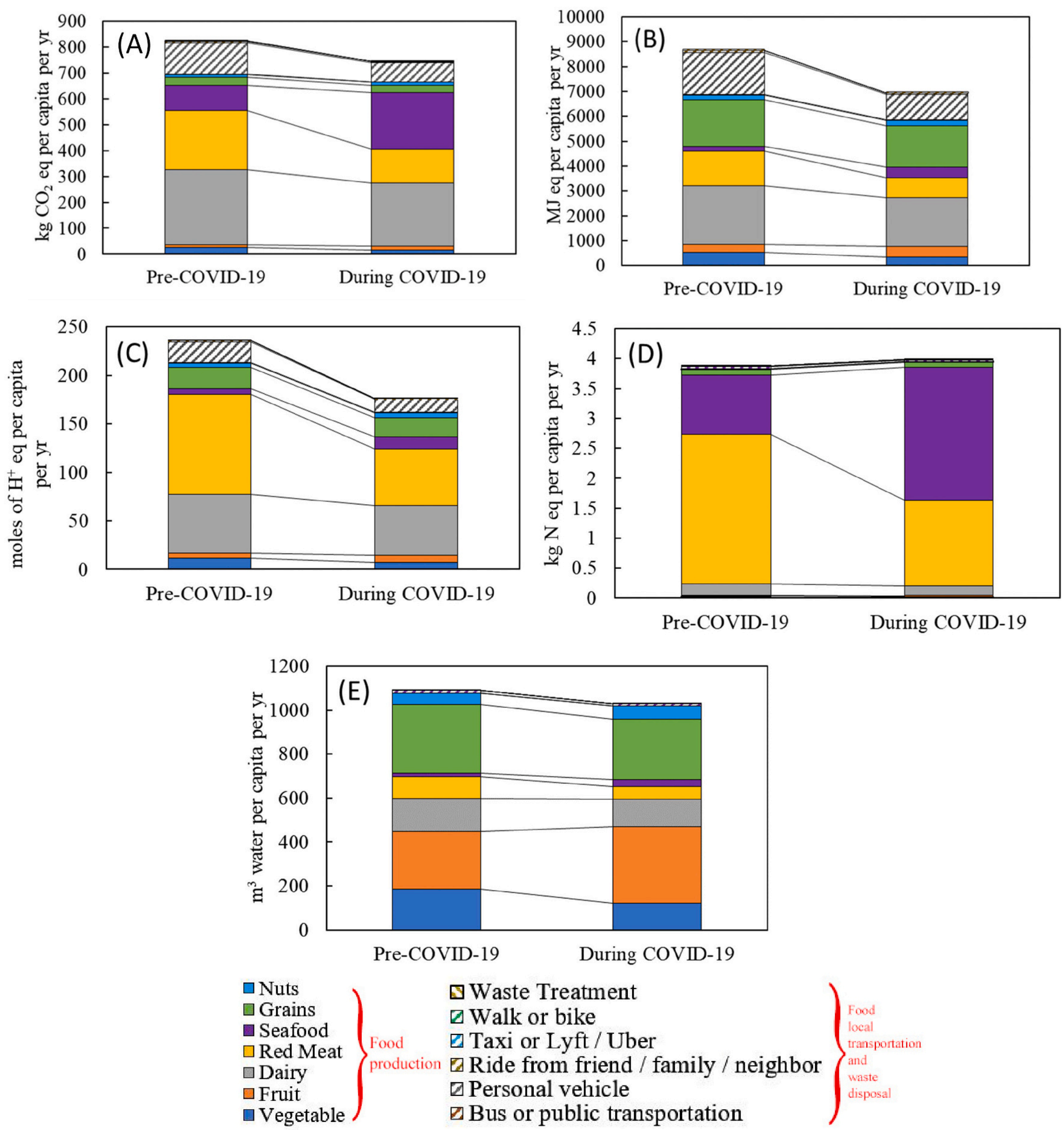

Fig. 2. The median values of total dietary (A) GWP, (B) CED, (C) AP, (D) EP, and (E) water resource depletion pre-COVID-19 and during COVID-19. The time frame for pre-COVID-19 was the calendar year of 2019, and the time frame for during COVID-19 was from October 2020 to February 2021. Food production-related impacts are represented by solid colors. Food local transportation and waste disposal related impacts are represented by slashes.

COVID-19 outweighed the increase in fruit-related depletion, resulting in a net decrease in total dietary water resource depletion.

The median value of total dietary EP during COVID-19 is only 3 % higher than pre-COVID-19 (Fig. 2D), mainly due to the higher seafood consumption and lower red meat consumption. The median consumption amount of seafood during COVID-19 was 126 % higher compared to pre-COVID-19. The main contributor to the total dietary EP pre-COVID-19 was the production of red meat (65 %) and seafood (25 %). The higher seafood-related EP during COVID-19 offset the lower red meat-related EP, thus making the median value of overall dietary EP fairly comparable to pre-COVID-19.

3.2. Comparing of dietary environmental impacts among stages during COVID-19

Food production is the dominating stage for all life cycle environmental impact categories. Specifically, the median value of GWP, CED, AP, EP, and water resource depletion occurring at the food production stage respectively contributed 84 %, 79 %, 90 %, 99 %, and 99 % of the median value of total impacts (Fig. 2). This trend is a result of higher environmental impacts from food production stage compared to of the transportation and waste disposal stages.

The magnitudes of environmental impacts from food production stage during COVID-19 differ from pre-COVID-19. For example, the median values of GWP, CED, AP, and water resource depletion occurring at the food production stage were respectively 4 %, 15 %, 24 %, and 5 % lower than pre-COVID-19. The median value of EP occurring at the food production stage was 3 % higher than pre-COVID-19. The differences in food production related impacts between pre- and during COVID-19 were mainly caused by the differences in food consumption discussed in Section 3.1.

The median values of local transportation and food waste disposal related GWP, CED, AP, EP and water resource depletion impacts were all 39 % lower than pre-COVID-19. The reduction of personal vehicle usage-related impacts during COVID-19 resulted in the overall reduction of food local transportation impacts during COVID-19.

The median values of GWP, CED, AP, EP, and water resource depletion impacts associated with food waste disposal were 61 % lower than pre-COVID-19. The median reduction magnitudes were 0.21 kg CO_2 eq per capita per year, 0.02 MJ per capita per year, 4.4×10^{-5} mol of H^+eq per capita per year, 1.5×10^{-10} kg N eq per capita per year, and 6.2×10^{-14} m^3 water per capita per year for GWP, CED, AP, EP, and water resource depletion, respectively. This reduction of life cycle impacts were caused by the 61 % reduction of food waste. However, food waste disposal had only minimal contribution (<0.01 %) to total dietary environmental impacts.

3.3. *Comparing of dietary life cycle impacts during COVID-19 among income groups*

The most likely values, which have the highest probability densities, of total dietary GWP, CED, AP, EP, and water resource depletion for each income group are listed in Table S6. Those values are all significantly different (z score > 3) across income groups during COVID-19 (Fig. 3). Those differences were mainly caused by the differences in food intake and waste among income groups.

The lowest income group showed the smallest total dietary impacts for GWP, CED, AP, EP, and water resource depletion categories. The lowest income group had the lowest food intake for the majority of food categories, including vegetables, fruits, red meat, seafood, grains, and nuts. Differently, the dairy intake of the lowest income group was comparable to the highest income group, and even higher than the second lowest and second highest income groups (Table S8). Additionally, it was noticed that the lowest income group also had the least amount of food waste (refer to Section 3.5). Overall, the lowest income group presented the lowest dietary environmental footprints, mainly due to their lowest intake amount of red meat, seafood, grains, and vegetable, which with high environmental densities, and their lowest amount of food waste.

The second-lowest income group ranked as the second lowest for the dietary GWP, CED, AP, and water resource depletion impacts. This is mainly attributed to their lower intake amount of vegetables, dairy, and red meat compared to the second-highest and highest income group. Furthermore, this group had the second-lowest food waste (refer to Section 3.5). The combination of relatively small amounts of food intake and waste led to that the second-lowest income group had the second-smallest food production-related GWP, CED, AP, and water resource depletion impacts. However, the second-lowest income group had the second highest most likely value of total dietary EP among all income groups due to their highest seafood intake rate among all the income

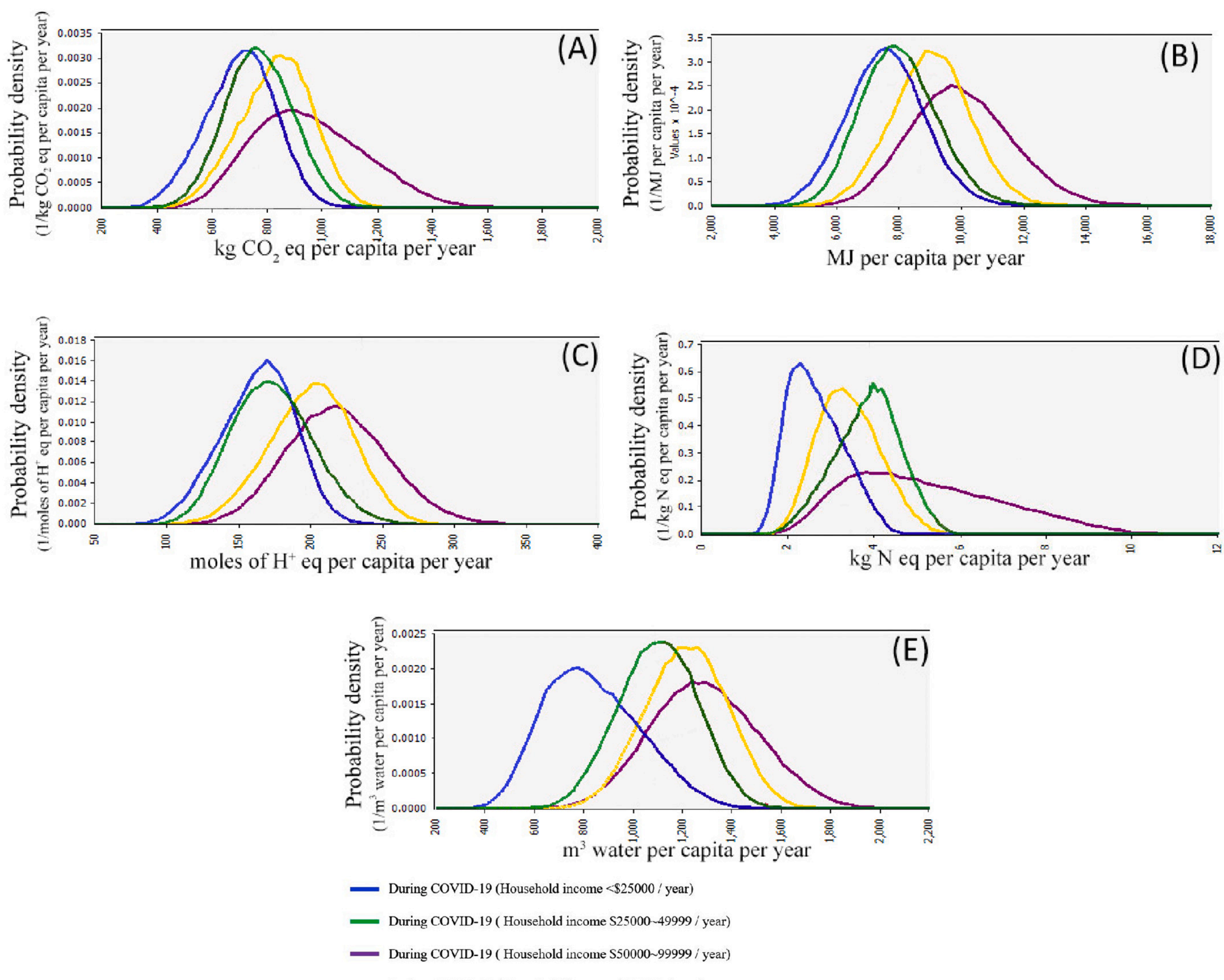

Fig. 3. Distributions of total dietary (A) GWP, (B) CED, (C) AP, (D) EP, and (E) water resource depletion during COVID-19 by income groups. The time frame for during COVID-19 was from October 2020 to February 2021.

groups. As seafood was the top contributor (56 %) to total dietary EP during COVID-19 (Fig. 2D), its production substantially contributed to the total dietary EP of the second-lowest income group.

The second-highest income group demonstrated the highest most likely values of total dietary GWP, CED, AP, EP, and water resource depletion among all income groups. This is primarily due to their high intake of red meat (Table S8). Their intake amount of other food categories was comparable to either the second-lowest or highest-income group. As previously discussed in Section 3.1, red meat production was one of the most important contributors to total dietary emissions. Furthermore, the second-highest income group reported the highest food waste compared to all other income groups (refer to Section 3.5). The combination of high red meat intake amount and food waste resulted in the second-highest income group having the highest food production-related dietary GWP, CED, AP, EP, and water resource depletion. In summary, the second-highest income group's dietary environmental impacts are driven by their highest red meat consumption as well as the highest food waste.

The highest income group ranked as the second highest group for the majority of impact categories. The group's intake amount of most food categories was the second highest, with nuts being the highest consumed (Table S8). However, nut production did not contribute significantly to total dietary emissions. The highest income group also had the second highest amount of food waste (see Section 3.5). Consequently, the group's food production-related emissions were responsible for their second-highest ranking in total dietary GWP, CED, AP, and water resource depletion among all income groups. The highest income group ranked as the third highest group in total dietary EP. The total dietary EP of the highest income group was surpassed by the second-lowest and second-highest income groups. The second-lowest income group had the highest consumption of seafood. Meanwhile, the second-highest income group had the highest consumption of red meat. Production of seafood and red meat are the top two contributors to total dietary EP either pre- or during COVID-19. The highest income group ranked the second highest for all environmental impact categories except eutrophication.

3.4. Comparing of food production stage's impacts during COVID-19 among income groups

The ranking of income groups for food production's impacts was consistent with the ranking of income groups for total impacts (Fig. 4). For example, the order of the income groups from the lowest to the highest impacts for GWP, CED, AP, and water resource depletion categories was the lowest income group, the second-lowest income group, the highest income group, the second-highest income group (see values in Table S7). Differently, the order of the income group from the lowest

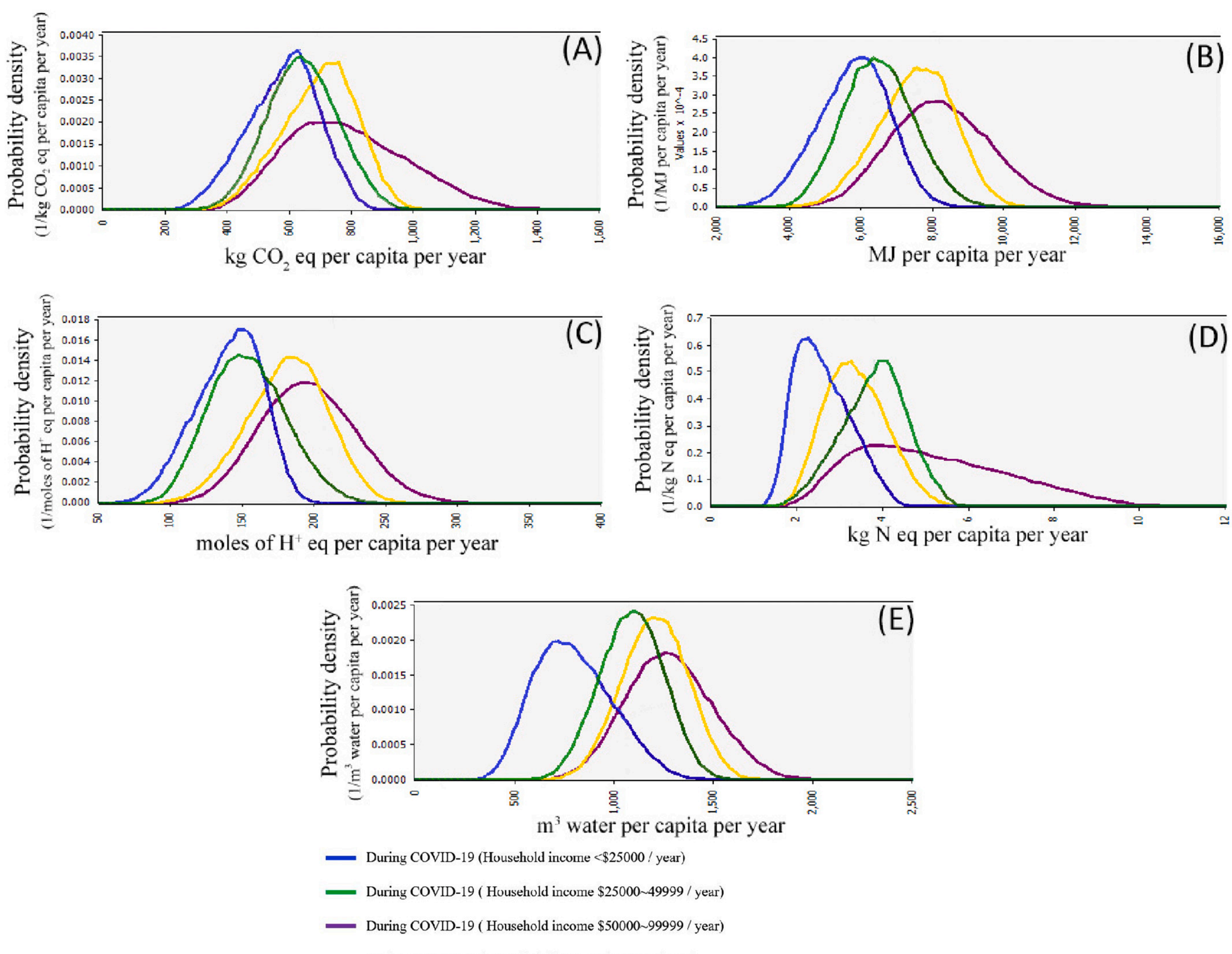

Fig. 4. Distributions of food production stage's (A) GWP, (B) CED, (C) AP, (D) EP, and (E) water resource depletion during COVID-19 by income groups. The time frame for during COVID-19 was from October 2020 to February 2021.

to the highest impacts for EP was the lowest income group, the highest-income group the second-lowest income group, and the second-highest income group. Food production was the most important contributing stage to the total dietary environmental impacts.

3.5. Comparing of waste disposal stage's impacts during COVID-19 among income groups

The second-highest income group had the highest estimated median values of food waste disposal GWP, CED, AP, EP, and water resource depletion, which were 2 % higher than the highest income group and 77 % ~ higher than the second-lowest and lowest income group (Fig. 5). The second-highest income group exhibited the highest estimated food waste median value (25.7 kg per capita per year), closely followed by the highest income group (25.1 kg per capita per year), while the second lowest and lowest income groups had estimated food waste amounts of ≤14.5 kg per capita per year. Higher income groups may lead to more household food waste since they face less constrained budgets and less efficient management of food purchases and allocations (Yu and Jaenicke, 2020). Higher food waste amounts made higher income groups have higher estimated food waste disposal impacts than lower income groups.

3.6. Sensitivity analysis

The life cycle impacts were sensitive to the varying ranges of input parameters for all environmental impact categories (Fig. S3). For total dietary GWP after COVID-19, per capita intake rates of dairy, seafood, and red meat emerged as the top three influential factors. The total dietary GWP varied by up to ±3.0 % when per capita diary intake rates varied ±10 %, or exhibited a variation of ±2.7 % in response to a ±10 % change in per capita seafood consumption rates. When per capita red meat intake rates varied ±10 %, the total dietary GWP fluctuated by ±1.6 %. The changes of GWP were within 0.3 %, when other input parameters, including per capita intake rates of grains, fruit, vegetables, and nuts varied ±10 %.

For total dietary CED after COVID-19, the per capita intake rate of diary was the most influential factor. A variation of ±2.6 % in total dietary CED was observed when per capita dairy intake rates varied ±10 %. Following dairy, per capita intake rates of grains also significantly influenced total dietary CED. Total dietary CED varied by ±2.2 % when intake rates of grains varied ±10 %. The total dietary CED showed variations of ±1.0 % when per capita red meat intake rates varied by ±10 %. The changes of total dietary CED were <0.6 %, when per capita intake rates of seafood, fruit, vegetables, and nuts, varied by ±10 %s.

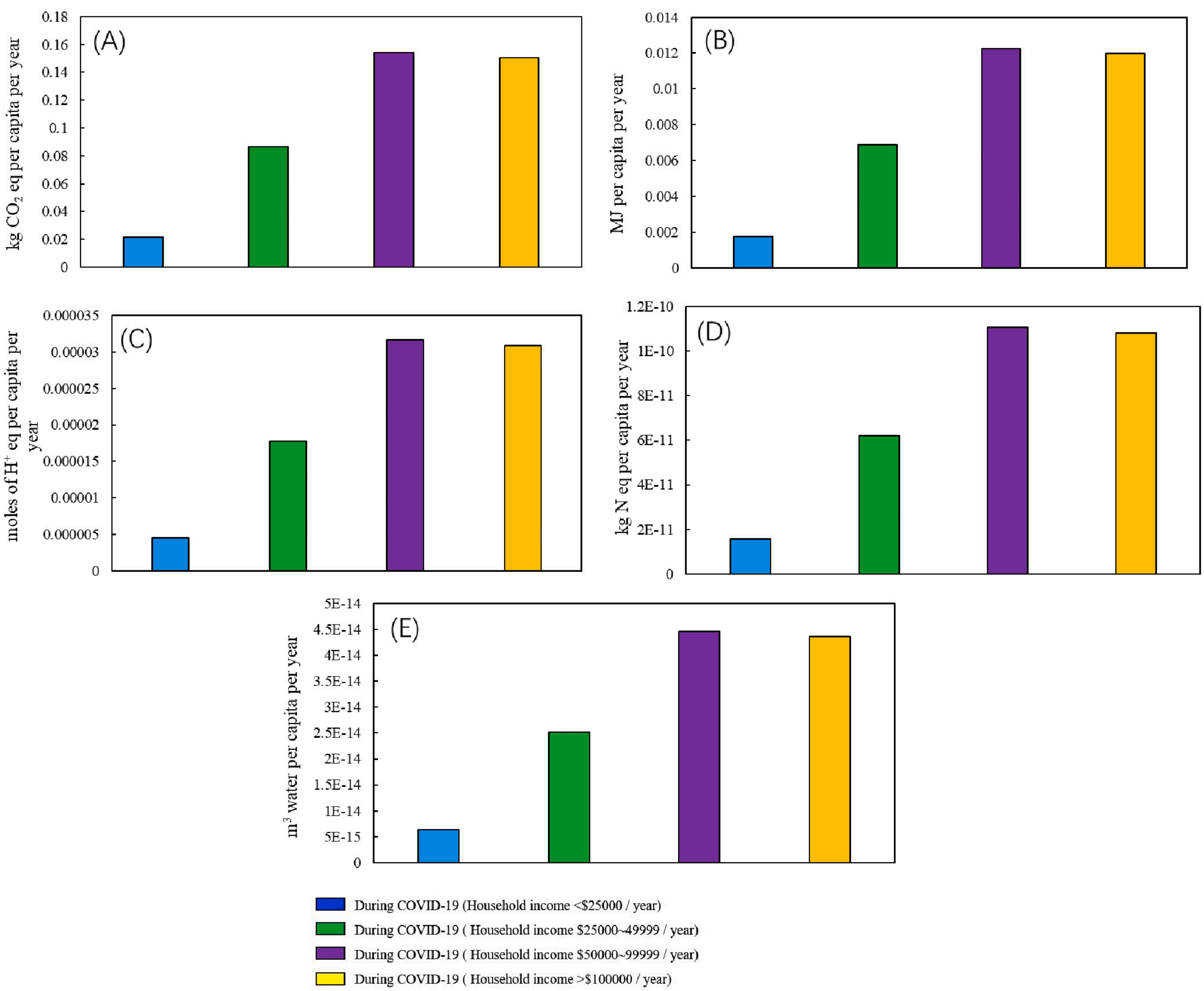

Fig. 5. Waste disposal stage's (A) GWP, (B) CED, (C) AP, (D) EP, and (E) water resource depletion median values by income groups. The time frame for during COVID-19 was from October 2020 to February 2021.

In the context of total dietary AP after COVID-19, per capita intake rates of red meat and dairy were the top two influential factors. The total dietary AP exhibited variations of up to ±3.1 % when per capita red meat intake rates varied by ±10 %. Variations of ±2.6 % were observed when per capita dairy intake rates varied by ±10 %. The changes of total dietary AP were no more than ±1.0 %, when per capita intake rates of grains, seafood, fruits, vegetables, and nuts varied by ±10 %.

Per capita intake rates of seafood and red meat were identified as the top two influential factors for total dietary EP after COVID-19. The total dietary EP displayed variations of up to ±5.1 % when per capita seafood intake rates varied by ±10 %. Additionally, variations of up to ±3.3 % were observed when per capita red meat intake rates varied by ±10 %. Variations in per capita consumption rates of vegetables, fruits, dairy, grains, and nuts by ±10 % resulted in no more than a 0.4 % change in the total dietary EP.

For total dietary water resource depletion after COVID-19, per capita intake rates of fruits and grains were identified as the top two influential factors. The total dietary water resource depletion varied by up to ±3.1 % when per capita intake rates of fruits varied by ±10 %. Changes in per capita intake rates of grains by ±10 % resulted in a total dietary water resource depletion variation of ±2.4 %. Variations in per capita consumption rates of vegetables or dairy by ±10 % resulted in a variation of ±1.1 % in the total dietary water resource depletion. Variations in the total dietary water resource depletion remained below 0.5 % in response to a ± 10 % fluctuation in per capita consumption rates of red meat, seafood, and nuts.

4. Discussion

4.1. Comparing of dietary environmental impacts during COVID-19 to pre-COVID-19

The differences in dietary environmental impacts between the pre-COVID-19 and during COVID-19 are fundamentally driven by the differences in dietary consumption. Consistent with this study, previous studies suggested reduction of red meat and dairy consumption due to the closure of restaurants and food services during early COVID-19 (Janssen et al., 2021; Palmer et al., 2021), and the decrease of meat supply and associated increase of meat prices (Ijaz et al., 2021). Other studies also found higher fruit and seafood consumption during COVID-19 (Bennett et al., 2021; Celorio-Sardà et al., 2021; Zupo et al., 2020). When both dairy and red meat consumption were reduced, people may increase seafood consumption to meet their caloric and protein requirements. Additionally, this study along with the existing studies found that the shopping frequency was reduced, likely due to individuals' perceived risk and the threat of COVID-19 (Janssen et al., 2021; S. Schmidt et al., 2021), eventually reducing the GWP, CED, AP, EP, and water resource depletion for food shopping.

However, Sharma et al. (2020) and Maestre et al. (2021) presented contradictory results to this study such as lower fruit consumption and higher meat consumption during COVID-19. Sharma et al. (2020) conducted a survey in April 2020 in Houston, Dallas, the District of Columbia, and Southwest Florida among low-income households with children. They found a 41.4 % decrease in fruit and vegetable intake due to fear of contracting COVID-19, disruption of employment status, financial hardship, and exacerbated food insecurity. Maestre et al. (2021) assessed Spanish food consumption patterns during COVID-19 home confinement (April to May 2020) and found increased consumption of red meat and grain and reduced consumption of fish, which they attribute to a greater tendency to choose more palatable food due to stress and social anxiety. However, their geographic, temporal and population coverage are fundamentally different from our study. Nevertheless, the changes in food consumption patterns including change including both amounts and types can fundamentally influence dietary environmental impacts.

During COVID-19, the food waste from the overall population was estimated to be reduced based on the survey responses. This result is consistent with Cosgrove et al. (2021), which revealed the median percentage of household food waste reduced by half during the pandemic, compared with pre-COVID-19. Cosgrove et al. (2021) observed a higher proportion of home-prepared meals during COVID-19 compared to the pre-COVID-19 period. Consequently, the decrease in dining out and the increase in home-prepared meals appear to be potential explanations for the reduction in household food waste during the pandemic (Cosgrove et al., 2021; Li and Roe, 2023).

4.2. Comparing of dietary environmental impacts during COVID-19 among income subgroups

Although the distributions of dietary environmental impacts among four income groups overlapped, their distributions and associated most likely values were significantly different. Total four studies including this study explored the differences in dietary environmental impacts among income groups. The different choices of functional units and study scope made the comparison different. This study found that the lowest income group and the second highest income group presented the lowest and highest dietary environmental impacts, respectively. Different from our study, two studies didn't find significant differences in dietary environmental impacts among income groups (Jones and Kammen, 2011; Rose et al., 2019). Recent studies also showed that low-income group were more likely to depend on inexpensive but energy-dense foods, may resulting in higher environmental impacts than high-income group (Bozeman et al., 2019).

Perhaps surprisingly, the group with the highest incomes didn't rank as the highest environmental impact group during COVID-19. Instead, the group with the second highest incomes had the highest environmental impact during COVID-19. The surveys in our study found that the second highest income group had the highest red meat consumption and second highest seafood consumption. The different food choices among income groups may be due to different nutritional and health perspectives. For example, unlike people with low incomes who may eat less meat (both red and white) due to poverty, people with high incomes may reduce meat consumption for a health-conscious lifestyle (Godfray et al., 2018). Therefore, the highest-income group may intentionally reduce red and white meat intake for health purposes, subsequently making the second highest-income group to be the one that consumed red meat the most.

4.3. Strengths and limitations

This study presents several strengths. First, this is one of the few studies investigating dietary environmental impacts (GWP, CED, AP, EP, and water resource depletion of food production, shopping, and waste disposal) during COVID-19. Second, this study is the first study identified the differences in food-related environmental impacts among income groups during COVID-19. By shedding light on these differences, the study offers valuable insights into simultaneously promoting environmental sustainability and equity.

We also recognize several potential weaknesses associated with study design. First, in this study, the primary data on food access and consumption during COVID-19 were provided by self-reported surveys. The self-report survey is a relatively straightforward way to collect data from numerous people efficiently and at an affordable cost. However, self-reporting of dietary behavior has intrinsic limitations, including social desirability bias and recall bias that are associated with under-reporting of food consumed or waste. In addition to self-reported surveys, alternative methods for evaluating food access and consumption include image apps (Dahlman, 2018) and on-site measurements (Kosīte et al., 2019). However, each approach has its limitations. Food consumption recorded by an image app may not be always accurate in quantifying food intake since participants may under-reporting food consumption or waste due to social desirability or forgetfulness

(Höchsmann and Martin, 2020). Conducting on-site measurements can be challenging due to social isolation during the early COVID-19 pandemic (Kosīte et al., 2019). In this study, we employed surveys and computational estimates. We conducted MC analyses to reflect the individual variability of food choices with the income group and included sensitivity analyses to reflect data uncertainty in the self-reporting survey and associated LCA.

Second, we recognized the limitation of using a pre-COVID-19 national dataset to present the local dietary consumption for the Capital Region of New York State. To address this limitation, we used a two-pronged approach. As previous mentioned, Morrison et al. (2011) suggested that there are minimal differences between regional and national food consumption when the age groups of regional and national populations are similar. In addition, we added the sensitivity analyses, which reflect the lower and upper bounds the food consumption. These sensitivity analyses aid us in understanding the uncertainty of using national food consumption to represent regional food consumption pre-COVID-19. Although it's ideal to compare food consumption in the Capital Region before and during COVID-19, the data unavailability made it impossible.

Additionally, the analyses may only reflect the food access and associated environmental impacts during the early phase of COVID-19 when the survey took place. Also, the food groups selected for this analysis (vegetable, fruit, dairy, meat, seafood, grain, and nut) are not exhaustive groups. For instance, food such as oils, beverages, and condiments are not part of this study. So, the results reflect only the consumption of selected food types and not all food types. We recommend future research to investigate the dietary environmental impacts of more comprehensive food groups in larger regions or during later phases of the COVID-19 pandemic.

4.4. Implications for sustainable food systems

Our estimates with bounding uncertainty suggested that life cycle eutrophication impact highly likely increase during early COVID-19 compared with pre-COVID-19. While future studies are needed to explore the transitory or permanent impacts of COVID-19 on dietary choices and impacts, the high possibility of increased eutrophication impact during pandemic calls for further attention for planning mitigating efforts.

Policymakers should consider the disparities among income groups and simultaneously maximize nutritional and environmental benefits. The policy should promote reducing dietary environmental impacts for high-income groups in order to effectively reduce overall environmental damage from societal food consumption. Meanwhile, the policy should ensure adequate food access and nutritional security for low-income groups, while avoiding the potential increases of dietary environmental impacts. Presently, existing policies primarily target improving nutritional access for the low-income population (Billings, 2023; DiNapoli, 2023; Nestle, 2019), yet there is a notable absence of measures aimed at curbing the environmental impacts of high-income groups. To promote environmental equity amidst efforts to mitigate dietary environmental impacts, policymakers should prioritize incentivizing lower environmental impact food consumption among higher-income groups. Policymakers should acknowledge the disparities among income groups when institute policies are tailored to reduce dietary environmental footprints.

Although food waste disposal has relatively small environmental impacts, production of the food which finally be wasted has a significant impact on the environment. The reported change in the amount of food waste and thus its environmental impact differed across income groups, with higher-income households having a greater tendency to report increasing food waste during the pandemic, leading to higher environmental impacts. Consumer food waste occurs at the last stage of the food supply chain, so that reducing food waste can be an effective strategy for mitigating dietary environmental impacts overall.

5. Conclusions

During the early months of COVID-19, residents in the NYS Capital Region reported changed their eating and shopping habits, and thus, further changed corresponding environmental impacts. The changes among environmental impact categories were inconsistent. During the COVID-19 period, reductions in the consumption of red meat, dairy, grains, and vegetables led to a decrease in overall dietary GWP, CED, AP, and water resource depletion. However, there was a slight increase in dietary EP attributable to higher seafood consumption during this time. The environmental impacts of food transportation and food waste management presented lower magnitudes than food production. Encouraging a shift towards environmentally friendly dietary behaviors can be a strategic consideration for policymakers, given the potential impact of dietary changes on environmental outcomes. Lower-income groups have lower dietary environmental impacts from the small amount of food consumption, while the second-highest income group has the highest dietary environmental impacts due to high intake rate of environmental impacts intense food and the highest food waste. Policymakers should prioritize encouraging eco-friendly food choices among higher-income groups. This study highlights the influence of unpredictable disasters on dietary environmental impacts, emphasizing the necessity of balancing environmentally sustainable and healthy diets through tailored strategies for different income groups.

CRediT authorship contribution statement

Tianhong Mu: Data curation, Investigation, Methodology, Writing – original draft, Formal analysis. **Beth Feingold:** Writing – review & editing. **Akiko Hosler:** Writing – review & editing. **Christine Bozlak:** Writing – review & editing. **Jiacheng Chen:** Writing – review & editing. **Roni Neff:** Writing – review & editing. **Mariana Torres:** Writing – review & editing. **Peter Crasto-Donnelly:** Writing – review & editing. **Natasha Pernicka:** Writing – review & editing. **Stacy Pettigrew:** Writing – review & editing. **Victor Russak:** Writing – review & editing. **Peyton Yourch:** Writing – review & editing. **Xiaobo Xue Romeiko:** Conceptualization, Data curation, Funding acquisition, Supervision, Writing – review & editing.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve writing language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Xiaobo Romeiko reports financial support was provided by FFAR.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.

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