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The carbon footprint of cold chain food flows in the United States

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Abstract

The food system is an important contributor to carbon dioxide (CO_2) emissions. The refrigerated food supply chain is an energy-intensive, nutritious and high-value part of the food system, making it particularly important to consider. In this study, we develop a novel model of cold chain food flows between counties in the United States. Specifically, we estimate truck transport via roadways of meat and prepared foodstuffs for the year 2017. We use the roadway travel distance in our model framework rather than the haversine distance between two locations to improve the estimate for long-haul freight with a temperature-controlled system. This enables us to more accurately calculate the truck fuel consumption and CO_2 emissions related to cold chain food transport. We find that the cold chain transport of meat emitted 8.4×10^6 t CO_2 yr^{-1} and that of prepared foodstuffs emitted 14.5×10^6 t CO_2 yr^{-1}, which is in line with other studies. Meat has a longer average refrigerated transport distance, resulting in higher transport CO_2 emissions per kg than processed foodstuffs. We also find that CO_2 emissions from cold chain food transport are not projected to significantly increase under the temperatures projected to occur with climate change in 2045. These county-level cold chain food flows could be used to inform infrastructure investment, supply chain decision-making and environmental footprint studies.

1. Introduction

Food systems are an important contributor to carbon dioxide (CO_2) emissions (Weber and Matthews 2008). Cold chain food systems are particularly important to consider, because they include high-value and nutritious foods (Montanari 2008) and require more energy to stabilize the inside temperature. Cold chain food flows are the temperature-controlled delivery of food products from producer to end consumer (Badia-Melis *et al* 2018), typically through refrigerated trucks. Trucks consume more energy and emit more CO_2 than other modes of transportation, with the exception of air (Weber and Matthews 2008, Davis and Diegel 2007). Most studies of the environmental impacts of food systems focus on the production of staple grains, with less attention given to the distribution of food that underpins complex supply chains (Davis *et al* 2021). In this study we fill a gap in the literature by evaluating the spatial geography of CO_2 emissions associated with cold chain trucking of food commodities in the United States.

The distribution of cold food supply chains should be evaluated to better understand how to provide safe and healthy food to customers in a more sustainable way (Badia-Melis *et al* 2018, Ndraha *et al* 2018, Shashi *et al* 2018). Previous studies on cold food supply chains have focused on their additional energy requirements (Tassou *et al* 2009), greenhouse effects (Xu *et al* 2021, Weber and Matthews 2008) and CO_2 emissions (Liu *et al* 2015, Tubiello *et al* 2021, Yang *et al* 2021). However, these studies primarily focus on large spatial scales (e.g. global), making it difficult to evaluate what is happening at high spatial resolution within a single country. High-resolution information (e.g. county) within a country is important to guide local policy and decision-making. Spatially detailed estimates of cold chain food flows could contribute to calculations of environmental impact and footprint, food supply chain decision-making and critical infrastructure investment.

Food transportation is typically responsible for just a small fraction of the total greenhouse gases (GHGs) emitted by the food sector. Food GHG emissions are dominated by the production phase, with transportation representing only 11% of the life cycle GHG emissions of food in the United States (Weber and Matthews 2008). However, there has been growing concern in recent years about whether the GHG emissions of cold chain food systems will increase with climate change (James and James 2010, Gogou *et al* 2015). This is because ambient temperatures along the freight routes affect carbon emission. As the ambient temperatures rise due to climate change, keeping perishable food commodities at their required temperatures will require an increase in the energy demands of food refrigeration systems to maintain the temperature of cold chain foods to ensure food safety (Kuo and Chen 2010, Shabani *et al* 2012, Ovca and Jevšnik 2009) and minimize food waste. Recent studies have suggested that an 8 °C increase in the ambient temperature would result in an 11% increase in average cold chain energy consumption (James and James 2010). Thus, it is particularly important to determine how a changing climate will impact the CO_2 emissions of cold chain food flows.

In this paper we focus on the county to county cold food supply chain of the United States for 2017, since it is a major food producer and consumer and one of the largest contributors to global GHG emissions (Xu *et al* 2021, Robinson *et al* 2016). Importantly, there are ample data sources available within the United States, enabling data-intensive studies of its food supply chain. Specifically, the Commodity Flow Survey (CFS) database provides detailed information on cold chain food flows by commodity group, transportation mode and value. CFS data are available between the 132 CFS zones (as for Freight Analysis Framework (FAF) zones) within the United States. This study builds on prior research by Lin *et al* (2019) and Karakoc *et al* (2022) to model and map the county-level food supply chain within the United States. The food flow model is a data-driven approach to estimating high-resolution food flows (Lin *et al* 2019), which builds on empirical patterns of food flow networks (Lin *et al* 2014b, Konar *et al* 2018). Both the availability of data and existing food flow models are important considerations in our selection of the United States for this study.

In this study, we estimate county to county cold chain food flows in units of both mass (kg) and value (US dollars, USD) in the United States using a data-driven approach that integrates a variety of available data within the country, building on the food flow model developed by Lin *et al* (2019). To the best of our knowledge, this is the first study to estimate county-scale cold chain food flows. Additionally, we calculate the corresponding CO_2 emissions of cold chain food flows between county pairs, taking into account spatial heterogeneity in ambient temperature. Additionally, we project the cold chain food flow CO_2 emissions with climate change, based on estimates of future temperature. The research questions that we address are: (1) Where are the cold chain food flows in the United States? (2) What are the cold chain carbon emissions in transportation by food commodity? (3) How are cold chain transport carbon emissions projected to change with climate change? We provide all our model estimates of inter-county cold chain food flows and associated carbon emissions with this paper.

2. Methods

We use the following equation to calculate the CO_2 emissions in cold chain food flows between counties in the United States:

$$f_{ij} = c \times w_{ij} \times d_{ij} \tag{1}$$

where f_{ij} represents the fuel consumption or CO_2 emissions from the delivery of cold chain food from county i to j, c is a constant consumption factor, d_{ij} is the distance by road between county i and j w_{ij} is the amount of cold chain food (kg) delivered from county i to j.

The following sections detail how we estimate each variable in equation (1). Section 2.1 explains the data sources that we make use of in this study to model county to county cold chain food flows. Section 2.2 describes how we calculate the roadway travel distance to achieve more accurate refrigerated trucking estimates. There is a detailed explanation of the consumption factor in section 2.3.

2.1. Cold chain food flows between counties

2.1.1. Data

In this section we list all the datasets used for this project in table 3. The CFS database provides information on commodity flows between the 132 CFS regions in the United States. These 132 CFS regions are typically the major metropolitan areas within each state or the remaining area in the state (CFS 2017) (see figure S1 for the map of CFS regions; https://stacks.iop.org/ERIS/2/021002/mmedia). The CFS database provides information for commodities according to the Standard Classification of Transported Goods (SCTG) (CFS 2017). We selected SCTG 01–07 because these commodity groups correspond to agricultural and food commodities. Table 1 provides a list of the food SCTGs available in the CFS database.

Table 1. List of SCTG food commodity groups in this study.

SCTG code	Food commodity
01	Live animals and fish
02	Cereal grains
03	Agricultural products (except for animal feed, cereal grains and forage products)
04	Animal feed, eggs, honey and other products of animal origin
05	Meat, poultry, fish, seafood and their preparations
06	Milled grain products and preparations, and bakery products
07	Other prepared foodstuffs, fats and oils

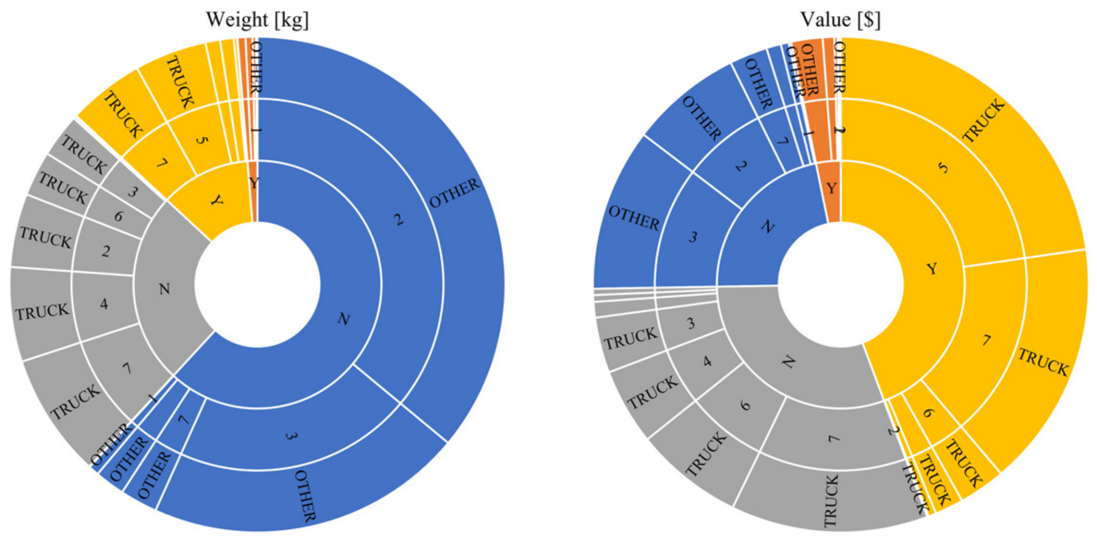

Figure 1. Sunburst plot of food flows in the United States as given by CFS data by weight (kg) (left) and value (US dollars) (right). 'Y' represents cold chain food flows; 'N' represents the non-refrigerated supply chain. The numbers represent food commodity groups as given by the SCTGs (provided in table 1). Food SCTGs are further broken down by transportation mode: 'truck' and 'other'. 'Other' refers to the sum of rail, waterway, air and multi-mode.

Table 2. Key parameters of this study.

Items	Description
SCTG	05, 07
Spatial resolution	County
Spatial boundary	Continental United States (no Hawaii/Alaska)
Year	2017
Mode	Truck
Fraction of cold chain food[a]	74%

[a]The ratio of refrigerated food covered by our study and total refrigerated food for all transportation modes and SCTG 01–07.

The CFS is an important data source for this cold chain study because it indicates refrigeration status. Figure 1 provides a sunburst plot of food flows by refrigeration status broken down by commodity group and transport mode. Cold chain food flows represent a higher proportion of food flows in terms of value [13% by weight; 48% for value]. The plots indicate food commodities as given by the SCTG coding system (refer to table 1). From figure 1, it is clear that the food groups SCTG 05 and SCTG 07 represent the bulk of refrigerated food transport in the United States. In the following, we use 'meat' and 'prepared foodstuffs' to refer to SCTG 05 and SCTG 07, respectively. Transport by truck is the dominant mode for cold chain deliveries (90%). For this reason, we restricted the scope of our analysis to cold chain truck transport of 'meat' and 'prepared foodstuffs' (see table 2).

The CFS relies on sampling, so it only covers about 60 000 establishments, mostly in the mining, manufacturing and wholesaling industries. For this reason, we also used the Freight Analysis Framework (FAF), which combines supplementary data to estimate shipping quantities from establishments not covered by the CFS (Oak Ridge National Laboratory 2020). The CFS serves as the foundation for the FAF. The same regional locations, commodity categories and method of transportation are used in both FAF and CFS data. The origin and destination in CFS/FAF are the beginning and the destination of a freight movement. FAF, however, makes

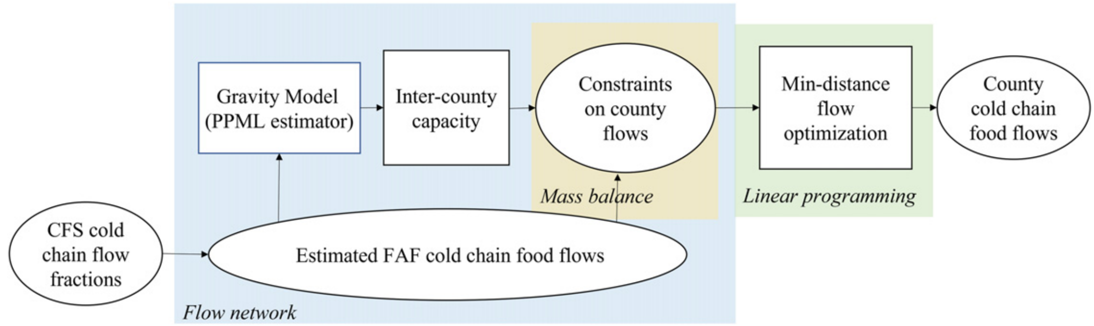

Figure 2. Schematic of the model components to estimate cold chain food flows between counties in the United States (PPML, Poisson pseudo maximum likelihood).

no distinction between the cold chain and the traditional supply chain. As a result, we used equation (2) to rescale the FAF flow data based on the refrigerated ratios available in the CFS

$$\frac{F_{\mathrm{FAR}}^{\mathrm{cold}}}{F_{\mathrm{FAF}}^{\mathrm{total}}} = \frac{F_{\mathrm{CFS}}^{\mathrm{cold}}}{F_{\mathrm{CFS}}^{\mathrm{total}}} \tag{2}$$

where F is the food flow information (in units of weight (kg)) contained in the FAF and CFS databases. Superscripts cold and total refer to cold chain food flows and total food flows, respectively. The rescaled FAF freight data were then used as the input to the flow estimation model and treated as the ground truth for cold chain food deliveries at the level of the FAF region.

Roadway travel distance is calculated using an open source routing machine (OSRM), as detailed in section 2.2. We collected data on population, personal income, employment, livestock production, meat packing capacity, refrigerated storage capacity, fruit and vegetable production, and port imports and exports from multiple sources, and these variables serve as the predictors in the regression model. The data on economic size, production, processing locations and port-level trade were collected at the county spatial scale and we then aggregated the county data into the FAF area to which they belong. Some variables are missing for some counties, but are available for larger regions (national or state level). Missing county data are filled in from larger spatial domains proportional to the county's population.

2.1.2. Model of cold chain flows between counties

We developed a model of cold chain food flows for 'meat' and 'prepared foodstuffs' delivered by refrigerated truck (see table 2). We fitted separate models for cold chain flows of 'meat' and 'prepared foodstuffs' to more accurately capture the influential variables for each food group. Figure 2 provides a methodological overview of the algorithm that we developed to estimate county to county cold chain food flows. Our county to county links inherit the CFS/FAF definition of origin and destination, so our results are most appropriate for estimating transportation flows without further differentiation of processes throughout the supply chain (e.g. production, processing, storage, consumption, etc). Our approach builds directly on the food flow model developed by Lin *et al* (2019), with a few important improvements to account for the refrigerated portion of the food supply chain.

Selection of independent variables was inspired by the gravity model, a bilateral international trade model in which the trade flow is proportional to the economic size of each nation and inversely proportional to the distance between nations (Bergstrand 1985). We built our gravity model between counties based upon the cross-sectional dataset developed from the public data sources listed in table 3. The data were merged to arrive at a dataset that captures features of each county's economic size, production and consumption, and inflow–outflow potential. Distance is an important variable in the gravity model as it proxies for the financial cost of transporting commodities from the origin to the destination (Anderson and Van Wincoop 2004, Egger 2008) (see section 2.2 where we explain how we calculate roadway travel distance to improve the accuracy of this variable). A dummy variable was introduced to distinguish the intrastate trade and interstate trade, which was expected to capture the border effect in analogy with the country border effect in bilateral international trade. The variables were selected based on the variance inflation factor with a threshold of 10 to avoid multicollinearity (Hair 2009).

Regression models were first developed for link-level flows between FAF zones. The model was composed of two regressions for each SCTG. The two regressions are: (1) the self-loop links were estimated with an ordinary least squares (OLS) estimator and (2) the inter-node links were estimated with the Poisson pseudo maximum likelihood (PPML) to deal with the presence of heteroscedasticity and many occurrences of zeros in

Table 3. A summary of the datasets used to model the county-level flow.

Data	References	Description	Purpose
CFS	Commodity Flow Survey (2017)	The CFS provides an in-depth multimodal view of national freight flows.Data for over 100 000 shippers include the origin and destination, type of commodities, value and weight of the freight and mode of transit	CFS data guided us in determining the focus of this study. We also used CFS data to calculate the refrigeration coefficients for each FAF region pair
FAF version 5	Oak Ridge National Laboratory (2020)	The FAF incorporates supplementary data to estimate freight quantities from establishments that are not covered by the CFS, which serves as the framework's foundation. FAF data use the same divisions of regional areas, commodity categories, and modes of transportation as CFS statistics	FAF data are used to train the FAF region-level regression model as well as to provide mass balance for county food flows simulation
Distance	OSRM (Luxen and Vetter 2011), United States Census Bureau (2020)	Travel distance via roadway between all OD pairs.	Travel distance is used in the regression model and to assign food flows to shortest paths in the linear programming algorithm. Travel distance is also used to calculate the carbon emissions in cold chain food flows
Employment	United States Census Bureau (2019)	Employment number by NAICS by county	As we assume the same production efficiency across the CONUS, employment is treated as production equivalents. We extracted the employment data of industries related to 'meat' and 'prepared foodstuffs' by matching the NAICS code to the SCTG code. Employments are variables in the regression model
IO table	US Bureau of Economic Analysis (2019)	Latest domestic commodity by commodity IO table in 2012 describes the demand and consumption relationships between 405 industries	The sum of the multiplication of production equivalents (employment) of all industries and input requirements of 'meat' and 'prepared foodstuffs' commodity for unit production in each industry represents consumption equivalents of 'meat' and 'prepared foodstuffs'. The consumption potential of 'meat' and 'prepared foodstuffs' are variables in the regression model
Population	United States Census Bureau (2019)	Population data per county	Population is a variable in the regression model
Personal income	US Bureau of Economic Analysis (2020)	Personal income per county	Income is a variable in the regression model
Unprocessed food and livestock production	US Department of Agriculture (2020)	Agricultural production and livestock inventory data by county on goods that are important raw materials for 'meat' and 'prepared foodstuffs'	Production of unprocessed fresh produce and livestock are variables in the regression model
Meat processing industry data	US Department of Agriculture (2021)	The number of large and medium meat processing plants by county	Meat packing capacity by county is a variable in the regression model
Refrigerated storage data	Infrastructure Foundation-Level Data (2019)	Refrigerated storage per county	Total refrigerated storage capacity by county is a variable in the regression model
Port trade data	US Bureau of Transportation Statistics (2020)	Data on the value and weight of shipments made by the United States to Canada and Mexico, broken down by commodity and US port of entry or exit	Port-level trade data are collected and assigned to the counties in which they are located. We consolidated the industries corresponding to the 'meat' and 'prepared foodstuffs' and keep only those freight flows that utilized the trucking mode. The amounts of import and export from/to port counties are variables in our regression model

the flow networks (Silva and Tenreyro 2006). The variables with a p-value larger than 0.05 were not statistically significant, so they were removed from the regression equation to prevent model overfitting. We used R^2, root mean square error and mean absolute error as the performance evaluation metrics. The PPML estimator provided better prediction performance for interregional flow than gamma pseudo maximum likelihood and OLS based on our flow data. The value of all coefficients and the performance of the models are provided in the supporting information (SI).

The regression model developed on FAF-level flow data is then applied to the county spatial scale to estimate flow potentials. This approach assumes that the regression models are the same across spatial resolutions as in Lin *et al* (2019). A linear programming (LP) algorithm is used to estimate actual cold chain food flows from the potential. The LP algorithm minimizes the roadway travel distance between US counties and requires mass balance, in which the sum of county inflows and outflows equals the inflows and outflows of their respective FAF zones.

2.2. Roadway travel distance

We improved upon prior studies by using roadway travel distance in our model rather than the great-circle distance: roadway travel distance better reflects the real road distance, as opposed to the haversine distance (i.e. great-circle distance), which is the angular distance between two points on the surface of a sphere. Routing problems have incorporated roadway travel distance (instead of haversine distance) in recent years (Boscoe *et al* 2012, Harja and Sarno 2018). However, to our knowledge, roadway travel distance has not yet been introduced into food flow models. Previous food flow simulations have used the haversine distance (Lin *et al* 2019, Smith *et al* 2017, Valerio *et al* 2020), making our approach both novel and more precise. This increase in precision is important to more accurately represent delivery distance and related GHG emissions.

In this study, we need to calculate the distances among 3000 counties, which represent the shortest path routing problems for 9 million origin–destination (OD) pairs. Due to the large amount of computation required, we use open-source routing software and Amazon Web Services (AWS) instance. Specifically, we use the roadway travel distance calculated by the OSRM, which is a high-performance routing engine for shortest paths in road networks (Luxen and Vetter 2011).

The geographic information for the OD pairs is determined by the latitude and longitude of the centroid of the FAF zones and counties. An AWS Linux m4.10 xlarge instance with 40 cpu and 140 GB memory is used to run the OSRM backend and calculate the travel distance between 3108 counties. For self-loops, the multiplication of the square root of the county area and a conversion ratio is used as the travel distance. The conversion ratio is the ratio of total travel distance and total haversine distance for all inter-county pairs.

We restrict our analysis to the continental United States (CONUS) because there is no clear roadway travel distance for Alaska and Hawaii. There is information on food flows between CONUS and Alaska/Hawaii, but we exclude these states due to roadway travel distance limitations. Additionally, we are most interested in the long-haul truck delivery of cold chain flows, rather than multi-modal transport, which warrants restricting our geographic scope to the CONUS (see table 2 where we clarify the scope of our study).

2.3. CO_2 consumption factor

There are two components that determine carbon emissions in cold chain transport: (1) motive emissions, which represent the emission linked to the truck's mobility, and (2) refrigeration emissions, which represent the emission associated with the temperature stability system. The motive CO_2 emissions are linearly related to fuel consumption, which equals the loaded distance multiplied by fuel intensity. The loaded distance is the weight multiplied by the distance

$$E_{m_{ij}} = e_f \times \mathrm{FI} \times d_{ij} \times w_{ij} \tag{3}$$

where $E_{m_{ij}}$ is the motive emission for the link from i to j, FI is the fuel intensity, which represents the amount of fuel required to deliver a unit amount of commodity per unit distance, and e_f is the emission conversion factor for converting fuel use into emissions. Long-haul truck FI is about 14.2–39.8 g tkm^{-1} (National Research Council *et al* 2010). We use the average FI of 27 g tkm^{-1}. Most long-haul trucks use middle-distillate diesel fuel (Davis *et al* 2009). The recommended e_f is 10 180 g of CO_2 emissions per gallon of diesel consumed, which assumes that all the carbon in the diesel is converted to CO_2 (National Highway Traffic Safety Administration 2010). In other words, refrigerated trailers emit about 85.4 g of CO_2 when transporting 1 t of goods over 1 km. The diesel density we use for this study is 0.85 kg l^{-1} (Speight 2011).

The implementation of temperature control systems consumes more energy. Prior research shows that the thermal energy requirements of trucks vary between 15% and 25% of the energy requirements for mobility regardless of vehicle type (Yang *et al* 2021, Stellingwerf *et al* 2018, Tassou *et al* 2009). Temperature regulation in cooled trucks accounts for 40% of the CO_2 emissions (Stellingwerf *et al* 2018, Tassou *et al* 2009). Diesel-driven vapor compression is widely used in the cold chain to remove heat from inside the truck (Tassou *et al* 2009). The amount of heat that needs to be removed in order to keep the temperature in the truck stable is related to the ambient temperature, as shown by

$$Q_{c_{ij}} = \frac{w_{ij}}{W} \times S \times \text{HTC} \times (T - T_\text{t}) t_{ij} \tag{4}$$

where $Q_{c_{ij}}$ is the heat that needs to be transferred, t_{ij} is the time needed to deliver the commodity from i to j calculated by the OSRM concerning the real road system, $T - T_\text{t}$ is the difference in air temperature between the inside and outside of the truck, $\frac{w_{ij}}{W}$ represents the number of trucks needed to deliver the weights of link ij (i.e. w_{ij}), W is the standard volume for each truck, S is the square root of the product of the inside and outside area of the truck and HTC is the heat transfer coefficient of the truck (W m^{-2} K^{-1}). Here, we assume a homogeneous truck type. The maximum load, W, is 30 t. The internal and external dimensions of the truck are assumed to be ($l \times w \times h$, in m) 13.35 × 2.46 × 2.5 and 13.56 × 2.6 × 2.75, respectively. Therefore S equals 151.9 m^2. HTC is assumed to be 0.7 W m^{-2} K^{-1} (Tassou *et al* 2009, Stellingwerf *et al* 2018).

Unlike in previous work, we consider the spatial heterogeneity at ambient temperature by converting equation (4) to the differential form shown in equation (5). This integral determines how much heat needs to be removed for a very short distance where the temperature is constant for that small distance:

$$\text{d}Q_c = \frac{w_{ij}}{W} \times S \times \text{HTC} \times (T(t) - T_\text{t})\text{d}t. \tag{5}$$

Note that here $T(t)$ is the ambient temperature at time t. To simplify the analysis, we assume a linear temperature change from i to j. Also, limited by the annual food flow information from the FAF and other statistical variables, we assume the same monthly transport volume. Integrating from the start to the end of the link i to j for each month, we get the new $Q_{c_{ij}}$ which includes the impact of heterogeneous spatial and seasonal ambient temperatures:

$$Q_{c_{ij}} = \sum_{m=1}^{12} \int_0^{t_{ij}} \frac{w_{mij}}{W} \times S \times \text{HTC} \times \left(T_{mi} + t \times \frac{T_{mj} - T_{mi}}{t_{ij}} - T_\text{t} \right) \text{d}t. \tag{6}$$

T_{mi} and T_{mj} are ambient temperature at i and j in month m, respectively, and w_{mij} equals w_{ij} divided by 12. Then the refrigeration emission is determined by equation (7). For the refrigeration emission, we should consider fuel usage and also the contribution of leaking refrigerants to GHG emissions (Adekomaya *et al* 2016):

$$E_{r_{ij}} = \frac{Q_{c_{ij}}}{\text{COP}} \times FI_r \times e_f \times e_r. \tag{7}$$

The coefficient of performance (COP) is a measure of how much thermal energy can be removed with the amount of electrical energy provided. We assume that the COP for chilled food transport (T_t at 2 °C) is 1 and a COP of 0.67 for frozen food (T_t at −18 °C) (Stellingwerf *et al* 2018). The electrical energy is provided by chemical energy produced by diesel consumption. FI_r is the fuel usage to provide unit electrical energy to cool the truck, assumed to be 3 l kW^{-1} h^{-1}. Then we convert the fuel use to carbon emissions by multiplying by e_f. e_r is the conversion constant taking the refrigerant leakage into account. We assume e_r to be equal to 1.21 as in Stellingwerf *et al* (2018). Historical monthly average temperatures for the year 2017 for each county are extracted from the US Climate Divisional Database (National Centers for Environmental Information 2021).

2.4. Climate change projections

To project future carbon emissions, we make the following assumptions. (1) Temperature changes are taken into account and other climate-related parameters (e.g. wind velocity, which can affect energy consumption for motion) are fixed to current climate values. (2) We assume that the weights of each link increase by the same ratio as population growth (i.e. 1.21) and that the structure of the network stays the same. A baseline scenario without changing the weights and structure of the network to reflect the future is also employed to look at how the emissions might vary with a temperature profile as given by the climate models. The monthly T_max and T_min projections under the RCP4.5 assumption are obtained from 20 statistically downscaling global climate models (GCMs) covering CONUS in the year 2045 from the MACAv2 database (Abatzoglou and Brown 2012). The 20 GCMs are derived from the Coupled Model Intercomparison Project phase 5 (CMIP 5). CMIP 5 promotes a standard set of model simulations to provide projections of future climate change (Sillmann *et al* 2013), which is widely used in climate change impact analysis (Oleson 2012, Knutti and Sedláček 2013). RCP4.5 represents the scenario where CO_2 concentrations peak in about 2040, with a peak atmospheric concentration of about 650 ppm (Moss *et al* 2010).

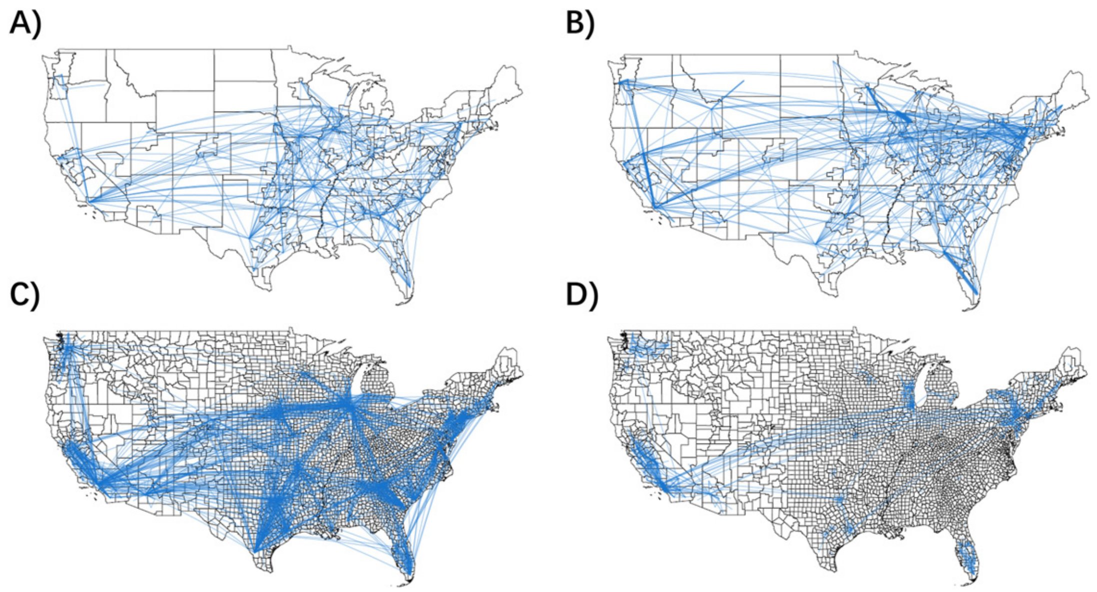

Figure 3. Cold chain food flows (kg) for (A) FAF-level network of 'meat', (B) FAF-level network of 'prepared foodstuffs', (C) county-level network of 'meat' and (D) county-level network of 'prepared foodstuffs'. We plot the top 0.1% of the county-level flows and the top 1000 FAF-level flows to most clearly illustrate the spatial patterns.

3. Results and discussions

3.1. Cold chain food flows between counties

We fitted the regression model at the FAF level. The regression equations shown in the SI quantify the relationship between the independent predictors and responses. Distance is one of the most important predictors among all variables, and contributes most to the calculation of flow potential. The distance coefficient is negative. This means that there is a higher flow potential when the origin and destination are close to each other. The state categorical variable captures whether two counties belong to same state. This variable also significantly influences the estimation of flow potential, with counties in the same state having higher flow potentials.

A map of cold chain food flows at the FAF spatial scale is shown in figures 3(A) and (B). Figures 3(A) and (B) present the FAF data scaled by the refrigerated weights from the CFS. Estimated county to county cold chain food flows follow the same spatial distribution as at the FAF spatial scale (see figures 3(C) and (D)). Some of the counties that stand out as those with the highest in- and out-going food flows are in California, Texas, Florida and the Midwest for 'meat'. Their corresponding FAF zones also stand out. In the 'prepared foodstuffs' maps, counties around Los Angeles, Chicago and Seattle, as well as their corresponding FAF zones, show up as prominent locations of cold chain flows. We also estimate the county to county flow in USD as shown in the SI. Our model estimates in both mass (kg) and value (USD) are provided in the supporting database.

Summary statistics of FAF and county-scale cold chain food flows are listed in table 4. There are 129 nodes at the FAF scale because we focus on CONUS and do not include Alaska/Hawaii. All 3108 counties participate in the cold food chain. The total mass (kg) captured by the network balances across spatial scales (by design). At the FAF scale, 'prepared foodstuffs' is denser than 'meat'. However, at the county scale it is the opposite. This can be explained by the fact that in the United States meat production is more spatially concentrated. Certain counties have slaughterhouses producing meat, which then distribute meat across the nation. 'Meat' includes seafood which also exhibits the same spatial concentration, such that certain international ports and seafood processing counties are responsible for the majority of seafood distribution. This differs from refrigerated 'prepared foodstuffs', which has processing locations more evenly distributed across the nation. Additionally, all 'meat' requires delivery by refrigerated truck (98.08%), while only a relatively small fraction (33.98%) of 'prepared foodstuffs' utilizes temperature control. Spatial concentration in 'meat' outflows is also shown in figure S7 in the SI.

The heatmap of county cold chain food inflows and outflows is shown in figure 4. Locations in California, the Midwest and the East Coast have relatively high cold chain food flows (both inflow/outflow), since these are hubs of production, distribution and consumption. The top 10 inflow and outflow counties are listed in table 5. Most of the top 10 inflow and outflow counties are located in California and Texas. Around 50%

Table 4. Summary statistics for FAF- and county-level cold chain food flow in the United States.

SCTG	No. of nodes	No. of links	Density	Mass (kg)	Average travel distance (miles)
			FAF network		
5	129	7637	0.46	9.46×10^{10}	468.78
7	129	11 022	0.66	2.27×10^{11}	353.37
			County network		
5	3108	2661 164	0.28	9.46×10^{10}	454.90
7	3108	867 531	0.09	2.27×10^{11}	326.17

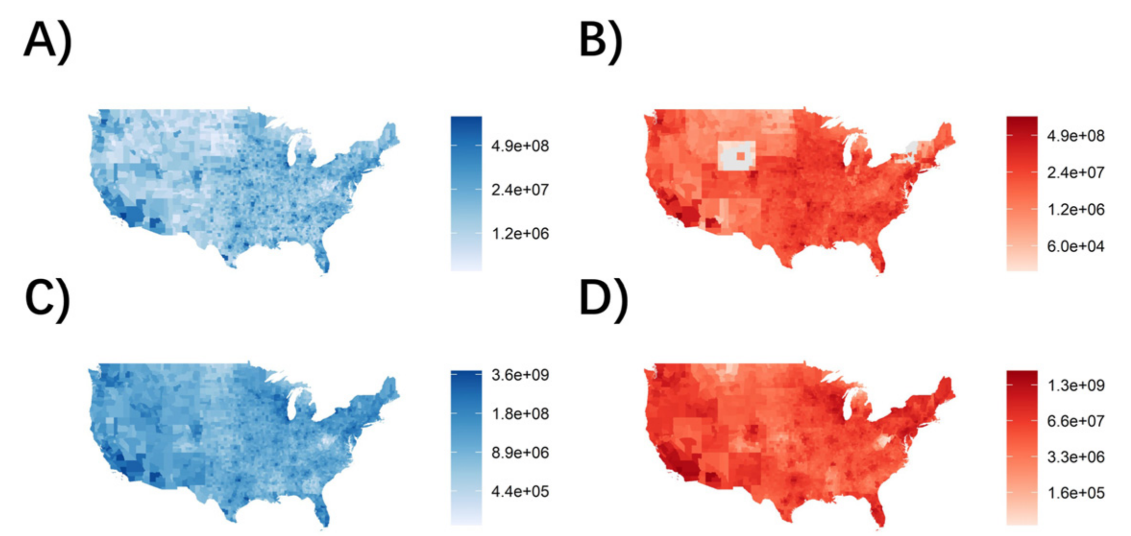

Figure 4. Heatmap of county-level cold food supply chain inflows and outflows in mass (kg): (A) inflow of 'meat', (B) outflow of 'meat', (C) inflow of 'prepared foodstuffs' and (D) outflow of 'prepared foodstuffs' commodities. Note that counties that are colored gray have no flows.

of the top 10 inflow counties are also top 10 outflow counties. Also, around 40% of the top 10 counties are same for 'meat' and 'prepared foodstuffs', with a few exceptions. For example, Hall County, Georgia shows up as a main county for 'meat', since it is the self-declared 'poultry capital of the world' (South 2020). This is because the model is prone to give higher weights to counties with high production. Similarities across counties and commodities indicate spatial concentration in food processing, distribution and consumption. There are no outflows for many counties in Wyoming because the cold chain outflows given in the FAF database for Wyoming are relatively small. Wyoming has only 2200 t of 'meat' for *in situ* consumption (self-link) and no export by truck to other states, according to FAF data. The possible flows between counties are first determined by the FAF-level regression model. We assume that the FAF flows are ground truth, and according to flow balance we have a constraint for the LP algorithm that the sum of flows between counties within Wyoming state should be less than or equal to the cold chain self-loop for Wyoming. Also, our model is prone to keeping links with less travel cost; in this case, export is mainly concentrated in the center of Wyoming. These top 10 inflow and outflow counties also align with figure 3.

We also examine the per capita cold food supply chain flows. The counties with lowest per capita inflows indicate areas with the lowest receipts of cold chain foods. Since some cold chain foods are particularly nutritious, these locations may represent areas that could be targeted to expand nutritional access. However, note that certain fresh and perishable foods are not included in our study, so these should be considered in future work. The top 10 counties with the lowest per capita receipts of 'meat' and 'prepared foodstuffs' are listed in table 6. The counties with lowest access to 'meat' are spatially distributed throughout the United States. The counties with the lowest per capita meat inflows are in Oregon, West Virginia and New Hampshire. The counties with the lowest per capita inflow of 'prepared foodstuffs' are all located in West Virginia. These findings align with reports of food insecurity in West Virginia (Feeding America 2021, United Health Foundation 2021, 13 WOWK TV 2021).

Table 5. Top 10 inflow and outflow counties for 'meat' and 'prepared foodstuffs' commodities in 2017.

'Meat'			'Prepared foodstuffs'		
Rank	Inflows	Mass (kg)	Rank	Inflows	Mass (kg)
1	Los Angeles County, CA	3.42×10^9	1	Tulare County, CA	4.73×10^9
2	Cook County, IL	2.40×10^9	2	Los Angeles County, CA	4.60×10^9
3	Harris County, TX	1.50×10^9	3	Orange County, CA	4.60×10^9
4	Maricopa County, AZ	1.37×10^9	4	Maricopa County, AZ	3.81×10^9
5	Dallas County, TX	1.33×10^9	5	Cook County, IL	3.52×10^9
6	Webb County, TX	1.30×10^9	6	Stanislaus County, CA	2.94×10^9
7	Hall County, GA	1.23×10^9	7	Dallas County, TX	2.63×10^9
8	Chatham County, GA	1.09×10^9	8	Harris County, TX	2.12×10^9
9	King County, WA	1.04×10^9	9	Lehigh County, PA	2.12×10^9
10	Alameda County, CA	8.19×10^8	10	Orange County, FL	2.05×10^9
Rank	Outflows	Mass (kg)	Rank	Outflows	Mass (kg)
1	Los Angeles County, CA	2.20×10^9	1	Los Angeles County, CA	4.25×10^9
2	Cook County, IL	1.28×10^9	2	Maricopa County, AZ	2.83×10^9
3	Hall County, GA	1.08×10^9	3	Riverside County, CA	2.19×10^9
4	Sussex County, DE	9.10×10^8	4	Cook County, IL	1.80×10^9
5	Fresno County, CA	8.34×10^8	5	Kings County, CA	1.70×10^9
6	Washington County, AR	6.56×10^8	6	Kern County, CA	1.64×10^9
7	Maricopa County, AZ	6.24×10^8	7	San Bernardino County, CA	1.48×10^9
8	Douglas County, NE	5.61×10^8	8	Hillsborough County, FL	1.34×10^9
9	King County, WA	5.39×10^8	9	Contra Costa County, CA	1.34×10^9
10	Marshall County, AL	5.15×10^8	10	Stanislaus County, CA	1.30×10^9

Table 6. Top 10 counties with the lowest per capita 'meat' and 'prepared foodstuffs' inflows.

'Meat'			'Prepared foodstuffs'		
Rank	Inflows	Mass (kg)	Rank	Inflows	Mass (kg)
1	Jackson County, OR	9.74	1	Calhoun County, WV	4.31
2	Josephine County, OR	14.26	2	Clay County, WV	6.21
3	Coos County, NH	15.37	3	Webster County, WV	8.11
4	Clay County, WV	15.59	4	Upshur County, WV	10.03
5	Cheshire County, NH	16.37	5	Gilmer County, WV	10.24
6	Webster County, WV	16.69	6	Braxton County, WV	11.80
7	Klamath County, OR	18.15	7	Boone County, WV	16.68
8	Douglas County, OR	19.76	8	Lincoln County, WV	22.82
9	Preston County, WV	20.08	9	Lewis County, WV	24.71
10	Sullivan County, NH	21.27	10	Randolph County, WV	26.40

3.2. Carbon emissions in cold chain food flows

The total quantity of carbon emissions associated with cold chain food trucking in the United States is 22.9 $\times 10^6$ t. The total CO_2 emissions for 'meat' are 8.4 $\times 10^6$ t, while they are 14.5 $\times 10^6$ t for 'prepared foodstuffs'. The carbon footprint of cold chain food flows between counties is shown in figure 5. California stands out as having the largest carbon emissions associated with cold food chain trucking. We also list the 10 counties with highest total carbon footprint of cold chain food transport in table 7. For 'meat' we observe similar total carbon footprint values among the top counties. However, for 'prepared foodstuffs' there is more variability in the carbon footprint of the top 10 counties. For example, the county with the highest carbon footprint of emissions is Los Angeles County, CA which is much larger than all other counties.

Our findings are generally consistent with the results provided by Liu *et al* (2015). Liu *et al* (2015) also employed FAF data and focused on transportation mode specific emission calculations of various pollutants. Note that Liu *et al* (2015) studied transportation of all food commodities and did not specifically focus on cold chain food transport. So our total emission estimates are different from those calculated by Liu *et al* (2015). However, both studies show a similar spatial pattern in the emissions of pollutants. Liu *et al* (2015) computed the spatial distribution of other pollutants such as particulate matter and NO_x emissions throughout the highways and railways in the United States. They concluded that the highest accumulation of emissions due to freight movement is observed around the highways in Texas, California and Florida for all food commodities considered together. Our results are similar, but available at a finer spatial resolution and only for CO_2 emissions. We estimate that the top 10 counties with the highest carbon emissions from cold chain food flows are

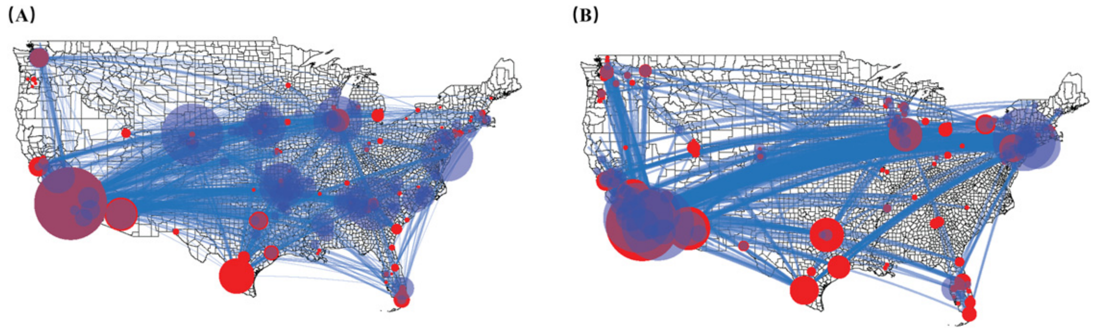

Figure 5. Map of carbon emissions associated with cold chain food trucking in the United States in 2017. The carbon footprint of county-level cold chain food flows for (A) 'meat' and (B) 'prepared foodstuffs'. The counties that have the highest carbon footprint inflow (red) and outflow (blue) are represented with bubbles, where the sizes of the bubbles are proportional to the carbon footprint.

Table 7. Counties with highest total carbon emissions for 'meat' and 'prepared foodstuffs' commodities in 2017.

'Meat'			'Prepared foodstuffs'		
Rank	County	CO_2e (t)	Rank	Carbon footprint	CO_2e (t)
1	Los Angeles County, CA	5.95×10^5	1	Los Angeles County, CA	6.31×10^5
2	Maricopa County, AZ	2.66×10^5	2	Orange County, CA	6.28×10^5
3	Webb County, TX	2.40×10^5	3	Maricopa County, AZ	4.28×10^5
4	Cook County, IL	2.22×10^5	4	San Bernardino County, CA	3.84×10^5
5	King County, WA	1.55×10^5	5	Cook County, IL	3.59×10^5
6	Hall County, GA	1.47×10^5	6	Riverside County, CA	3.13×10^5
7	Dallas County, TX	1.44×10^5	7	Tulare County, CA	3.12×10^5
8	Alameda County, CA	1.40×10^5	8	Dallas County, TX	2.80×10^5
9	Riverside County, CA	1.39×10^5	9	Orange County, NY	2.47×10^5
10	San Bernardino County, CA	1.34×10^5	10	Lehigh County, PA	2.15×10^5

located in Texas and California (see table 7). Figure 5 also illustrates that the counties with the largest carbon emissions in cold chain food flows are primarily located in Texas, California and Florida.

We calculated the per capita carbon footprint of cold chain food inflows and outflows for each county (shown in figure 6). For 'meat' commodities, the average per capita carbon footprint of cold chain food outflows is 0.14 t and the standard deviation is 0.31 t. The average per capita carbon footprint of cold chain food inflows for 'meat' is 0.03 t and the standard deviation is 0.04 t. For 'prepared foodstuffs', the average per capita carbon footprint of cold chain food outflows is 0.17 t and the standard deviation is 0.50 t. The average per capita carbon footprint of cold chain food inflows of 'prepared foodstuffs' is 0.08 t and the standard deviation is 0.12 t. The average per capita outflow is larger than the average per capita inflow, reflecting the concentration of production.

3.3. Impact of roadway travel distance

How does our use of the roadway travel distance influence estimates of the carbon footprint? We computed the travel distance between counties rather than using the haversine distance as in previous work (Lin *et al* 2019). As shown in figure 7, we find that there are an additional 64.79 miles (per unit commodity) traveled when we use the roadway travel distance. There are 78.71 more miles for 'meat' and 58.98 more miles for 'prepared foodstuffs'. This corresponds to about 1.02×10^6 t more CO_2 emissions for 'meat' (12.1%) and 1.84×10^6 t more for 'prepared foodstuffs' (12.7%). The average travel distance of 'meat' is longer: 454.9 miles compared with 326.3 miles for 'prepared foodstuffs'. Roadway travel distance is a real measure, whereas haversine distance is an approximation, so the CO_2 calculations of our approach are higher and more accurate.

3.4. Climate change impact on carbon emissions

In this study, we take into account the spatial and temporal variations in temperature. In figure 8, we plot the increase in estimated carbon emissions for 2017 and 2045. Here we assume that the weights of each link increase by the same ratio as population growth (i.e. 1.21) and that the structure of the network stays the same. There are two parts to the emissions: motive emissions and refrigeration system emissions. Refrigeration emission accounts for 29.9% and 29.8% total emission for 'meat' and 'prepared foodstuffs', respectively, in 2017. These

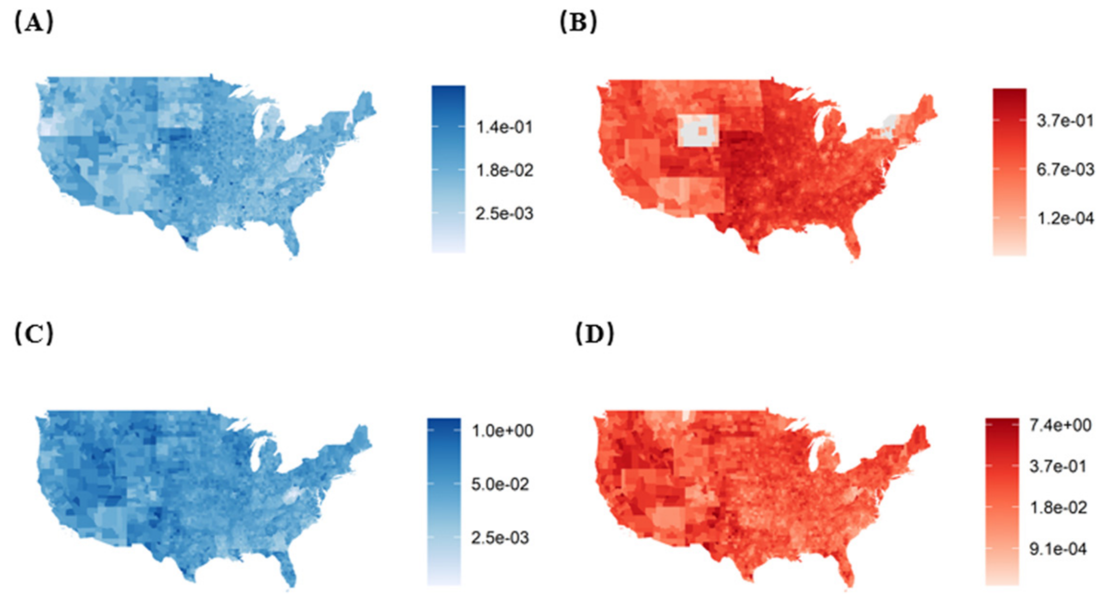

Figure 6. Heatmap of the per capita carbon footprint of cold chain food flows (in units of t): (A) per capita carbon footprint of cold chain food inflows of 'meat', (B) per capita carbon footprint of cold chain food outflows of 'meat', (C) per capita carbon footprint of cold chain food inflows of 'prepared foodstuffs' and (D) per capita carbon footprint of cold chain food outflows of 'prepared foodstuffs'. Counties that are colored gray have no flow.

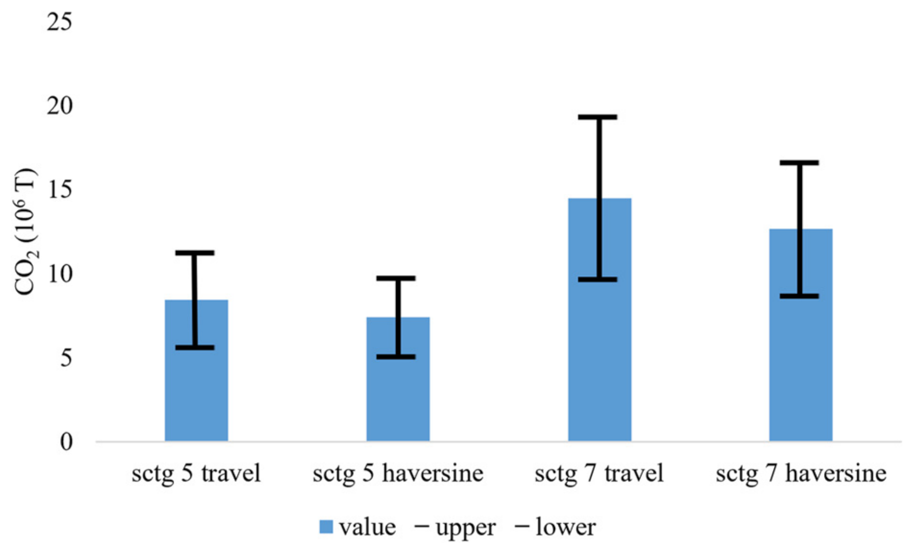

Figure 7. Comparison of total carbon emissions for cold food supply chains with haversine and travel distances for 'meat' and 'prepared foodstuffs' commodity flows on a county-level network. The black bars represent the extreme situation where a refrigeration truck emits 44.9 g CO_2 (lower bound) and 125.9 g CO_2 (upper bound) to deliver 1 t of goods a distance of 1 km.

ratios are estimated to increase to 30.46% and 30.37% in 2045. The amount of increase in carbon emission due to temperature when we remove the impact of expansion of the frozen market is only 0.25×10^6 t (about 1% of the total emissions in 2017).

3.5. Potential opportunities to reduce carbon emissions in cold chain food flows

Here, we qualitatively discuss the opportunities for reducing GHG emissions in cold food supply chains based on other studies. There are six key factors that impact the carbon emissions of cold chain delivery, i.e. transportation mode, distance between OD pairs, quantity being shipped, temperature requirement, load optimization and truck type (Singh *et al* 2015). Increasing deliveries through rail and road–rail would help to reduce transportation emissions in the cold chain (Hwang and Ouyang 2014, Liu *et al* 2015). However, the special requirements of the temperature control system and delivery time in refrigerated supply chains make it challenging to transition more to rail. Future research and industry developments of decision-making tools to analyze alternative combinations of distance, weights of shipments and loading in order to reduce the

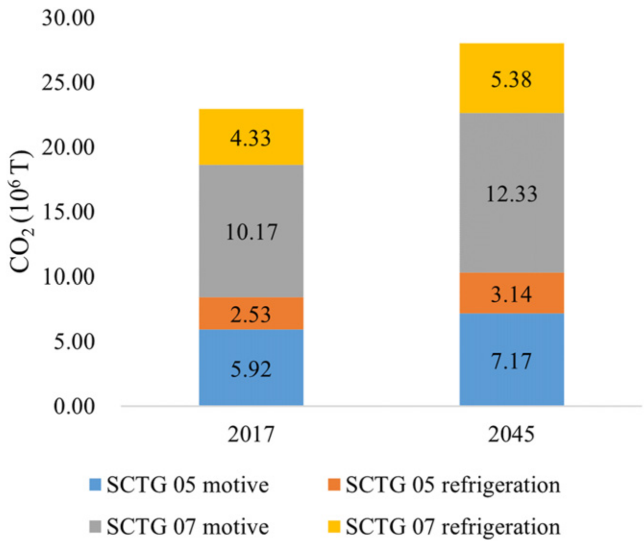

Figure 8. Comparison of estimated carbon emissions in 2017 and 2045.

inefficiencies in current temperature-controlled transportation systems would be a helpful advance. In recent years, many models, for example the vehicle routing problem (VRP) (Toth and Vigo 2014), Green vehicle routing problem (GVRP) (Lin *et al* 2014a), load-dependent VRP (Stellingwerf *et al* 2018) and multi-objective LP (Robinson *et al* 2016), have been presented to optimize operational routing decisions for diverse commodity transportation networks. Truck and fuel selection also are significant contributors to the energy usage and carbon emissions. For long-haul truck transportation, electrifying trucks with batteries or hydrogen fuel cells is an important opportunity for emission reduction compared with diesel-powered trucks (Mauler *et al* 2022, Tong *et al* 2021). Research is under way to develop novel materials to reduce the energy used in refrigeration (Walsh *et al* 2013, Ahmed *et al* 2010, Yan *et al* 2019, Roeth 2020). As suggested in other studies, many of these policy, technology and engineering opportunities could be employed to reduce carbon emissions in refrigerated food supply chains in the future.

4. Conclusions

In this study, we simulated cold chain food flows at county-level spatial resolution together with their associated carbon emissions in transport. To do this we built a novel model of cold chain food flows that uses the real roadway travel distance. There are 78.71 more miles traveled per unit 'meat' and 58.98 more miles per unit 'prepared foodstuffs' when roadway travel distance is used instead of the commonly used haversine distance. This corresponds to 1.02×10^6 t more CO_2 emissions for 'meat' (12.1%) and 1.84×10^6 t more for 'prepared foodstuffs' (12.7%). We find that the cold chain transport of 'meat' emitted 7.1×10^6 t CO_2 yr^{-1} and 'prepared foodstuffs' emitted 12.2×10^6 t CO_2 yr^{-1}, which is in line with other studies. The amount of increase in carbon emissions due to ambient temperature changes associated with climate change is 2.5×10^5 t (about 1% of total emissions in 2017).

Our findings suggest that transport emissions in cold food supply chains are currently a small portion of the carbon footprint of the food system and unlikely to significantly increase under climate change. Yet, as efforts intensify to decarbonize the economy, including the food system, it is important to address all opportunities to reduce carbon emissions. Energy-related CO_2 emissions were about 5.14 billion tons in the United States in 2017. The carbon emissions related to cold chain transportation estimated in this study would thus account for 0.1% of the total emissions in the United States. However, GHG emissions from cold chain food transport in the United States is about 20 Mt, which is equivalent to the total annual GHG emissions of some countries such as Ghana and the Republic of the Congo (WRI 2014). Note that this study provides a conservative estimate of the carbon emissions associated with cold chain food flows because we do not include traffic conditions. This paper focuses on a relatively coarse temporal scale (e.g. annual) and large spatial domain (e.g. long-haul delivery between counties for the entire CONUS), while the impact of traffic jams occurs at the sub-annual time scale and in the short haul, especially the 'last mile' transportation, which is outside the purview of this large-scale work.

Future research could improve upon our work. As more data become available, it will become possible to assemble a panel dataset for use in creating a generalized model of cold chain food flows with predictive capabilities. We focused on the truck mode of transport in this study, since it is the main mode for movement of refrigerated food. Future research could extend this work to more accurately examine the load and fuel selection. Future research could also incorporate processing through the full supply chain in addition to the transport flows considered here. Our study provides more precision in estimating the carbon emissions in cold chain food flows, which could inform efforts to decarbonize transportation of food systems. We make the complete dataset on county-resolution cold chain food flows and associated carbon emissions available with the paper. These estimates may enable future research and inform decision-makers about infrastructure investments and environmental impacts.

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Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.13012/B2IDB-8455093_V1. Data will be available from 1 April 2022.

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