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Assessing the carbon footprint of fresh produce assembly and distribution in the U.S.

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Assessing the carbon footprint of fresh produce assembly and distribution in the U.S.

Abstract Transportation is the largest end-use contributor toward global warming. The contemporary food system provides consumers with convenience, extensive choice, and the year-round availability of fresh produce. In this paper, these achievements are recognized within the context of the associated environmental impacts. While many analyses have considered the energy and material efficiency of various options for food production and packaging, very few studies have investigated the environmental impacts of the transport components of food supply chains. This analysis adds to the existing literature by considering the GHG emissions associated with the aggregation and distribution of fresh produce products consumed by American households. We use a two-stage hybrid approach to identify the most efficient fresh produce assembly and distribution patterns. In the first stage, the facility location problem is formulated as a cost minimization problem. The result obtained in the first stage is used in the second stage to develop a travel distance minimization problem to optimize the design of the supply chain network. This approach allows the simultaneous consideration of two dimensions of sustainability including carbon footprint and the total cost of the supply chain design. The proposed approach generates a tradeoff analysis between environmental emissions and associated costs for making informed decisions on designing sustainable supply chains.

Keywords climate policy, fresh produce supply chain, facility location, optimization

1. Introduction

Climate change is one of the most pressing challenges and greenhouse gas (GHG) emissions are one of the major causes of global warming. Food consumption is responsible for one-quarter of all GHG emissions in the world (Vermeulen, Campbell and Ingram 2012). The production and distribution of food have long been known to be a major source of GHG and other environmental emissions, and it is seen by many environmental advocates as one of the major ways concerned consumers can reduce their “carbon footprints”, a measure of the total consumer responsibility for greenhouse gas emissions (Weber and Matthews 2008). In the literature, there are many attentions and analyses that have considered the energy and material efficiency of various options for food

production and packaging. In recent years, an increasing emphasis has been placed on the emissions of GHG during the transportation of products and commodities (Cooper, and Ozawa 2009; Fresán, Harwatt and Sabaté 2018; O'Donnell, Goodchild, Weber and Matthews 2008; Xu et al. 2015). However, very few studies have investigated the environmental impacts of the transport components of fresh produce supply chains. A considerable amount of the total food intake by mass (30%) is represented by fruits and vegetables, which constitute the largest food group consumed in the U.S. (Juraske Et al. 2009). It is imperative to consider sustainability in the agri-food supply chain, since it relates to marked environmental impacts.

Policymakers and commercial companies in various countries have recognized the necessity to assess these environmental impacts and, on that basis, identify mitigation solutions (Stoessel et al. 2012). Private companies, such as Walmart, calculate the carbon footprint of some of their products and share this information with their customers, while others use such environmental information for supply chain management decisions (Sundarakani et al. 2010). Assessing GHG emissions from transporting fresh produce contributes to environmentally friendly agricultural policy development.

This study examines the carbon footprint of transporting fresh produce products in the U.S. Measuring transportation-related carbon footprint involves careful choice of the scope of the analysis, and there is much uncertainty in the results (Wakeland, Cholette and Venkat 2012). We do not simply assess food miles¹ and GHG emissions using historical fresh produce transportation data in the U.S. Instead, we use an optimization model to solve a food hub location model to identify the most efficient fresh produce assembly and distribution patterns. Based on this, we compute the transportation distance per unit of shipment and then calculate the GHG emissions associated with transportation.

The optimization model has two objective functions, an economic one and an environmental one. The first (economic) objective is to minimize the costs of hub setup, product handling, and product transportation. The second (environmental) objective is to minimize the total transportation distance, including assembly distance and distribution distance, or food miles. Due to a conflict, it

¹ Food miles are defined as the distance between the production source and the retail store, or “farm-to-fork.”

is impossible to optimize two objectives simultaneously. This research proposes a two-stage hybrid solution methodology. In stage one, we take into consideration only the first objective function to solve the optimization problem and obtain a minimized cost value of the first objective function. In stage two, we set the cost value from stage one as a constraint while taking into consideration the second objective function only to resolve the model. Eventually, we identify the product transportation patterns that minimize the overall supply chain cost while considering the environmental aspect. To examine the tradeoff between systematic costs and GHG emissions, we design several scenarios with different environmental constraints. Based on those, we explore potential strategies to mitigate GHG emissions from shipping fresh produce products. This analysis adds to the existing literature by considering the GHG emissions associated with the transportation, and distribution of fresh produce products while minimizing the supply chain costs.

2. Model Specification

We build a national produce product assembly and distribution model to describe how the millions of pounds of imported or domestically grown produce, including 22 vegetable and 35 fruit commodities, move from numerous farms to millions of people throughout the country. It is assumed that hub locations are endogenously determined. We mathematically formulate this product flow pattern problem as a mixed-integer linear programming model. In stage one, we solve the model to meet the economic objective. The model chooses from a finite number of possible hub locations to build a certain scale of hubs in order to balance the trade-offs between initial setup costs and expected transportation costs. Constraints are added to ensure that total production by region and average per unit supplier and shipping costs match observed statistics and ensure that the operations of hubs at different scale levels follow the rule of economies of scale. We solve the model for hub locations (counties) and the scale of hubs in each of those locations to minimize the costs. In stage two, with an additional constraint that the total cost value is no more than the one from stage one, we solve the model to meet the environmental objective. Eventually, the solutions of hub locations and product transportation patterns will satisfy both objectives. Based on the stage two solutions, we identify the carbon footprint of fresh produce assembly and distribution in the U.S.

We study the location decisions of regional food hubs that serve small and medium growers and conventional commodity-scale aggregation and distribution facilities such as merchant wholesalers. Both offer solutions to regional or local produce commodity aggregation and distribution. The model assumes that one or more individual hubs (also called establishments) can be built in each of the counties selected as facility locations². The optimization model identifies not only the optimal establishment locations but also the optimal size and the number of establishments in each of these locations while considering the economic and environmental objectives.

Interest in solving resource allocation and utilization problems in perishable supply chain systems using optimization approaches has been growing steadily in recent years (De Keizer et al.; 2017; Ge, et al., 2018a, 2018b, 2019, 2022; Lejarza and Baldea 2022; Yakavenka et al. 2020). Aligning problem complexity with the mixed-integer optimization capacity, we present a mixed-integer programming-based optimization model for solving a cost minimization problem. The costs include fixed and variable costs associated with facility operation, costs of fresh produce aggregation and distribution, and shrinkage costs during transportation. A mixed-integer model is constructed to identify the optimal locations and scales of establishments. The location problem considers up to 3,109 potential establishment locations (counties), 2,467 domestic production nodes (counties), 81 import nodes (counties), 34 exports nodes and 3,109 consumption nodes (counties). The following notation is introduced for the models.

Sets:

$I=\{1,2,3,\dots,i\}$ denotes commodity groups;

$M=\{1,2,3,\dots,m\}$ denotes a set of custom port districts for import;

$R=\{1,2,3,\dots,r\}$ denotes custom port districts for export;

$F=\{1,2,3,\dots,f\}$ denotes a set of domestic production nodes;

$S=\{1,2,3,\dots,s\}$ denotes a set of establishment candidate locations;

$G=\{1,2,3,\dots,g\}$ denotes a set of consumption nodes;

² In the U.S. fresh produce supply chain systems, counties where hubs are located may contain varying numbers of individual hubs called establishments. The number of establishments in these counties ranges from one to several hundred.

$U=\{1,2,3,\dots,u\}$ denotes levels of handling capacity of establishments, i.e., the volume of products assembled into an establishment annually;

$V=\{1,2,3,\dots,v\}$ denotes transportation mileage categories;

Parameters and exogenous variables

h_u^0 denotes the fixed costs of u level establishment operations. Its value is expected to be positively correlated with establishment's handling capacity u ;

h_u^1 denotes the marginal cost of u level establishment operations. Its value is expected to be negatively correlated with establishment's handling capacity u ;

$a_{f,i}^1$ denotes domestic production of commodity i at production location f ;

$a_{m,i}^2$ denotes import of commodity i at import port m ;

$c_{g,i}^1$ denotes consumption of commodity i at consumption node g ;

$c_{r,i}^2$ denotes export of commodity i at export port r ;

$d_{f,s}$ denotes the distance between production location f to establishment location s ; to more accurately evaluate the shipping costs, we use impedance miles rather than actual miles to indicate the distance between a pair of nodes (Oak Ridge National Laboratory 2011);³

$d_{m,s}$ denotes the distance between import port m to establishment location s (impedance miles);

$d_{s,g}$ denotes the distance between establishment s to consumption node g (impedance miles) ;

$d_{s,r}$ denotes the distance between establishment s to export port r (impedance miles) ;

t_v denotes trucking rate for mileage category v (\$ per thousand pounds per impedance mile);

δ_i denotes shrinkage rate of commodity i per thousand pounds per impedance mile;

³ Impedance represents a measure of the amount of resistance, or cost, required to traverse a path in a network or to move from one element in the network to another. High impedance values indicate more resistance to movement.

w_i denote shrinkage cost for commodity i (\$ per thousand pounds per impedance mile)

p_s denotes the probability of locating at least one establishment at location s ;

θ denotes the average of all p_s for selected establishment locations;

Q_u^1 denotes the upper bound of quantity of products handled annually at u level establishment;

Q_u^2 denotes the lower bound of quantity of products handled annually at u level establishment;

Decision and endogenous variables:

$x_{f,s,i,u}^1$ denotes quantity of commodity i shipped from domestic production node f to u level establishment location s ;

$x_{m,s,i,u}^2$ denotes quantity of commodity i shipped from import port m to u level establishment location s ;

$y_{s,g,i}^1$ denotes quantity of domestically produced commodity i shipped from establishment location s to consumption node g ;

$y_{s,g,i}^2$ denotes quantity of imported commodity i shipped from establishment location s to consumption node g ;

$y_{s,r,i}^3$ denotes quantity of domestically commodity i shipped from establishment location s to export port r ;

$k_{s,u}$ denotes the number of u level establishments at establishment location s ;

Objective functions:

C denotes annual operating costs of an establishment, and

$TC = \sum_s TC_s$ denotes system-wide total annual costs

In the model, product imports and exports are fixed according to observed statistics in the U.S. (USDA/ERS 2012), as a means of disaggregating products into different flows. The optimization model assumes that individual producers/importers are indifferent over the destination of their products and handlers are indifferent regarding which producers/importers deliver products to their facilities and to where they ship their products.

We assume that the cost function comprises establishment operating costs, shipping costs of moving all domestically grown and imported fresh produce to establishments, shipping costs of transporting all aggregated fresh produce to export ports and consumers across the U.S, and shrinkage costs associated with transportation. The operating costs of an establishment are disaggregated into fixed cost (h^0) and variable cost, which is indicated by the marginal cost (h^1) times quantity of products handled at the establishment (Q). Fixed costs are borne by owners regardless of transportation and supplier logistic services produced. For each unit of products handled up to the capacity to which an establishment is built, a per-unit handling cost (marginal cost) is incurred. In addition, produce aggregation and distribution at establishment locations involves the shipment from surrounding production and import regions via a domestic freight network that connects all nodes and establishments.

Since domestic shipments for produce commodities are almost exclusively by truck (Volpe, Roeger and Leibtag 2013), this study assumes that all shipments are transferred by land using trucks. As indicated by Agricultural Refrigerated Truck Quarterly Database (USDA/AMS, 2021), the truck rates differ across mileage categories, a) local movements—500 miles and less; b) short distance movements—between 501 and 1,500 miles; c) medium distance movements—between 1,501 and 2,500 miles; and d) long distance movements—greater than 2,500 miles. The longer the mileage, the lower the truck rate. We apply different truck rates for different shipping ranges.

Fresh produce products are commonly shipped in a controlled and modified atmosphere that differs across commodities. For example, for highly perishable fresh berries, desired transit temperature is between 31 to 32 °F and desired relative humidity is between 90 to 95 percent (USDA/ERS 2008). For non-highly perishable root vegetables, desired transport temperature is between 50 and 60 °F and desired relative humidity is 90 percent. As a result, transportation cost differs across commodities. Based on literature (Parcon, Loke and Leung 2010; USDA/AMS 2021), we compute the trucking rate for different categories across different mileage categories. The trucking rate ranges from \$0.05 to \$0.189 per thousand pounds per mile.

Produce products suffer shrinkage during transportation. Product shrinkages were determined from USDA's Loss Adjusted Food Availability (LAFA) Dataset, which reports the total percentage of specific fruits and vegetables in the U.S. that are lost between post-harvest and

delivery to market. The shrinkage rate varies widely across commodities due to their biological diversity and different respiration characteristics (de Keizer et al. 2017). Based on the fresh produce shrinkage rate for individual commodities (USDA/ERS, 2021), we calculate the rate for each of the 11 categories, which is reflected by the weighted average shrinkage rate of all varieties that are classified into the category. Due to a lack of detailed data, the analysis used herein assumes that losses are distributed equally across product assembly and distribution stages. Given the average fresh produce transportation distance to reach the terminal market in the U.S. (NCAT, 2008), we compute the shrinkage rate per thousand pounds per mile for each category. Using the average farm prices of commodities from 2012 (equivalent to the buy prices paid by hubs) (USDA/NASS Quick Stats, 2021), we compute the weighted average farm price for each category and then convert shrinkage in weight to loss in dollars. The shrinkage rate ranges from 0.0029 percent to 0.0086 percent per mile and the shrinkage cost ranges from \$0.010 to \$0.066 per thousand pounds per mile for the 11 fresh produce categories.

It is assumed that establishing and operating establishments is motivated by cost minimization. The basic algorithms of the problem are summarized and presented by an objective function and combinatorial constraints. The model aims to select effective establishment locations from a candidate set of establishment locations to minimize the overall supply chain cost, subject to satisfying system constraints. The objective function and system constraints of the model to solve this problem are given in equations (7) to (14).

Minimize

$$\begin{aligned}
 Obj_1 = & \sum_{s \in S} \sum_{u \in U} \{h_{s,u}^0 \cdot k_{s,u}\} && \text{Fixed costs of} \\
 & && \text{establishment operating} \\
 & + \sum_{f \in F} \sum_{s \in S} \sum_{m \in M} \sum_{i \in I} \sum_{u \in U} \{h_u^1 \cdot [x_{f,s,i,u}^1 (1 - \delta_i \cdot d_{f,s}) \\
 & && + x_{m,s,i,u}^2 (1 - \delta_i \cdot d_{m,s})]\} && \text{Variable costs of establishment} \\
 & && && \text{operating}
 \end{aligned} \tag{1}$$

$$\begin{aligned}
& + \sum_{f \in F} \sum_{s \in S} \sum_{m \in M} \sum_{i \in I} \sum_{u \in U} \{ (t_v + w_i) \cdot (d_{f,s} \cdot x_{f,s,i,u}^1 \\
& \quad + d_{m,s} \cdot x_{m,s,i,u}^2) \} \quad \text{Transportation costs and shrinkage costs (assembling)} \\
& + \sum_{s \in S} \sum_{g \in G} \sum_{r \in R} \sum_{i \in I} \{ (t_v + w_i) \cdot (d_{s,g} \cdot y_{s,g,i}^1 + d_{s,g} \\
& \quad \cdot y_{s,g,i}^2 + d_{s,r} \cdot y_{s,r,i}^3) \} \quad \text{Transportation costs and shrinkage costs (distribution)}
\end{aligned}$$

$$Obj_2 = \quad (2)$$

$$\begin{aligned}
& \sum_{f \in F} \sum_{s \in S} \sum_{m \in M} \sum_{i \in I} \sum_{u \in U} (d_{f,s} \cdot x_{f,s,i,u}^1 + d_{m,s} \cdot x_{m,s,i,u}^2) \quad \text{Assembly distance} \\
& + \sum_{s \in S} \sum_{g \in G} \sum_{r \in R} \sum_{i \in I} (d_{s,g} \cdot y_{s,g,i}^1 + d_{s,g} \cdot y_{s,g,i}^2 + d_{s,r} \\
& \quad \cdot y_{s,r,i}^3) \quad \text{Distribution distance}
\end{aligned}$$

Subject to:

$$\sum_{s \in S} \sum_{u \in U} x_{f,s,i,u}^1 = a_{f,i}^1 \quad \forall f, i \quad (3)$$

$$\sum_{s \in S} \sum_{u \in U} x_{m,s,i,u}^2 = a_{m,i}^2 \quad \forall m, i \quad (4)$$

$$\sum_{s \in S} (y_{s,g,i}^1 + y_{s,g,i}^2) = c_{g,i}^1 \quad \forall g, i \quad (5)$$

$$\sum_{s \in S} y_{s,r,i}^3 = c_{r,i}^1 \quad \forall r, i \quad (6)$$

$$\sum_{f \in F} \sum_{u \in U} \{ x_{f,s,i,u}^1 \cdot (1 - \delta_i \cdot d_{f,s}) \} = \sum_{g \in G} y_{s,g,i}^1 + \sum_{r \in R} y_{s,r,i}^3 \quad \forall s, i \quad (7)$$

$$\sum_{m \in M} \sum_{u \in U} x_{m,s,i,u}^2 \cdot (1 - \delta_i \cdot d_{m,s}) = \sum_{g \in G} y_{s,g,i}^2 \quad \forall s, i \quad (8)$$

$$\begin{aligned}
& \sum_{f \in F} \sum_{m \in M} \sum_{i \in I} \{ x_{f,s,i,u}^1 \cdot (1 - \delta_i \cdot d_{f,s}) + x_{m,s,i,u}^2 \cdot (1 - \delta_i \cdot d_{m,s}) \} \\
& \geq Q_u^1 \cdot k_{s,u} \quad \forall s, u \quad (9)
\end{aligned}$$

$$\sum_{f \in F} \sum_{m \in M} \sum_{i \in I} \{x_{f,s,i,u}^1 \cdot (1 - \delta_i \cdot d_{f,s}) + x_{m,s,i,u}^2 \cdot (1 - \delta_i \cdot d_{m,s})\} \leq Q_u^2 \cdot k_{s,u} \quad \forall s, u \quad (10)$$

$$x_{f,s,i,u}^1 \geq 0, x_{m,s,i,u}^2 \geq 0, y_{s,g,i}^1 \geq 0, y_{s,r,i}^2 \geq 0, y_{s,g,i}^3 \geq 0 \quad \forall f, s, r, g, i, u \quad (11)$$

$$k_{s,u} \in \{0, 1, 2, 3 \dots\} \quad \forall s, u \quad (12)$$

Equation (1) states the objective function that minimizes total cost. Equation (2) states the objective function that minimizes the total transportation distance. Equation (3) ensures that the total quantity of commodity i transported from production region f to all establishments S is equal to the total quantity produced in region (county) f . Equation (4) ensures that the total quantity of commodity i shipped from import port f to all establishments S are equal to total quantity imported in region (county) f . Equation (5) ensures that the total quantity of domestically produced (for domestic consumption only) and imported commodity i shipped from all establishments S to consumers in region g equal to the total consumption of consumers in region g . Equation (6) ensures that the total quantity of domestically produced commodity i shipped from all establishments S to all export ports equal to the total quantity of export observed. Equations (7) and (8) state a balance between the inbound flow and outbound flow of commodity i for an establishment. Equations (9) and (10) impose the upper and lower bounds of handling capacity for building u level establishments in facility location s . Equation (11) requires that shipments from farms to establishments and from establishments to export nodes and consumers are not negative. Equation (12) provides (a) whether to build ($k_{s,u} > 0$) or to not build ($k_{s,u} = 0$) establishment(s) in location s ; (b) the number of establishments to build in facility location s if it is selected as a facility location.

First, we take into consideration only the first objective function, and use LP solver to obtain an optimum solution, whose value is considered the lower bound LB_1 of first objective function. Then, we use Eq. (13) as a constraint along with constraints (3)-(12), while taking into consideration the second objective function only.

$$\text{Objective function 1} = LB_1 \quad (13)$$

In this way, the second objective can be optimized without sacrificing the first objective. Then we can obtain a solution that minimizes the GHG emissions from transportation, given the minimum costs.

3. Empirical Evidence of Economies of Scale

Plentiful evidence shows that the facilities have cost functions with economies of scale (Camargo, Miranda and Luna 2009; Dupont 2008; Horner and O’Kelly 2001). The operating costs per unit of output are decreasing as the scale of output increases (der Broek et al. 2006; Ollinger, MacDonald and Madison 2005; Teratanavat, Salin and Hooker 2005). Mosheim and Lovell (2009) investigate the trend of increasing farm size in the U.S. and concluded that scale economies represent the driving force toward consolidation and scaling up farm size. In this study, we incrementally introduce economies of scale when identifying establishment locations. The scale economies add complexity to the endogenous decision on the number and scale of establishments. In this manner, the operating cost of an establishment is formulated on the quantity of product handled by the establishment and is endogenously responsive to quantity by rewarding the managers for greater quantity handled.

To identify empirical evidence of the scale effect inherent in hub operations, we collect and analyze data on the scope and scale of fresh produce establishment operations. We first compile 2012 Economic Census data (U.S. Census Bureau 2012) on annual sales and operating costs of fresh fruit and vegetable wholesales establishments (Census Bureau, 2012). The dataset is comprised of 152 observations for (i) number of establishments, (ii) total annual operating costs, and (iii) total annual product sales. Sale values for establishments are converted to quantity of products handled in these establishments based on the 2012 wholesale price for commodities marketed in the U.S. (USDA/NASS, 2020).

To reveal the fixed costs and variable costs to operate an establishment, we calculate the average quantity handled at all establishments for each observation and the average operating costs for the establishments. Dividing both the annual handled quantity and annual operating cost observations

by the total number of establishments transforms the 152 observations into county-wide establishment averages.

As shown in Equation (14), the operating cost of a u level establishment, C_u , is comprised of fixed and variable costs.

$$C_u = h_u^0 + h_u^1 \cdot Q_u, \quad (14)$$

where Q_u indicates the total quantity handled at a u level establishment.

To facilitate identifying the pattern of scale effects, we order the quantity handled at those establishments from low value to high value. Four hierarchy types with almost equal data sample sizes are defined based on quantity handled by each establishment. The quantity handled at type 1 establishments ranges from 1,851 to 12,610 thousand pounds (TPs) with an average of 7,567 TPs. The quantity handled at type 2 establishments ranges from 12,714 to 26,217 TPs with an average of 19,735 TPs. The quantity handled at type 3 establishments ranges from 26,539 to 43,139 TPs with an average of 34,891 TPs. The quantity handled at type 4 establishments ranges from 43,387 to 145,437 TPs with an average of 61,510 TPs. Following the functional form of Equation (14), ordinary least square (OLS) regression is used to estimate the relationship between the operating cost (C_u) and the quantity handled at the establishment (Q_u) for each type of establishment (Table 1).

Table 1. Regression Relationships between Operating Cost and Quantity Handled (Scale Effect).

Type (1,000 lb)	Variables	Coefficients (US\$)	t Stat	P -value	F	R^2	Obs
Type 1	h_1^0	121,650*	1.476	0.148	30.97	0.46	39
(1,851-12,610 with an average of 7,567)	h_1^1	56.08***	5.565	0.000			
Type 2	h_2^0	425,607***	1.996	0.053	14.85	0.29	38
(12,714-26,217 with an average of 19,735)	h_2^1	40.64***	3.854	0.000			

Type 3	h_3^0	998,813**	1.603	0.101	4.34	0.09	37
(26,539-43,139 with an average of 34,891)	h_3^1	27.06**	1.531	0.134			
Type 4	h_4^0	2,419,736***	5.408	0.000	4.59	0.11	38
(43,387-145,437 with an average of 61,550)	h_4^1	9.89**	1.610	0.098			

Note: *** significant at the 0.05 level; ** significant at the 0.1 level; * significant at the 0.15 level

As shown in Table 1, most cost parameter estimates exhibit highly significant t -statistics at the 0.05 level. The other cost parameters are also significant at the 0.1 or 0.15 level. The F values for regressions are also highly significant, confirming the reliability of regressed relationships. The R -square, in a range of 0.09 to 0.46, is not high but still reasonable for cross-section data due to the sole independent variable in Equation (14). Generally, the regression results are sound and consistent with expectations. The results show that fixed costs increase with the establishment scale, and the unit marginal costs decrease with the establishment scale, i.e., the larger the establishment scale, the less the marginal cost for one unit increases in the volume handled. In addition, for all four establishment types, average per-unit costs decline with increases in total quantity handled, since fixed costs are spread among more units of product throughput. While the higher fixed costs and transportation costs for larger hubs reduce the incentives to build large capacity hubs, the marginal cost difference between hub types provides incentives to build large hubs to take advantage of the scale effect. However, the average per-unit costs in a large-scale establishment are significantly lower than those in a small-scale establishment under the condition that an establishment's handling capacity meets the maximum bound of its level.

The regression results for fixed costs and marginal costs quantitatively reflect the effects of varying influential factors on establishment operation at an aggregation level. The optimization model strictly follows the cost results shown in Table 1 for each built establishment at a location. Because our regression results are likely to reflect roughly the average fixed and variable costs across all

observations, we set the throughput limits of modeled establishments equal to the average throughput across all observations used for cost regression for each grouping.

4. Data

Based on 2012 USDA/NASS data, farms in 2,570 counties in 47 continental states grew vegetable and fruit crops for the fresh market (USDA/NASS 2021). Combined production for the subset level of these crops produced in each county is converted to a common unit (1,000 pounds) and summed to a single annual production statistic per county.⁴ Fresh produce import data by county of unloading for the calendar year 2012 are compiled from U.S. Census Bureau (2012) sources. 81 counties across 30 continental states import fresh produce from international sources beyond the U.S. The distribution of production and imports across counties is different in spatial and temporal patterns. Fresh produce exports pass through 34 custom ports located at different counties. Export volume by categories for the year 2012 is from USDA/ERS (2012). Figure 1 shows continental U.S. fresh produce production and import distribution across counties for all categories and for category 6 (melons). Produce production and import quantity could differ significantly across locations between categories.

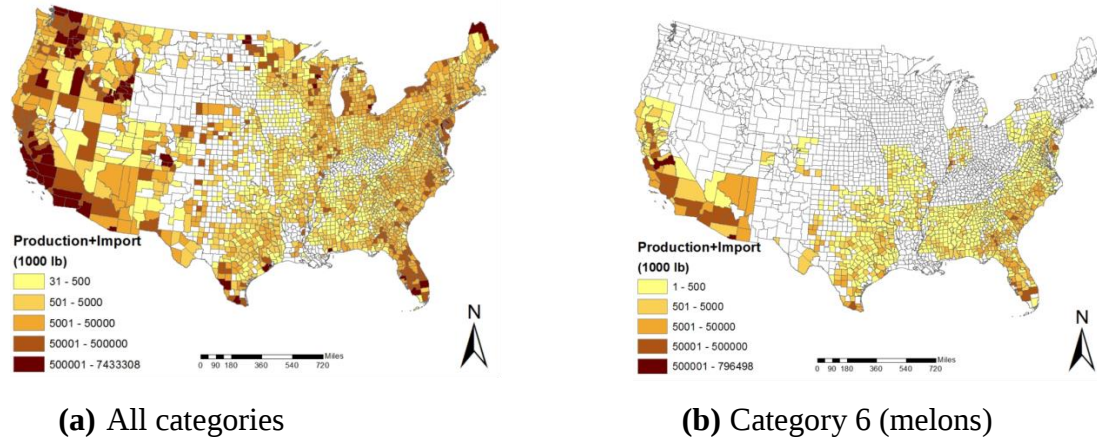


Figure 1. Fresh produce production and imports across U.S. counties.

⁴ We use data compiled using the method described in Ge et al. (2015) and Yi et al. (2021).

This study assumes a market-clearing condition in which the production and import of fresh produce are equated to the export plus demand. This is a reasonable assumption, given that we are reconciling historical market data with a specific model of how this produce is aggregated and distributed. The volume of consumption for each county is calculated based on consumption by eight age groups, e.g., <6, 6-12, 13-17, 18-34, 35-44, 45-54, 55-64, 65+ (U.S. Census Bureau Population Estimates Program (PEP) 2012; Produce for Better Health Foundation 2015).

In this study, the facility location problem involves a large-scale optimization model. The amount of memory and the computational effort needed to solve such problems grow significantly with the number of variables and constraints. To solve the model with a reasonable computation time, we avoid extensive identification of the varieties of fresh produce commodities at the county level. Following the literature (e.g., USDA/ERS, Agricultural Marketing Resource Center), based on the composition and consumption pattern of commodities, we categorize the production, import, export and demand of vegetable and fruit commodities into eleven categories. Table 1 shows the eleven categories and the share of each category in the total production and imports.

Table 2. Fresh Produce Categories.

No.	Categories	List of varieties
1	Leafy vegetables	cabbage, celery, lettuce, spinach, brussels sprout, escarole, endive
2	Flower vegetables	cauliflower, broccoli, artichoke, asparagus
3	Fruit vegetables	pepper, cucumber, eggplant, okra, tomato, pumpkin, sweet corn, squash, zucchini
4	Root vegetables	potatoes, sweet potatoes, yams, turnip, beet, carrot
5	Bulb vegetables	garlic, onion
6	Melons	cantaloupes, honeydews, watermelons
7	Berries	blackberry, blueberry, boysenberry, cranberry, loganberry, raspberry, currants, strawberry, grape, other berries
8	Tropical fruits	avocado, banana, date, fig, guavas, kiwi, papayas, pineapple, mango

9	Stone fruits	apricot, cherry, tart, nectarine, olive, peach, plum, prune, persimmon
10	Citrus fruits	tangerine, mandarin, oranges, grapefruit, lime, kumquat, other citrus, tangelo
11	Pomes	apple, pear

The proportionality constant specifying the rate of emission per unit of weight and distance is called the "emission factor", and is expressed in units of grams of "carbon dioxide equivalent"⁵ per ton of freight per mile traveled (g CO₂-eq/ton-mile). Typical values for various transportation modes, using numbers based on an EPA publication (TERC 2022), are 253 g CO₂-eq/ton-mile for diesel trucks, 27 g CO₂-eq/ton-mile for rail, and 41 g CO₂-eq/ton-mile for domestic water transportation. Other sources provide somewhat different numbers, but these values are reasonably representative of the consensus.

5. Results

The facility location optimization problem is compiled in GAMS and solved using the linear programming solver CPLEX. The computing procedure is iterative, starting with an arbitrarily chosen set of random initial locations for given numbers of facilities with varying handling capacity levels, and then production and import nodes are allocated to these facilities and facilities direct their throughput to consumption nodes or export nodes. The iterative procedure of the optimization model is repeated to gradually improve these locations and leads to the minimum total costs. The optimal-seeking procedure is terminated when the total costs are below a set value defined by the relative gap of 0.001. All computational executions were performed on a computer with 4 cores, 3.07 GHz CPU and 96 gigabytes RAM. It takes 100-450 hours to solve the model in each stage or in different scenarios.

⁵ The "equivalent" in carbon dioxide equivalent accounts for emissions of other gases besides carbon dioxide, like methane and nitrous oxide, that also have greenhouse warming potential.

Establishment Locations

We solve the model specified in Section 2 to meet the two objectives. it is obvious that the supply chain design changes when we focus on different objectives. The solution from stage two indicates that the average transportation distance for all categories reduces by 10.2 miles or 1 percent as compared with that from stage one's solution. This is achieved by changing the establishment locations and increasing the number of establishments. Figure 2 shows the location solution for the model after subsequently minimizing costs and food miles. All four types of establishments emerge in 544 facility locations. The number of establishments in facility locations ranges from 1 to 75. The type 4 establishments represent most of these locations. In total 485 locations locate 2,378 type 4 establishments. Only a limited number of locations are selected to build type 1, type 2 and type 3 establishments. There are 5 locations for type 1 establishments, 6 locations for type 2 and 55 locations for type 3, representing 6, 7 and 60 establishments at these locations respectively. Besides, two types of establishments coexist in 7 locations. They are named “dual-type” locations (purple spots in Figure 3) where there are one type 1 plus one or several establishments in other types. As shown in the figure, concentrated hub clusters are located in California, the Pacific Northwest, Florida and the Northeast where fresh produce production and consumption are both high. There are few or no hubs in the Rocky Mountain States and the Plain States.

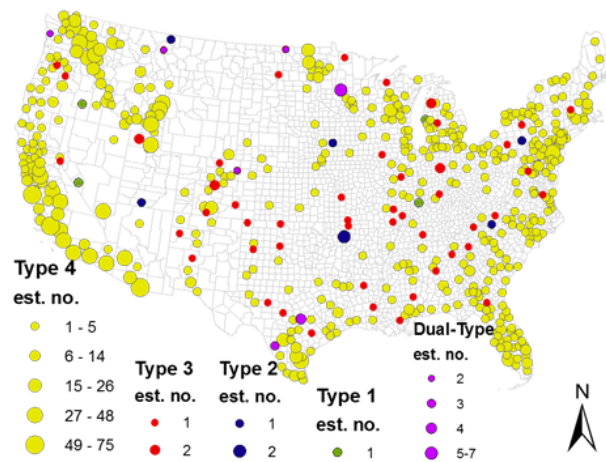


Figure 2. Establishment locations and numbers

Transportation Patterns

Figure 3 shows the aggregation and distribution patterns of melons (category 6) across counties. Some establishments serve the local community, e.g., establishments in the Pacific Northwest and Great Lakes regions. They aggregate commodities locally from small- and medium-sized fruit and vegetable farms and transport them to local consumers, notably for niche products and rural markets. In the U.S., the most fruit and vegetable production takes place on relatively large farms (MacDonald, Korb and Hoppe 2013). Establishments adjacent to those farms deliver aggregated products to more distant consumers. Those large establishments in California, Arizona, Texas and Florida distribute products to consumers spreading over broad regions to satisfy their demands.

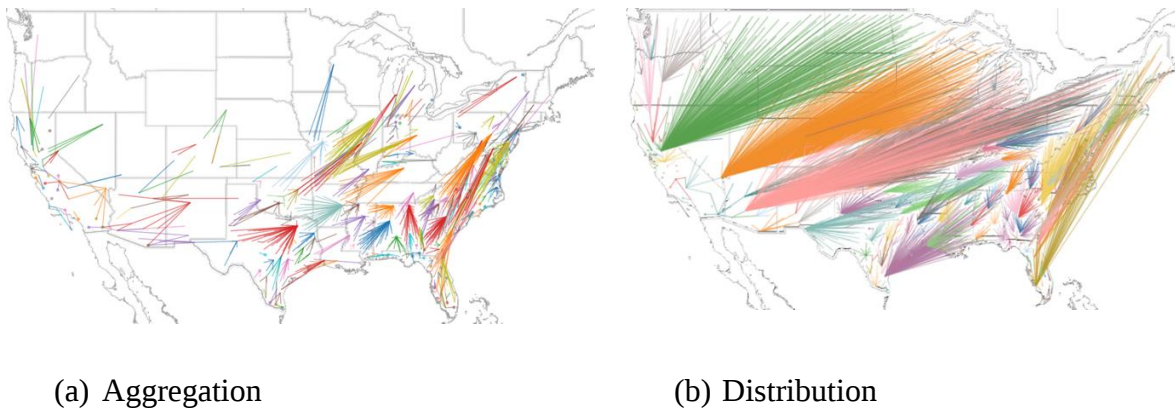


Figure 3. Aggregation and distribution patterns of fruit vegetables. Lines in the same color indicate the aggregation routes (from multiple production nodes) or distribution routes (to multiple consumption nodes) of a county-level facility.

Food miles

Based on product assembly and distribution patterns, we calculate the transportation distance from farm to consumers for each unit of fresh produce product. The varying production and import locations and establishment locations lead to different food miles across counties. As shown in Figure 4, the assembly distance of melons ranges widely from 24 to 3,027 miles with an average of 818 miles (assembly 81 + distribution 737). The assembly distance of all categories ranges from 77 to 2,627 miles. Most melons are produced in the West Coast of the U.S., Arizona and Southern

U.S. Melons have to be shipped long distance to other regions for consumption. The average transportation distance for all categories ranges from 77 to 2,627 miles with an average of 1,087 miles (assembly 98+distribution 989). In general, fresh produce products consumed in the Western U.S. and Texas travel shorter distances than those consumed in the Middle West, South and Northeast of U.S. California, Washington, Arizona and Texas account for more than half the domestically produced fresh produce products for the fresh market. The shipping distance of produce products consumed in these regions and neighboring regions is significant shorter than that in other regions.

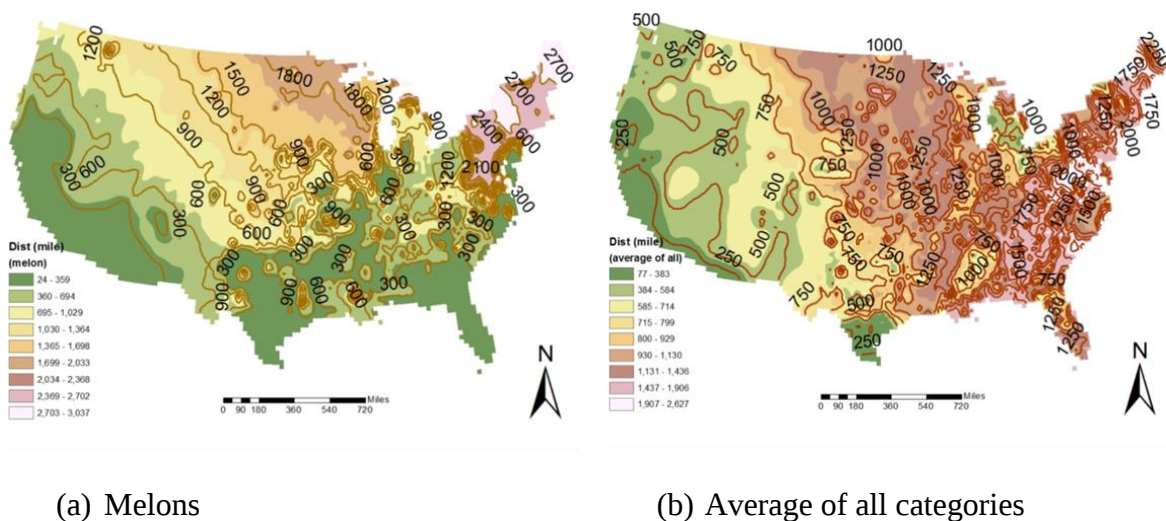


Figure 4. Food miles

GHG Emissions

Based on the transportation distance per unit of shipment and the total consumption in each county, we calculate the total GHG emissions at the county level. Figure 5 shows the GHG emissions from shipping stone fruits to consumption nodes. As the figures show, Metropolitan and urban areas have larger GHG emissions, although transportation distance per unit of shipment is not high. Huge consumption in those areas leads to high GHG emissions. The Northeast generally suffers a food deficit and have to import products that could be thousands of kilometers away. High GHG emissions in the region are attributed to longer food miles. Comparatively, in Rock mountain states and some states in the Middle West, GHG emissions

are lower due to the lower consumption level, although the transportation distance is longer than in other regions.

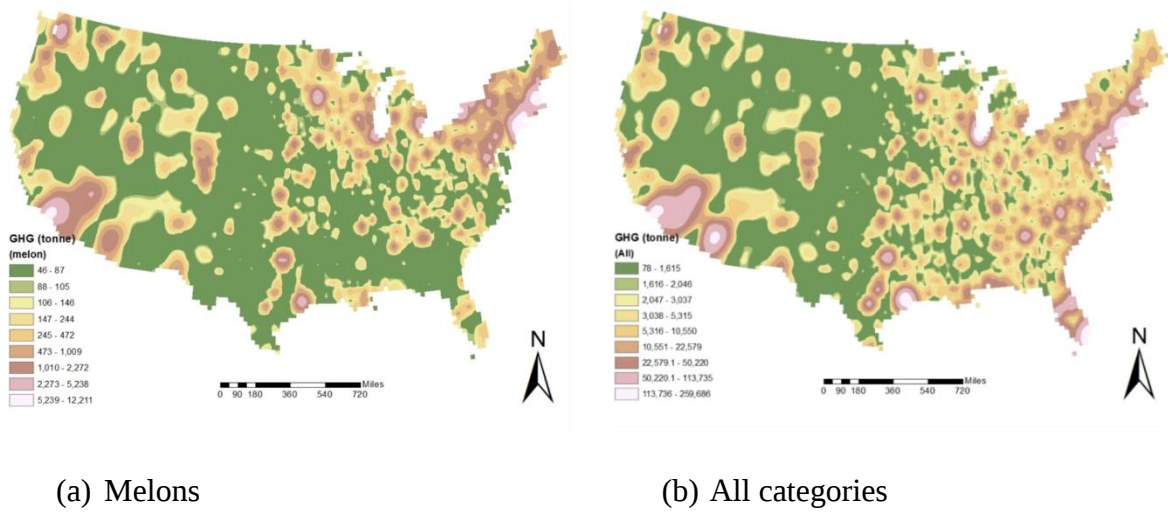


Figure 5. GHG emissions across counties

The Tradeoff between Costs and Food Miles

This section examines how the total costs respond to a reduction in the average food mile. A balance between environmental emission and cost could be achieved based on establishing a tradeoff using the optimization model. Ten scenarios are generated under different levels of reduced transportation distance (equivalent to GHG emissions). First, we solve a transportation distance minimization problem (objective 2) without the cost constraint (Equation (13)) and obtain a lower bound of total transportation distance, LBD. The total transportation distance from the optimization model solved previously (i.e., the stage 2 solution) works as an upper bound. Then we calculate the difference, D , between the lower bound and the upper bound, and use equation (15) as a constraint where we relax the LBD by a certain percentage. For each $n=1,2,\dots,10$, we optimize the first objective function, this we are able to a set of 10 solutions.

$$\text{Objective function 2} \leq LBD + 10\% \times n \times D \quad (n=1,2,\dots,10) \quad (15)$$

Based on a range of solutions from different scenarios, we constructed a distance-cost trade-off curve (Figure 6). Our results suggest the total costs increase with the reduced food miles. In these scenarios, the reduced distance ranges from 1 percent to 10 percent (or about 10 miles to 100 miles). Not surprisingly, the total costs increase with a growing speed as the average transportation distance decreases. As the required reduction in distance increases, the decrease in the marginal cost margin will lead to more dispersed locations and more establishments with a smaller scale. While facilitating producers and customers' access to establishments for services, the establishment operating costs increase. A higher reduction in transportation distance is correlated with higher operating costs. It costs about \$3.56 billion to reduce the average transportation distance by 10 percent or by 100 miles.

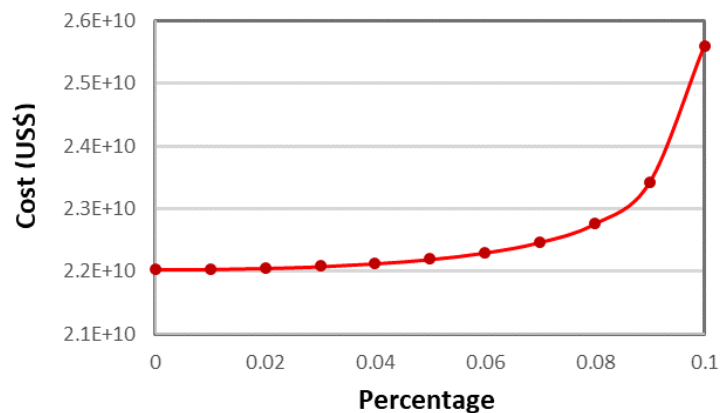


Figure 6. Cost vs. transportation distance reduction

Our solution suggests that the number of establishments and their locations both increase with the reduction in the average transportation distance. When the reduced percentage increases from 1 to 10, the number of establishments increases from 2,458 to 3,127. More type 1, type 2 and type 3 establishments emerge and the number of type 1 establishments diminishes. The number of establishments locations increases from 544 to 990. As a result, produce products are consolidated and distributed by more small-scale establishments located at more locations dispersed geographically across the county. The producers or consumers previously served by these facilities are now served by closer ones. This leads to shorter transportation distances but higher costs to build establishments.

GHG emissions can be reduced by locating more establishments at more dispersed locations. Although a reduction in food miles leads to different establishment locations and transportation patterns, a large amount of GHG emission (e.g., 8 percent) can be attained with a modest increase in the cost of the supply chain network. The increased costs are not trivial, but neither are they cataclysmic for a multibillion-dollar food facility network. To this end, such a change could be of great value due to the potential environmental benefits that might be significant. Understanding these tradeoffs between costs and reliability helps inform facility location plans that are more environmentally friendly.

Carbon Tax

Economists have long argued that a well-designed carbon tax is the most economically efficient way to reduce carbon emissions (IMF 2019). The main purpose of a carbon tax is to price carbon emissions in order to reduce the amount of carbon in the atmosphere and mitigate the adverse effects of climate change. Carbon pricing can significantly reduce carbon emissions and help meet climate goals (Pomerleau and Asen 2019).

Our model provides a preliminary assessment of the effect of carbon tax on the reduction in GHG emissions from fresh produce transportation. Imposing a carbon tax of \$60 per ton of GHG emissions on shipping fresh produce products reduces food miles by 15 miles as compared to the results without imposing the carbon tax. As shown in Figure 7, this is equivalent to a reduction of GHG emissions by 1.35 percent in total. In the figure, the red line indicates the costs arising from GHG emission reduction (by percentage) while the blue line indicates the reduced amount of carbon tax due to the reduction of GHG emissions. The intersection of the two lines represents the optimal solution for GHG emission reduction under the given carbon tax.

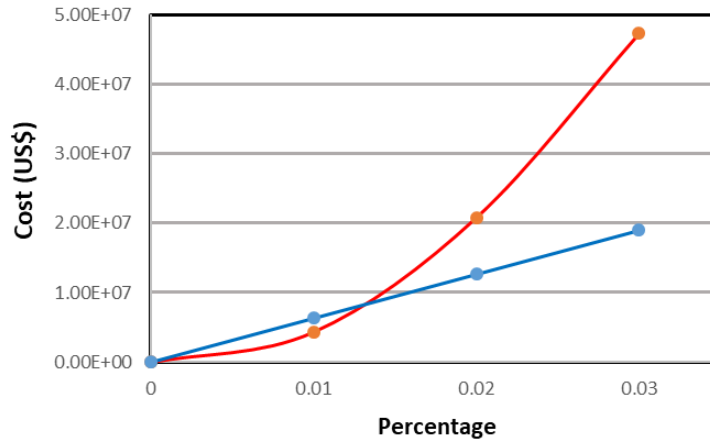


Figure 7. GHG emission reduction under carbon tax

A carbon tax internalizes these external costs on the environment by adding them to the price of the fresh produce products. As a result, the full cost of the fresh produce products, including the external costs to the environment, are paid for by the consumer of the products. On average, the carbon tax adds about \$0.02/pound to the final prices of products. However, the value differs across fresh produce categories, ranging from \$0.01 to \$0.03/pound. This disincentivizes consumers from consuming carbon-intensive products, leading to lower carbon emissions. The extent to which supply chain participants adopt GHG emission reduction activities would depend on their costs, potential revenues, and other economic incentives created by climate policy.

6. Discussions

Agriculture could play a key role in the U.S.'s efforts to combat climate change if food supply chain members engage in actions that reduce GHG emissions or remove GHGs from the atmosphere. The Federal Government is considering offering carbon offsets and incentive payments to encourage supply chain participants to pursue these climate-friendly activities as part of a broader effort to combat climate change.

There are various possible ways to reduce GHG emissions from shipping fresh produce. Our results suggest a necessity of building short supply chains. The transportation patterns in our solution represent the shortest way to ship fresh produce products from field to fork under the given cost constraint. Previous studies confirmed that short supply chains can avoid unnecessary

transport and minimize carbon emissions (Jones 2002). Short supply chains are characterized by a reduced number of intermediaries essential to provide the consumer with the final product. Besides a reduced number of intermediaries, the basic criteria in defining short supply chains are the shortest distance between producers and consumers (Markuszczyńska et al., 2012).

Local food systems bring environmental benefits through reduced transport externalities. The focus on increased food miles due to increased international trade in food has prompted many environmental advocates, retailers, and others to urge a “localization” of the global food supply network (Jones 2002; Weber and Matthews 2008). Weber and Matthews (2008) show that for the average American household, “buying local” could achieve about a 4–5% reduction in GHG emissions due to large sources of carbon emissions in the production of food. In the agricultural adaptation domain, land use change may help mitigate GHG emissions. That is, to expand local production for those regions that suffer consumption deficit, such as the middle west, rocky mountain states, and the west south central. Expansion of local production in those regions enables people to eat more local food and thus reduce imports from other regions. When fresh products are sourced locally, the assembly and distribution chain becomes shorter and then GHG emissions from transporting products can be mitigated. However, to what extent local production can be expanded is subject to land availability and productivity, water stress and labor availability in the region. If there are tangible improvements associated with a shift to a more local food system, then it is important that the potential social, economic, and environmental benefits of these alternatives be described and, as far as possible, quantified. In addition, further expansion of local food systems requires the engagement of and a collaborative partnership between public and private sectors. It is also important to improve legal regulations intended to support small food producers. Further research into these issues is required.

Given land use pattern, planned planting and harvesting helps smooth production. This can narrow down the gap between demand and supply in regions where consumers suffer a periodic shortage of food supply. For example, farmers can harvest earlier or postpone harvesting corresponding to demand. In this way, these regions can improve the supply consistency and reduce the probability to import products from other regions.

Switching transportation modes represents another way to reduce GHG emissions. When comparing across transportation modes, there is roughly an order of magnitude difference between the life-cycle freight emission factors for truck, rail, and containership (86, 13, and 4.6 gCO₂e/tkm, respectively) (CPA 2020). The existing rail business for fresh produce only accounts for a very limited proportion of all fresh produce shipments (less than 5 percent). There is a great potential to reduce GHG emissions by using more freight rail transportation instead of truck transportation. Bell and Horvath (2020) found that the GHG emissions associated with transporting fresh produce by rail from Florida to New York City are roughly five times lower per kilogram of oranges than by truck. However, there may be practical limitations to increasing the proportion of fresh produce products by rail, including railroad network constraints and the additional time required for loading and unloading. The distribution centers and stores of the multiple retailers, in particular, are located for ease of access to the motorway network and customers arriving by car. Over the last 50 years, the U.S. has developed centralized just-in-time distribution systems that are dependent on road freight. A shift to rail would require major new infrastructure in terms of the relocation of distribution centers, new rail freight lines and terminals, or both. An assessment of the infrastructure network was outside the scope of this paper but merits future consideration.

Using self-driving trucks is another transportation option. Self-driving trucks more energy efficient in transporting products, especially for long-distance shipping. The trucking industry is foregoing ahead with automation technology. It is very likely that we will see widespread use of self-driving trucks over the coming decade. A self-driving truck would be able to deliver across the U.S. in 2 days instead of 5 days, which means it can bring down the cost by about 4 times and can increase the distance driven in a day by more than 2 times. This represents a great potential to reduce GHG emissions from transporting fresh produce.

7. Conclusion

This research proposes an integrated two-stage hybrid approach for sustainable fresh produce supply chain network design. The analysis explores the spatial structure of the U.S fresh produce assembly and distribution system that might result if these supply chain activities were regionally coordinated. We identify the most efficient fresh produce assembly and distribution patterns and assess the associated product carbon footprint. This method allowed the connection of

sustainability criteria to the supply chain network design decisions in agri-food supply chains. This two-step process can be used by a decision maker as a decision support tool to assist them in choosing the supply chain design decision that best suits their preferences in terms of economic and environmental performances.

Optimal resource allocation can only be obtained through building a coordinated system in which fresh produce supply chain participants work together to jointly minimize total supply chain costs or carbon footprint. To this end, our model can work as a tool to conduct a cost-benefit analysis for policymakers when making environmental policy decisions.

References

- Bell, E.M., and A. Horvath. 2020. Modeling the carbon footprint of fresh produce: effects of transportation, localness, and seasonality on US orange markets. *Environmental Research Letters* 15: 034040.
- Camargo, R.S., G. Miranda, and H.P.L. Luna. 2009. Benders decomposition for hub location problems with economies of scale. *Transportation Science* 43 (1): 86–97.
- Corrugated Packaging Alliance (CPA)/PE-Americas and Five Winds International. 2010. Corrugated Packaging Life-cycle Assessment Summary Report.
- De Keizer, M., R. Akkerman, M. Grunow, J.M. Bloemhof, R. Haijema, and J.G.A.J. van der Vorst. 2017. Logistics network design for perishable products with heterogeneous quality decay. *European Journal of Operational Research* 262 (2): 535-549.
- der Broek, P. Schutz, L. Stougie, and A. Tomasgard. 2006. Location of slaughterhouses under economies of scale. *European Journal of Operational Research* 175 (2):740-750.
- Dupont, L. 2008. Branch and Bound Algorithm for a facility location problem with concave site dependent costs. *International Journal of Production Economics* 112 (1): 245-254.

- Fresán, U., H. Harwatt, and J. Sabaté. 2018. Developing a methodology for estimating transport-related CO2 emissions for food commodities. *Economics Journal of Sustainable Development* 11 (6): 47-58.
- Ge, H., P. Canning, S. Goetz, and A. Perez 2018a. Effects of scale economies and production seasonality on optimal hub locations: The case of regional fresh produce aggregation. *Agricultural Economics* 49 (2): 157–169.
- Ge, H., P. Canning, S. Goetz, and A. Perez. 2018b. Optimal locations of fresh produce aggregation facilities in the United States with scale economies. *International Journal of Production Economics* 197: 143–157.
- Ge, H., P. Canning, S. Goetz, and A. Perez. 2019. Embedding economies of scale concepts in the model of optimal locations of fresh produce aggregation hubs. *Agricultural and Resource Economics Review* 48 (3): 365-387.
- Ge, H., M. Gómez, C. Peters. 2022. Modeling and optimizing the beef supply chain in the Northeastern U.S. *Agricultural Economics*. Published online. DOI: 10.1111/agec.12708.
- Horner, M.W., and M.E O’kelly. 2001. Embedding economies of scale concepts for hub network design. *Journal of Transport Geography* 9 (4): 255-265.
- International Monetary Fund (IMF). 2019. “Fiscal Policies for Paris Climate Strategies—From Principle To Practice,” available at: <https://www.imf.org/en/Publications/Policy-Papers/Issues/2019/05/01/Fiscal-Policies-for-Paris-Climate-Strategies-from-Principle-to-Practice-46826>.
- Jones, A. 2002. An environmental assessment of food supply chains: A case study on dessert apples. *Environmental Management* 30 (4): 560–576.
- Juraske, R.; Mutel, C. L.; Stoessel, F.; Hellweg, S. 2009. Life cycle human toxicity assessment of pesticides: Comparing fruit and vegetable diets in Switzerland and the United States. *Chemosphere* 77 (7): 939–945.

Lejarza, F., and M. Baldea. 2022. An efficient optimization framework for tracking multiple quality attributes in supply chains of perishable products. *European Journal of Operational Research* 297 (3): 890-903.

Markuszevska, A., A. Prior, A. Strano, B. Bálint, B. Midoux, C. Bros, C. Koutsaftaki, C., Jochum, C. Buffet, D. McGlynn, F. del Bravo, H. Valtari, J. Czaja, P. Saal-asto, P. Töyli, R. Kokovkin, M. Redman, S.R. Mazili, S. Silm, S. Watson, S. Leporati, T. Marran, and Hudson. 2012. “Local Food and Short Supply Chains. EU Rural Review.” A Publication from the European Net-work for Rural Development. Available at: <https://enrd.ec.europa.eu/sites/default/files/fms/pdf/E8F24E08-0A45-F272-33FB-A6309E3AD601.pdf>

Mosheim, R. and K. Lovell. 2009. Scale economies and inefficiency of U.S. dairy farms. *American Journal of Agricultural Economics* 91(3): 777-794.

National Center for Appropriate Technology (NCAT). 2008. Food miles: Background and marketing. Available at: <https://attra.ncat.org/product/food-miles-background-and-marketing/>

O'Donnell, B., A. Goodchild, J. Cooper, and T. Ozawa. 2009. The relative contribution of transportation to supply chain greenhouse gas emissions: A case study of American wheat. *Transportation Research Part D: Transport and Environment* 14 (7): 487-492. Available at: <https://doi.org/10.1016/j.trd.2009.05.003>

Ollinger, M, J.M. MacDonald, and M. Madison. 2005. Technological change and economies of scale in U.S. poultry processing. *American Journal of Agricultural Economics* 87(1): 116–129.

Teratanavat, R., V. Salin, and N. Hooker. 2005. Recall event timing: Measures of managerial performance in U.S. meat and poultry plants. *Agribusiness* 21 (3): 351-373.

Pacala, S., and R. Socolow. 2004. Stabilization wedges: solving the climate problem for the next 50 years with current technologies. *Science* 305: 968–972.

Parcon, H, M, Loke, and P. Leung. 2012. Costs of transporting fresh fruits and vegetables to Honolulu from Hilo and Los Angeles. College of Tropical Agriculture and Human Resources, University of Hawai'i at Manoa, Economic Issues EI-18.

Pomerleau, K, and E. Asen. 2019. “Carbon Tax and Revenue Recycling: Revenue, Economic, and Distributional Implications.” Available at: <https://taxfoundation.org/carbon-tax/>

Produce for Better Health Foundation. State of the Plate, 2015 Study on America’s Consumption of Fruit and Vegetables, Produce for Better Health Foundation. Available at: <http://www.PBHFoundation.org>. Accessed August 2017.

Stoessel, F., R. Juraske, S. Pfister, and S. Hellweg. 2012. Life cycle inventory and carbon and water footprint of fruits and vegetables: Application to a Swiss retailer. *Environmental Science & Technology* 46: 4253-3262.

Sundarakani, B., R. de Souza, M. Goh, S.M. Wagner, and S. Manikandan. 2010. Modeling carbon footprints across the supply chain. *International Journal of Production Economics* 128 (1): 43–50.

Transportation Environmental Resource Center (TERC). 2022. Intermodal choices and greenhouse gases. <https://www.tercenter.org/ghgcomparisons.php>

U.S. Bureau of Census. 2012 Population Estimates. “Population Estimates Program.”

U.S. Department of Agriculture (USDA), Agricultural Marketing Service (AMS). 2021. Agricultural Refrigerated Truck Quarterly Database. Available at: <https://www.ams.usda.gov/services/transportation-analysis/agricultural-refrigerated-truck-quarterly-datasets>

U.S. Department of Commerce, Bureau of Census. 2012. “Wholesale Trade: Geographic Area Series: Summary Statistics for the United States, States, Metro Areas, Counties, and Places: 2012.” 2012 Economic Census: EC0742A1. Available at: <https://www.census.gov/wholesale/index.html>

U.S. Department of Agriculture, Economic Research Service (ERS). 2021. Loss Adjusted Food Availability. Available at: <https://ers.usda.gov/data-products/food-availability-per-capita-data-system/>

U.S. Department of Agriculture, Economic Research Service. 2012. Data by category – U.S. imports and exports. Available at: <https://www.ers.usda.gov/data-products/>

U.S. Department of Agriculture, Economic Research Service. 2008. Protecting perishable foods during transport by truck. Transportation and Marketing Programs. Handbook Number 669.

<https://www.ams.usda.gov/sites/default/files/media/TransportPerishableFoodsbyTruck%5B1%5D.pdf>

U.S. Department of Agriculture (USDA), National Agricultural Statistics Service (NASS). Quick Stats. Accessed in April 2021, available at: https://www.nass.usda.gov/Quick_Stats/index.php

Vermeulen, S. J., B.M. Campbell, and J.S. Ingram. 2012. Climate change and food systems. *Annual Review of Environmental Resource* 37: 195–222.

Volpe, R., E. Roeger, and E. Leibtag. 2013. How Transportation Costs Affect Fresh Fruit and Vegetable Prices. Washington, D.C.: U.S. Department of Agriculture, Economic Research Service, Economic Research, Rep. 160, November.

Wakeland, W., S. Cholette, and K. Venkat. 2012. Food transportation issues and reducing carbon footprint. Book chapter. J.I. Boye and Y. Arcand (eds.), *Green Technologies in Food Production and Processing*, Food Engineering Series, DOI 10.1007/978-1-4614-1587-9_9, © Springer Science+Business Media, LLC 2. pp. 221-236.

Weber, C.L., and H.S. Matthews. 2008. Food-miles and the relative climate impacts of food choices in the United States. *Environmental Science and Technology* 42 (10): 3508-3513.

Xu, Z., D. Sun , X. Zeng, D. Liu, and H. Pu. 2015. Research developments in methods to reduce the carbon footprint of the food system: A review. *Critical Reviews in Food Science and Nutrition* 55(9): 1270-1286.

Yakavenka, V., L. Mallidis, D. Vlachos, E. Lakovou, and Z. Eleni. 2020. Development of a multi-objective model for the design of sustainable supply chains: the case of perishable food products. *Annals of Operations Research* 294: 593-621.

Yi, J., S. Cohen, S. Rehkamp, M.I. Gomez, H. Ge, and J. Jaromczyk. 2021. Completing the data: maximum likelihood estimation of data suppressions in the Census of Agriculture. Paper presented at the Agricultural & Applied Economics Association Annual Meeting, Austin, TX, August 1–3, 2021.