Postharvest Biology and Technology 153 (2019) 61–68

Contents lists available at ScienceDirect

Postharvest Biology and Technology

journal homepage: www.elsevier.com/locate/postharvbio

Modeling postharvest loss and water and energy use in Florida tomato operations

Ratna G. Suthar[a,*], Jorge I. Barrera[b], Jasmeet Judge[a], Jeffrey K. Brecht[c], William Pelletier[b], Rachata Muneepeerakul[b]

[a] Center for Remote Sensing, Agricultural and Biological Engineering. University of Florida, Gainesville, FL, United States
[b] Agricultural and Biological Engineering, University of Florida, Gainesville, FL, United States
[c] Department of Horticultural Sciences. University of Florida, Gainesville, FL, United States

ARTICLE INFO

Keywords:
Postharvest operations
Fresh produce systems
Water and energy consumption
Postharvest loss
Optimization

ABSTRACT

With a growing worldwide population, feeding 10 billion people by the year 2050 is the next global challenge. Fresh produce systems account for a significant fraction of total food and resource consumption due to their perishable nature, with postharvest quality being a key challenge. Production models for fresh produce are widely used and well adapted, whereas postharvest operations (PO) models have only recently been developed. The overarching goal is to quantify interactions of food quality, water and energy use in PO. In this study, an existing PO model was enhanced and implemented for a field grown tomato operation in Florida. Model estimates were compared with data from a representative operation, and were upscaled to obtain statewide estimates. The enhanced model was found to be the most sensitive to harvest frequency, quantity shipped to customer, and quantity harvested. At maximum grower profit, the model estimated water and energy quantities roughly 20% lower for each operation. The representative operation exceeded optimal water and energy usage because the farmers, despite having efficient production, commonly ”over-produce” far beyond optimal levels for reasons including risk of loss, tradition, low market prices, and large fixed costs of operation. Postharvest loss estimated by the model was 22% of quantity harvested for the representative operation. The upscaled regional postharvest losses were at 16% for the state of Florida. Operation-specific water and energy use from the case study were upscaled to give regional monthly estimates of 50.3 million liters and 28.3 million kWh, respectively. Such interactions provide insights into postharvest decisions made by commercial operations and impacts of these decisions on the food, water and energy system. The integrated modeling framework in this study can be extended to other crops and quantify interactions of water, energy and, postharvest losses to optimize efficient management practices.

1. Introduction

Fresh produce systems account for a significant fraction of total food waste due to the perishable nature of produce and and high sensitivity to environmental conditions during production, harvest, packing, storage, and transportation (Widodo et al., 2006; Murthy et al., 2009). A recent report by the UN Food and Agricultural Organization (FAO) projects the world population to be 9.15 billion by 2050, which will require current food production to increase by 60% (Gustavsson et al., 2011). Food availability and accessibility can not only be increased by efficient production (Tilman et al., 2011; Benke and Tomkins, 2017), but also by reducing losses during the production and postharvest operations (McNamara and Tata, 2015; Hodges et al., 2011; Soto-Zamora et al., 2005; Kader, 2004). It is a waste of resources to produce food and not have it reach the consumer at a quality fit for consumption (Bourne, 2014). Reduction of food losses benefits farmers, consumers, and the environment. In addition, postharvest losses (PHL) also result in nutrient losses, negatively impacting food security. Such losses contribute to 2-3% forfeiture in GDP from nutrition-related decrease in human health (Gebhardt et al., 2008). Quantifying resource consumption and losses in the fresh produce system is critical to understanding food security.

A significant amount of resources such as water, energy, and labor are consumed by the fresh produce system. Recently, there have been concerns regarding agricultural energy and water consumption (Shukla and Jharkharia, 2013). Overall, agriculture represents approximately

* Corresponding author.
E-mail address: rsuthar@ufl.edu (R.G. Suthar).

https://doi.org/10.1016/j.postharvbio.2019.03.004
Received 23 May 2018; Received in revised form 5 March 2019; Accepted 6 March 2019
0925-5214/

70% of global freshwater withdrawals, the majority of which is displaced from its original source, referred to as "consumed" (Christian-Smith et al., 2011). At the same time, current farming practices are a major source (19–29%) of anthropogenic greenhouse gas emissions (Vermeulen et al., 2012). Production of fresh market horticultural commodities is labor-intensive, with labor costs comprising roughly 30% of the total production cost (VanSickle and McAvoy, 2015). Pressures from drought, climate change, natural disaster, and increasing concerns over future food security have given attention to the interdependencies among three important natural resources, food, energy and water, which is also known as the food-energy-water (FEW) nexus (Beck and Walker, 2013b,a). In the FEW nexus, a constraint in one of these resources can inhibit access to another resource, which can negatively affect future global food security (Sanders and Masri, 2016). For example, shifts in food consumption patterns, such as organic food choices, reduce both water and energy usage at the production level (Zimmerman et al., 2016; Tuomisto et al., 2012). In contrast, such shifts increase cost of labor required for organic production and postharvest operations (Pimentel et al., 1983). Achieving sustainability and food security requires more than focusing on production or on markets or on consumer behavior, but an integrated approach to the overall food system that considers the necessary feedback mechanisms among the various production and postharvest stages (Ingram, 2011; Allen and Prosperi, 2016).

Modeling the energy and water use of a fresh produce system requires an integrated view of production and postharvest stages. Life cycle analysis (LCA) is a common holistic approach which considers environmental impacts during production and postharvest stages (Roy et al., 2009; Andersson et al., 1994; Stoessel et al., 2012). While certain types of LCA allow for derivation of water and energy consumption values, it does not incorporate the trade-offs of these consumption patterns on the costs of production, product quality, and pricing (Michalski, 2015; Ekvall et al., 2007). Because of this limitation, the typical LCA approach may not provide information adequate for deciding how to make the system more efficient and resilient.

Alternatively, linking existing biophysical crop production models and postharvest models can also provide an integrated view of the fresh produce system. Crop simulation models are well developed and widely-used for simulating growth and development for a variety of crops such as corn, green bean, potato, and rice, providing estimates of within-season root-zone water balance, crop water use, biomass, and yield at harvest (for example, DSSAT- (Jones et al., 2003); APSIM- (Keating et al., 2003); and EPIC- (Williams et al., 1989)). For modeling postharvest operations (PO), supply chain models are commonly used (Blackburn and Scudder, 2009; Soto-Silva et al., 2016). However few account for deterioration of quality which is a primary indicator of PHL during PO (Ahumada and Villalobos, 2009). Postharvest quality is affected by all handling operations including harvest, packing, cooling, storage, and travel distance until reaching the customer (Sargent et al., 2000; Maul et al., 2000; Kader, 1984). It is important to quantify water and energy required to maintain quality of fresh produce, not only for consumers, but also for retailers, food service vendors, and other businesses that play a central role in supplying fresh produce (Aldaya and Hoekstra, 2010; Ingram et al., 2012). Insights from PO models that quantify PHL, accounting for quality, water and energy use are highly relevant for commercial PO decisions, that need to be considered by postharvest researchers.

In general, PO models provide optimal decision variables by either minimizing cost or maximizing profit with respect to constraints on given resources. However, few models integrate quality features such as shelf life and rejection of shipments in the optimization of cost/profit objectives (Ahumada and Villalobos, 2009; Shukla and Jharkharia, 2013; Rong et al., 2011). Ahumada and Villalobos (2011) developed a PO model that optimizes grower profit while accounting for the value of preserving quality by incorporating biological maturation functions and shelf life attributes. This model was implemented using a synthetic dataset for tomato and pepper in North America. Ghezavati et al. (2017) modified the Ahumada and Villalobos (2011) model by incorporating site-specific components in the model using data from a tomato distributor in the Maghdid region of Iran. However, the model was not evaluated using regional data and the focus of their study was to improve computational efficiency of the algorithm. None of the PO models to date are able to quantify water and energy consumption. Given the importance of maintaining quality and reducing loss in fresh produce systems, it is necessary to develop a model for PO that explicitly accounts for water and energy consumption, in addition to food quality (Bazilian et al., 2011).

The overarching goal of this study is to address the above gaps and understand the interactions of postharvest food quality, water, and energy use in PO for fresh tomatoes. Tomatoes are an ideal crop for developing and evaluating PO models due to their modeling complexity, sensitivity to environmental conditions, and economic importance (Johnson, 2006; Alexander and Grierson, 2002). Specifically, objectives of this study are to 1) enhance and implement an existing PO for field-grown fresh tomatoes in the Florida region, 2) evaluate the model predictions of water and energy consumption with data from representative operations to customers such as retailers or food service agents, and 3) upscale model estimates to obtain PHL at a regional scale, for the state of Florida. Such a modeling framework can be extended to predict water and energy consumption for other crops such as cucumber, peppers, and eggplant (Ahumada and Villalobos, 2011; Marcelis, 2001).

2. Methods

2.1. Postharvest operations for fresh tomatoes in Florida

Florida is ranked first in the US for production value of fresh-market tomatoes representing almost all of the fresh-market, field-grown tomato production during the season (Vilsack and Clark, 2012; FloridaTomatoes.org, 2013). Florida tomato production represents 42% of the 1.6 billion of tons of U.S. fresh-market field-grown tomato production valued at 500 million dollars (Vilsack and Clark, 2007). Tomato production occurs from October through June in four tomato growing

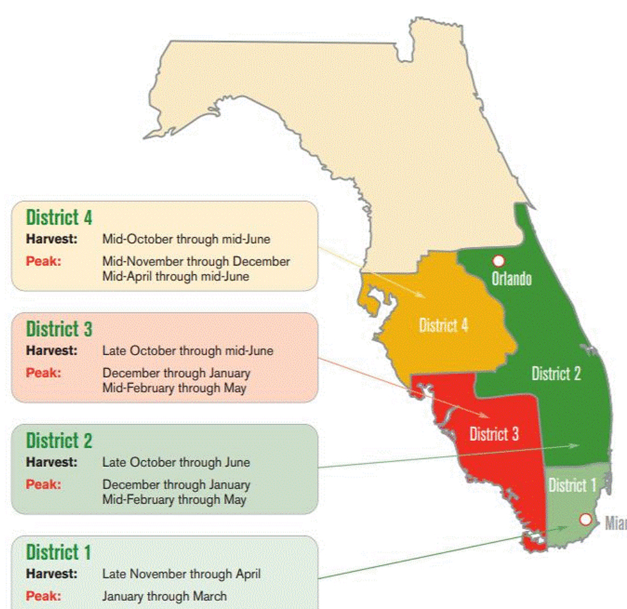

Fig. 1. Tomato growing regions in the state of Florida (FloridaTomatoes.org, 2015).

districts, as shown in Fig. 1. It is a common practice for producers to not only cultivate but also pack and ship their product to their customers which are buyers such as retailers and food service agents. These producers are often termed grower-shippers. In the field, tomatoes are harvested at the mature green stage. Once shipped to the packinghouse, they are rinsed by a heated chlorinated water dump flume system which transfers them to the packing line. Here they are dried, mechanically sized, hand-sorted, hand-graded, and may be waxed before being packed into 11 kg (25-lb) boxes, which are palletized. The percent of the produce that is packed compared to the amount that is delivered to the packinghouse is referred to as ‘packout’. The packout reflects the losses due to grading, handling and mechanical damage. Almost all packing facilities ship their product to a repacking facility where bulk produce is re-washed via misting, re-sorted and re-graded to the finished product based upon customer demand. This loss at the repacker level is similar to the packout at the packinghouse level. Mechanical damage after packing is rare. Customer preference determines if the fruit are ripened with ethylene gas at the grower's packinghouse prior to shipping. For ripening, tomatoes are kept in specialized rooms at 20-22 °C, with 85-95% relative humidity. The duration of the treatment depends upon the harvest maturity and customer demand. Typically, they are ripened until greater than 90% are showing red color. The fruit are cooled in separate refrigerated storage rooms to no lower than 13 °C and held for 1-2 days prior to shipping. Tomatoes are then shipped in refrigerated truck-trailers at 13-25 °C for control of further ripening during transit. The trailer temperature is adjusted so that the fruit arrives at the destination facility at the desired ripeness stage.

Most Florida tomatoes are shipped to destinations along the Eastern coast of the US, with shipping times ranging from 1 to 4 days. The buyers have respective distribution centers (DCs), where tomatoes are combined with other produce items into final shipments of mixed loads for delivery to their outlets where the produce is made available to the consumer, including retail stores and food service. Henceforth, the term *outlet* will refer to a retail store or food service provider and the term *buyer* will encompass the DC and its respective outlets. The amount of tomatoes shipped out of a DC may be less than the amount entering that facility if decay or disorders such as chilling injury, irregular ripening or overripening develop during storage. This loss at the DC level will also be referred to as packout in this study. An accept or reject decision is made upon arrival of the products at a DC. Alternatively, a price adjustment may be negotiated if the product requires re-sorting before it can be sent to the retail stores or re-sold by the re-packer. The products may be briefly stored at DCs and re-packers for one to a few days before further distribution.

2.2. Model structure

In this study, we enhance the PO model developed by Ahumada and Villalobos (2011). It is a mixed integer linear program for multiple crops and transportation modes. As shown in Fig. 2a, the original model accounts for flows from packing house directly to DC and from warehouse [1] directly to customers,[2] in addition to the traditional sequential flows among operations. In the model, an objective function maximizes the income of the grow-shipper given an array of customers, market price, and transportation costs. The objective function comprises terms (1a) - (1k) below.[3]

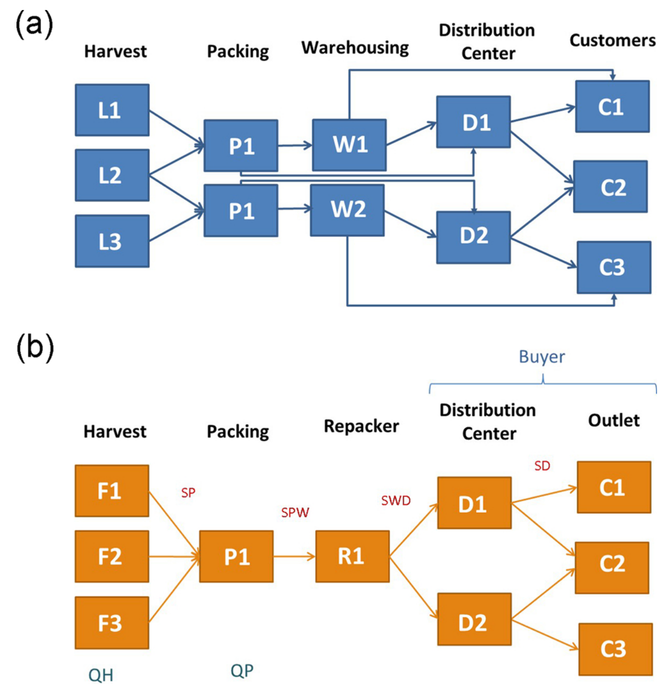

Fig. 2. (a) Model Structure in Ahumada et al. 2011. (b) Flow of product in the enhanced PO model for implementation in Florida: Multiple plots ship to same packinghouse and then repacker, two distribution centers which ship to the buyer's outlets where the product is made available to the consumer such as food service and retail stores.

$$\max \Big[\sum_{tki} PC_{tki} \Big(\sum_{qfr} SC_{tkqwir} + \sum_{qfr} SW_{tkqwir} + \sum_{hqdr} SD_{htkqdir} \Big) + \sum_{tk} PN_{tk} \Big(\sum_{hqw} SWO_{htkqw} \Big) \Big] \tag{1a}$$

$$+ \sum_{hj} PS_j \cdot QS_{hj} \tag{1b}$$

$$- \sum_{tkw} Z_{tkw} \cdot PN_{tk} \tag{1c}$$

$$- \sum_{hpq \in P(j)} (CH_j + CF_j) \cdot QH_{hpq} \tag{1d}$$

$$- \sum_{tkd} X_{pv} \cdot LBH_j \cdot C_{labor} \tag{1e}$$

$$- SP_{hpqf} \cdot CSP \tag{1f}$$

$$- \sum_{hqwf} CK_k \cdot QP_{hkqf} \tag{1g}$$

$$\Big[- \sum_{tkw} Invw_{tkw} \cdot CI_w - \sum_{tkd} Invd_{tkd} \cdot CID_d \Big] \tag{1h}$$

$$\Big[- \sum_{tfir} NTI_{tfir} \cdot CT_{fir} - \sum_{twir} NTW_{twir} \cdot CTW_{wir} - \sum_{tdir} NTD_{tdir} \cdot CTD_{dir} - \sum_{tfwr} NTP_{tfwir} \cdot CTPW_{fwr} - \sum_{tfdr} NTK_{twir} \cdot CTPD_{fdr} - \sum_{twdr} NTC_{twdr} \cdot CTWD_{wdr} \Big] \tag{1i}$$

[1] The warehouse term will represent the re-packer described in Section 2.1.
[2] The term ”customer” used by the Ahumada and Villalobos (2011) model shown in Fig. 2a represent ”outlets” in the Florida case in Fig. 2b, as previously described in Section 2.1.
[3] The model indices, parameters, and variables are defined in A.

$$\left[-\sum_{\text{tkqwir}} \mathrm{SC_{tkqwir}}\cdot\mathrm{PC_{tki}}\mathrm{PROB_{tkq}} - \sum_{\text{tkqwir}} \mathrm{SW_{tkqwir}}\cdot\mathrm{PC_{tki}}\cdot\mathrm{PROB}_{t-\mathrm{hkq}} - \sum_{\text{hqdr}} \mathrm{SD_{tkqdir}}\cdot\mathrm{PC_{tki}}\cdot\mathrm{PROB}_{t-\mathrm{hkq}}\right] \tag{1j}$$

$$\frac{1}{8}\left[-\sum_{\text{tkqwir}} \mathrm{SC_{tkqwir}}\cdot\mathrm{PC_{tki}}\cdot\mathrm{COL_{tkq}} - \sum_{\text{tkqwir}} \mathrm{SW_{tkqwir}}\cdot\mathrm{PC_{tki}}\cdot\mathrm{COL}_{t-\mathrm{hkq}} - \sum_{\text{htkqdir}} \mathrm{SD_{htkqdir}}\cdot\mathrm{PC_{tki}}\cdot\mathrm{COL}_{t-\mathrm{hkq}} - \sum_{\text{htkqwr}} \mathrm{SWO_{htkqwr}}\cdot\mathrm{PN_{tk}}\cdot\mathrm{COL}_{t-\mathrm{hkq}}\right] \tag{1k}$$

The term (1a) of the objective function represents sales and accounts for all routes to the customer, such as: warehouse to customer, DC to customer and open market sales. Terms (1b) and (1c) represent sales from salvaged products and purchase from open market, respectively. Term (1d) accounts for the fixed cost of growing and harvest, and (1e) considers cost of labor utilized in each specific harvest pattern. Additional costs are included in term (1f) for shipping from plot to packinghouse, in term (1g) for packing and labor, in term (1h) for inventory storage in warehouse and DC, and finally, in term (1i) for shipping containers to customer.

As explained in Ahumada and Villalobos (2011), a unique aspect of the objective function is the estimated cost of postharvest losses that depends upon the probability of rejection by customer (PROB) in term (1j), price penalty of products below desired quality term (1k), and physiological ripening. The physiological ripeness throughout the PO for each product is a function of initial maturity, time and temperature during storage and transportation (Tijskens and Evelo, 1994). In the model, the temperature is assumed constant. Equation (2) can be used to estimated the change in ripeness over time (Hertog et al., 2004).

$$H(t) = H_{\max} + \frac{H_{\min} - H_{\max}}{1 + \left(e^{\mathrm{Kt}(H_{\min} - H_{\max})}\frac{H_{\min} - H_0}{H_0 - H_{\max}}\right)} \tag{2}$$

Where $H(t)$ as the quantitative value for the color (ripeness) of the fruit in Hue angle at t days after harvest and is used as the COL parameter in term (1k). (H_{min}) is the lowest ripeness (color) that can exist, typically 1 in tomatoes. (H_{max}) is the highest ripeness that can exist, typically stage 5 in tomatoes. (H_0) denotes the initial maturity at harvest, while K is the temperature rate constant in units of per hue-days.

Model constraints include those related to harvest, packing, and shipping (Ahumada and Villalobos, 2011). The main constraints on harvest and packing are applied to quantity harvested (QH) in term (1d), quantity packed (QP) in term (3), quantity salvaged (QS) in term (1b), and available labor (LAH) in term (1e). Main constraints on shipping and shelf-life are applied to decision variables SC, SW and SD as seen in term (1a), and inventories in warehouse (INVW) and DC (INVD) as seen in terms (4) and (5). Detailed description of these constraints are given in Ahumada and Villalobos (2011).

2.3. Model enhancements and implementation for Florida

The flows of the model described earlier in Fig. 2a were modified to represent US fresh tomato postharvest operations illustrated in Fig. 2b.[4] Because the flows between modules occur in a sequential manner in the US, the sales directly from warehouse, from packing house to outlet and from warehouse to outlet were removed from term (1a). Repacking facilities replaced warehouses in the original model. The objective function was modified to exclude terms for salvaged produce (1b) and transportation (1i), since shipping cost is paid by the outlet. In the US, transportation of tomatoes is primarily via refrigerated trucks, therefore only one form of transportation was considered. Furthermore, the model was simplified to include only one crop, tomato.

Several enhancements were made to the model to improve estimates of PHL, allow for quantification of water and energy consumption, and increase its applicability for Florida. Constraints for quantity packed, inventory in warehouse, and inventory in DC in terms (1g) and (1h) were modified to include packout percentages that consider realistic losses due to grading, sorting and mechanical damage. Since smaller sized tomatoes result in higher quantities per box, the losses due to packout for such products were assumed to be higher. The bold faced terms shown in Equations (3), (4) and (5), represent packout percentages for packinghouse (PKO), repacker (PWR) and DC (WIR), respectively.[5]

$$\mathrm{QP_{hkqf}} = \mathbf{PKO_{kq}} \sum_{p} \mathrm{VG_{hpk}SP_{hpqf}} \tag{3}$$

$$\mathrm{INVW_{htkqw}} = \mathrm{Invw_{ht-1kqwr}} + \mathbf{PWR_{kq}} \textstyle\sum_f \mathrm{SPW_{htkqfwr}} - \sum_i \mathrm{SW_{ht4kqwir}}$$
$$\text{for all } t \geq \mathrm{h, k, w, q} \text{ where } t_4 = t + \mathrm{TiW_{wir}} \text{ and } t_5 = t + \mathrm{TiWD_{wdr}} \tag{4}$$

$$\mathrm{INVD_{htkqd}} = \mathrm{Invd_{ht-1kqwr}} + \textstyle\sum_f \mathrm{SPD_{htkqfdr}} - \sum_i \mathrm{SD_{ht_6kqdir}} + \mathbf{WDCR_{kq}} \sum_w \mathrm{SWD_{htkqwdr}}$$
$$\text{for all } t \geq \mathrm{h, k, d, q} \text{ where } t_6 = t + \mathrm{TiD_{dir}} \tag{5}$$

Incorporating the actual cost structure of water and energy would increase model complexity, therefore a simplified fixed rate per box was assumed for the Florida case. The fixed rates were calculated from monthly water and energy bills and quantity of boxes produced by a representative operation in Florida. At the DC level, energy consumption was calculated using costs from Energy Information Administration (EIA) database (EIA, 2015) and energy use of cold storage was estimated for the given volume of product (U.S. Cooler, 2015). Energy use during shipping includes refrigeration during transit time and fuel required for transportation distance. The water and energy parameters were introduced into the objective function for the packing house in term (1g), where $CK = PC_{water} + PC_{energy}$ and for repacker and DC into terms (1h) where $CI = RP_{water} + RP_{energy}$ and $CID = DC_{water} + DC_{energy}$, respectively.

To better portray the change of ripeness over time, the COL parameter was recalculated using a more realistic storage temperature of 13 °C, instead of 15 °C, using Equation (2). Most tomato operations in the US harvest at mature green, as shown in Table 1 instead of red ripe as assumed by the original model (Ahumada and Villalobos, 2011). Therefore the distribution of maturity at harvest was assumed to be Poisson with the mean at stage 1, ranging from USDA color stages of 1 through 3. It is difficult to account for ripening via ethylene gas using Equation (2). Change in ripeness was depicted by a realistic forward time shift. The behavior of the non-linear regression model by Hertog using dataset for fruit ripened in air at 13 °C shows that it takes 6-8 days of storage to reach the required > 90% red color. In addition, Chomchalow et al., (2002) observed that it takes around 7 days to ripen in air (without ethylene treatment) from mature green to red ripe at 15°C. In this study, we used 6 day forward shift in the storage time to depict ethylene induced ripening for the buyer's desired preference.

The model was implemented for a Florida grow-shipper whose practices were similar to 90% of its peers in Florida, henceforth referred to as the representative operation. The model can also be modified for any size and type of operation. Even though the model can easily take input of an extended period (season or year), obtaining complete datasets to run and evaluate the model for an extended time period continues to be a problem for modeling postharvest operations. In this study, implementation was done for the month of February 2015, which was a good representative period in terms of weather and production

[4] The term "customer" used by Ahumada and Villalobos (2011) in Fig. 2a is analogous to the term "outlet" in the enhanced mode in Fig. 2b.

[5] The parameters and variables in equations 3, 4, and 5 are defined in A.

Table 1
Standards of USDA Tomato classification of ripeness (Saltveit, 2005).

Maturity	USDA	Hue angle
Mature Green (H_{min})	1	115.00
Breaker	2	83.90
Turning	3	72.95
Pink	4	61.80
Light-red	5	48.00
Rep Ripe	6	41.30
Over-ripe (H_{max})	6+	37.00

Table 2
Datasets used in this study.

Data Type	Sources
Water and Energy Costs	FL Operation
Quantities Shipped &Packout Rates	FL Operation
Materials and Labor Costs	FL Operation
Packing and Repacking facility output	FL Operation
Yield	USDA NASS
Yield Size and Color Distribution	Florida Tomato Annual Report
Product Prices	Florida Tomato Annual Report

and consisted of two 12 day planning periods. The model maximizes profit which accounts for the cost of water and energy consumption. Input parameters for the model were obtained from Florida Tomato Committee Annual Report (FloridaTomatoes.org, 2015) and USDA NASS (NASS, 2013). The percentage of total shipments in February was assumed to be the same as the seasonal yield, and was used to obtain the monthly yield for February. Table 2 shows the operation-specific data obtained from interviews with a representative operation with a farm size of 670 acres. Optimal decision variables of harvest frequency, shipping quantities among modules, and total water and energy were calculated for shipping to outlet destination. The representative operation shipped to about 50 destinations during the month of February, including food service agents, retailers and restaurants. Out of the 50, three destinations were chosen based upon varying distances from the representative operation: Jacksonville (closest), Charlotte, and New York (farthest). All three buyers preferred ethylene treatment prior to receiving.

2.4. Model evaluation and upscaling for Florida

Sensitivity analyses was conducted using AMPL CPLEX to obtain the three parameters to which the maximum profit was most sensitive. In addition we analyzed the profit and SD as response to changes in market prices. The enhanced model also allowed for determination of optimal stages for strictest quality control would maximize profit. This was obtained by assessing different packout rates at stages in PO, from lowest to highest quality control.

The model decision variables were compared with those derived from information obtained from a representative tomato grow-shipping company. Model outputs of optimal production quantities and water and energy consumption were scaled up to obtain regional estimates of PHL, and water and energy consumption. The estimate of PHL in the model was obtained as the difference between product reaching the outlet (SD) and the harvested quantity (QH). It was upscaled to obtain regional estimates and percent loss in PO in Florida was computed as a ratio of the upscaled PHL to the regional production data reported by USDA (NASS, 2015), as shown in Eq. (6).

$$\%\text{Loss} = \frac{\left(\frac{\text{QH} - \text{SD}}{C_{\text{Farm}}}\right) C_{\text{FL}}}{H_{\text{FL}}} \times 100 \tag{6}$$

where C_{Farm} represents the individual farm acreage, and C_{FL} and H_{FL} represent the total acreage harvested (32,200 acres) and total number of boxes harvested (21,638,400 boxes in this study) in Florida for the 2014–2015 growing season, respectively. was obtained by using an equation similar to Eq. (6) with QH-SD replaced with case-specific consumption.

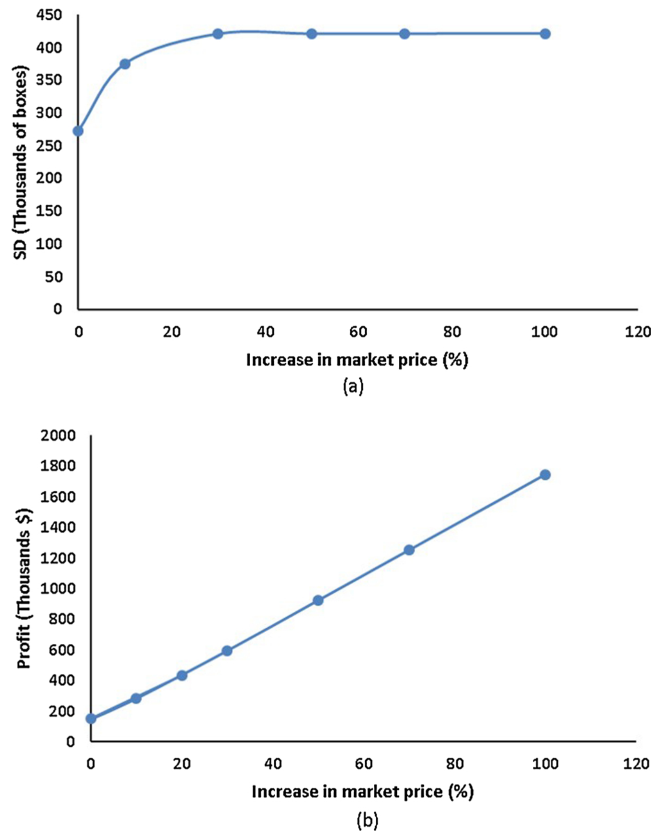

Fig. 3. a) Optimal profit b) boxes shipped to outlet (SD) as functions of % increase in market price as estimated by the enhanced PO model.

3. Results and discussion

Overall, the objective of maximum profit was found to be most sensitive to decisions regarding harvest frequency (X), followed by quantity shipped to outlet (SD), and quantity harvested (QH). As expected, the profit increased linearly with the market price, as shown in Fig. 3a. However, Fig. 3b shows that an increase beyond 40% of current market price does not contribute to profitability but not due to increase in SD. At this point, the supply elasticity reduces from 2.8 to zero, and it is no longer profitable to produce more boxes. However, any increase in profit beyond this point is due to increase in market price per box, as shown in Fig. 3a. This reveals that even in the expectation of a price spike, the farmer should not be investing in production capacity beyond the 420,000 boxes per month.

In the enhanced model, the PHL occurs at three levels; packinghouse, repacker and DC. Profit was maximized when lower packout rate occured earlier in the PO, at the packinghouse level. This is because money is not spent on transporting and refrigerating products that will eventually be graded out at later stages. Thus, the strictest quality controls should be carried out at the earlier phases of PO.

3.1. Florida Case Study

For the month of February, the objective maximum monthly profit in the enhanced model was estimated to be $440 per acre. Estimated optimal harvest frequency of 1-2 times per week complies with standard practices of the representative operation. The optimal quantity harvested (QH) was 348,935 boxes, which was about ~ 20% lower than the USDA-derived QH value of 448,224 boxes. The value of the estimated QH was the same as quantity shipped from plot to packinghouse (SP). These are typically not the same due to PHL caused by exposure to temperature stress and additional handling errors in the field, which is not accounted for in enhanced model. Optimal quantities packed (QP) was estimated to be 309,688 boxes, compared to the 369,168 boxes packed by the representative operation. It may indicate that the representative operation produces more than the optimal quantity required to maximize profit. Farmers, despite having efficient production, continue to "over-produce" for various reasons, including risk of loss, tradition, low market prices, and large fixed costs of operation (CNN, 2001; Nunn, 2018; Dafulla, 2017). The optimal QP is the same as the quantity shipped from packinghouse to repacker (SPW). This implies no losses occur in transit from packinghouse to repacker. Quantity shipped from repacker to DC (SWD) was estimated at 287,671 boxes, and quantity shipped from DC to outlet (SD) 273,077 boxes. Considering the above optimal decision variables, the total PHL was estimated at 22% of the QH. The SD from the representative operation was 40% lower at 203,517 boxes for the three destinations. This is because the scenario in this study is limited to three destinations. In reality, the produce was shipped to 50 destinations, as mentioned above. PHL from fluctuating storage temperatures and stressful environmental conditions throughout the handling process, are not accounted for in the model, which assumes a constant transportation temperature of 13 °C. However, temperature fluctuations have been shown to impact PHL (Nunes and Emond, 2003; Aung and Chang, 2014). While published reports of temperatures for tomatoes in the postharvest distribution system are scarce, in a study by Dea et al. (2008), shipments of (non-precooled) tomatoes by sea from Puerto Rico to Florida and subsequently within Florida by refrigerated truck had temperature variation of 19 °C. However, in the Florida case, tomatoes are routinely cooled before shipping and there is only one mode of transportation. Therefore a much smaller temperature deviation can be expected. A Florida study on strawberry transport to California by Pelletier et al. (2011) noted that the fruit temperatures had increased by a minimum of 0.8 °C and a maximum of 5 °C during a 4 day trip. We found that the average increase of 3 °C results in PHL increased by less than 1%. However, it should be noted that the distribution of temperature change is highly unpredictable. In addition to fluctuating temperatures, chilling injury and water losses are also significant factors that cause quality loss and ultimately PHL (Beckles, 2012; Maul et al., 2000; Kader, 1984), modeling of which are beyond the scope of the study.

The water and energy use estimated by the enhanced model and that those obtained from the representative operation are shown in Tables 3 and 4 , respectively. The water usage was maximum during packing and repacking operations, with the use being four times higher in packing than repacking, due to handling of larger quantities. Model estimates of water use during packing and repacking are lower than the reported values by the representative operation by 22% and 16%, respectively. This is a result of lower QH and QP estimated by the model, because the water use per box for each operation were obtained from representative operation. Overall, total water use estimated by the model is 21% lower than observed values obtained from representative operation, as shown in Table 3. In contrast to the water usage that is highest during packing operations, shipping accounts for the largest portion of energy use, as shown in Table 4. Model estimates of energy use during shipping were nearly 26% higher than obtained values, for the three destinations due to lower SD in the representative operation. Similar to the water use values, model estimates of energy use during packing and repacking are 22% and 16% lower, respectively, than the reported values. At the DC level, model estimates of energy use were estimated to be 20% lower than the representative operation. Overall, the model estimate of total energy use in PO was only 2% higher than the representative operation. The model indicates that operations for one box uses 0.81 L of water ad 2.0 KwH of energy. Currently the model uses fixed rates for water and energy and doesn't allow consideration of tradeoffs. A more complete incorporation of production technologies is needed to address efficiency tradeoffs and cases of water and energy scarcity scenarios.

Table 3
Comparison of water cost (USD) and use (Liters) predicted by model and from representative operation.

	Water (L)		Difference (%)
	Model	*Producer*	
Packing			
cost	$13,697	$17,671	
use	826712	1066613	−22
Repacking			
cost	$1,774	$2,122	
use	221736	265329	−16
Total Use	1,048,448	1,331,942	

Table 4
Comparison of energy cost (USD) and use (kWh) predicted by model and from representative operation.

	Energy (kWh)		Difference (%)
	Model	*Producer*	
Packing			
cost	$16,369	$21,027	
use	128579	165166	−22
Repacking			
cost	$10,556	$12,584	
use	119054	141920	−16
DC			
cost	$670	$847	
use	7443	9414	−20
Shipping			
cost	$416,949	$330,833	
use	307917	244220	26
Total Use	562,993	560,720	

3.2. Florida regional estimates

Regional losses were calculated by upscaling optimal decision variables from the case study. Using Eq. (6) and the acreage of the representative farm mentioned in Section 2.3, the loss per acre was 113 boxes. Overall, out of 21.6 million boxes of tomato harvested in the state of Florida, loss due to PHL was 3.6 million boxes, resulting in 16% monthly PHL. Accounting for average temperature increase of 3 °C resulted in 2% PHL. Operation-specific water and energy use from the case study were upscaled to give regional monthly estimates of 50.3 million liters and 28.3 million kWh, respectively.

4. Conclusion

In this study, we enhanced a model for maximizing profit in fresh produce postharvest operations. The enhanced model allows consideration of postharvest losses, water and energy consumption. This study addresses a significant gap in the quantification of the interactions of PHL, water, and energy during postharvest operations. Evaluation of the model with data from representative producer in Florida and the upscaled results for the state of Florida were compared with reported values. Overall, the model estimated water and energy quantities roughly 20% lower for each operation. It is commonly reported that farmers produce beyond optimal levels for many reasons including potential risk of loss and large fixed costs of operation. PHL estimated by the model was 22% of quantity harvested for the representative operation. The upscaled regional PHL were at 16% for the state of Florida, which is in agreement with recorded values of fresh produce PHL. Overall, operation-specific water and energy use from the case study were upscaled to give regional monthly estimates of 50.3 million liters and 28.3 million kWh, respectively. Such an integrated modeling framework can be extended to other crops and quantify interactions of water, energy and, postharvest losses to optimize efficient management practices. Such a PO model can be coupled with production models to provide an integrated view of the food system that considers the dynamics in the pre and postharvest stages, incorporating feedback mechanisms.

Acknowledgements

This study was supported by the University of Florida Graduate School Fellowship. We would like to thank the reviewers for their insights regarding this paper. Finally, we are grateful to the Florida grower-shippers who provided the data used for this study.

Appendix A. Table of Indices, parameters and variables

Indices	
$d \in D$	distribution centers
$f \in PF$	packaging facilities
$k \in K(j)$	products of crop j (package, grade)
$p \in P$	plot formed by the area in location l planted with crop j
$r \in TM$	transportation mode
$t \in T$	planning periods (days)
$v \in V(j)$	harvesting patterns for crop j
$w \in W$	warehouses available for storage
Parameters	
AP_p	Total area planted in plot p hectares
C_{labor}	hourly cost of field labor
CF_j	fixed cost per box of crop j
CH_j	cost of harvesting a box of crop j
CI_w	cost at warehouse w per pallet of product (pallet/day) including use of water (RP_water) and energy (RP_energy)
CID_d	cost of inventory at DC d per pallet of product (pallet/day) including use of water (DC_water) and energy (DC_energy)
CK_k	cost of packing a box of product k which includes packing and casing and use of water (PC_water) and energy (PC_energy)
COL_{thkq}	expected color product k with initial color q after n days of harvest ($n = th$)
CSP	cost of shipping from plot to packinghouse
CTD_{dir}	cost of transportation from DC d to customer i by mode r
$CTPD_{fdr}$	cost of transportation from facility f to DC d by mode r
$CTPW_{fwr}$	cost from packing facility f to warehouse w by mode r
CTW_{wir}	cost of transportation from warehouse w to customer i by mode r
$CTWD_{wdr}$	cost of transportation from warehouse w to DC d by mode r
EH_{hpv}	Expected harvest in units of 0.45 kg (pounds)
MOP	Maximum amount of field personal to hire
PC_{tki}	price per product k on period t sold to customer i
PN_{tk}	price per product k on period t in the open market
$PROB_{thkq}$	estimate of the probability that the product with color q is not accepted by customers based on the time elapsed ($n = th$)
PS_j	salvage price of crop j
SH_{hv}	if pattern v requires harvest in period h (yes or no)
Ti_{fir}	days from packing facility f to customer i by transportation mode r
TiD_{dir}	days from DC d to customer i by transportation mode r
$TiPD_{fdr}$	days from packing facility f to DC d by transportation mode r
$TiPW_{fwr}$	days from packing facility f to warehouse w by transportation mode r
TiW_{wir}	days from warehouse w to customer i by transportation mode r
$TiWD_{wdr}$	days from warehouse w to DC d by transportation mode r
VG_{hpk}	percentage of product k from plot p at period h (%)
VQ_{vjq}	percentage of crop j with quality q in by pattern v (%)
VS_{hj}	percentage of crop j salvaged at period h (%)
Decision Variables	
INV_{dhtkqd}	inventory in DC d of product k at period t with quality q harvested at h
INV_{whtkqw}	inventory in warehouse w of product k at period t with quality q harvested at h
LBH_j	labor hours required to harvest one hectare of crop
NTC_{twdr}	number of containers sent to DC d from warehouse w in time t by mode r
NTD_{tdir}	number of containers sent to customer i from DC d in period t by mode r
NTI_{tfir}	number of containers sent to customer i from facility f in period t by mode r
NTK_{tfdr}	number of containers sent to DC d from facility f in time t by mode r
NTP_{tfwr}	number of trucks sent from facility f to warehouse w in period t by mode r
NTW_{twir}	number of containers to customer i from warehouse w in period t by mode r
Opl_h	operator hours hired in the field at time h
QH_{hpq}	harvest (boxes) of quality q from plot p in period h
QP_{hkqf}	quantity of product k with quality q packed at facility f in period h
QS_{hj}	quantity salvaged of crop j in harvesting period h
SC_{tkqfir}	product k of quality q shipped from facility f to customer i in period t by mode r
$SD_{htkqdir}$	product k of quality q harvested at h shipped from DC d to customer i in period t by mode r
SP_{hpqf}	quantity of crop with quality q to ship from plot p to facility f in period h
$SPD_{htkqfdr}$	product k of quality q harvested at h shipped from facility f to DC d in period t by mode r
$SPW_{htkqfwr}$	product k of quality q harvested at h shipped from facility f to warehouse w in period t by mode r
$SW_{htkqwir}$	product k of quality q harvested at h shipped from warehouse w to customer i in period t by mode r
$SWD_{htkqwdr}$	product k of quality q harvested at h shipped from warehouse w to DC d in period t by mode r
SWO_{htkqw}	product k with quality q harvested at h sold from warehouse w in period t (Open market)
X_{pv}	area of plot p harvested using pattern v (Hectares)
Z_{tkw}	quantity to purchase of product k, in period t for warehouse w

References

Ahumada, O., Villalobos, J.R., 2009. Application of planning models in the agri-food supply chain: A review. Eur. J. Oper. Res. 196, 1–20 URL: http://www.sciencedirect.com/science/article/pii/S0377221708001987.

Ahumada, O., Villalobos, J.R., 2011. Operational model for planning the harvest and distribution of perishable agricultural products. Int. J. Prod. Econ. 133, 677–687. https://doi.org/10.1016/j.ijpe.2011.05.015. URL: http://www.sciencedirect.com/science/article/pii/S0925527311002210, towards High Performance Manufacturing.

Aldaya, M., Hoekstra, A., 2010. The water needed for italians to eat pasta and pizza. Agric. Syst. 103, 351–360. https://doi.org/10.1016/j.agsy.2010.03.004. URL: http://www.sciencedirect.com/science/article/pii/S0308521X1000034X.

Alexander, L., Grierson, D., 2002. Ethylene biosynthesis and action in tomato: a model for climacteric fruit ripening. J. Exp. Bot. 53, 2039–2055. https://doi.org/10.1093/jxb/erf072.

Allen, T., Prosperi, P., 2016. Modeling sustainable food systems. Environ. Manag. 57, 956–975. https://doi.org/10.1007/s00267-016-0664-8.

Andersson, K., Ohlsson, T., Olsson, P., 1994. Life cycle assessment (lca) of food products and production systems. Trends Food Sci. Technol. 5, 134–138.

Aung, M.M., Chang, Y.S., 2014. Temperature management for the quality assurance of a perishable food supply chain. Food Control 40, 198–207.

Bazilian, M., Rogner, H., Howells, M., Hermann, S., Arent, D., Gielen, D., Steduto, P., Mueller, A., Komor, P., Tol, R.S., et al., 2011. Considering the energy, water and food nexus: Towards an integrated modelling approach. Energy Policy 39, 7896–7906.

Beck, M.B., Walker, R.V., 2013a. Nexus security: governance, innovation and the resilient city. Front. Environ. Sci. Eng. 7, 640–657.

Beck, M.B., Walker, R.V., 2013b. On water security, sustainability, and the water-food-energy-climate nexus. Front. Environ. Sci. Eng. 7, 626–639.

Beckles, D.M., 2012. Factors affecting the postharvest soluble solids and sugar content of tomato (solanum lycopersicum l.) fruit. Postharvest Biol. Technol. 63, 129–140.

Benke, K., Tomkins, B., 2017. Future food-production systems: vertical farming and controlled-environment agriculture. Sustain. Sci. Pract. Policy 13, 13–26. https://doi.org/10.1080/15487733.2017.1394054.

Blackburn, J., Scudder, G., 2009. Supply chain strategies for perishable products: the case of fresh produce. Prod. Oper. Manag. 18, 129–137.

Bourne, M., 2014. Food security: postharvest losses. J. Encyclopedia Agric. Food Syst. 3.

Christian-Smith, J., Gleick, P.H., Cooley, H., 2011. US water policy reform. The World's Water Volume 8. Springer, pp. 143–155.

CNN, 2001. Produce Overproduction Squeezing Farmers. URL: http://edition.cnn.com/TRANSCRIPTS/0007/20/tod.03.html.

Dafulla, 2017. Agricultural Overproduction and the Deteriorating Environment. URL: http://www.e-ir.info/2016/07/07/the-evolution-of-the-european-unions-common-security-and-defence-policy/.

Dea, S., Brecht, J.K., Nunes, M.d.N., Emond, J.P., Chau, K.V., et al., 2008. Impact of environmental conditions during distribution on tomato fruit quality and decay. Proceedings of the Florida State Horticultural Society, Florida, USA 121, 289–296 2008.

EIA, 2015. Electric Power Monthly with Data for February. URL: https://www.eia.gov/electricity/monthly/.

Ekvall, T., Assefa, G., Bjrklund, A., Eriksson, O., Finnveden, G., 2007. What life-cycle assessment does and does not do in assessments of waste management. Waste Manag. 27, 989–996.

FloridaTomatoes.org, 2013. Tomato 101. URL: http://www.floridatomatoes.org/wp-content/uploads/2013/01/Tomato_1011.pdf.

FloridaTomatoes.org, 2015. Florida Tomato Committee Annual Report.

Gebhardt, S., Lemar, L., Haytowitz, D., Pehrsson, P., Nickle, M., Showell, B., Thomas, R., Exler, J., Holden, J., 2008. Usda national nutrient database for standard reference, release 21. United States Department of Agriculture, Agricultural Research Service.

Ghezavati, V.R., Hooshyar, S., Tavakkoli-Moghaddam, R., 2017. A benders' decomposition algorithm for optimizing distribution of perishable products considering post-harvest biological behavior in agri-food supply chain: a case study of tomato. Central Eur. J. Oper. Res. 25, 29–54. https://doi.org/10.1007/s10100-015-0418-3.

Gustavsson, J., Cederberg, C., Sonesson, U., Van Otterdijk, R., Meybeck, A., 2011. Global food losses and food waste. FAO Rome.

Hertog, M.L., Lammertyn, J., Desmet, M., Scheerlinck, N., NicolaLtdc:ı:rtdc, B.M., 2004. The impact of biological variation on postharvest behaviour of tomato fruit. Postharvest Biol. Technol. 34, 271–284.

Hodges, R.J., Buzby, J.C., Bennett, B., 2011. Postharvest losses and waste in developed and less developed countries: opportunities to improve resource use. J. Agric. Sci. 149, 37–45.

Ingram, J., 2011. A food systems approach to researching food security and its interactions with global environmental change. Food Security 3, 417–431.

Ingram, J., Ericksen, P., Liverman, D., 2012. Food Security and Global Environmental Change. Routledge.

Johnson, D.D., 2006. Eliminating fruit and vegetable planting restrictions: how would markets be affected? Economic Research Service ERR-30, USDA.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The dssat cropping system model. Eur. J. Agron. 18, 235–265.

Kader, A., 1984. Effects of postharvest handling procedures on tomato quality. Symposium on Tomato Production on Arid Land 190 209–222.

Kader, A.A., 2004. Increasing food availability by reducing postharvest losses of fresh produce. V International Postharvest Symposium 682 2169–2176.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N., Meinke, H., Hochman, Z., et al., 2003. An overview of apsim, a model designed for farming systems simulation. Eur. J. Agron. 18, 267–288.

Marcelis, L.F., 2001. Yield and quality prediction of vegetables: the case of cucumber. Worcester Polytechnic Institute.

Maul, F., Sargent, S., Sims, C., Baldwin, E., Balaban, M., Huber, D., 2000. Tomato flavor and aroma quality as affected by storage temperature. J. Food Sci. 65, 1228–1237.

McNamara, P.E., Tata, J.S., 2015. Principles of designing and implementing agricultural extension programs for reducing post-harvest loss. Agriculture 5, 1035–1046. https://doi.org/10.3390/agriculture5041035. URL: http://www.mdpi.com/2077-0472/5/4/1035.

Michalski, W., 2015. Critiques of life cycle assessment. Worcester Polytechnic Institute.

Murthy, D.S., Gajanana, T., Sudha, M., Dakshinamoorthy, V., et al., 2009. Marketing and post-harvest losses in fruits: its implications on availability and economy. Marketing 64.

NASS, 2013. Quick stats. United States Department of Agriculture. National Agricultural Statistics Service.

NASS, 2015. USDA 2015 Season Vegetable Highlights. URL: https://www.nass.usda.gov/Statistics_by_State/Florida/Publications/Annual_Statistical_Bulletin/2016/E1thru18Veg-2016.pdf.

Nunes, M.d.N., Emond, J.P., 2003. Storage temperature. Postharvest Physiol. Pathol. Vegetables 209–228.

Nunn, S., 2018. U. S. Farmers Are Producing Too Much Food. Here's Why They Can't Stop. URL: https://blogs.wsj.com/economics/2018/02/05/u-s-farmers-are-producing-too-much-food-heres-why-they-cant-stop/.

Pelletier, W., Brecht, J.K., do Nascimento Nunes, M.C., Ltdc:É:rtdcmond, J.P., 2011. Quality of strawberries shipped by truck from California to Florida as influenced by postharvest temperature management practices. HortTechnology 21, 482–493.

Pimentel, D., Berardi, G., Fast, S., 1983. Energy efficiency of farming systems: organic and conventional agriculture. Agric. Ecosyst. Environ. 9, 359–372.

Rong, A., Akkerman, R., Grunow, M., 2011. An optimization approach for managing fresh food quality throughout the supply chain. Int. J. Prod. Econ. 131, 421–429. https://doi.org/10.1016/j.ijpe.2009.11.026. URL: http://www.sciencedirect.com/science/article/pii/S0925527309004290, innsbruck 2008.

Roy, P., Nei, D., Orikasa, T., Xu, Q., Okadome, H., Nakamura, N., Shiina, T., 2009. A review of life cycle assessment (lca) on some food products. J. Food Eng. 90, 1–10.

Saltveit, M., 2005. Postharvest biology and handling. Crop Prod. Sci. Hortic. 13, 305.

Sanders, K.T., Masri, S.F., 2016. The energy-water agriculture nexus: the past, present and future of holistic resource management via remote sensing technologies. J. Cleaner Prod. 117, 73–88.

Sargent, S.A., Ritenour, M., Brecht, J., 2000. Handling, cooling and sanitation techniques for maintaining postharvest quality. University of Florida Cooperative Extension Service, Institute of Food and Agriculture Sciences, EDIS.

Shukla, M., Jharkharia, S., 2013. Agri-fresh produce supply chain management: a state-of-the-art literature review. Int. J. Oper. Prod. Manag. 33, 114–158.

Soto-Silva, W.E., Nadal-Roig, E., GonzLtdc:á:rtdclez-Araya, M.C., Pla-Aragones, L.M., 2016. Operational research models applied to the fresh fruit supply chain. Eur. J. Oper. Res. 251, 345–355.

Soto-Zamora, G., Yahia, E.M., Brecht, J.K., Gardea, A., 2005. Effects of postharvest hot air treatments on the quality and antioxidant levels in tomato fruit. LWT-Food Science and Technology 38, 657–663.

Stoessel, F., Juraske, R., Pfister, S., Hellweg, S., 2012. Life cycle inventory and carbon and water foodprint of fruits and vegetables: Application to a swiss retailer. Environ. Sci. Technol. 46, 3253–3262. https://doi.org/10.1021/es2030577. pMID:22309056.

Tijskens, L., Evelo, R., 1994. Modelling colour of tomatoes during postharvest storage. Postharvest Biol. Technol. 4, 85–98.

Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. Proc. Natl. Acad. Sci. 108, 20260–20264.

Tuomisto, H.L., Hodge, I., Riordan, P., Macdonald, D.W., 2012. Does organic farming reduce environmental impacts?.-a meta-analysis of European research. J. Environ. Manag. 112, 309–320.

U.S. Cooler, 2015. Refrigeration Sizing Estimate. URL: http://www.uscooler.com/refrigeration-sizing-estimate.

VanSickle, J., McAvoy, E., 2015. Production budget for tomatoes grown in southwest Florida and in the palmetto-ruskin area of Florida. URL: fred.ifas.ufl.edu/pdf/iatpc/files/FLTomBudget2015.docx.

Vermeulen, S.J., Campbell, B.M., Ingram, J.S., 2012. Climate change and food systems. Annu. Rev. Environ. Resour. 37.

Vilsack, T., Clark, C., 2012. Census of Agriculture-united states. National Agricultural Statistics Service, Washington, DC Tech. Rep.

Vilsack, T., Clark, C.Z., 2007. Census of Agriculture. United States Department of Agriculture.

Widodo, K.H., Nagasawa, H., Morizawa, K., Ota, M., 2006. A periodical flowering-harvesting model for delivering agricultural fresh products. Eur. J. Oper. Res. 170, 24–43.

Williams, J., Jones, C., Kiniry, J., Spanel, D., 1989. The epic crop growth model. Trans. ASAE 32, 497–0511.

Zimmerman, R., Zhu, Q., Dimitri, C., 2016. Promoting resilience for food, energy, and water interdependencies. J. Environ. Stud. Sci. 6, 50–61. https://doi.org/10.1007/s13412-016-0362-0.