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Towards Environmentally Sustainable and Cost-Effective Food Distribution in the U.S.

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Towards Environmentally Sustainable and Cost-Effective Food Distribution in the U.S.

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Abstract

Distribution centers (DCs) and supermarkets have an important role in food sustainability, but no previous research has accounted for their environmental impact. The purpose of this research was to assess environmental sustainability of grocery, perishables, and general merchandise DCs; to estimate food storing and retailing impact; and to provide cost-effective strategies to reduce DCs' environmental impacts. The importance and relevance of the research is threefold: improving sustainability of DCs, food storing, and food retailing. The main method used in this research was the life cycle assessment (LCA) method. An initial study calculated environmental impacts of the Wal-Mart Stores, Inc. DCs, which combined a building energy consumption simulation, a process modeling tool for conveyors, regional water consumption and scarcity, and an LCA model of DCs' material and construction environmental impacts. Further research provided an in-depth analysis of refrigerated zones within DCs and supermarkets in the United States. The study represents an initial attempt at assessing the environmental impact of food storage and retailing. We developed a model for calculating environmental impact of food storing and retailing in different states. Drawing on the data about DCs' energy consumption and the impact of climate change, a multi-objective optimization model including cost, non-renewable fossil energy use, and climate change was developed. The optimization model used on-site solar panels and off-site wind technologies to find cost-effective energy mixes, which will reduce environmental impacts and shift DCs from energy consumers to energy producers and net zero DCs. We found solutions to the Pareto-optimal zero energy DCs, which were achieved by installing roof solar panels and/or erecting wind turbines at nearby locations. A pairwise Monte Carlo analysis showed when the switch to renewable energy became superior in terms of reducing fossil energy use and environmental impact. The research has

shown variation of environmental impacts by building type, size, state, and climate zone; has identified which food has the highest and lowest storage and retailing impacts; and has found a feasible option to increase solar and wind energy use in DCs. Supporting datasets for chapters 2, 3, and 4 are included in Appendices 1, 2, and 3, respectively.

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Dedication

This dissertation is lovingly dedicated to my mother, Visnja Burek. Her support, encouragement, and love have sustained me throughout my life.

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List of Published Papers

Burek, J., Nutter, D., (2018). Life Cycle Assessment of Grocery, Perishable, and General Merchandise Multi-Facility Distribution Center Networks. Energy and Buildings. https://doi.org/10.1016/j.enbuild.2018.06.021 Chapter 2

Burek, J., Nutter, D., (in review). Environmental Performance of Chilled and Frozen Food Post-Processing Storing and Retailing. Chapter 3

Burek, J., Nutter, D., (in review). Life Cycle Assessment-Based Multi-Objective Optimization of the Electricity Mix for the Grocery, Perishable, and General Merchandise Multi-Facility Distribution Center Network. Chapter 4

1. Introduction

The generation and distribution of electricity accounted for nearly 40% of U.S. greenhouse gas (GHG) emissions (Weber et al. 2010). In the United States, electricity generation was dominated by fossil energy sources (77.6%) including coal, nuclear energy, and natural gas (US EIA 2017a). Electricity consumption in buildings accounted for 74% of total electricity use in the United States and commercial buildings alone consumed 36.6% (US EIA 2017b). In the coming years, GHG emissions of commercial buildings are expected to increase at a rate of 1.8% per year (U.S. Green Building Council 2005).

Commercial buildings include office buildings, lodging, amusement, warehouses, distribution centers (DCs), and retail centers (RCs) such as supermarkets. Researchers are focused on reducing energy use and environmental impacts of buildings through energy conservation strategies (Fernandez et al. 2017; S. A. Tassou et al. 2011) and through shifting buildings' fossil fuel dependency from the electrical power grid to distributed renewable energy sources including solar and wind (Weißenberger, Jensch, and Lang 2014; Whitehead et al. 2014; Blengini and Di Carlo 2010; Griffith, Torcellini, and Long 2006). Very little has been written in terms of sustainability of DCs and supermarkets.

In this research, we focused on DCs and RCs including grocery DCs (GDCs), perishables DCs (PDCs), general merchandise (GMDCs) and supermarkets. DCs are warehouses used for (1) receiving bulk shipments from processors and manufacturers, (2) temporary storage, (3) grouping customized retail orders, and (4) distribution of goods from DC to point-of-sale. Refrigerated and non-refrigerated DCs are among the highest energy use facilities in the United States. Refrigeration in commercial buildings accounted for the largest share of annual electricity consumption of 14%, followed by ventilation (11.2%), lighting (10.6%), and space cooling (10.6%) (US EIA 2017b).

GDCs, PDCs, GMDCs, and RCs are primary food distribution components (MWPVL International 2010), and have an important role in food distribution and sustainability. Food distribution includes processes that occur between producers, retailers, and customers from packaging, transport, and storage to delivery to the consumer. The role of DCs in the food supply chain is to move and store food and other products and to service RCs and supermarkets with food products. There is an important discussion in the world about cold food supply chain and frozen vs. chilled food. On one hand chilled food has a lower shelf-life and higher food loss rate. On the other hand, frozen food requires more refrigeration. A lot of research has been done on food movement (Schewel and Schipper 2012), food choices (Lin, Dang, and Konar 2014), food-miles (Weber and Matthews 2008), and localizing production (Cleveland et al. 2011).

In the United States, food distribution is a highly competitive industry with the main purpose to get products to consumers as cheaply and efficiently as possible (Ellickson 2015). The top 75 North American food retailers have more than 49,890 RCs and 533 DCs with estimated area of 26,060,045 m^2 (MWPVL International 2010). Food supply chain consists of network of the suppliers (farmers), manufacturers, distributors, retailers, and end customers (Chan and Chan 2005). Thus, all DCs and RCs owned by a certain business are called a distribution-retail network. Walmart Stores Inc., Amazon.com Inc., and Target Corporate are the top three largest distribution-retail networks in the United States (MWPVL International 2010). In 2012, the construction of RCs and warehouses accounted for 43% of the total commercial building revenue, and warehouses alone used 300,000 TJ of energy (Alegria 2012). This is about 7% of total energy use of all commercial buildings (US EIA 2016).

Food sustainability research often omitted the post-processing food storing at DCs, food retailing at supermarkets, and food consumption at home (Blonk Consultants 2018; Djekic et al. 2013; Wernet et al. 2016; Stoessel et al. 2012; Nijdam, Rood, and Westhoek 2012). In recent years, achieving a low carbon impact supply chain is a major goal of producers, distributors, and retailers because it shows corporate responsibility and brand image (Walmart 2010; Walmart 2015). Food sustainability assessment must include food distribution to reveal possible pathways, impacts, and losses of different food distribution systems. Thus, the main motivation for this research was to bridge data gaps in environmental assessment of DCs and PDCs, food storing and retailing, and to find cost-effective strategies to reduce fossil energy use and climate change impact of building and consequently food storing and retailing. In this study, the primary method used was life cycle assessment (LCA), which provided a system-wide modeling of the supply chain and allowed for identification of environmental, economic, and social hot spots. In addition, we combined LCA and quantitative methods including Monte Carlo uncertainty analysis and multi-objective optimization. The research included activities such as collecting and managing large datasets, modeling complex systems, and finding interconnectedness between data and results. This research represents a first attempt at (1) evaluating environmental impact of GDCs, PDCs, and GMDCs, (2) at allocating storing and retailing impact to different food categories, (3) at reducing environmental impacts of a large scale multi-facility DC and supermarket network by installing solar and wind energy, and (4) at finding the optimal zero energy DCs networks.

1.1. Introduction to the life cycle assessment method

LCA is a standard method to assess environmental impacts of products, processes, services, and whole buildings holistically, over their entire life cycle (i.e., from cradle-to-grave).

Principles, requirements, and guidelines to perform LCA are given in International Standards: ISO 14040:2006, ISO 14044:2006, and ISO 14046:2014 (ISO 2006a; ISO 2006b; ISO 2014b). The ISO 14040:2006 defines the principles and framework and provides a clear overview of the practice, applications and limitations of LCA to a broad range of potential users and stakeholders, including those with a limited knowledge of life cycle assessment. The ISO 14044:2006 provides requirements and guidelines and is designed for the preparation of, conduct of, and critical review of, life cycle inventory (LCI) analysis. It also provides guidance on the impact assessment phase of LCA (i.e., life cycle impact assessment (LCIA) and on the interpretation of LCA results, as well as the nature and quality of the data collected. The ISO 14046:2014 established framework for a water footprint (ISO 2014b). Over the past decade, the LCA method has become an important instrument for developing an overall framework on sustainable production and consumption patterns and a more rational use of natural resources, which has been used globally.

The two primary frameworks are attributional and consequential LCA. Attributional LCA is a system modeling approach in which environmental impacts are divided among products based on a functional unit and according to allocation principles (mass, energy, or economic). Consequential LCA is a system modeling approach in which activities in a product system are linked so that activities are included in the product system to the extent that they are expected to change because of a change in demand for the functional unit. To achieve goals and scopes defined in chapters of this study, we used the attributional LCA.

In addition, there are three possible approaches used in current LCAs: a process-chain analysis (PCA) and an input/output analysis (IOA), and hybrid [4]. The PCA calculates the energy embedded in and the emission-equivalents caused by the production of materials used in application. The IOA works with economic sectors related to the manufacturing activities. The hybrid combines IOA and PCA. The PCA looks at the materials and converts them – considering all underlying production steps-into the corresponding amount of energy used and GHG emitted. Shortcomings of the PCA are that the method is intrinsically incomplete - some processes cannot be expressed in an amount of material and are therefore likely to be overlooked. The IOA divides a product into its economical components. Each input that contributes to the creation of the final product is ascribed to an economic sector. For each sector an average product is calculated, which is characterized by an amount of energy needed and an amount of GHG emitted. The main shortcoming of the IOA is that all products are identified as an average product of the covering sector.

The PCA, which includes itemized inputs and outputs for each LCA stage, was chosen as a more suitable methodology for this research due to process-based data of building operation, regional aspect of the LCA modeling and impact assessment, data availability in the current databases, and uncertainty analysis. The database used in this work was DataSmart 2016, which contains only attributional process LCI database based on Ecoinvent 2 method and data uncertainty (LTS 2016). System modeling was based on the attributional approach. In the attributional approach, inputs and outputs are attributed to the functional unit and multi-output system processes are partitioned based on allocation rules (Finnveden et al. 2009). In this research, allocation was avoided in the whole-building assessment because data were available separately for each building operation. On the contrary, allocation was extensively used when attributing storing and retailing impact to different food items.

Simapro 8.4. software and Athena Impact Estimator v5.2 were used to carry out the LCAs according to the steps outlined in the ISO 14040 standard (ISO 2006a; PRé Consultants

2015; Athena Sustainable Materials Institute 2017b). These steps were: (1) goal and scope definition, (2) inventory analysis, (3) impact assessment, and (4) interpretation, as shown in Figure 1.

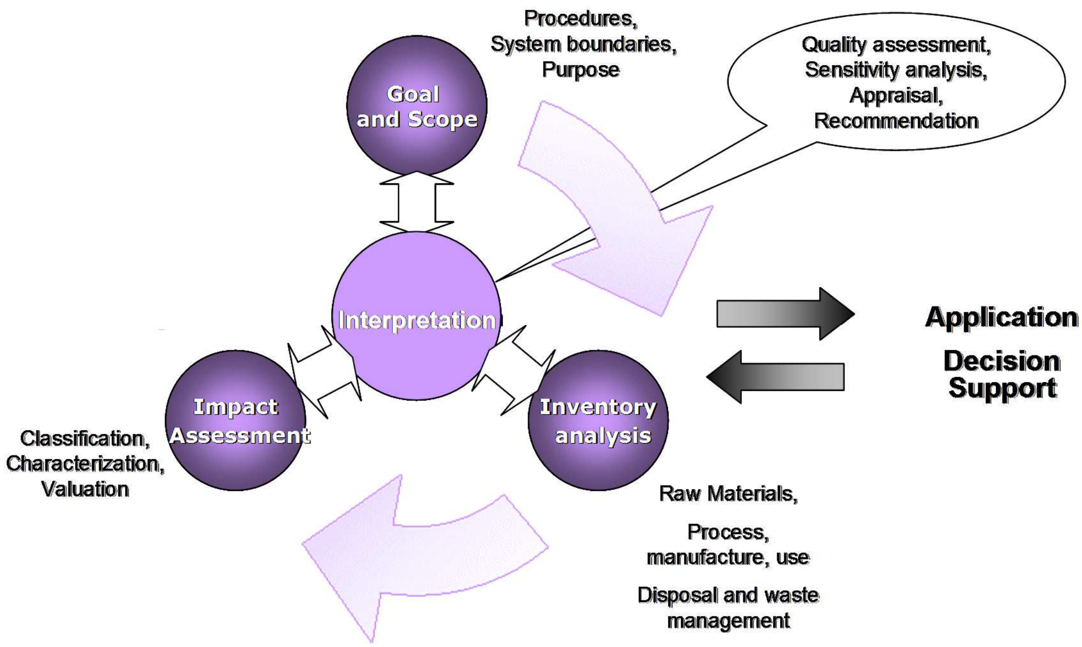

Figure 1. The ISO 14040 standard framework and steps for conducting and reporting LCA studies. Curved arrows show order of primary steps in the LCA. White double-headed arrows show interconnectedness between interpretation and other LCA steps. Black arrows show iterative nature of the LCA.

The goal and scope defines the goal and intended use of the LCA, states reasons for carrying out the study, specifies intended audience, and scopes the assessment concerning system boundaries, function and flow, required data quality, technology and assessment parameters. The scope of the study’s depth, breadth, and detail needs to be enough to address the stated goal. In addition, the goal states whether the results will be used to make comparative assertions intended to be disclosed to the public (ISO 2006a). During the goal and scope phase, LCA researchers make a selection of impact categories, category indicators, and characterization models (Curran 2017a). The ISO standard does not include specific guidance on attributional and consequential LCA, but this choice may also affect the goal and scope of the study.

The life cycle inventory (LCI) analysis is an activity for collecting data of relevant energy and material inputs, resources and intermediate products, and outputs (emissions to air, water, and soil, and waste treatments) for all the processes in the product system (ISO 2006a).

Life cycle impact assessment (LCIA) is the phase of the LCA where inventory data on inputs and outputs are translated into indicators about the product system's potential impacts on the environment, human health, and the availability of natural resources. LCIA is defined as the phase in the LCA aimed at understanding and evaluating the magnitude and significance of the potential environmental impacts of a product system (ISO 2006b).

Interpretation is the phase where the results of the LCI and LCIA are interpreted according to the goal of the study and where sensitivity and uncertainty analyses are performed to qualify the results and the conclusions. Interpretation allows researchers, policy makers, and industry to interpret the results of each of the former steps and to point out the key factors for an environmental policy and decision making. Interpretation is closely connected to the goal and scope definition, LCI, and LCIA, as shown in Figure 1 (Curran 2017b).

Over the past 10 years, the LCA method has become a standard to evaluate building and food sustainability. The LCA method is part of building codes including California Green Building Code, the ASHRAE 189.1 Standard, ICC 700, the International Green Construction Code (IgCC), and Leadership in Energy and Environmental Design (LEED) (Al-Ghamdi and Bilec 2015; Scheuer and Keoleian 2002; Suh et al. 2014a; Ortiz, Castells, and Sonnemann 2009). The environmental performance of green building code and certification systems has been examined by various authors (Suh et al. 2014b; Blengini and Di Carlo 2010; Al-Ghamdi and Bilec 2015; Trusty 2011; Gilbraith, Azevedo, and Jaramillo 2014). In food production systems, LCA is part of guidance for assessing the environmental performance of livestock supply chains LEAP (FAO 2017).

The LCA method was used throughout this study to (1) assess environmental impacts of different distribution and retail centers and compare different distribution and retail center options, (2) to identify environmental ‘hot-spots’ (impact driving LC stage, processes, and substances) over the entire life cycle, and (3) to provide the benchmark and framework for a tool that may help improve the existing distribution and retail center network in the United States, as shown in Figure 2.

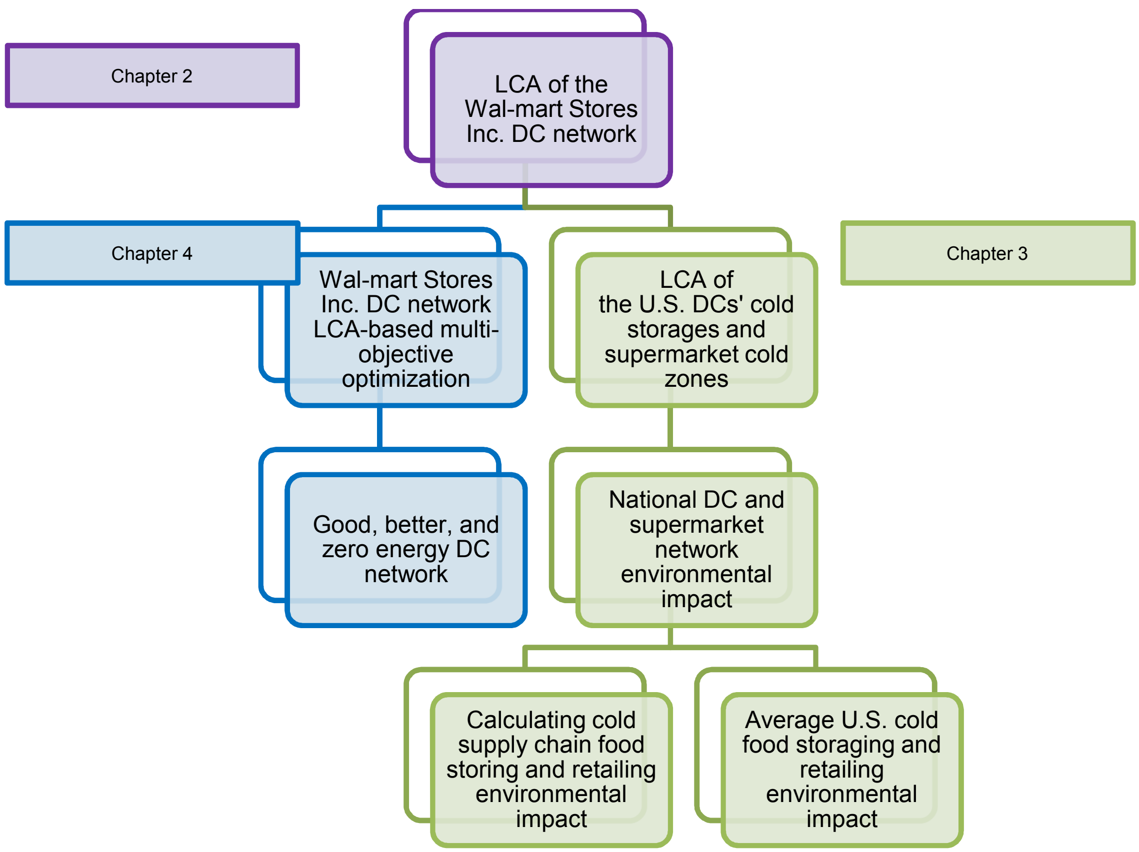

Figure 2. Research outline and themes presented in chapters 2, 3, and 4.

1.2. Relevant work in the field

Previous research in the area of environmental sustainability for building and construction sectors showed the use of LCA as a tool for making building design decisions (1) at the product level (e.g., comparison of alternative products for fulfilling a given function), (2) at the assembly level (e.g., interior or exterior walls, roofs and so on), and (3) at the whole building level, which includes the building's operation (Al-Ghamdi and Bilec 2015; Frees 2008; Safaei, Freire, and Henggeler Antunes 2015; Suh et al. 2014a; Whitehead et al. 2014; Allacker, Souza, and Sala 2014; Scheuer and Keoleian 2002; Medineckiene, Turskis, and Zavadskas 2011; Rossi et al. 2012; Brejnrod et al. 2017; Iwaro and Mwasha 2013; Xing, Xu, and Jun 2008; Borg, Paulsen, and Trinius 2001; Olinzock et al. 2015; Hernandez and Kenny 2010; Anastaselos, Giama, and Papadopoulos 2009; Ibn-Mohammed et al. 2013; Hsu 2009; Ramesh, Prakash, and Shukla 2010; Melià et al. 2014; Densley Tingley, Hathway, and Davison 2017; Tang, Cai, and Li 2011; Torgal et al. 2014; Cabeza et al. 2014; Napolano et al. 2015; Almutairi et al. 2015; Weißenberger, Jensch, and Lang 2014; Althaus et al. 2005; Abd Rashid and Yusoff 2015; Sathre and González-García 2014). Most whole-building LCAs focused on energy use, GHG emissions, and water consumption (Ramesh, Prakash, and Shukla 2010; R.H. Crawford 2011; Ibn-Mohammed et al. 2013).

In a whole-building LCA, the building use and operation phases had the highest environmental impacts, which were driven by the electricity generation, transmission, and distribution rather than material for building construction (Collinge et al. 2013; De Meester et al. 2009; Abd Rashid and Yusoff 2015). Earlier research showed that environmental impact of residential buildings varied for different locations due to site-dependent electricity production characteristics, i.e. fuel mix (Mutel, Pfister, and Hellweg 2012; Al-Ghamdi and Bilec 2017). Regional electricity generation energy sources determined impact contributors, the magnitude of impacts, and which substance flows affected specific environmental impacts the most (Al-Ghamdi and Bilec 2017). In special cases, building materials and manufacturing became the largest contributor to the GHG emissions (Faludi and Lepech 2012). That was the case when local electricity generation energy sources were renewable.

Even though published building and LCA review papers showed broadening of the LCA research in the building and construction sector (Abd Rashid and Yusoff 2015; Chau, Leung, and Ng 2015; Sartori and Hestnes 2007; Cabeza et al. 2014; Khasreen, Banfill, and Menzies 2009); not much LCA research has been done on DCs and supermarkets in the United States (Richman, Pasqualini, and Kirsh 2009). In the research published by Richman, Pasqualini, and Kirsh (2009), the authors used the LCA to evaluate improvements in cold storage warehouses by defining the best roof insulation materials for each climate zone. The research did not include different combined refrigerated and non-refrigerated food storages, or the non-refrigerated storages. Thus, in the chapter 2, we focused on building LCAs for PDCs, GDCs, and GMDCs, which were owned by the Wal-Mart Stores Inc.

An increasing amount of literature is devoted to food production and processing LCA, with the main conclusion that agricultural production has the largest share in environmental impacts (Beccali et al. 2010; Ingwersen 2012; Blanke and Burdick 2005; Roy et al. 2008; X. Zhu and van Ierland 2004; Iribarren et al. 2010; Ziegler, Nilsson, and Walther 2003; Hogaas and Eide 2002; Henderson et al. 2012; Kim et al. 2013; Thoma, Popp, Nutter, Shonnard, Ulrich, Matlock, Kim, Neiderman, Kemper, East, Adom, et al. 2013). Most of the food LCA research rarely included post- processing life cycle stages, which violated the LCA standard (Sanjuán, Stoessel, and Hellweg 2014; Zufia and Arana 2008; Virtanen et al. 2011; Roy et al. 2009; Hospido et al. 2009; Beccali et al. 2010). LCA studies that included storing and retailing, often attributed environmental burdens to one product, which limited storage and retail data and models widespread use for other products (Beccali et al. 2010; Ingwersen 2012; Blanke and Burdick

2005; Roy et al. 2008; X. Zhu and van Ierland 2004; Iribarren et al. 2010; Ziegler, Nilsson, and Walther 2003; Hogaas and Eide 2002; Henderson et al. 2012; Kim et al. 2013; Thoma, Popp, Nutter, Shonnard, Ulrich, Matlock, Kim, Neiderman, Kemper, East, Adom, et al. 2013; Burek et al. 2018). With nearly 0.93 billion square meters of floor space in the United States, DCs have an important role in food distribution and sustainability. Many researchers focused on changing dietary patterns to provide sustainable and healthy diets (Kim and Thoma 2018; M. C. Heller and Keoleian 2015; Carlsson-Kanyama, Ekström, and Shanahan 2003). DCs and RCs are important because of healthy food availability and accessibility within stores. Thus, we included current volume capacities and amount of food stored in each state. The environmental impacts of storing and retailing in DCs and supermarkets, respectively, need to be properly allocated to each product/food. Current LCA research does not adequately account for storing and retailing of different food categories. Omitting food distribution and retailing from food LCAs is a data gap that may affect the overall impacts of food. Thus, in the chapter 3, the main theme was how to calculate environmental impacts of PDCs storage and supermarket cold zones for different food categories.

In the United States, 30% of commercial building energy is used inefficiently or unnecessarily, for example, due to overcooling (Derrible and Reeder 2015). Energy savings are the most important metrics of buildings' sustainability because operational energy use is a primary cost and environmental impact driver (Ibn-Mohammed et al. 2013). Maximizing building energy efficiency and reducing system costs is necessary in the ongoing effort to improve energy use in buildings (EPA 2008; Liu, Claridge, and Turner 2002; U.S. Green Building Council 2013). In addition, a shift towards lowering environmental impact has become a part of green building certification programs such as LEED (U.S. Green Building Council

2013). An alternative option to improve building sustainability is by using renewable energy. In literature, one particular case of buildings, for which the use of renewable energy were evaluated using the LCA method, namely zero energy buildings (Cao and Alanne 2018; Griffith, Torcellini, and Long 2006; Hasik et al. 2017; Hernandez and Kenny 2010; Weißenberger, Jensch, and Lang 2014; Hoque and Iqbal 2015; Tognetti, Grosse-Ruyken, and Wagner 2015). Zero energy buildings combine both energy efficiency and renewable energy generation. Recent work demonstrated that finding cost-effective optimum solutions for energy efficiency and renewable energy use in buildings was often solved using single-objective or multi-objective optimization. LCA-based single-optimization problems have been the focus of numerous studies (1) to reduce the environmental impacts of building's hybrid combined cooling heating and power system and (2) to evaluate effectiveness of CO_2 reduction strategies in the building sector (Karan, Mohammadpour, and Asadi 2016; J. Wang et al. 2015). Noteworthy studies with focus on multi-objective problems were conducted with the goals (1) to increase renewable energy in building cooling, heating, and power systems and (2) to improve building energy efficiency through retrofitting (J. J. Wang et al. 2014; B. Wang, Xia, and Zhang 2014). In chapter 4, we use LCA and cost to build a multi-objective optimization model, which will find optimal solutions for solar and wind energy use in different DCs.

1.3. Justification and overall goal and scope for research

In the United States, warehouses are specialized for different products, for example, perishables, grocery, general merchandise, fashion, import, construction, and data warehouses. There has been as yet no systematic examination of environmental impacts of different types of warehouses for food distribution including perishables, grocery, and general methandise. Global cold supply chain is rapidly expanding, which may facilitate changes in food production and distribution. DCs and RCs are primary components of the post-processing cold food supply chain. The sustainability of cold food supply chain is ambiguous and focuses on food production and direct impacts of energy use and refrigerant, but rarely considers variable factors in storing and retailing, which may change the environmental profile of the food system. Finally, the cost of renewable energy has decreased. The new residential construction is successfully making a shift towards zero energy buildings. Although considerable progress has been made in zero energy residential buildings, implementing renewable energy in commercial buildings has been a more recent endeavour. Achieving zero energy is particularly challenging for refrigerated warehouses, which are energy intensive.

The ISO standard requires specifying goal and scope for LCA research (ISO 2006a). The overall goals of this research were (1) to evaluate environmental impact of GDCs, PDCs, and GMDCs using the LCA, as presented in chapter 2; (2) to bridge the data gap in food LCAs and enable full sustainability assessment of food storing and retailing, as presented in chapter 3; and (3) to find cost-effective strategies to reduce DCs environmental impact using multi-objective optimization, which will lead to improvement without burden shifting, as presented in chapter 4.

The scope of study included GDCs, PDCs, and GMDCs, and RCs and frozen and chilled food. The functional unit for DCs and RCs was m^3 and m^2. For food storing and retailing, the functional unit was kg. The system boundary was post-processing food storing and retailing. The gate-to-gate system boundary for DC and RC included building operation, construction, material, and end-of-life. The system boundary exluded transport of food from food processor to DC or RC and food agricultural production, processing, and packaging.

The intendent audience for this study are researchers in the areas of (1) green building, (2) sustainability of food and distribution, (3) multi-objective optimization, (4) LCA, and (5) quantitative analysis. The research will also be of interest to retail industry such as supply chain managers and for future DC retrofitting and planning. For each theme presented in chapters 2, 3, and 4 was specific goals and scopes were further elaborated.

1.4. Introduction to chapter 2

The scope of the research presented in chapter 2 was to perform LCA of the Wal-Mart Stores, Inc DC network. This research is an LCA of a globally impactful business and it will contribute to rethinking the global supply chain through whole-building multi-facility network analysis. The research outcomes are based on comprehensive whole-building LCA of different three types of DCs and their multi-facility state-level networks. The goal of this research was to (1) assess the environmental impacts of three types of food DCs in the United States using the LCA method, (2) show environmental impact similarities and differences among three types of DCs, (3) investigate relationships between climate zones, energy demand, electricity generation energy sources, and (4) quantify total state-level environmental impact based on current number and sizes of Wal-Mart Inc. Stores DCs in each state. Primary hypotheses were that climate conditions, the year of the building's construction, building materials, state-level sources of electrical power, energy demand for refrigerated and non-refrigerated spaces, and conveyor lengths change the magnitude of the environmental impacts across the U.S. First, the research identified similarities and differences between environmental impacts among the DCs. Second, the research investigated relationships between climate zones, energy demands, energy sources, building materials, and the environmental impacts of individual DCs.

1.5. Introduction to chapter 3

Global food cold supply chain is expanding at 4.2% annualized growth rate (Salin 2016). In the United States, gross refrigerated storage capacity has increased from 3 billion cubic feet in

2001 to 4.17 billion cubic feet in 2015, an increase of 28% (USDA NASS 2016). The scope of research presented in chapter 3 included frozen and chilled storage, and supermarkets in the United States. The post-processing storage and retailing is less studied in LCA studies due to difficulties in data collection of intrinsic properties related to the refrigeration technology and building operation. DC coolers and freezers, supermarket walk-in freezers, multi-deck and display cases, glass door freezers, and domestic refrigerators and freezers depend on temperature conditions. Previous LCA research accounted only for electricity consumed by the refrigeration equipment and refrigerant loss in the refrigerated and frozen storage. Electricity consumption of the refrigerated and frozen storage was often based on estimates or literature data.(Sanjuán, Stoessel, and Hellweg 2014) Lights, refrigerant loss and emissions, heating, ventilation, and air conditioning (HVAC), and interior equipment were not included in current LCAs. Previous research omitted the dock area used to load and unload the food, which is the largest refrigerated area in the DC. The dock keeps humidity of the freezers and coolers during summer and uses energy to defrost all winter, and the room air replacement is up to two times in one hour with outdoor air.(NREL 2012; Stoeckle 2000) Researchers estimated dock electricity demand was ¼ of one freezer and dock energy use.(Stoeckle 2000) Building water consumption was least modelled in the LCAs although non-agricultural water consumption is the fastest-growing. (Bijl et al. 2016) Storage time and throughput speed also vary for each food item and depends on supermarket demand and sales and spoilage. Thus, food LCAs need to include factors that impact cold distribution, which will impact the environmental profile of the food system and carry greater environmental impacts (Heard and Miller 2016).

1.6. Introduction to chapter 4

Sustainable distribution is defined by moving food and products between processor and consumer with the lowest environmental, cost, and social impact without compromising the efficiency of the conventional distribution functions. The objective of the research presented in chapter 4 was to optimize solar and wind energy use in the Wal-Mart Stores Inc. DC network based on a set of environmental and cost criteria. The research was drawing from the LCA results of the Walmart Stores Inc. DC network. The scope of the research included in chapter 4 was an LCA-based a multi-objective optimization of solar and wind energy use in DCs. The key questions we addressed in this research were: What was the environmental impact of DCs and supermarkets zones in different states? What was the environmental impact of different chilled and frozen foods? We reported water, energy, and food storage impact of freezers and coolers in DCs and supermarkets based on their geographic location. The required knowledge included modelling zone-level refrigerated storage facility and supermarkets and collecting data on different food storage capacity, supermarket sales, and average food prices. The multi-facility building network case study was based on the whole U.S. cold food supply DC network. The primary goals were (1) to compare the environmental performance of the existing DC in one state to an existing DC of the same type in another state using the Monte Carlo pairwise comparison, which would enable finding and prioritizing improvements for locations that currently perform the worst, (2) to find tradeoffs between the building’s energy consumption and on-site energy production in a spatial LCA-based multi-objective optimization model, which included economic (energy costs) and environmental outcomes (non-renewable fossil energy and climate change) of the building’s energy consumption and production, (3) to find the LCA-based cost-effective way to reduce the impact of climate change and fossil energy resource use by installing flat roof solar panels at existing DCs, and/or by purchasing off-site wind energy, (4) to compare current building's energy use and optimum solutions using the LCA-based Monte Carlo uncertainty pairwise comparisons, (5) to find the least-costly DC network, which was superior to the existing DC network, and (6) to find the optimal zero energy DC network.

1.7. The broader context

Environmental sustainability is the greatest challenge in research today due to growing population. Ensuring sustainability is iterative process because growing population will always challenge sustainability efforts. To address global challenges, the Sustainable Development Goals (SDGs) and 2030 targets were defined in 17 areas including poverty, inequality, climate, environmental degradation, prosperity, and peace and justice, which require immediate action and improvements (United Nations 2015). This research contributed to 5 SDGs: Goal 2: zero hunger; Goal 6: water scarcity; Goal 7: affordable and clean energy, Goal 9: infrastructure, and Goal 13: climate action (United Nations 2015).

Reducing energy and water consumption and anthropogenic environmental impacts and building innovative sustainable systems is a complex challenge. Consequences of a change in systems can be unknown and difficult to predict. Reduction in one environmental impact can increase cost and other environmental impacts. Systems are interconnected, for example, water-energy, food-water-energy, land-energy, etc. Inter-disciplinary and cross-disciplinary research presented in this researchwas necessary to open a pathway towards environmental sustainability of food distribution.

In sum, this research provided broad discussion about the environmental impacts of DCs and supermarkets food storage zones through network analysis and provides a national benchmark about the environmental impact of food. The models originating from this research are comprehensive process-based LCA models, which include accurate and reproducible building energy data. The models can be adapted for any other cold supply chain in the world; they allow performing scenario analysis including the indirect factors, such as change in technology and supply chain effects and external factors such as refrigerator choice and energy efficiency. The multi-objective model can be expanded to include a complete toolbox of other renewable energy and building improvements.

This research contributes to sustainable food distribution research and policy. The results will serve as a benchmark to improve sustainability of DCs, and consequently food distribution. This research should be of interest to readers in the areas of building sustainability, sustainability of food and distribution, LCA, and network analysis. The research will also be of interest to retail industry such as supply chain managers and for future DC planning. The assessment combined the U.S. electric grid, commercial building network, and food systems.

1.8. Overall context for the research manuscripts

The dissertation was assembled in the "Published/Publishable Manuscripts" format consistent with the University of Arkansas Graduate School Guide formatting requirements. Each manuscript represents one chapter in this dissertation. Chapter 2 is a published manuscript named "Life Cycle Assessment of Grocery, Perishable, and General Merchandise Multi-Facility Distribution Center Networks" and published in Energy and Buildings journal (Burek and Nutter 2018d). Chapter 3 is a manuscript named "Environmental Performance of Chilled and Frozen Food Post-Processing Storing and Retailing" and submitted for review in a journal (Burek and Nutter 2018a). This paper aimed to contribute to food LCAs by producing information regarding storing and retailing of food items, which is often disregarded. Chapter 4 is a manuscript named "The LCA-Based Multi-Objective Optimization of the Distribution Center Network" and submitted for review in a journal (Burek and Nutter 2018c). This manuscript examined strategies to reduce the environmental impacts of the Walmart Stores Inc. DC network and examined pathways to achieve the zero energy DC network using the multi-objective optimization. The technologies to reduce environmental impacts and to obtain the zero energy DC network involved installing new solar panels and wind turbines, i.e., DCs were shifted from energy consumers to energy producers. Primary benefits of solar and wind energy use are reducing dependency on fossil energy sources and climate change. The subject of inquiry was to find the most cost-effective way to mitigate the impact of climate change for DCs in different locations and to achieve the zero energy DC network.

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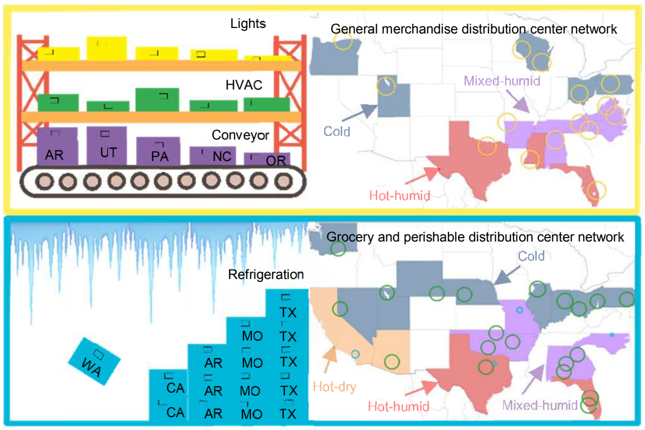
2.1. Graphical Abstract



2.2. Abstract

Buildings consume half the global electricity and generate one third of greenhouse gas (GHG) emissions. Distribution centers (DCs) have an important role in food distribution and sustainability. Omitting food distribution from food life cycle assessments (LCAs) is a data gap that may affect the overall impacts of food. We showed multi-facility state-level environmental impacts of the largest DC network in the United States. Our method included regional resolution of the life cycle inventory (LCI) combined with the regional life cycle impact assessment (LCIA) method. Three types of food DCs in different climate zones were assessed using the LCA method. Primary energy use in grocery and perishable DCs was refrigeration (80%) and in general merchandise were conveyor systems (50%). Building material and lighting became relevant for non-refrigerated spaces and in low-energy impact states. The location-specific provenance of electricity energy sources such as coal affected the process and substance impact contributors and magnitude of the environmental impacts, for example, in the energy, climate,

water, and land nexus. Water impact depended on energy sources and local water availability. Land use was dominated by activities in the supply chain and not building construction area. Achieving a low environmental impact supply chain is a major goal of producers, distributors and retailers. Energy efficiency through green building standards and distributed energy may improve sustainability of DCs.

2.3. Introduction

The generation and distribution of electricity comprises nearly 40% of U.S. greenhouse gas (GHG) emissions (Weber et al. 2010). Buildings account for 70% of electricity use (U.S. Green Building Council 2013). In the coming years, GHG emissions of commercial buildings will increase at a rate of 1.8% per year (U.S. Green Building Council 2005). Commercial buildings include office buildings, lodging, amusement, distribution centers (DCs), and retail centers (RCs) such as supermarkets. In 2012, the construction of RCs and warehouses accounted for 43% of the total commercial building revenue (Alegria 2012). Warehouses used 300,000 TJ of energy in 2012. This is about 7% of total energy use of all commercial buildings (US EIA 2016).

Product and food distribution includes processes that occur between producers, retailers, and customers. Figure 1 shows food distribution in the United States. DCs and RCs are primary food distribution components. A DC and RC network is defined as sum of DCs and RCs in one state. Post-processing distribution and consumption was rarely included in food life cycle assessments (LCAs), which may affect overall product sustainability. Food LCAs that reported cradle-to-grave LCA results accounted for the average RCs' energy use and excluded DCs (Kim et al. 2013; Thoma, Popp, Nutter, Shonnard, Ulrich, Matlock, Kim, Neiderman, Kemper, East, Adom, et al. 2013). One exception in this data gap is research by Burek et al., which accounted for average DC energy use in the United States (2017b). With nearly 0.93 billion square meters of floor space in the United States, DCs have an important role in food distribution and sustainability, and their life cycle energy and environmental performance need to be assessed.

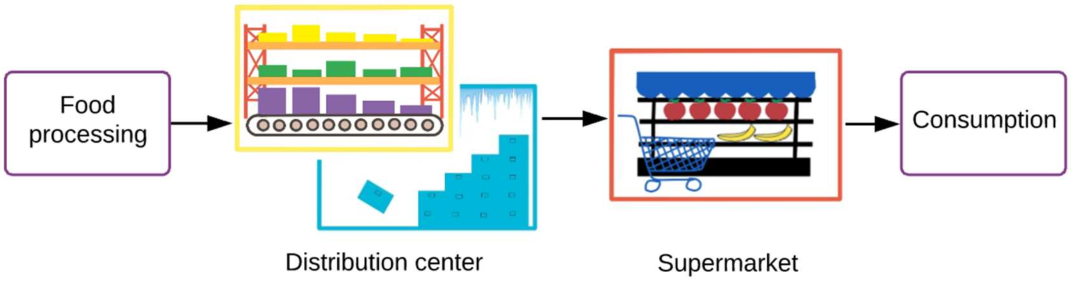


Figure 1. Food distribution in the United States includes processes between producers, retailers, and consumers.

Energy savings are the most important metrics of buildings' sustainability because operational energy use is primary cost and environmental impact driver (Ibn-Mohammed et al. 2013). In the United States, 30% of commercial building energy is used inefficiently or unnecessarily, for example, due to overcooling(Derrible and Reeder 2015). EnergyPlus is one of many building simulation tools to evaluate energy efficiency of commercial buildings (U.S. Department of Energy 2010; H. Wang and Zhai 2016). For a more informed approach than energy efficiency evaluation, the building and construction sectors have been using the LCA method. Researchers used LCA to analyze improvements in the United States cold storage warehouses by defining the best roof insulation materials for each climate zone (Richman, Pasqualini, and Kirsh 2009). Both the EnergyPlus software and LCA have been used in combination to evaluate environmental sustainability of concrete material and identified improvement opportunities (Miller, Gregory, and Kirchain 2016). However, most building LCA studies focused on energy use, GHG emissions, and water consumption (Ramesh, Prakash, and Shukla 2010; R.H. Crawford 2011; Ibn-Mohammed et al. 2013).

In a whole-building LCA, building use and operation phases had the highest environmental impact driven by electricity generation, transmission, and distribution rather than material for building construction (Collinge et al. 2013; De Meester et al. 2009; Abd Rashid and Yusoff 2015). Earlier research showed that environmental impact of residential buildings varied for different locations due to site-dependent electricity production characteristics, i.e. fuel mix (Mutel, Pfister, and Hellweg 2012; Al-Ghamdi and Bilec 2017). Regional electricity generation energy sources determined impact contributors, the magnitude of impacts, and which substance flows affected specific environmental impacts the most (Al-Ghamdi and Bilec 2017). The U.S. regional electricity GHG emission factors are well documented (Weber et al. 2010; Mutel, Pfister, and Hellweg 2012). In special cases, building materials and manufacturing became the largest contributor to the GHG emissions (Faludi and Lepech 2012). That was the case when local electricity generation energy sources were renewable.

The goal of this research was to conduct LCAs of distribution networks in the United States, which will bridge the data gap and enable full sustainability assessment of food and products. In this paper, we assessed the environmental impact of grocery (G), perishable (P), and general merchandise (GM) DCs using the LCA method. Primary hypotheses are that climate conditions, the year of building construction, building materials, state-level sources of electrical power, energy demand of refrigerated and non-refrigerated spaces, and conveyor length change the magnitude of the environmental impacts across the U.S. First, the research identified environmental impact similarities and differences among different types of DCs. Second, the research investigated relationships between climate zones, energy demand, electricity generation energy sources, building materials and the environmental impact of individual DCs and state-level DC networks. For our case study, we chose locally, regionally, and globally impactful business Wal-Mart Stores, Inc. The evaluation is science-based, independent, and objective, and it does not disclose or use the company's internal data on energy use. Results will serve as a benchmark of the environmental performance of the DC networks and for future work, which will include strategies to obtain zero energy food distribution networks (Hernández et al. 2010). DCs networks models will allow LCA food and product practitioners to include DC burdens in their LCAs, which will enable science-based, environmentally sound decisions in the supply chain management.

2.4. Materials and methods

The LCA method is used as the mainstream quantitative method to assess environmental impacts of products, processes, services, and whole buildings over the entire life cycle (ISO 2006a). At the time of this writing, it has been over ten years since the establishment of ISO 14040/44 series LCA standards (ISO 2006b; ISO 2006a). The ISO revises and appends existing standards and develops new standards (ISO 2006b; ISO 2006a; ISO 2014b; ISO 2014a). In building environmental assessment, the LCA is used to make environmental design decisions at the product-, assembly-, and whole-building level, which includes structural components and operating effects (Abd Rashid and Yusoff 2015; Cabeza et al. 2014; Chau, Leung, and Ng 2015; Collinge et al. 2013; Khasreen, Banfill, and Menzies 2009). Interest in sustainable buildings and infrastructure is growing, which prompted development of several building specific LCA-based sustainability tools (R.H. Crawford 2011). The Building for Environmental and Economic Sustainability (BEES) tool measures the environmental performance of building products (Lippiatt 2007). Athena Impact Estimator 5.2 evaluates whole buildings and assemblies (Athena Sustainable Materials Institute 2017a). Finally, the Building Industry Reporting and Design for Sustainability (BIRDS) measures energy, environmental, and cost performance of prototype commercial buildings (Lippiatt et al. 2013). Currently, BIRDS neither includes DCs nor allows the modeling of custom buildings. Thus, we built LCA models for our custom distribution center buildings in Athena Impact Estimator 5.2 (Athena Sustainable Materials Institute 2017b) and SimaPro 8.4 software (PRé Consultants 2015).

2.4.1. Goal and scope

This research is LCA of a globally impactful business and it will contribute to rethinking the global supply chain through network analysis. The research outcomes are based on comprehensive whole-building LCA of different three types of DCs and their multi-facility state-level networks. The goal of this research was to (1) assess the environmental impacts of three types of food DCs in the United States using the LCA method, (2) show environmental impact similarities and differences among three types of DCs, (3) investigate relationships between climate zones, energy demand, electricity generation energy sources, and (4) quantify total state-level environmental impact based on current number and sizes of Wal-Mart Inc. Stores DCs in each state.

LCA models were based on process-LCA method, which includes itemized inputs and outputs for each LCA stage (PRé Consultants 2015). System modeling was based on the attributional approach. In the attributional approach, inputs and outputs are attributed to the functional unit and multi-output system processes are partitioned based on allocation rules (Finnveden et al. 2009). In this research, allocation was avoided because the functional unit was based on the whole building and data were available separately for each building operation. The choice of LCA method and approach was based on need to include U.S. state-level electricity production for regional assessment, available only in the process-based attributional LCA DataSmart 2016 database (LTS 2016).

2.4.2. System boundary and functional unit

The system boundary was at the whole-building level from cradle-to-grave as shown in Figures 2a and 2b. Primary LCA stages were (1) building use and operation and (2) infrastructure. Infrastructure LCA models included construction material production (envelope and insulation), building construction, and the end of the building life (building demolition and material disposal) (R.H. Crawford 2011). Building use and operation stage included refrigeration, refrigerant loss, lights, heating, ventilation, and air conditioning (HVAC), machinery, water consumption, and conveyors for each location. The main difference between DCs is existence of refrigeration and insulation in GDCs and PDCs (Figure 2a) and conveyor in GMDCs (Figure 2b). The chosen functional unit for the assessment was 1 m^2 of DC floor space. State-level results reflect the sum of DC areas in each state.

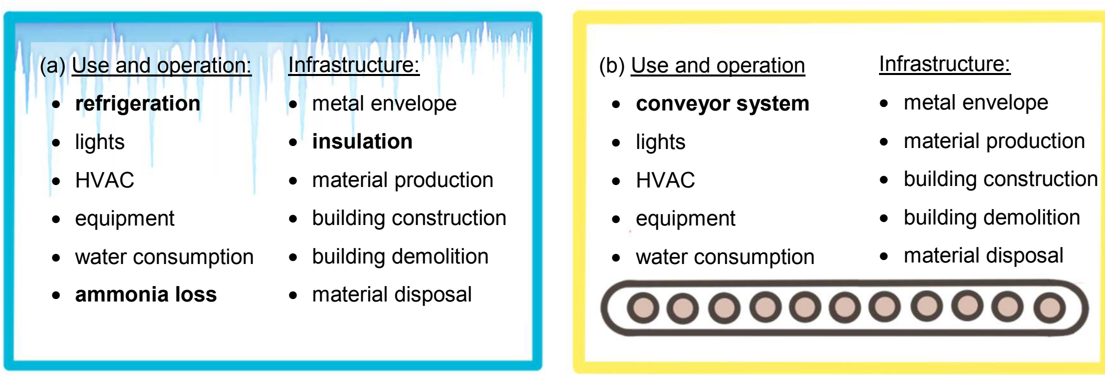


Figure 2. System boundary for a whole-building LCA. Figure 2a shows a system boundary for GDCs and PDCs (blue) and Figure 2b for GMDCs (yellow).

2.4.3. Wal-Mart Stores, Inc. distribution center network

The assessment included all of Wal-Mart Stores, Inc.'s locations for GDCs, GMDCs and PDCs in the United States (Table 2). Wal-Mart Stores, Inc. is an American multinational corporation and the world's largest retailer (2013). Its impacts on the global economy and consumers are well known (Basker 2007; Jantzen, Pescatrice, and Braunstein 2009; Brunn

2006). Research showed that Wal-Mart Stores, Inc. has a positive economic impact (2007). Yet, we know little about Wal-Mart Stores, Inc.'s environmental impact in the United States and the world. Figure 3 shows three types of typical Wal-Mart Stores, Inc. DCs: GMDC, GDC, and PDC. GMDC is a non-refrigerated warehouse with a metal panel envelope and conveyor system that distributes non-food items and shelf stable food. The floor area and conveyor length of a GMDC may be up to 115,000 square meters and 39 kilometers, respectively. GDCs have non-refrigerated and refrigerated areas for dry grocery and fresh dairy, meat, produce, and frozen food. The refrigerated grocery building envelope is made of insulated metal panels. Typically, the ratio of the non-refrigerated to refrigerated areas is 1.2-1.7. To calculate the ratio, we used a Google Earth area calculator (Figure 3). The years of construction of DCs range from 1983 to 2011 categorized as pre-2004 and post-2004 because buildings older than 2004 have higher energy demand due to older building standard (MWPVL International 2013). Data about building floor areas, types, locations, years of construction, and conveyor lengths were obtained from publicly available economic data (2013). The DC network building inventory, location, year of construction, area, conveyor length, and refrigerated/ambient ratio is given in Table 2. The main U.S. DC network is shown in Figure 4.

(a) GMDC (b) GDC (c) PDC

Figure 3. Aerial view of typical Walmart DCs including (a) GMDC, (b) GDC, and (c) PDC. Conveyor system (16-39 km) is only in the GMDCs.

Table 2. GDC, PDC, and GMDC network building inventory.

No.	DC type	TMY3 locations	State	Year of construction	Area (m^2)	Conveyor length (km)	Refrigerated Ratio
1	GDC	Montgomery 722260	AL	pre-2004	82,684	-	1.2
2	GDC	Birmingham 722280	AL	pre-2004	81,755	-	1.3
3	GMDC	Birmingham 722280	AL	pre-2004	111,484	18	-
4	GDC	Fort Smith 723440	AR	pre-2004	78,968	0	1.3
5	GMDC	Little Rock 723405	AR	pre-2004	102,193	16	-
6	GMDC	Bentonville 723444	AR	pre-2004	111,484	19	-
7	GDC	Casa Grande 722748	AZ	pre-2004	81,299	-	1.3
8	PDC	Riverside 722869	CA	post-2004	48,310	-	-
9	GDC	Lakeland Linder 722119	FL	pre-2004	92,903	-	1.2
10	GDC	Sarasota 722115	FL	post-2004	87,329	-	1.2
11	GMDC	Fort Pierce 722103	FL	post-2004	111,484	19	-
12	GDC	Athens 723110	GA	pre-2004	81,755	-	1.3
13	GDC	Greater Rockford 725430	IL	post-2004	92,903	-	1.2
14	GDC	Central Illinois 724397	IL	pre-2004	86,688	-	1.4
15	GDC	Indianapolis 724380	IN	post-2004	91,974	-	1.2
16	PDC	Kansas City 724460	MO	pre-2004	41,806	-	-
17	GMDC	Jackson 722350	MS	pre-2004	111,484	19	-
18	GMDC	Fayetteville 723035	NC	pre-2004	111,484	39	-
19	GMDC	Charlotte 723140	NC	pre-2004	111,484	19	-
20	PDC	Raleigh 723060	NC	pre-2004	37,161	-	-
21	GDC	North Platte 725620	NE	pre-2004	81,755	-	1.4
22	GDC	Reno-Tahoe 724880	NV	post-2004	82,684	-	1.4
23	GDC	Pittsburgh 725200	OH	pre-2004	81,755	-	1.3
24	GMDC	Port Columbus 724280	OH	pre-2004	102,193	16	-
25	GDC	Oklahoma 723530	OK	pre-2004	79,897	-	1.5
26	GDC	Tulsa 723560	OK	post-2004	83,046	-	1.2
27	GMDC	Eastern Oregon 726880	OR	pre-2004	109,161	17	-
28	GDC	Harrisburg 725115	PA	post-2004	83,613	-	1.2
29	GMDC	State College 725128	PA	pre-2004	110,555	17	-
30	GMDC	Allentown 725170	PA	pre-2004	103,981	16	-
31	GMDC	Knoxville 723260	TN	pre-2004	111,484	19	-
32	GDC	Houston 722436	TX	pre-2004	83,706	-	1.2
33	GDC	Fort Worth 722596	TX	pre-2004	82,498	-	1.3
34	GMDC	Tyler 722448	TX	pre-2004	111,484	19	-
35	GMDC	Fort Worth 722595	TX	pre-2004	111,484	19	-
36	GMDC	Amarillo 723630	TX	pre-2004	111,484	19	-
37	GMDC	Houston 722430	TX	post-2004	111,484	19	-
38	GMDC	San Antonio 722530	TX	pre-2004	111,855	18	-
39	PDC	Dallas-Redbird 722599	TX	pre-2004	39,019	-	-
40	GDC	Ogden 725750	UT	pre-2004	81,290	-	1.3
41	GMDC	Salt Lake City 725720	UT	post-2004	111,484	19	-
42	GMDC	Petersburg 724014	VA	pre-2004	111,484	19	-
43	GMDC	Charlottesville 724016	VA	post-2004	111,484	19	-
44	GDC	Yakima 727810	WA	post-2004	81,755	-	1.3
45	GMDC	Madison 726410	WI	post-2004	111,484	19	-
46	GMDC	Eau Claire 726435	WI	pre-2004	108,697	17	-
47	GDC	Cheyenne 725640	WY	post-2004	82,684	-	1.7

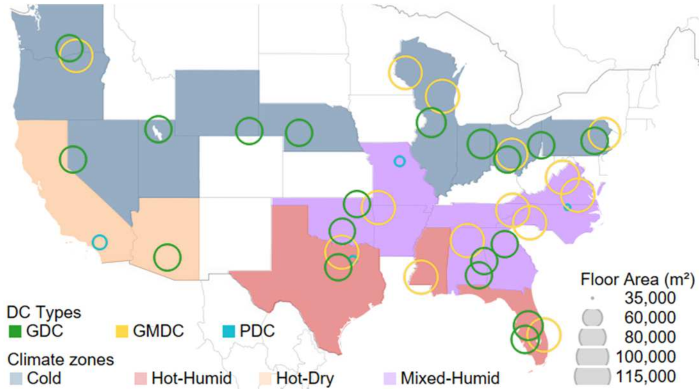


Figure 4. Wal-Mart Stores, Inc. DCs network map. Map shows GMDCs (yellow), PDCs (blue), and GMDCs (green) in different states and climate zones. The size of the circle shows floor area (m^2).

2.4.4. Life cycle inventory (LCI)

Primary LCI data were obtained from energy and process models: EnergyPlus™ 2.12, and SuperProDesigner® 9.0, as shown in Figure 5 (U.S. Department of Energy 2010; Athena Sustainable Materials Institute 2017b; Intelligen Inc. 2015). EnergyPlus is a whole building energy simulation tool used to model energy consumption in buildings. Output Excel reports of each EnergyPlus simulation include annual results of energy consumption for heating, cooling, refrigeration, ventilation, and lightings, which were linked to SimaPro process-LCA models using the external link function. One limitation of EnergyPlus software was that it focused only on energy consumption of building envelope and lights, but it did not include modeling of other operating effects. DCs also have a constant throughput of products and packaging via conveyors, which creates an additional environmental burden. The Department of Energy (DOE) models excluded building materials, water use, refrigerant loss, and conveyors. Therefore, data from DOE models fell short of generating a comprehensive environmental assessment.

SuperPro Designer process modeling tool was developed to calculate conveyor energy use based on the conveyor length and annual operation hours. The output data was total energy use of annual conveyor operation per km of conveyor. According to building measurements, conveyors can consume up to 50% of building energy (Schneider Electric 2010). Because measured data on conveyor energy use was confidential and not easily available, we modeled conveyor energy use in the SuperPro Designer software, as shown in Figure 5 (Intelligen Inc. 2016). Conveyor power demand was estimated at 20,515 kWh per km of conveyor belt per year. Conveyor system energy demand was between 40 and 70% depending on the building size and conveyor length (20-35 km). The Excel report from SuperPro Designer was connected to Simparo model using the external link function.

Athena Impact Estimator was used to model impact of building envelope and insulation material production, building construction, and demolition (Athena Sustainable Materials Institute 2017a). Input data for Athena Impact Estimator were obtained from the EnergyPlus input files, which included material data (material type, area, and thickness) for reference non-refrigerated and refrigerated warehouses. The output of the Athena Impact Estimator was building material cradle-to-grave system-based LCIs for refrigerated and non-refrigerated warehouse in Excel, which was connected to Simparo model using the external link function. Athena Impact Estimator input and output data are reported in Appendix, Table A1 and Table A2.

Building water consumption and cooling water losses were obtained from literature and calculated, respectively. Data for refrigerant use and losses were also collected from literature. The steps and data sources to obtain LCI inventory data from energy, LCA, process models, and literature and build whole-building process-LCA models along summary are shown in Figure 5. Many building LCA studies did not submit actual models and did not provide numerical results (Säynäjoki et al. 2017). Once this project is completed, all models will be available via Mendeley data and submitted to open source LCI database, which will ensure reproducibility. The models used for this research can be modified to include other types of DCs in different locations around the world.

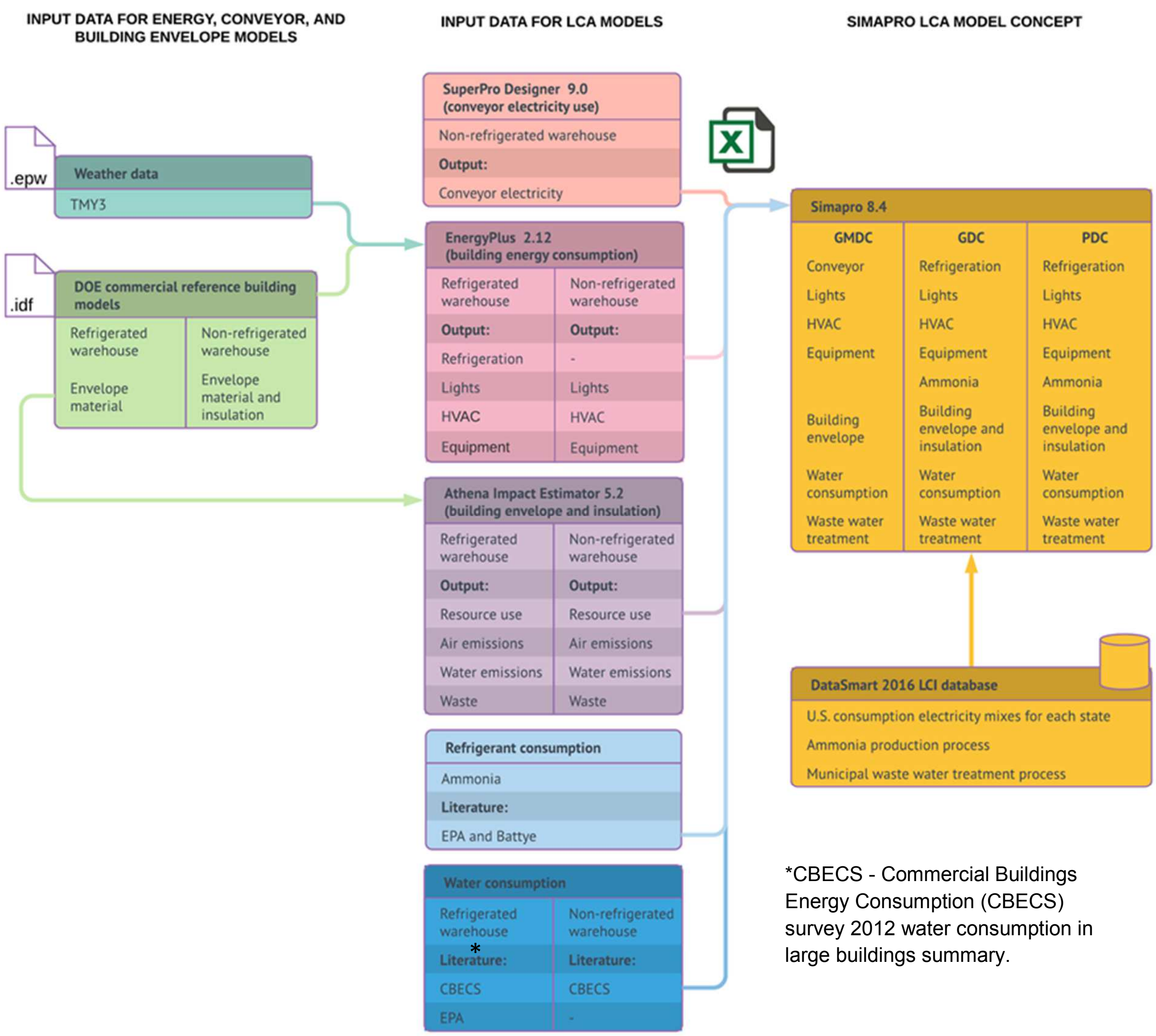


Figure 5. Data sources and tools used to collect data for whole-building LCA models.

2.4.4.1. Whole-building non-refrigerated and refrigerated warehouse energy consumption modeling with EnergyPlus

In 2012, the average electricity and natural gas use of warehouses was 71 kWh/m^2 and 5.9 m^3/m^2 per year, respectively (US EIA 2016). Literature data from 2002 shows cold storages used from 430 to 650 kWh/m^2 per year and 70% of total energy use was refrigeration (Richman, Pasqualini, and Kirsh 2009). The energy use intensity national average non-refrigerated DC was 2,800 MJ/m^2, which does not include the whole life cycle (US EIA 2016). The U.S. Environmental Protection Agency's (EPA) Energy Star Portfolio Manager reported energy use to be between 538 to 6,458 MJ/m^2 for refrigerated and non-refrigerated DCs (U.S.Environmental Protection Agency (EPA) 2013). On average, Leadership in Energy and Environmental Design (LEED) certified buildings used 32% less electricity. It is unknown whether any of the DCs in the United States are LEED certified. Since 2009, there has been an increase in Energy Star certified warehouse buildings, but none of the reported warehouses belonged to the assessed DC network (Energy Star 2017). Therefore, all buildings in the network were considered DOE reference buildings.

DOE input files for reference non-refrigerated and refrigerated warehouses were used to model energy use of Wal-Mart Stores, Inc. DC network using EnergyPlus software (DOE 2015; NREL 2012). Reference non-refrigerated warehouse models were for different U.S. climate zones and years of construction, but only one U.S. average refrigerated warehouse model was available (Torcellini et al. 2008). A basic criterion in EnergyPlus design of non-refrigerated and refrigerated DCs is to minimize operational energy (Gupta and Rao 1978). EnergyPlus simulations provided yearly consumption of energy use for refrigeration, lighting, equipment, and HVAC. Table 3 shows a summary of EnergyPlus results. The DOE reference warehouse model results showed that energy requirements of buildings vary in different climate zones and internal loads depend on the type and age of the DC (Deru et al. 2011). Thus, we simulated different DCs in different climate zones (Figure 4). The EnergyPlus software included data for local climate conditions through weather elements based on a 1991-2005 typical meteorological year (TMY3) data sets (Wilcox and Marion 2008). Post-1980 and new construction building reference models meet ASHRAE 90.1-1989 and 90.1-2004 standards, respectively. The refrigerated warehouse model was modified to calculate energy use for the whole year and for different locations in climate zones. We mapped DOE templates to existing Wal-Mart Stores, Inc. DC locations. All DCs form the Wal-Mart Stores, Inc. DC network.

This research shows higher energy use for non-refrigerated and refrigerated DCs than reported median value in literature (Table 3). Median value was based on joint non-refrigerated and refrigerated warehouses survey data, and data included only 9% of refrigerated warehouses (EIA 2012; Energy Star 2015). EnergyPlus results show that the lowest combined energy use including electricity and natural gas was for a GDC 950 kWh/m^2 and 1.3 m^3/m^2 per year, respectively, and the highest was for a PDC (982 kWh/m^2 and 17 m^3/m^2). GMDCs used between 56–185 kWh/m^2 and 1.5- 16 m^3/m^2 of natural gas per year.

Table 3. GDC, PDC, and GMDC EnergyPlus results for refrigeration, lighting, and HVAC. For GDC, values outside parenthesis are for a non-refrigerated space and inside for a refrigerated space. PDCs have only refrigerated space and GMDCs only non-refrigerated space.

No.	DC type	TMY3 locations	State	Refrigeration (MJ/m^2)	Lighting (MJ/m^2)	HVAC (MJ/m^2)	Total (MJ/m^2)
1	GDC	Montgomery 722260	AL	0 (3,444)	102 (75)	207 (66)	309 (3,584)
2	GDC	Birmingham 722280	AL	0 (3,372)	102 (75)	238 (67)	340 (3,539)
3	GMDC	Birmingham 722280	AL	0	491	1,151	271
4	GDC	Fort Smith 723440	AR	0 (3,404)	102 (75)	349 (79)	450 (3,557)
5	GMDC	Little Rock 723405	AR	0	102	357	459
6	GMDC	Bentonville 723444	AR	0	102	358	459
7	GDC	Casa Grande 722748	AZ	0 (3,372)	102 (75)	170 (62)	271 (3,509)
8	PDC	Riverside 722869	CA	(3,345)	(75)	(55)	(3,476)
9	GDC	Lakeland Linder 722119	FL	0 (3,514)	102 (75)	123 (58)	224 (3,647)
10	GDC	Sarasota 722115	FL	0 (3,547)	102 (75)	94 (53)	195 (3,676)
11	GMDC	Fort Pierce 722103	FL	0	142	214	356
12	GDC	Athens 723110	GA	0 (3,373)	142 (75)	147 (66)	289 (3,514)
13	GDC	Greater Rockford 725430	IL	0 (3,213)	102 (75)	693 (124)	795 (3,412)
14	GMDC	Central Illinois 724397	IL	0	102	532	634
15	GDC	Indianapolis 724380	IN	0 (3,251)	102 (75)	542 (102)	644 (3,428)
16	PDC	Kansas City 724460	MO	(3,301)	(75)	(96)	(3,472)
17	GMDC	Jackson 722350	MS	0	102	230	331
18	GMDC	Fayetteville 723035	NC	0	102	313	415
19	GMDC	Charlotte 723140	NC	0	102	260	362
20	PDC	Raleigh 723060	NC	(3,368)	(75)	(72)	(3,514)
21	GDC	North Platte 725620	NE	0 (3,251)	102 (75)	542 (102)	644 (3,428)
22	GDC	Reno 724880	NV	0 (3,251)	102 (75)	542 (102)	644 (3,428)
23	GDC	Pittsburgh 725200	OH	0 (3,209)	102 (75)	542 (102)	644 (3,428)
24	GMDC	Port Columbus 724280	OH	0	102	485	586
25	GDC	Oklahoma 723530	OK	0 (3,391)	102 (75)	331 (76)	433 (3,541)
26	GDC	Tulsa 723560	OK	0 (3,394)	142 (75)	203 (79)	345 (3,548)
27	GMDC	Eastern Oregon 726880	OR	0	102	374	476
28	GDC	Harrisburg 725115	PA	0 (3,259)	142 (75)	281 (101)	422 (3,425)
29	GMDC	State College 725128	PA	0	102	500	601
30	GMDC	Allentown 725170	PA	0	102	484	586
31	GMDC	Knoxville 723260	TN	0	102	345	447
32	GDC	Houston 722436	TX	0 (3,507)	102 (75)	153 (61)	254 (3,643)
33	GDC	Fort Worth 722596	TX	0 (3,463)	102 (75)	197 (65)	298 (3,603)
34	GMDC	Tyler 722448	TX	0	102	209	311
35	GMDC	Fort Worth 722595	TX	0	102	197	298
36	GMDC	Amarillo 723630	TX	0	102	335	437
37	GMDC	Houston 722430	TX	0	142	119	260
38	GMDC	San Antonio 722530	TX	0	102	160	261
39	PDC	Dallas 722599	TX	(3,510)	(75)	(65)	(3,650)
40	GDC	Ogden 725750	UT	0 (3,085)	102 (75)	427 (77)	529 (3,238)
41	GMDC	Salt Lake City 725720	UT	0	142	227	369
42	GMDC	Petersburg 724014	VA	0	102	300	401
43	GMDC	Charlottesville 724016	VA	0	102	260	362
44	GDC	Yakima 727810	WA	0 (3,094)	102 (75)	464 (84)	566 (3,253)
45	GMDC	Madison 726410	WI	0	142	358	500
46	GMDC	Eau Claire 726435	WI	0	102	828	930
47	GDC	Cheyenne 725640	WY	0 (3,027)	102 (75)	518 (82)	620 (3,184)

2.4.4.2. Refrigerant consumption and loss in refrigerated warehouses

According to DOE refrigerated warehouse input file, DCs typically use ammonia refrigerant. The consumption of ammonia for refrigeration applications in the United States was estimated at 270,000 ton/year (Battye et al. 1994). Ammonia use in refrigeration systems is a mature technology. It was assumed all the ammonia is emitted into the atmosphere and the relationship between ammonia consumption and emissions were at a steady state (Battye et al. 1994). The reported equipment refrigerant capacity in warehouses is 0.24 kg/m^2, which accounts for refrigerant change (EPA 2016). During the building's 60-year life span, the assumed building lifetime, refrigerant will be changed three times. Lifetime of commercial buildings varies from 15 – 50 years for offices (Aktas and Bilec 2011). We assumed 60-year life span of DCs because the oldest DC in Alabama is 34 years old.

2.4.4.3. Water consumption and cooling losses in warehouses

Average warehouses have the lowest (139 L/m^2) water consumption of all commercial buildings used of water per year (Energy Information Administration (EIA) 2016). PDCs and GDCs have higher consumptive water than GMDCs due to refrigeration. By consumptive water we refer to water used in cooling systems that was lost due to evaporation, drift, and blowdown and was not returned to the watershed. California, which has the largest capacity of cold storages, is phasing out cooling systems' water discharge to rivers and ocean because 50% of power plants discharge water has a temperature higher than allowed (USDA NASS 2016; World Nuclear News 2007). We assumed total 20% of water is lost due to evaporation (3%) (Powers 2016), drift (not reported), and blowdown (10%) (US EPA WaterSense 2017). According to the U.S. EPA, make-up water in cooling systems is 6.8 L per ton hour of cooling. Average refrigeration energy of 3,331 MJ/m^2 is equal to 789 ton-hour of cooling (US EPA WaterSense 2017). An additional make-up water for refrigeration in PDCs and GDCs was 5,365 L/m^2.

2.4.4.4. DataSmart 2016 state-level electricity production models

To model site-dependent environmental impacts, we chose a state-level electricity mix as a right spatial scale because that is electricity that DC will purchase. The process-LCA models were built using the SimaPro software and the DataSmart database, which included U.S. state-level electricity production, distribution, and imports (LTS 2016; PRé Consultants 2015). DataSmart database is process-LCA database. Some researchers suggest that hybrid-LCA likely provides more accurate results despite aggregation in Input-Output (IO) models because process-LCA includes truncation and allocation (Pomponi and Lenzen 2018; Robert H. Crawford 2008; Majeau-Bettez, Strømman, and Hertwich 2011). Other authors argue that hybrid-LCA does not necessarily provide more accurate results because the aggregation may introduce more errors (Yang, Brandao, and Heijungs 2018). The use stage of buildings is the main contributor to environmental impacts (Goldstein and Rasmussen 2017), and electricity mix influences the most building's total environmental performance (Heeren et al. 2015). Average U.S. electricity production climate change impact is 0.166 and 0.190 kg CO_2-eq/MJ for hybrid- and process-LCA, respectively (Wood et al. 2015; LTS 2016). State-level electricity production climate change impact varies between 0.032-0.328 kg CO_2-eq/MJ, as shown in Appendix, Table A3. Current U.S electricity process-, IO-, and hybrid-LCA models are highly aggregated and limited to national average (Wernet et al. 2016; Wood et al. 2015). Since building use and operation stage is energy intensive, using the average U.S. energy mix is not suitable. The Comprehensive Environmental Data Archive (CEDA) 5 IO database includes regionalized U.S. electricity mixes for 26 regions (VitalMetrics 2014). The IO data in CEDA 5 is dollar impact. In the United States, electricity rates and prices vary for each state, adding to an additional conversion step for EnergyPlus output data reported in MJ. State-level electricity is a mix of regional electricity production, imports, and exports. The U.S. state electricity production, export, and imports were provided only in DataSmart database (LTS 2016).

The U.S. LCA database DataSmart shows that fossil energy use depends on the fuel and grid production mix to produce power in each state (LTS 2016). State electricity generation profiles included electricity generation by energy sources (LTS 2016). DataSmart LCI state-level electricity production models were based on a U.S. energy consumption overview (U.S. Energy Information Administration 2015). Imported electricity from Canada and Mexico was estimated from the electric power annual report (U.S. Energy Information Administration 2016). The electricity mix was composed of specific sub-region data based on statistical data (North American Electric Reliability Corporation 2016).

2.4.5. Life cycle impact assessment (LCIA) method choice

Neither the ISO standard nor building codes firmly establish which LCIA method needs to be selected. The number of LCA impact methods including different impact categories is increasing. The ISO standard requires a multi-impact approach, but the choice of a specific method is left to the practitioner (ISO 2006a). Building code guidelines state measures to lower GHG emissions from the energy supply, increase renewables, and reduce factors that contribute to health impacts over a product life cycle. Thus, the assessment needs to include impact categories that will help reduce climate change, dependence on fossil fuels in building operation, and hazardous substances in building materials. In addition, the water-energy-land-climate nexus identified priorities to enhance data and modeling and understand regional differences (Faeth and

Hanson 2016). The impact category choice also needs to include two intersectoral resource indicators: water and land and their environmental impacts.

Recent developments in comprehensive LCIA are presented in ReCiPe 2016 and IMPACT World+ methods (M. A. J. Huijbregts et al. 2016; Bulle et al. 2017). ReCiPe 2016 provides characterization factors that are representative for the global scale (M. A. J. Huijbregts et al. 2016). IMPACT World+ includes global scale characterization factors for all impact categories. In addition, it includes globally regionalized factors for water, land, freshwater and terrestrial acidification, and freshwater and marine eutrophication (Bulle et al. 2017). At the moment, ReCiPe 2016 does not include regional characterization factors. Another difference between ReCiPe 2016 and IMPACT World+ methods is water footprint method. ReCiPe 2016 characterization factor accounts water consumed, i.e., the amount of water that watershed is losing. IMPACT World+ adopted the Available Water Remaining (AWARE) method. AWARE is the state of the art and recommended method to evaluate the water scarcity footprints, which meets the ISO 14046 standard (Boulay et al. 2017; ISO 2014b). Methane has a Global Warming Potential (GWP) of 28–36 over 100 years (IPCC 2014). A higher GWP 36 was used in ReCiPe 2016 and lower GWP 28 in the IMPACT World+ LCIA method. Uniform System for the Evaluation of Substances (USES) characterization factors were used for human toxicity in ReCiPe 2016 (Van Zelm, Huijbregts, and Van De Meent 2009). Human toxicity in IMPACT World+ is adopted from the USEtox method consistent with scientific consensus on characterizing human and ecotoxicological impacts of chemicals (Rosenbaum et al. 2008). Ionizing radiation, ozone depletion, and mineral resource use are similar in both methods. The exception is that ReCiPe 2016 included dinitrogen monoxide, but the characterization factor is considered preliminary. Land biodiversity, water consumption damage to health and ecosystems, freshwater and terrestrial acidification, and freshwater and marine eutrophication were not compared because ReCiPe 2016 includes only global damage factors and metrics are not in the equivalent units. We chose the IMPACT World+ LCIA method because food distribution has a local, regional, and global impact, and because it includes best practices recommended by the international consensus.

The IMPACT World+ assesses the magnitude of global environmental impact potential, but also provides country-level resolution (Bulle et al. 2017). Because regional electricity generation has different energy sources, we included non-renewable fossil and renewable energy resource use indicators from Cumulative Energy Demand (CED) method (Hischier et al. 2010). The fossil energy characterization factors in CED are equal or higher than in corresponding IMPACT World+ method. AWARE characterization factors for each building location are multiplied with water consumption inventory (WULCA 2017). Water consumption inventory is water use that was not released back into the original watershed (Bayart et al. 2010). We also report water use linked health and ecosystem damage categories. The IMPACT World+ assessed water impact to health, ecosystems, and thermal pollution. IMPACT World+ building on-site water damage factors for human health were zero because the U.S. water ability, or lack thereof, to meet human demand is low. DataSmart water and land resource flows were mapped to flows in the IMPACT World+ method. This ensured that the most important flows were captured both in built models and the DataSmart database. Selected resource use, environmental impacts, and damage categories are based on the IMPACT World+ method (Bulle et al. 2017). Their definitions are presented in Table 1.

Table 1. List of resource, impact, and damage categories and definition in IMPACT World+ LCIA, AWARE, and CED methods (Bulle et al. 2017).

Resource/impact/damage categories	Unit	Definition
Climate change	kg CO_2-eq	The GHG emissions are based on a short-term Global Warming Potential for a 100-year time horizon.
Fossil energy use	MJ	Total non-renewable (fossil) energy used.
Renewable energy use	MJ	Total renewable energy used.
Human toxicity	CTUh[a]	Estimated increase in morbidity due to chemical emitted into both for cancer and non–cancer diseases.
Ionizing radiation	Bq C-14 eq[b]	Human exposure efficiency relative to U^{235}.
Land use	ha.yr arable	Includes land occupation and land transformation.
Land biodiversity	PDF[c].m^2.yr	The characterization factors relate land occupation to biodiversity loss.
Marine eutrophication	kg N eq	Nitrogen is a limiting nutrient causing marine eutrophication, respectively.
Mineral resources use	kg	It uses the material competition scarcity index, which represents the fraction of material needed in the future but not able to adapt to a full dissipation of the easily available stock.
Respiratory organics	kg NMVOC[d] eq	Refers to emissions of NMVOC
Water resource use	m^3	It refers to remaining water available per area after human and aquatic ecosystem demand has been met, relative to world average.
Water use impacts to human health	DALY[e]	Damage on human health due to water use is linked both to water scarcity and to adaptation capacity in the region affected by this scarcity. It does not account for water quality.
Water use impacts to aquatic ecosystems and thermally polluted water	PDF.m^2.yr	It includes freshwater and groundwater impacts to freshwater and terrestrial ecosystems, respectively. Thermally polluted water accounts for cooling water.

[a] CTUh – comparative toxic unit for human
[b] Bq – becquerel, SI unit for radioactivity
[c] PDF – potentially disappeared fraction (of species)
[d] NMVOC – non-methane volatile organic compounds
[e] DALY – disability-adjusted life year (DALY). Quantifies the burden of disease from mortality and morbidity.

2.5. Results and discussion

Results show strong links between impact categories and input data selected. All input data were found relevant in at least one impact category. In addition, EnergyPlus results of regional evaluation showed different energy requirements to operate a warehouse in different climates. The input data that affect climate change are climate zone, year of construction, and energy sources in different states. GDCs have larger refrigerated areas compared to their adjunct ambient areas and PDCs are fully refrigerated; thus, the total environmental impact of GDCs and PDCs is largely dependent on the refrigeration load.

Electricity generation from coal is the single largest contributor to most impact categories across many states. There is no significant evidence to suggest that the year of construction has an impact on LCIA for these types of buildings. Building materials come into consideration when examining amounts of mineral resources used and show an impact on human toxicity. Out of all building operations, including HVAC and lighting, conveyors (when present) have the highest impact on GMDCs. Numerical results are provided in Appendix, Table A4 and A5.

2.5.1. Energy use, climate change, and correlated impacts

Figures 6, 7, and 8 show the fossil energy use, renewable energy and climate change impact for GDCs, PDCs, and GMDCs in different climate zones of the United Sates. The use of fossil fuels is an important driver of environmental impacts of buildings. Overall, fossil energy use per m^2 in the Eastern U.S. is higher than in the Western U.S. But, in comparable climates, including hot-humid, mixed-dry, and hot-dry, the fossil energy use is similar for GDCs; therefore, the refrigeration load is overruling the higher natural gas share in fuel mix used to produce electricity in Western states. Refrigeration is mainly based on cooling food/product and not very dependent on climate zones because the building envelop is so well insulated. The PDCs in Texas, Missouri, and North Carolina have higher fossil energy use than California. California and Washington have the highest use of natural gas and hydropower electricity, respectively.

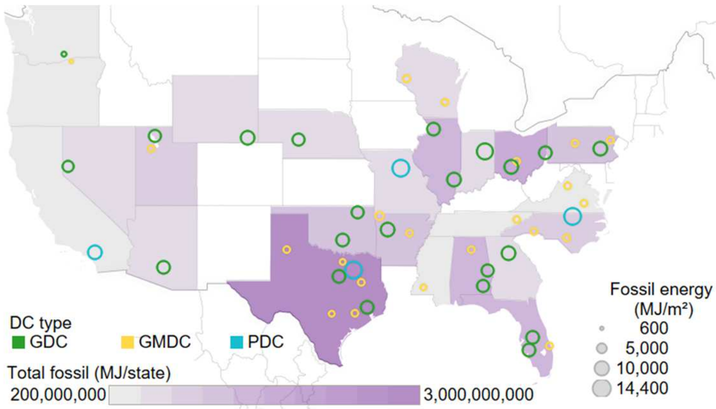


Figure 6. This choropleth of the United States shows state-level fossil energy use (MJ/state) from all DCs in one state. The color of the circle shows the DC type. The size of the circle shows fossil energy use per square meter (MJ/m^2).

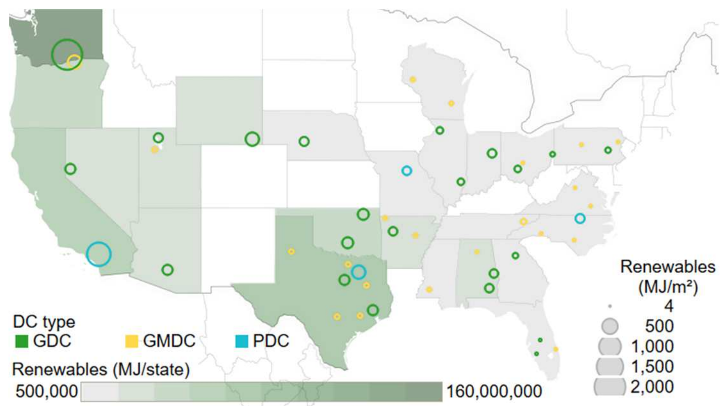


Figure 7. This choropleth map of the United States shows state-level renewable energy use (MJ/state) from all DCs in one state. The color of the circle shows DC type. The size of the circle shows renewable energy use per square meter (MJ/m^2).

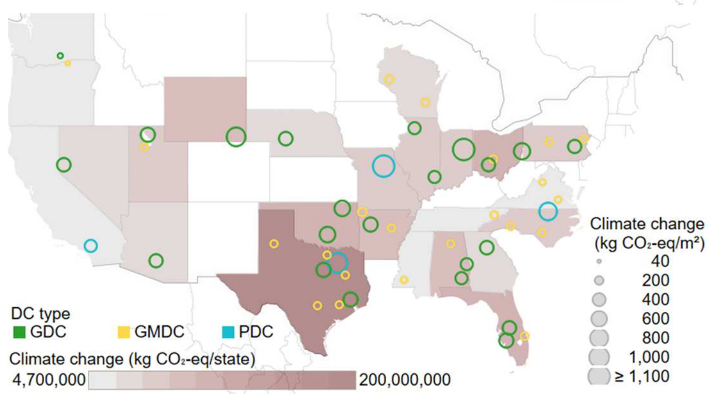


Figure 8. This choropleth map of the United States shows state-level climate change ($CO_{2\text{-}eq}$/state) from all DCs in one state. The color of the circle shows DC type. The size of the circle shows climate change impact per square meter ($CO_{2\text{-}eq}$ /m^2).

The fossil energy use and climate change impact are correlated in Arkansas, Georgia, Alabama, Texas, Florida, Utah, Missouri, Wisconsin, Ohio, Oklahoma, Utah, and Oregon, as seen in Figure 9. Overall, PDCs have the highest fossil energy use. In states with similar energy fuel profiles, climate zones show little effect on the GDCs. For example, in Pennsylvania, Texas, and Arkansas, fossil energy use is dominated by coal electricity generation. In Wyoming and Missouri, 80% of electricity is generated from coal. Thus, the Wyoming GDC's climate change impact scores above the North Carolina PDC. On the other hand, almost 50% of California's electricity generation comes from natural gas, which has a lower GHG emission factor than coal. 80% of Oregon's electricity comes from natural gas; with lower energy demand this GMDC has the lowest climate change impact. The GDC in Washington State has the lowest fossil energy use and climate change impact. Utah has lower fossil energy use than other GMDCs, but a higher climate change impact because of electricity generation from coal. One GMDC in Arkansas has the highest fossil fuel use and climate change impact because of their 39-km conveyor system.

Respiratory inorganics, human toxicity, land occupation, aquatic eutrophication, terrestrial acidification, ozone depletion, and aquatic ecotoxicity are not shown, but correlated quite well with the climate change impact dominated by the types of energy sources to generate electricity for GDCs and PDCs.

2.5.2. Impacts from water consumption on human health and ecosystems

Although the average in-house warehouse water use is low, LCA results on water consumption are important due to energy generation and water relationship, so-called energy-water nexus. Equally important is to report water impacts because they depend on the regional water scarcity.

Refrigerated PDCs and GDCs have higher water consumption than GMDCs. Arizona, Wyoming, and Nebraska have the highest water footprint per m^2 and total state for GDCs due to the highest water scarcity midpoint characterization factors at the building locations, which were attributed to building make-up water for refrigeration systems (Figure 10). Building water consumption affects the ecosystems and up to 70% is directly attributed to make-up water for cooling systems (Figure 11). The impact of water use on human health from buildings is similar across the U.S. and depends on higher water used in refrigerated PDCs and GDCs (Figure 12).

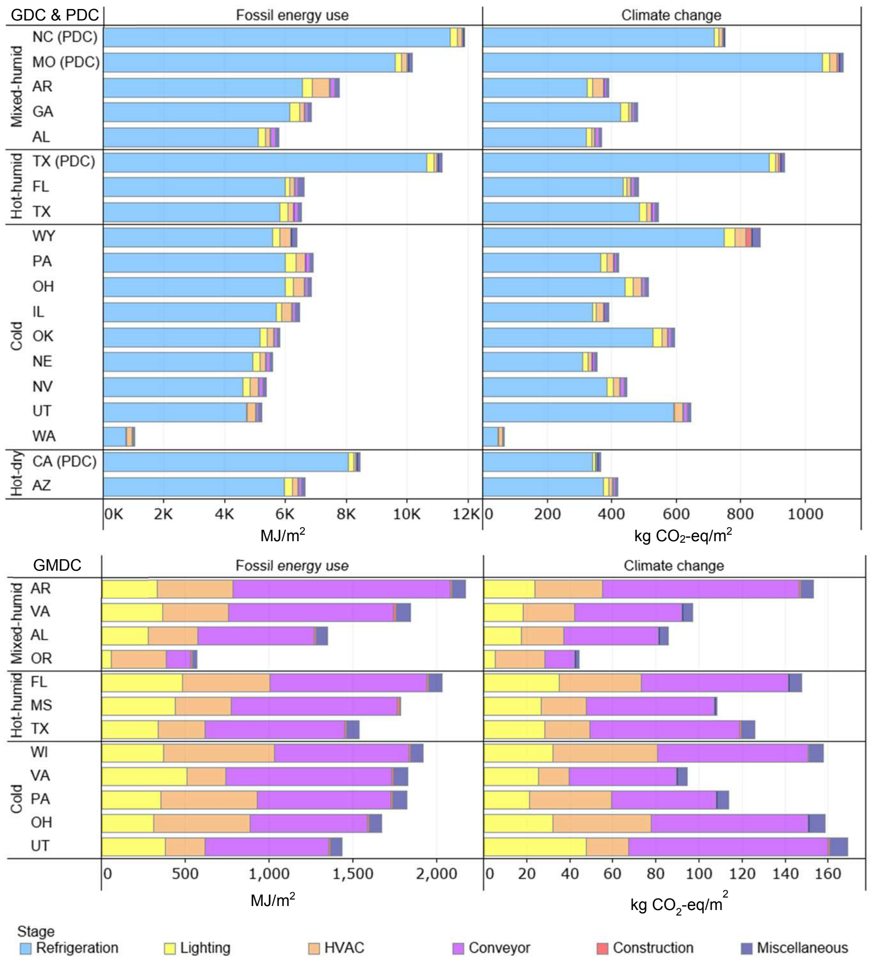
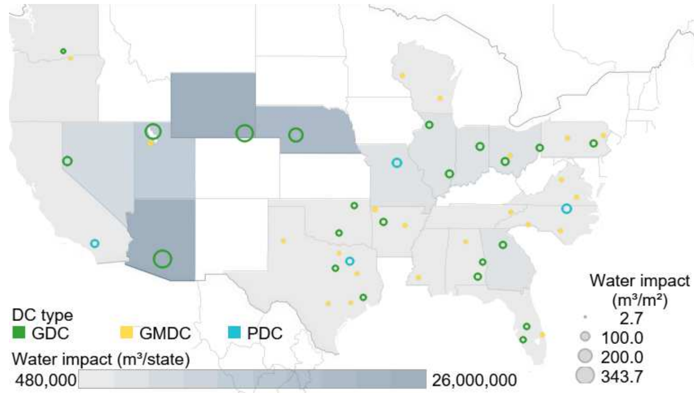


Figure 9. LCIA results for fossil energy use (MJ/m^2) and climate change impact (kg $CO_{2\text{-eq}}$/m^2) for GDCs, PDCs, and GMDCs in mixed-humid, hot-humid, cold, and hot-dry climate zones.

2.5.3. Impacts of land use on biodiversity

The sources of land use and biodiversity impacts are land transformation and construction of the DCs and supply chain resource mining land such as coal waste disposed at the mine site. Figures 13 and 14 show the relative importance of land use of building construction compared to the` resource extraction in the supply chain. Land use in the supply chain is more important to the biodiversity impact than the building construction site. This means in addition to water there is a relationship between energy and land use, known as the water-energy-land nexus.

Figure 10. This choropleth map shows state-level water impact (m^3/state). The circle color shows the DC type. The circle size shows water impact per square meter (m^3/m^2).



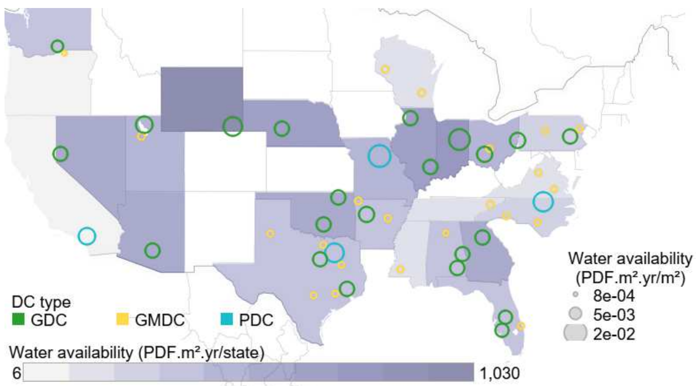
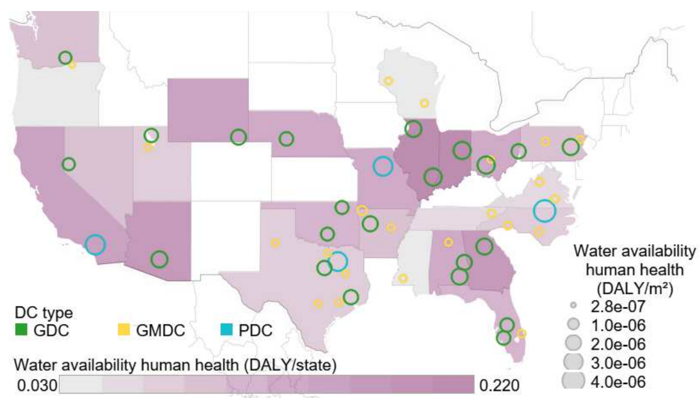


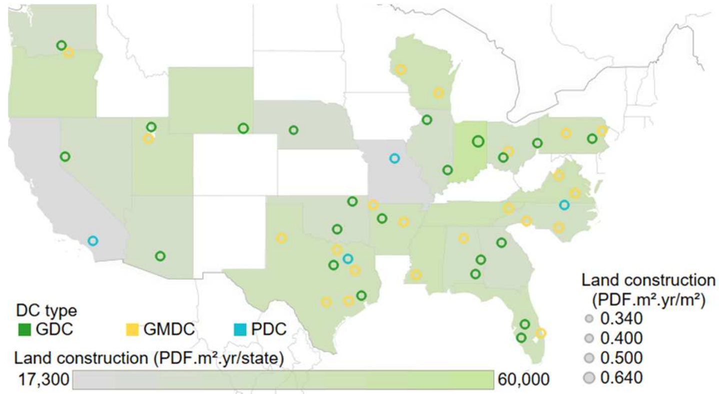
Figure 11. This choropleth map shows state-level water consumption effects on ecosystems (PDF.m^2.yr/state). The circle color shows the DC type. The circle size shows ecosystems damage per square meter (PDF.m^2.yr/m^2).

Figure 12. This choropleth map shows state-level water consumption effects on human health (DALY/state). The circle color shows the DC type. The circle size shows human health damage per square meter (DALY/m^2).



Resource extraction can be from 45% (Nevada) up to 85% (Indiana) of total land use for GDCs. The magnitude of resource extraction depends on fossil fuel types and their share in the power production ration. Larger land use is reported for states dominated by electricity production from coal. For GMDCs, building construction land use is up to 45% (Arkansas). For a PDC in California, the occupation of the water bodies for hydropower plants is 60%. PDC building construction sites and coal plant dump sites have less than 5% land use.

Figure 13. This choropleth map shows state-level land biodiversity impact from DC building construction site (PDF.m^2.yr/state). The circle color shows the DC type. The circle size shows biodiversity impact per square meter (PDF.m^2.yr/ m^2).



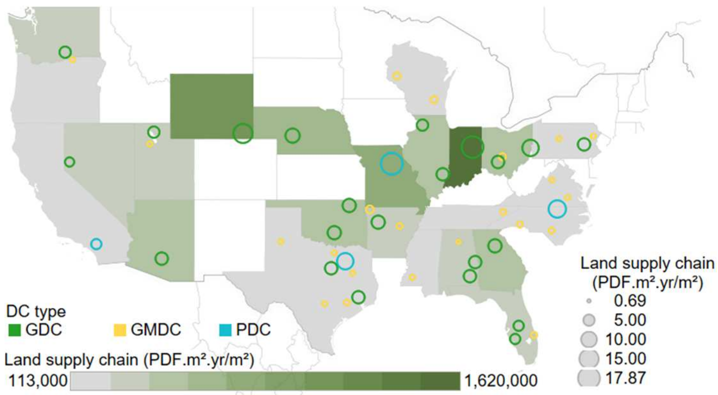


Figure 14. This choropleth map shows state-level land biodiversity impact from DC supply chain (PDF.m^2.yr/state). The circle color shows the DC type. The circle size shows biodiversity impact per square meter (PDF.m^2.yr/ m^2).

2.5.4. A matter of construction

The most important mineral resource in DCs is iron ore. For GDCs and PDCs, the iron from the supply chain is higher than for GMDCs. Because GMDCs use less energy, mineral resources become relevant in the impact to human toxicity (Figure 15).

2.5.5. Other impact categories

Ionizing radiation is pronounced in states that use more nuclear power, as shown in Figure 16. Respiratory organics vary across the United States, and are influenced by coal and natural gas electricity generation. Building wastewater is connected to the municipal sewer and is the single largest contributor to marine eutrophication (Figure 16).

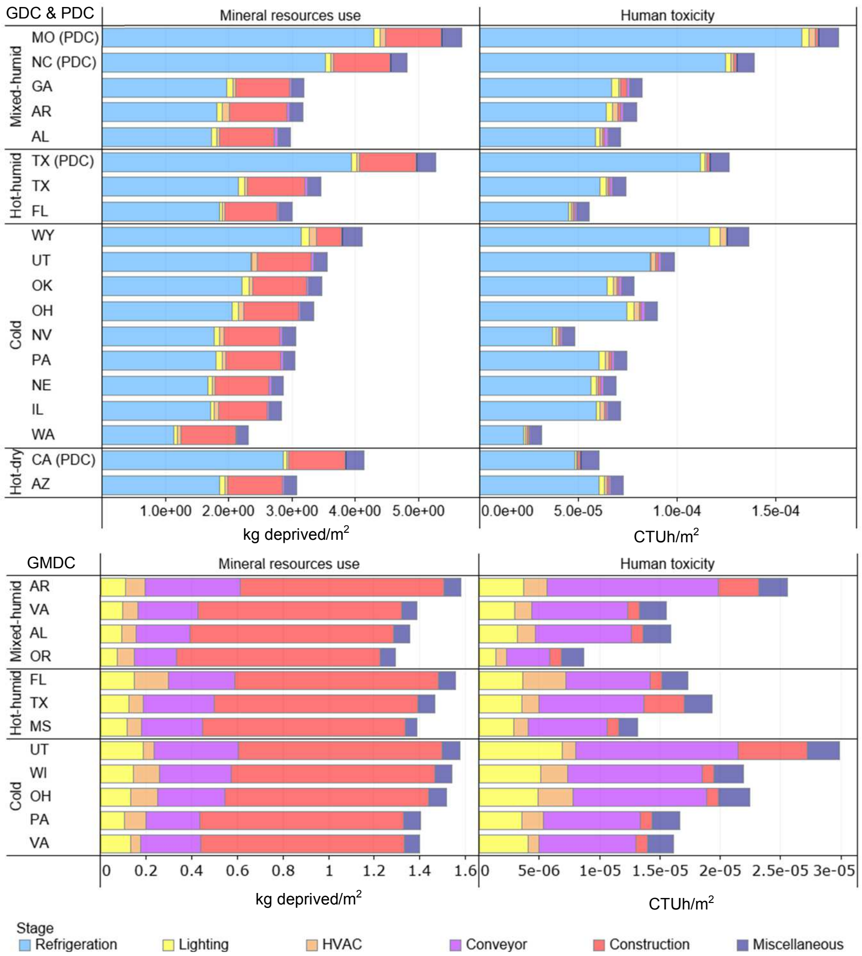


Figure 15. LCIA results for mineral resource use (kg deprived/m2) and human toxicity (CTUh/m2) for GDCs, PDCs, and GMDCs in mixed-humid, hot-humid, cold and hot-dry climate zones.

2.6. Conclusion

This research demonstrates that the current LCA techniques can be used to assess the environmental performance of DC network buildings in different climate zones. Variability in the environmental impacts of DCs is linked to location, conveyor length, material, and building types. All input data have relevant environmental impact contributors. Thus, the LCA of a warehouse must include, at the least, the input data reported here. While reducing energy use in buildings remains one of the most important ways to reduce environmental impacts, location determined the energy sources used to generate electricity.

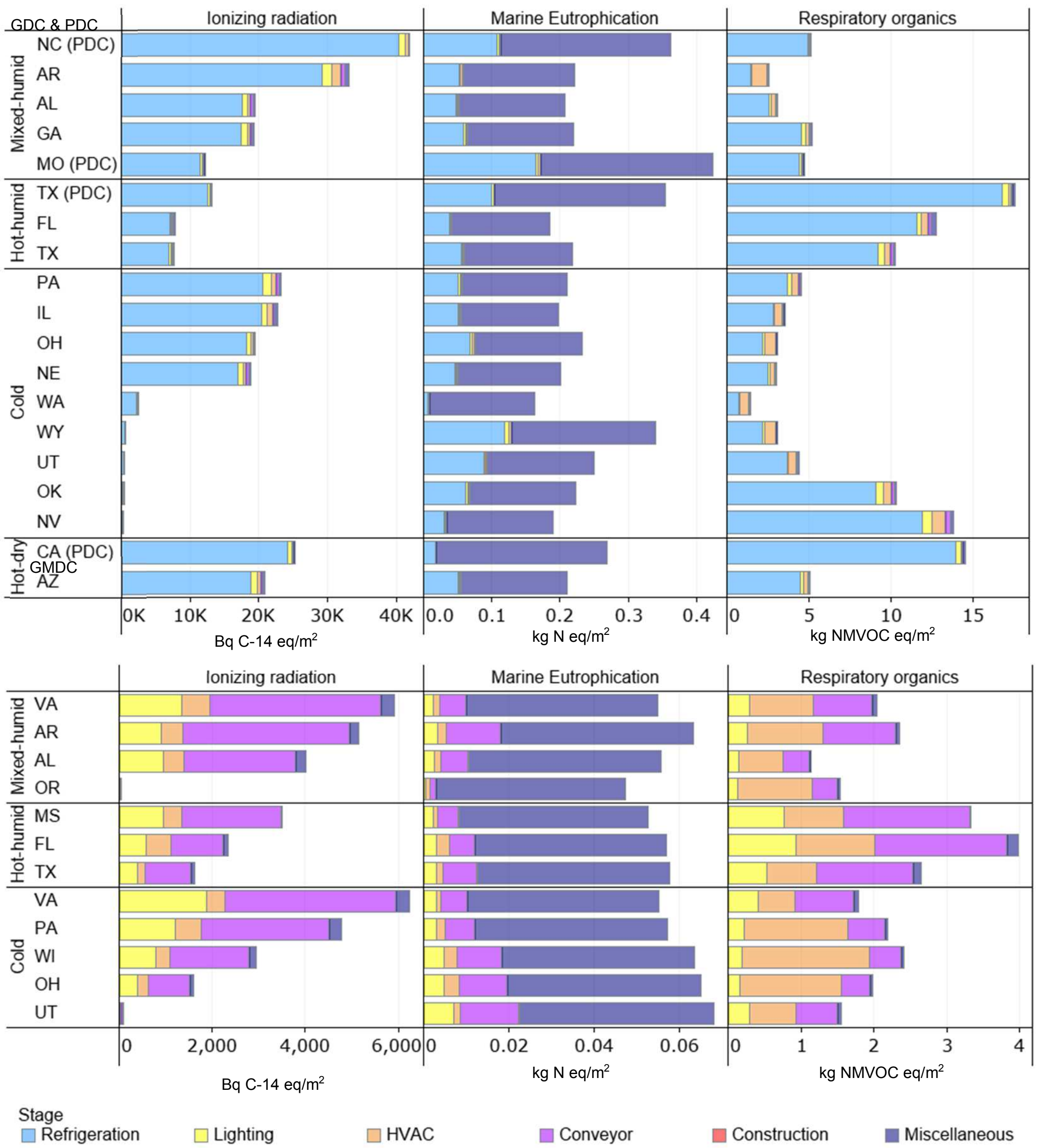


Figure 16. LCIA results for ionizing radiation (Bq C-14 eq/m^2), marine eutrophication (kg N eq/m^2), and respiratory organics (kg NMVOC eq/m^2) for GDCs, PDCs, and GMDCs in mixed-humid, hot-humid, cold and hot-dry climate zones. Miscellaneous refers to wastewater treatment.

Location-based energy sources in the electricity mix were the main environmental impact contributor. In many states, the dominant fossil fuel is coal. In California, it is natural gas. DC buildings in Washington State were found to have the lowest climate change impact due to hydropower. However, climate zones have little effect on energy demand. This is because the primary impact contributors are refrigeration for GDCs and PDCs and conveyors in GMDCs. Both refrigeration and conveyors are energy intensive, but their electricity use is largely independent of climate zones. The regional building assessment is critical for western states, which, unlike the other states, use significantly more natural gas and hydropower instead of coal to generate electricity.

To ensure the environmental sustainability of DC buildings in the United States, focusing only on energy efficiency is not enough because the primary impact reduction opportunity is linked to the energy source and not just reductions in energy demand (specifically for buildings constructed after 2004). The solution is to treat environmental impacts of buildings same as energy efficiency. Washington State and Oregon DCs are low-energy and low-impact buildings from the LCA perspective. However, by-definition, low-energy buildings are specially designed buildings, which demand less energy than if built conventionally (Sartori and Hestnes 2007). It should be noted that, as energy demand decreases from PDCs to GMDCs or as the building relies more on renewable sources, the material impact becomes more relevant. The main material in the warehouse building construction, iron ore, is still abundant. However, metal sources may be depleted if demand continues to grow exponentially (Ottelé, Perini, and Haas 2014). Water and land impacts are location and energy source dependent. Harmonizing flows to reflect the chosen LCIA method is a critical part of the LCA. Identifying water and land flows in the database and replacing them with proper flows for the selected IMPACT World+ LCIA method is time consuming and inefficient, but a necessary step to do before any impact calculations.

Current sustainable practices in warehousing include input variables for building scenario: just in time technique (excluding storage), solar photovoltaic roof panels, skylights, ground source heat pumps, solar thermal collectors, energy efficient light systems with motion sensor, rainwater harvesting, low water use appliances, sustainable building materials, choice of insulation material, thickness of insulation material, and green roofs. To reduce environmental impacts of buildings, LCA method was to some extent applied in green building standards ASHRAE 189.1, ICC 700, International Green Construction Code (IgCC), LEED v4, and the U.S. California Green Building Code (Trusty 2011). Green building standards are not required to use the full suite of the environmental impact categories, for example, the LEED v4 standard aims at reducing water, energy, and GHG emissions with caveat that no impact categories may increase more than 5% (U.S. Green Building Council 2017; Trusty 2011). Researchers showed that whole-building LCA results are comparable to reductions achieved by applying green building codes (Suh et al. 2014b). However, the research focused on one prototype office buildings in the United States, which means there might be discrepancies between different locations due to a state-level electricity generation. The LEED v4 provides credit system for warehouses and DCs together with schools, retail, data centers and hospitality. Because DCs are different than other buildings in the category, differences between the whole-building LCA and LEED v4 may be more pronounced. Thus, warehouses and DCs may consider further expansion of credits in next iteration of LEED v4.

In conclusion, understanding DCs' environmental impacts are expected to change future food sustainability research. This research has established standard procedures for evaluating DCs, identifying the most important operations, and identifying many differences between them. Future food LCAs must include food distribution to measure overall sustainability of food. Retailers have shown interest in reducing post-processing distribution cost by improving distribution pathways, environmental impacts, and losses in different food distribution systems. This work assessed distribution centers from the black box perspective and focused only on building operation elements. In the continuation of this research, the authors will evaluate pots-processing cold food supply chain and calculate the environmental impact of food storage and retailing. Future work will assess environmental impacts of two post-processing elements of the national U.S. cold food supply chain: DC and supermarket networks. DCs will be dissected to freezer and cooler zones and supermarkets to produce, sales, bakery, and deli zones. This information will be used to calculate national environmental impact of food per kg in DCs and supermarkets. To complete the food distribution network, we also propose to include transport network (processing plant to DC and DCs to supermarkets) for different food categories. Next, we plan to link food production network either as process- or hybrid-LCA models. To improve DCs and supermarkets networks environmental performance, future study will include the optimization of the distribution network with the net-zero, low-energy, least-cost, and least-impact objectives.

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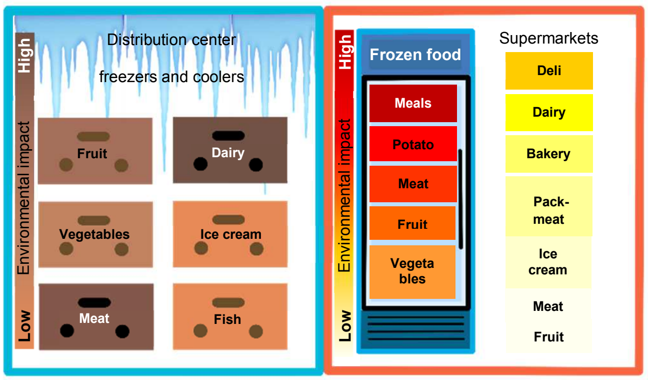
3. Environmental performance of chilled and frozen food storing and retailing

Burek, J., Nutter, D., (in review). Environmental Performance of Chilled and Frozen Food Post-Processing Storing and Retailing

3.1. Graphical abstract



3.2. Abstract

Perishable food is stored in refrigerated warehouses called perishables distribution centers (PDCs) and transported to supermarkets. PDCs and supermarkets are energy intensive commercial buildings due to refrigeration. Cold food supply chain increases the energy intensity of the food system, but environmental impacts of food post-processing storing and retailing are a data gap. The life cycle assessment (LCA) was used to calculate environmental impacts of perishable food storing and retailing. The energy demand, electricity generation, and water scarcity are dependent of building location. EnergyPlus building envelope simulation was used to build state-level LCA models for coolers and freezers within PDCs and perishables, sales, bakery, and deli departments within supermarkets. In PDCs, one food category is stored in a temperature-controlled storage unit. The refrigerated dock unloading area accounted for 80% of total PDC energy used. Allocation was used to divide dock area between different storage units. In supermarkets, the allocation based on a square meter facing food area was used to gain knowledge about environmental impact of chilled and frozen food within the sales and

perishables department. This research reported state-level global warming, energy, and water environmental impacts of PDCs' freezers and coolers and refrigerated and non-refrigerated supermarket's departments. In addition, the study presented energy and water consumption and global warming potential of perishable food storing and retailing processes, which included average food storing and retailing time. A broad discussion about energy-water-food nexus provided a national benchmark about environmental impacts of food storage and retailing. Flexible and adaptive formulae, procedures, and data provided can be used to assess environmental impact of food storing and retailing in any state. As the food cold chain expands this research may inform future PDC and supermarket planning, food traceability, and strategic management.

3.3. Introduction

The global cold food supply chain is expanding at 4.2% annual growth rate (Salin 2016). In the United States, gross refrigerated storage capacity has increased 28%, from 3 billion cubic feet in 2001 to 4.17 billion cubic feet in 2015 (USDA NASS 2016). The number of supermarkets/grocery stores has reached 38,571 in the United States (Statista 2017), and the total usable refrigerated storage volume was 96,955 m^3 (USDA NASS 2018). Freezers had 76% of total storage volume and coolers 24% (USDA NASS 2018), as shown in the Appendix, Table A1. The average volume of freezers and coolers was calculated by dividing the total volume by the number of establishments. The size of the freezers ranged between 3,771– 137,664 m^3 and coolers between 650– 47,831 m^3 (USDA NASS 2016), as shown in the Appendix, Table A1. The major goals in food research in the next decade include (1) improving the efficiency of food systems, (2) improving sustainability of agriculture, and (3) increasing the resiliency of food systems (NAS 2018).

The consumer's demand for a variety of refrigeration dependent food such as salads, green vegetables, berries, fresh pasta, ready meals, ice creams, and desserts has increased in developed countries (Dorward 2012). The demand for chilled and frozen food has created a more refrigeration-dependent food supply chain (Dorward 2012). Increase of refrigerated storage capacity and frozen and chilled sections within sales and perishable departments in supermarkets has increased energy use attributed to food storing and retailing (Dallemand et al. 2015). According to Bishop (2015), the share of refrigerated space in average supermarkets was estimated to be 18%. Chilled food has 10.4% share and frozen food 7.8% of total supermarket space (Bishop 2015).

The life cycle assessment (LCA) method has been used to quantify the environmental impact of food production. LCAs of food production and processing have been well researched with the main conclusion that agricultural production has the largest environmental impact (Beccali et al. 2010; Ingwersen 2012; Blanke and Burdick 2005; Roy et al. 2008; X. Zhu and van Ierland 2004; Iribarren et al. 2010; Ziegler, Nilsson, and Walther 2003; Hogaas and Eide 2002; Henderson et al. 2012; Kim et al. 2013; Thoma, Popp, Nutter, Shonnard, Ulrich, Matlock, Kim, Neiderman, Kemper, East, and Adom 2013; Jungbluth 2007; Tukker and Jansen 2006; Dorward 2012; M. Heller et al. 2016). Dorward et al. (2012) analyzed opportunities to reduce food chain greenhouse gas (GHG) emissions in UK. The breakdown of food cradle-to-grave GHG emissions included agriculture (45%), food manufacturing and packaging (19%), transport (12%), retailing (7%), catering (6%), and consumption (11%).

From the processing plant, food is transported to distribution centers (DCs) and supermarkets. Previous research modelled food logistics networks, food transport refrigeration, transport efficiency, optimization of food flows in the U.S., transport optimization for fresh food quality and included food-miles relative impacts based on food choices (S. a. Tassou, De-Lille, and Ge 2009; Nakandala, Lau, and Zhang 2016; Soysal, Bloemhof-Ruwaard, and Van Der Vorst 2014; Weber and Matthews 2008; Blanke and Burdick 2005; Pimentel 2006; Mundler and Rumpus 2012; Bortolini et al. 2015; Robinson et al. 2016; Validi, Bhattacharya, and Byrne 2014a; Validi, Bhattacharya, and Byrne 2014b; Zhang and Chen 2014). In this study transport and flows of food between cold storages and supermarkets were not considered.

Perishable food requires refrigeration during transport, storing at perishables distribution centers (PDCs), and retailing. The post-processing food distribution storing, retailing, and consumption is not often included in the LCA research and current LCI databases (Blonk Consultants 2018; Djekic et al. 2013; Wernet et al. 2016; Stoessel et al. 2012; Nijdam, Rood, and Westhoek 2012). Some authors reported overall supermarket energy consumption (M. C. Heller and Keoleian 2003), others focused on refrigerated section (WRAP 2010), and the single food item section (Kim et al. 2013).

Previous LCA research accounted only for electricity consumed by the refrigeration equipment and refrigerant loss in the average refrigerated storage (González-García et al. 2013; BSI 2008; Kim et al. 2013; WRAP 2010). Coolers and freezers, supermarket walk-in freezers, multi-deck and display cases, glass door freezers have different temperature conditions based on the requirements of a food item (Man and Jones 2000). Electricity consumption of the refrigerated and frozen storage was often based on estimates or literature data (Sanjuán, Stoessel, and Hellweg 2014). Building water consumption was least modelled in LCAs, although the non-agricultural water consumption is the fastest-growing (Bijl et al. 2016). Literature values for PDCs, freezers, coolers, and supermarkets are provided in Table 1.

Less than one third of LCA studies included food retailing (M. Heller et al. 2016). The post-processing cold storing and retailing of food is less studied in LCA studies due to difficulties in data collection of intrinsic properties related to the refrigeration technology and building operation. PDCs and supermarkets are seldom (Fantin et al. 2012; Daneshi et al. 2014; Stoessel et al. 2012; Burek and Nutter 2018d) included in LCAs of food also because of proprietary data. When included, the burdens are often attributed to one product, which limits published storage and supermarket data widespread use (Beccali et al. 2010; Ingwersen 2012; Blanke and Burdick 2005; Roy et al. 2008; X. Zhu and van Ierland 2004; Iribarren et al. 2010; Ziegler, Nilsson, and Walther 2003; Hogaas and Eide 2002; Henderson et al. 2012; Kim et al. 2013; Thoma, Popp, Nutter, Shonnard, Ulrich, Matlock, Kim, Neiderman, Kemper, East, and Adom 2013; Foster et al. 2006). Literature values for food storing and retailing are presented in Table 1.

According to Foster et al. (2006) frozen food had the highest energy demand. Refrigerated perishable and canned food had 30-50% lower energy consumption than the frozen food (Foster et al. 2006), for example, storing and retailing of fresh carrots was 8% of total cradle-to-grave GHG emissions, frozen carrots were 38%, and canned 0% (Foster et al. 2006). In Burek et al. (2018), the fluid milk environmental impact of storing was based on the non-refrigerated and refrigerated walk-in unit floor space for warehouses. The length of stay of milk at the distribution center (24h) was also considered (Burek et al. 2018). Storage time and throughput speed also vary for each food item and depends on supermarket demand and sales and spoilage. Food shelf-life is depended on temperature of storage, i.e., the lower the temperature the longer the product shelf-life (Man and Jones 2000). Foster et al. (2006) claimed that throughput for yogurt and milk at retail is high, and thus, the energy use was less than 1% of total milk supply chain. However, in the United States fluid milk and yogurt had 12% distribution and retailing losses, which did not reach the consumer, due to presumably expiration date (Thoma, Popp, and Nutter 2013; Thoma, Kim, and Burek 2016a). Thus, a percent of food will stay longer than average at PDCs and supermarkets due to food losses (M. C. Heller and Keoleian 2015).

Most research does not mention refrigerated dock, which has 80% of the total PDC environmental impact (Burek and Nutter 2018d). High variability between different literature results leads to need to provide PDCs' freezers and coolers templates, which will enable calculating environmental impacts of food storing and retailing in different locations. However, existing LCA research does not provide consistent methods and assumptions to calculate storing and retailing of perishable food. Food LCAs need to include factors that impact cold distribution, which will impact the environmental profile of the food system and carry greater environmental impacts (Heard and Miller 2016).

Table 1. Literature data for energy consumption food refrigeration and allocated to different food products.

PDC	Freezer	Cooler	Super-market	Food type	Food storing	Food retailing	Reference
84-96 kWh/m^3/year	-	-	-	-	-	-	(Burek and Nutter 2018d)
			1,117* kWh/m^2/year				(Mylona, Kolokotroni, and Tassou 2017)
88-176 kWh/m^3/year	-	-	429- 877 kWh/m^2/year				(Energy Star 2015)
-	-	-	747–1,082 kWh/m^2/year	-	-	-	(Spyrou et al. 2014)
-	28-120 kWh/m^3/year	25-85 kWh/m^3/year	-	-	-	-	(J. Evans et al. 2013)
-	-	-	-	Fluid milk	0.0025 kWh/kg	0.048 kWh/kg	(Thoma, Popp, Nutter, Shonnard, Ulrich, Matlock, Kim, Neiderman, Kemper, East, Adom, et al. 2013; Burek and Nutter 2018d)
-	-	-	-	Yogurt	-	0.186 kWh/kg	(González-García et al. 2013)
-	-	-	556 kWh/m^2/year	Cheese	-	-	(Kim et al. 2013)
-	-	-	795-810 kWh/m^2/year	-	-	-	(DECC 2013)
-	-	-	850-1,500 kWh/m^2/year	-	-	-	(S. A. Tassou et al. 2011)
253 kWh/m^3/year	-	-	33 kWh/m^3	-	-	-	(WRAP 2010)
-	71 kWh/m^3/year	57.3 kWh/m^3/year	-	-	-	-	(James and James 2010)
40-61 kWh/m^3/year	-	-	-	-	-	-	(Richman, Pasqualini, and Kirsh 2009)
15 – 132 kWh/m^3/year	-	-	-	-	-	-	(Prakash and Singh 2008)
-	-	-	-	Apples	0.225 kWh/kg	-	(Foster et al. 2006)
-	-	-	-	Cheese	-	1.11 kWh/kg	(Foster et al. 2006)
-	-	-	-	Ice cream	-	0.055 kWh/kg	(Foster et al. 2006)
-	-	-	-	Butter	-	0.833 kWh/kg	(Foster et al. 2006)
-	-	-	-	Beef	-	0.611 kWh/kg	Foster et al., 2006)
-	-	-	-	Fish fingers	-	0.527 kWh/kg	Foster et al., 2006)
-	-	-	-	Frozen cod	-	0.555 kWh/kg	Foster et al., 2006)
-	-	-	-	Fresh salmon	-	0.069 kWh/kg	Foster et al., 2006)

*315 m^2 frozen food store

Previous research focused on Walmart Stores Inc. multi-facility grocery, general merchandise, perishable DCs and differences between their whole-building environmental impact, and excluded supermarkets (Burek and Nutter 2018d). In this research, we focused only on PDCs and supermarkets in the context of food storing and food retailing. PDCs are refrigerated warehouses (cold stores) for perishable (chilled and frozen) commodities. PDCs provide temperature conditions and humidity to store food for different storage times and prevent food degradation and food waste (Chen, Hsu, and Wang 2018). As in the case of Walmart Stores Inc., PDCs can be single buildings at a location or can also include separate non-refrigerated storage at the same location, which are then called grocery DCs (GDCs) (Burek and Nutter 2018d). Perishable food included in this research were raw fruits and vegetables; dairy; meat, fish, and poultry; ice cream; frozen fruit; frozen vegetables; frozen meat; and frozen fish and seafood.

This research provided multi-facility LCAs of PDCs and supermarkets in different locations, which we called network. The research identified key drivers that impact the environmental profile of the cold food system. By including physical factors, network multi-facility LCAs, and economic aspect of food, this research provided a systemic yet flexible approach to calculate the non-renewable energy use, global warming potential, and water scarcity of refrigerated raw and frozen fruits and vegetables, dairy, and meat, in any location in the United States. Default coefficients were provided for the non-renewable fossil energy use, global warming potential, and water scarcity for food storage in the PDC and for refrigerated food areas of sales, perishables departments at the supermarket. Developed formulas are flexible to adjust volume/area, price, and storage time.

3.4. Materials and methods

3.4.1. The life cycle assessment (LCA) method

The LCA is a standard method to assess environmental impacts of products, processes, services, and whole buildings over the entire life cycle (from cradle-to-grave) (ISO 2006a; ISO 2006b). In contrast to previous research where we used a whole-building LCA to evaluate environmental impact of DCs including perishables, general merchandise, and grocery (Burek and Nutter 2018d), this research focused only on PDCs and went from a whole-building LCA to PDCs' freezers and coolers LCAs, which were defined by the food category stored. Supermarkets were out of scope in our previous research but were included in this research, with focus on refrigerated areas within the sales and produce departments. All PDCs' storages and supermarkets' departments models included material for construction, operation (use phase), and end-of-building life and disposal, as explained in previous research (Burek and Nutter 2018d), and shown in Figure 1.

The PDC's frozen and chilled storage volumes in each state were reported by the USDA NASS (2018). Some states were excluded from this research because USDA did not disclose their capacity volumes (USDA NASS 2018). This research included 27 states for which both cold storage capacity and supermarkets floor areas were available in the USDA storage capacity and the U.S. census reports (USDA NASS 2018; U.S. Census Bureau 2012), as shown in the Appendix, Table A1 and A2. The environmental impacts were analyzed for chilled and frozen food storage units in PDCs and supermarket sections, while in previous research the focus was on equipment and processes' contribution such as HVAC, refrigeration, and lights (Burek and Nutter 2018d). Thus, rather than having one whole-building model for each state with a functional unit of m^3 or m^2, each PDC zone is considered in isolation and by use of allocation and additional data it provides assessment of particular food item storing and retailing.

EnergyPlus building simulation was used to obtain energy use for the whole-building PDCs, but also for freezers and coolers and dock zones in the PDC and for supermarkets' departments (US-DOE 2015). The EnergyPlus building simulation is hourly-based and includes weather information. Thus, the data extracted from the EnergyPlus is high resolution. The environmental impact of cold store depends on the type and performance of its refrigeration system, the building properties and climatic conditions, food storing temperature, and humidity requirements. These properties were accounted in EnergyPlus building simulation models (US-DOE 2015). However, the cold store functioning also depends on logistics operations such as cross-docking and food heat and mass transfer during loading, which was not taken into consideration (Fikiin and Markov 2014). Food safety is another property, which was only partially addressed by proper storing temperature and humidity conditions.

Figure 1 shows data sources and steps necessary to build comprehensive models of chilled and frozen food storing and retailing. The EnergyPlus provided direct data for PDCs' coolers, freezers, and the subfreezer, but data for dock, refrigerant loss, building material and construction, were allocated. Similarly, EnergyPlus provided allocated data for each supermarket department, as shown in Figure 1. Most chilled and frozen food is located either in sales or produce (vegetables and fruit) departments. However, sales and produce departments have both refrigerated and non-refrigerated sections, which were resolved using allocation. The output of allocation were chilled and frozen department areas. For storing, allocation is complete, and models can be used to evaluate storing of different chilled and frozen food items, as shown in Figure 1. For supermarkets, additional allocation step was done for different food items, as shown in Figure 1. Step 3 show a list of food items considered in the assessment, but only food items from produce and sales departments were analyzed in more detail.

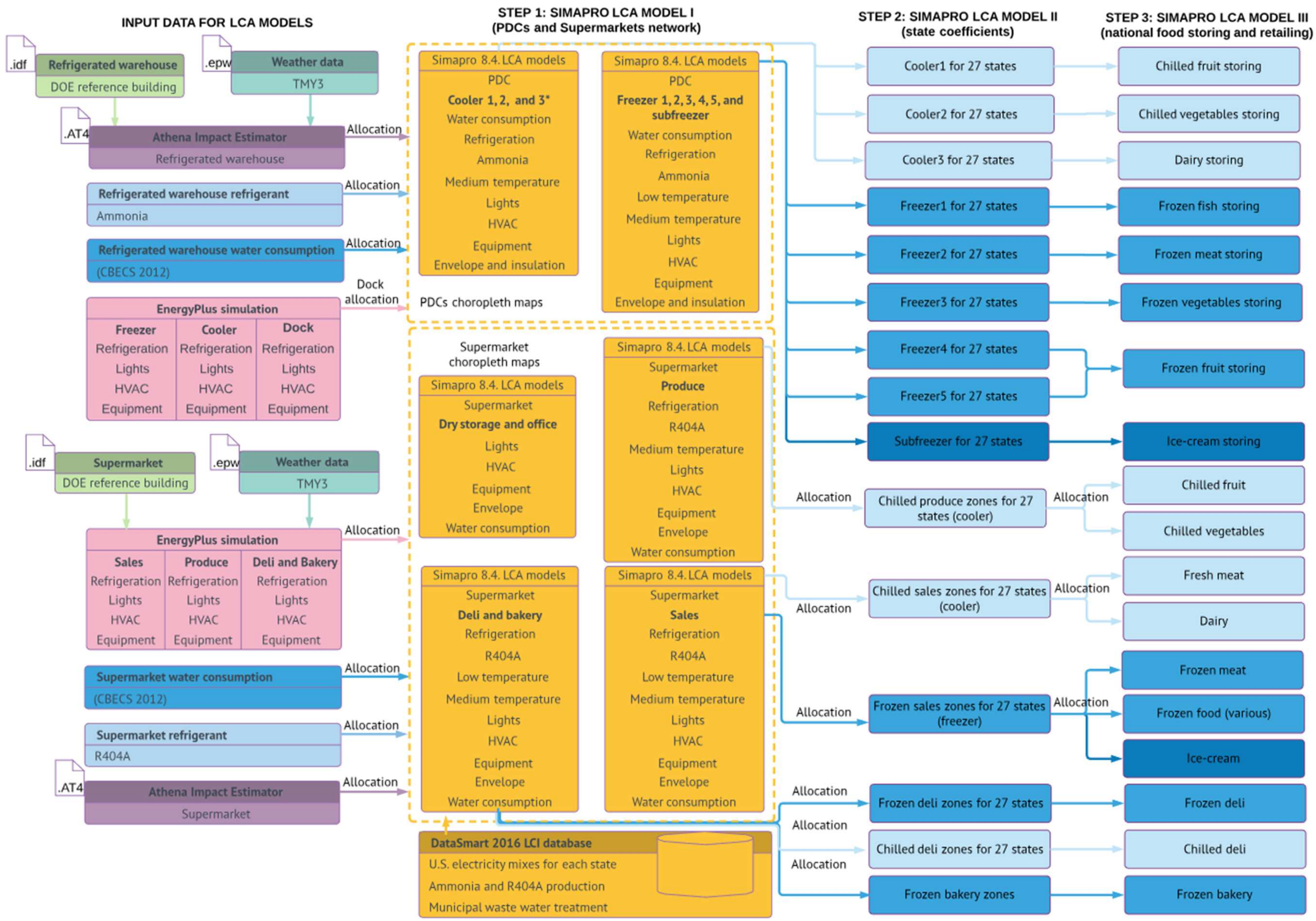


Figure1. Data sources for EnergyPlus building simulation and tools used to collect data for whole-building LCA models.

3.4.2. Goal and scope

The goal of this research was to perform an LCA of storing and retailing of different chilled and frozen food items, as shown in Figure 1. Primary outcomes of this research were (1) to provide state-level cold and frozen storage LCAs, which were dependent on food properties and temperature, (2) to provide state-level supermarkets' departments LCA, (3) to build comprehensive LCIs of PDCs' storage zones with allocated dock, which will enable calculating all door-to-door environmental impacts of food handling and storing at the PDCs, (4) to build comprehensive LCIs of chilled produce department sections and frozen and chilled sales department sections within the supermarket, which will enable one to calculate environmental impacts of food retailing, (5) to calculate national environmental impacts of food storing and retailing by connecting all freezers, coolers, and supermarket sections into a multi-facility network, (6) and to provide coefficients and formulae which will enable to calculate the state-level environmental impacts of different food storing and retailing scenarios.

The system boundaries were (1) a whole-building PDC and supermarket LCA as shown in Figure 1, step 2 and (2) door-to-door storing and retailing of different food items in freezers and coolers, as shown in Figure 1, step 3.

3.4.3. Functional units for cold storage zones and supermarket departments' refrigerated aisles

In the Ecoinvent 3.4. database, all infrastructure (buildings, equipment, etc.) was reported as pieces (p) (Weidema et al. 2013). However, PDCs and supermarkets have refrigerated and non-refrigerated zones and energy use between refrigerated storage and department aisles depends on the food item refrigeration requirements. Thus, p is not a good functional unit for DCs and supermarkets. Food products at DCs are stacked and occupy vertical shelves and horizontal shelves to minimize storage space. At supermarkets, food is stacked to maximize consumer visibility and access. The perishables DC (PDC) height varies from 10.7 to 33 meters and supermarket height is around 6 meters. The USDA reported coolers and freezers capacity in m^3 for states and U.S (USDA NASS 2016). Thus, functional unit for DCs was m^3 and for supermarkets was m^2.

3.4.4. Functional unit for food storing and retailing

Chilled and frozen food has different primary and secondary packaging. Perishable food is typically transported from the food processing plant on pallets and stacked on pallets or racks at the PDC storage. Defining a functional unit for different food products, even for similar products, can be challenging (Kendall and Sonja 2014). Tassou (2008) used mass of each food type contained in a pallet as a functional unit. For storing at warehouses, pallet-day, which included storing time and amount of food stored on pallets, may be a suitable unit. However, even the same food category can have different primary and secondary packaging, as shown in the case of milk (Burek et al. 2018). In addition, pallets vary how much weight they can hold and stack. In the bulk of LCA research, functional unit for food was typically on a mass or volume basis (Alessandro Dalla Riva et al. 2018; Thoma, Kim, and Burek 2016b; Thoma, Popp, and Nutter 2013; Thoma et al. 2011; Putman et al. 2017). Recent research used nutritive values to develop functional unit (Kendall and Sonja 2014; Arsenault et al. 2012; M. C. Heller, Keoleian, and Willett 2013).

In recent publications, the functional unit definitions of food production, transport, and consumption varied, which depended on the food LCA system boundary (cradle-to-grave and cradle-to-gate food LCAs) and the final life cycle (LC) stage: (1) at the farm-gate LC stage, the functional unit was kilogram of food produced (A. Dalla Riva et al. 2018; Thoma, Popp, Shonnard, et al. 2013; Daneshi et al. 2014; Putman et al. 2017); (2) at the processing-gate LC stage, it was kilogram of packaged food produced and a processing sequence of products (Djekic et al. 2013; Daneshi et al. 2014; Nutter et al. 2013; Berlin and Sonesson 2008); (3) at the retailers LC stage, consumer-facing linear meters was used as the space metric and kilogram of product at the point of sale (Kim et al. 2013; Stoessel et al. 2012); and (4) at the consumption stage, the functional unit was based on kilograms consumed, the role of food in a diet or based on meal (Kendall and Sonja 2014; Burek et al. 2018; Kim et al. 2013; Thoma, Popp, Nutter, Shonnard, Ulrich, Matlock, Kim, Neiderman, Kemper, East, Adom, et al. 2013). The functional unit for food transportation was ton-kilometers or food-kilometers (Weber and Matthews 2008; US EPA 2015; Tognetti, Grosse-Ruyken, and Wagner 2015).

Food items under consideration have different temperature requirements and shelf-life (Reid et al. 2003; Man and Jones 2000). Thus, we considered storing and retailing to represent a process, such as blow molding in Ecoinvent 3.4., which contained all inputs and outputs except the plastic material (Weidema et al. 2013). Similarly, chilled and frozen food storing and retailing models have all door-to-door inputs and outputs, but excluded food agricultural production, processing, packaging, and transport. The cold storage models describe processes within the PDCs from door-to-door including loading and storing, as shown in Figure 1. We chose mass based functional unit, i.e., kilograms of food stored, because food-stocks in coolers and freezers were reported in kilograms. The supermarket departments' refrigerated zones included 24 hours of retailing of a kilogram of food product at a certain temperature, as shown in Figure 1. For supermarkets, we considered the square foot facing food, which was used to calculate the share of total store space of each perishable food category (Bishop 2015). Based on the space, food item sales, and price, we calculated kilograms of food per category allocated to each refrigerated space. Thus, the functional unit of food retailing was one kilogram of food retailed.

3.4.5. Warehouse zones volume-based allocation

The average PDC is not sufficient to model environmental impacts of food items because food products have different properties and storage requirements. At the PDC, one product category is stored in an insulated and refrigerated room. The Department of Energy (DOE) EnergyPlus refrigerated warehouse model represents a foundational template for the refrigerated food storage (Field, Deru, and Studer 2010). The data used in EnergyPlus refrigerated warehouse model has been vetted by the U.S. national laboratories, ASHRAE, industry, academics, and other EnergyPlus users (Field, Deru, and Studer 2010). The refrigerated warehouse model was based on building energy efficiency standards, building code requirements, and energy benchmarking for frozen food (Prakash and Singh 2008; California Energy Commission 2008; Hong 2009). The DOE refrigerated warehouse reference building model (26,720 m^2 floor area and 10.7 m height) was considered a baseline for building a national level PDC network (NREL 2012). The DOE refrigerated warehouse template provided thermal zoning for 9 food storages, refrigerated food receiving and shipping area (dock), and 4 offices (US-DOE 2015). Direct expansion air chillers with compressors provided refrigeration to all zones (US-DOE 2015). The 9 refrigerated food storage zones were: 3 coolers (at a temperature of 4 degrees Celsius), 5 freezers (at a temperature of -18 degrees Celsius), and 1 sub-freezer (at a temperature of -25 degrees Celsius). Dock space was maintained at 10 degrees Celsius and offices at 20 degrees Celsius.

Figure 2 shows a floor plan of a the DOE reference refrigerated warehouse building example file used in EnergyPlus simulation (US-DOE 2015). Food freezes over a range of temperatures and the quality of frozen foods is affected by the rate of freezing (Cengel and Boles 2013). For most fresh produce, a correct temperature management is the most important factor in storage life (Frontline Services 2018). The dock keeps humidity of the freezers and coolers during summer and used energy to defrost all winter, and the room air replacement was up to two times in one hour with outdoor air (NREL 2012; Stoeckle 2000). Separated zones with temperature conditions were provided for refrigerated (fruit, vegetables, and dairy) and frozen (meat, fish, fruit, and ice-cream) food items. Two refrigerated fruit zones in the baseline PDC operate at 2 different temperatures. Fresh meat products were not stored in the DC due to limited shelf life (WPSA 2004; Nychas et al. 2008). The refrigerated dock area was used to unload perishables and served as an air curtain between the outside and refrigerated storage zones. The PDC area (m^2) and volume (m^3) of each zone is also provided in Figure 1.

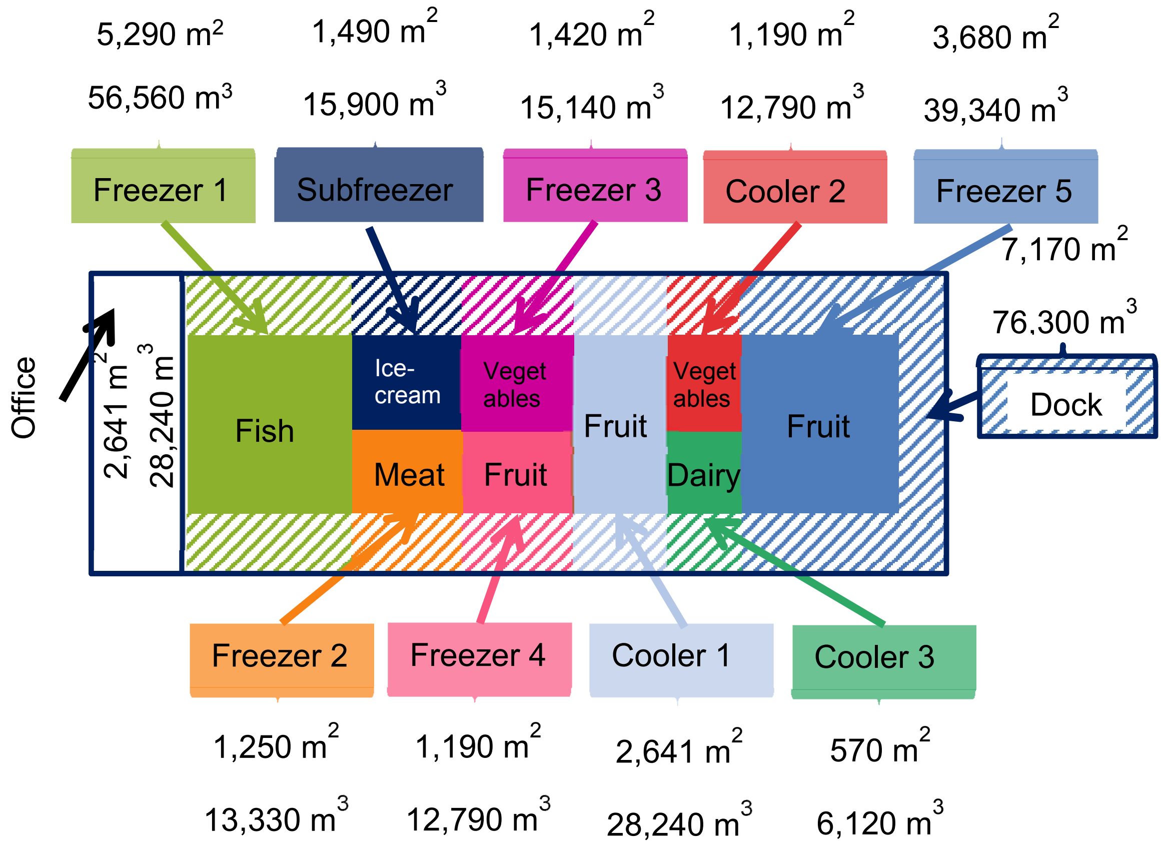


Figure 2. PDC floor area, storage zones, zone area and capacity and food category stored in each zone. Multi-color 45 degree stripe pattern fills around the storage areas represent different dock areas allocated to each storage.

3.4.6. Food allocation to PDCs' storages and amount of food in storages

Food properties which were considered by the EnergyPlus template included specific heat, density, thickness, and conductivity, which were reported in Table 2. Food product thermal load brought to PDCs at higher temperatures than the storage temperature increased energy use by 61% (Prakash and Singh 2008). This product temperature at entry was not directly considered in the EnergyPlus template. However, the DOE model simulated target energy use based on the DOE survey data and implicitly accounted for any differences between the food and storage (EIA 2012). Zanoni and Zavanella (2012) observed relationships between food quality and degradation, storage temperature, and energy consumption. Perishable chilled and frozen food required storage in specific conditions of temperature and humidity to preserve food and to prevent degradation (Zanoni and Zavanella 2012). However, food degradation was not considered.

Table 2. Food properties assigned for storing building simulation in EnergyPlus (US-DOE 2015).

Name	Ice Cream	Frozen Meat	Frozen Vegetables	Frozen Fruit	Frozen Fish	Fresh Fruit	Fresh Vegetables	Dairy
Thickness (m)	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
Conductivity (W/m-K)	0.045	0.118	0.056	0.035	0.103	0.035	0.056	0.048
Density (kg/m^3)	1,121	1,057	593	865	1,041	865	593	1,346
Specific Heat (J/kg-K)	2,720	2,343	1,841	1,966	2,176	3,807	4,017	3,891
Storage	Subfreezer	Freezer2	Freezer3	Freezer4&5	Freezer1	Cooler1	Cooler2	Cooler3
Temperature (degree Celsius)	-25	-18	-18	-18	-18	4	4	4
Humidity (%)	-	-	-	-	85	-	-	-

One refrigerated food storage contained only one food product, thus the energy demand of the storage was attributed to one food category, as shown in Figure 2. Also, each food item went through the dock area (food unloading and handling). The dock space was allocated to different storages proportionally to the size of storage, as shown in Figure 2 and reported numerically in the Appendix, Table A4.

The EnergyPlus template did not include data on the amount of food in freezers and coolers. To calculate national averages of food stored at coolers and freezers per m^3, we used the USDA values for total U.S. freezers and coolers capacity and national average monthly stocks in cold storage (USDA NASS 2018; USDA NASS 2016), as reported in Appendix, Table A1 and A7. Because the USDA reported only total cooler and freezer capacity, the volume storage available for each food category was based on the DOE EnergyPlus template, i.e. chilled fruit had the largest storage capacity (60%) of total coolers, followed by chilled vegetables (27%), and dairy (13%). According to the DOE, frozen fish had the largest volume (37%) out of total freezer space, followed by frozen fruit (34%), frozen vegetables (10%), ice-cream (10%), and frozen meat (9%). The USDA NASS (2018) reported monthly stocks in all warehouses for food commodities.

Food can be stored for varying lengths of time. The actual ship date (ASD) that product leave a manufacturer's plant or the PDC was not specified in the USDA NASS (2018). However, the food products included in the USDA NASS (2018) survey were normally stored for 30 days or more. Because, monthly data can vary due to the way the firms report their data, we calculated average monthly stocks for dairy products, chilled fruit, chilled vegetables, frozen fruit, frozen vegetables, and frozen red meat in cold storage, as shown in Table 3. Frozen fish and ice-cream stocks were not reported in the USDA NASS (2018), and thus were excluded from the analysis (USDA NASS 2018).

Table 3. Allocation of chilled and frozen food products to coolers and freezers (kg/m^3/month).

	Cooler	Freezer	Cooler (m^3)	Freezer (m^3)	Average monthly stocks in cold storage (kg/month)	Average monthly stocks in cold storage (kg/m^3/month)
Total	-	-	21,713,882	70,095,294	-	-
Dairy products	13%	-	2,822,805	-	116,017,607	41.1
Chilled fruit	60%	-	13,028,329	-	427,472,009	32.8
Chilled vegetables	27%	-	5,862,748	-	201,163,298	34.3
Frozen fruit	-	34%	-	23,832,400	690,538,746	29.0
Frozen vegetables	-	10%	-	7,009,529	1,046,230,662	149
Frozen meat	-	9%	-	6,308,576	487,832,715	77.3

Table 3 shows total freezer and cooler capacities and how much food on average is stored over a month. Chilled food showed a linear increase of cooler size proportionally with the food stocks. Frozen fruit had the largest storage capacity, and frozen vegetables had the smallest storage capacity and the largest number of items stored. This can be explained by more efficient stacking of frozen vegetables than frozen fruit and frozen meat but could not be verified.

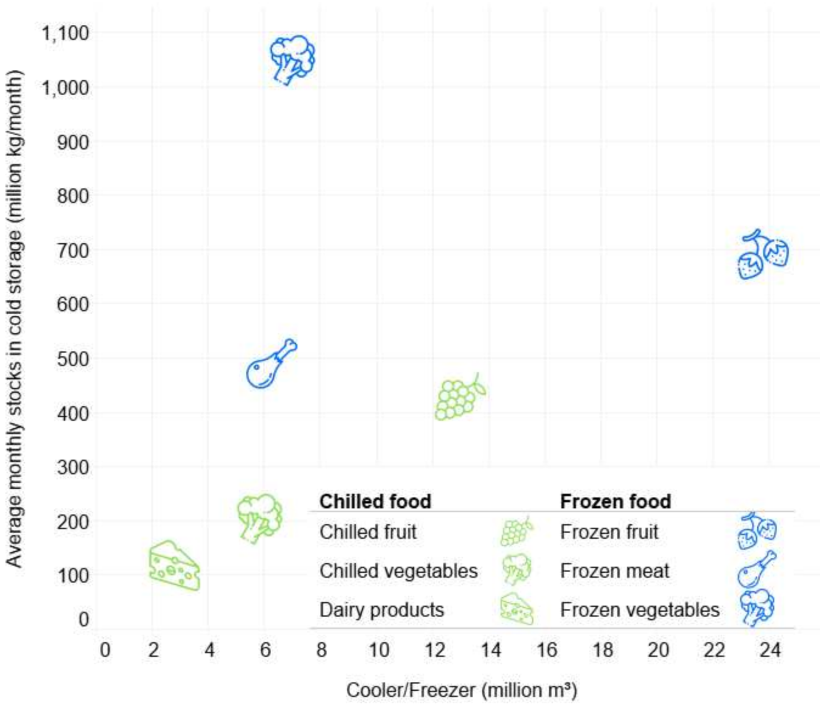


Figure 3. National average monthly stocks in freezers and coolers at the PDC.

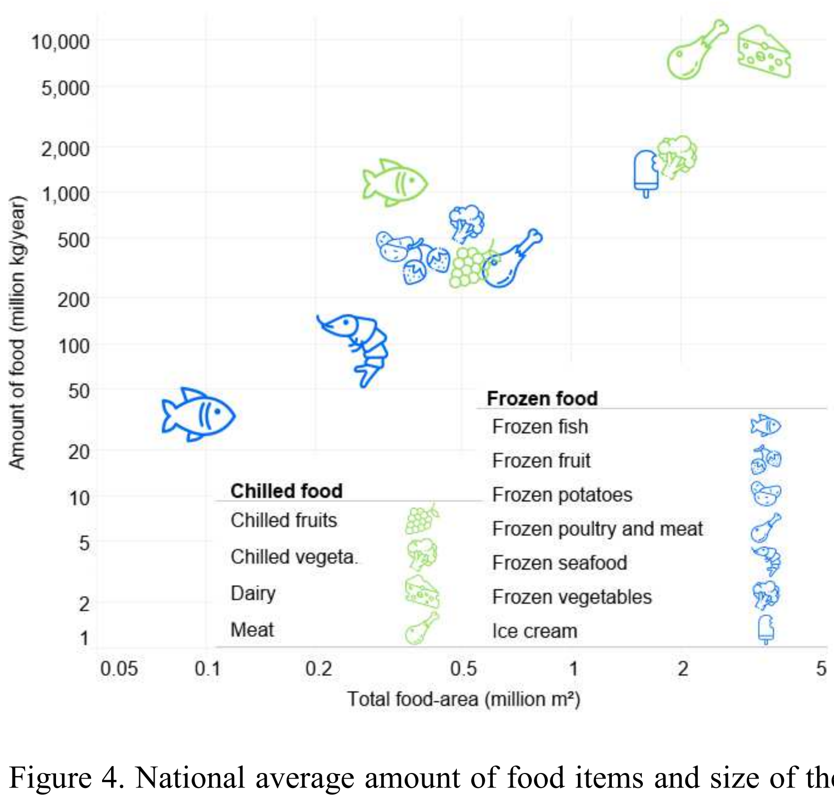


Figure 4. National average amount of food items and size of the area where they are located at the Supermarket. Size of the icon show difference in cost.

3.4.7. The national cooler and freezer network

All coolers and freezers in the United States were considered a national cold storage network. The USDA did not report dock and office volumes, but, according to allocation based on the input template, the dock volume share was 28% and 5%, respectively of total zone and dock. Thus, the freezer and cooler values were increased by 28% to account for the dock and 5% to account for the office space. The freezer volume is higher than the cooler volume, and the freezer-cooler ratio varied across states between 1.4 and 15.6 (average 5.8), as reported in the Appendix, Table A1. We accounted for this difference in the models, but sub-compartmental zoning of coolers and freezers remained the same as in Figure 1. The average PDC size (without the dock area) was an estimated 84,230 m^3, the smallest PDC was 4,421 m^3 (Arkansas) and the biggest 161,399 m^3 (Indiana). California, Florida, Texas, and Wisconsin had the highest total refrigerated storage capacity, as shown in Appendix, Table A1.

3.4.8. Chilled and frozen food allocation to supermarket department zones and refrigerated aisles

In 2015, the median size of the supermarkets in the United States was 3,837 m^2 (Food Marketing Institute 2015a). The reference DOE supermarket building model (4,181 m^2 floor area and 6 m height) was considered a baseline for the national level supermarket network (DOE 2015). The DOE supermarket reference model included thermal zoning for 6 zones: sales, produce, bakery, deli, dry storage, and office. The supermarket area (m^2) and volume (m^3) of each department was given in Figure 2. However, within each department there are refrigerated and non-refrigerated aisles. Supermarket mangers use allocation to determine how much shelf space a product gets, which is based on product movement and profitability (Food Marketing Institute 2018).

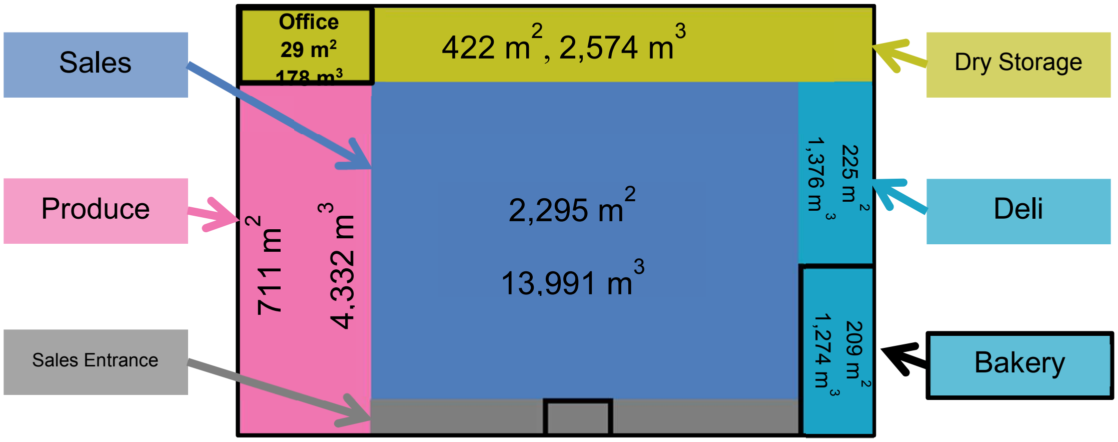


Figure 5. Supermarket departments, floor area (m^2), and volume (m^3) based on the DOE supermarket EnergyPlus template.

The sales zone is the largest department in the supermarket. Sales, produce, deli and bakery have refrigerated and non-refrigerated areas. The EnergyPlus supermarket template provides a design length of cases in different departments, as reported in Table 3 (NREL 2012). We assumed width of 1.5 m to calculate the share of the total refrigerated supermarket space, which amounted to 14% of total supermarket. However, refrigerated areas in recent years have increased to 18.2% of total supermarket space (Bishop 2015). Thus, we used more recent data about the share of total store space from the grocery store SuperStudy (Bishop 2015), as shown in Table 3. The SuperStudy allocation was based on the display stock, i.e., products which were moved from backroom storage to sales and perishable floors. In addition, Bishop (2015) provided a share of total store space for 70 chilled or frozen food items. We calculated the share of total store space for each food item in Table 3, column 5. Columns 6, 7, and 8 in Table 3 show a calculated chilled and frozen food items share in sales, deli, and produce departments, which was used to allocate refrigeration energy within the departments to chilled and frozen food areas only. Figure 4 shows the national yearly food and areas occupied in the supermarket and relative prices. Frozen fish and seafood were the most expensive food items among food categories in supermarkets but occupied the least space. The amount of food in supermarkets is proportional to space they occupy, except for fresh fish, as shown in Figure 4.

Table 3. Supermarket refrigeration cases and their length (NREL 2012). The width of each unit is assumed to be 1.5 m.

Food items	Refrigeration Case	Category	Supermarket zone	Share of total store space (Bishop 2015)	Food allocation to zone (%)		
					Sales (2,295 m^2)	Deli (225 m^2)	Produce (711 m^2)
Fresh meat	Multi-deck meat cases	Cooler (4.4ºC)	Sales	2.03%	3.70%*	-	-
Fresh meat	Meat walk-in display	Cooler (4.4ºC)	Sales			-	-
Chilled deli	Multi-deck meat cases	Cooler (4.4ºC)	Deli	2.20%	-	40.9%	-
Chilled deli	Meat walk-in display	Cooler (4.4ºC)	Deli		-		-
Fruits and vegetables	Other multi-deck cases	Cooler (4.4ºC)	Produce	-	-	-	-
Chilled fruits	Other multi-deck cases	Cooler (4.4ºC)	Produce	0.50%	-	-	2.94%
Chilled vegetables	Other multi-deck cases	Cooler (4.4ºC)	Produce	1.78%	-	-	10.5%
Dairy	Other multi-deck cases	Cooler (4.4ºC)	Sales	3.10%	5.65%	-	-
Seafood	Other multi-deck cases	Cooler (4.4ºC)	Sales	0.30%	0.55%	-	-
Chilled food (other)	Other walk-in units	Cooler (4.4ºC)	Sales	0.49%	0.89%	-	-
			Total chilled	10.4%	248 m^2	92 m^2	95 m^2
Frozen potatoes	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.30%	0.55%	-	-
Frozen fish	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.09%	0.16%	-	
Frozen seafood	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.23%	0.42%	-	-
Frozen vegetables	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.47%	0.86%	-	-
Frozen fruit	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.37%	0.67%	-	
Frozen poultry and meat	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.63%	1.15%	-	-
Frozen breakfast	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.59%	1.07%	-	-
Frozen pizza	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.75%	1.37%	-	-
Frozen snack	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	0.52%	0.95%	-	-
Frozen food (other)	Glassdoor reach-in cases	Freezer (-17.7ºC)	Sales	2.42%	4.41%	-	-
Frozen food (other)	Walk-in unit	Freezer (-24.7ºC)	Sales			-	-
Ice-cream	Single-level open cases	Freezer (-12ºC)	Sales	1.47%	2.68%	-	-
			Total frozen	7.84%	328 m^2	-	-
			Total chilled and frozen	18.2%	576 m^2	-	-

*% area occupied by chilled and frozen food in supermarket departments, i.e. sales department.

3.1.1. National amount of food in supermarket zones

California, Texas, Florida, and New York have the most supermarket floor space and supermarket sales, as shown in Appendix, Table A2 (U.S. Census Bureau 2012). Amount of food is wasted in distribution centers and supermarkets due to quality degradation and expiration date. Zero waste means that over 90% of the waste that the facility produces was diverted away from landfills (Scholz, Eriksson, and Strid 2015b). Current food waste was estimated at 0.0045 per dollar of company revenue (Kester 2013). Retailers such as Safeway divert food waste in distribution centers and supermarkets using following strategies: just-in-time ordering, food banks, animal feed, biofuel, and composting (USDA 2018). In terms of LCA, this would require the system expansion, which was omitted due to lack of data about amount of waste for each food category and variation within the food category. Tomato, pepper, and bananas had the largest wasted mass (4.5-7%) in the produce department, and meat had meat 3.5%, (Scholz, Eriksson, and Strid 2015a).

Table 4. Supermarket food sales (Food Marketing Institute 2015b), average food category price (USDA CNPP 2008; USDA CNPP 2004), and calculated kg of chilled and perishable food.

Food items	Supermarket zone	Sales (million $/year)	Average price ($/kg)	Amount of food (million kg/year)	Food item areas (million m^2)	Amount of food ($kg/m^2/day$)	Average shelf-life	Assumed time at retail
Meat, fish, and poultry	Sales	70,753	-	-	-	-	-	
Meat	Sales	61,597	7.12	8,648	2.22	10.7	6-10 days	4.00 days
Fish and seafood	Sales	9,156	8.00	1,145	0.330	9.51	2-7 days	2.25 days
Total produce	Produce	58,296	-	-	-	-	-	
Chilled fruits	Produce	1,714	5.10	336	0.547	1.68	2-5 days	1.75 days
Chilled vegetables	Produce	6,121	3.66	1,671	1.95	2.35	3-20 days	5.75 days
Dairy	Sales	44,736	5.28	8,473	3.39	6.85	20 days – 6 months	46.3 days
Frozen food	Sales	30,521	-	-	-	-	-	
Frozen potatoes	Sales	1,175	2.69	437	0.330	3.63	8-10 months	4.50 months
Frozen fish	Sales	342	10.1	34	0.096	0.970	2-6 months	2.00 months
Frozen seafood	Sales	897	10.1	89	0.252	0.968	3.4-10.2* months	6.86* months
Frozen vegetables	Sales	1,837	3.04	604	0.516	3.21	5.2-22.8* months	7.30* months
Frozen fruit	Sales	1,431	4.09	350	0.402	2.39	3.75-24* months	6.94* months
Frozen poultry and meat	Sales	2,456	6.65	369	0.690	1.47	7.93-19.4* months	7.98* months
Frozen breakfast	Sales	2,285	5.60	408	0.642	1.74	2-4 months	1.50 months
Frozen pizza	Sales	2,926	7.90	370	0.822	1.23	1-2 months	0.750 months
Frozen snack	Sales	2,029	7.00	290	0.570	1.39	1-2 months	0.750 months
Frozen food (other)	Sales	9,418	7.00	1,345	2.65	1.39	1-2 months	0.750 months
Ice cream	Sales	5,723	4.35	1,316	1.61	2.24	2 months	0.750 months
*(Man and Jones 2000)								

3.4.9. Life cycle inventory(LCI)

3.4.9.1. PDC's food storages and dock energy consumption

The DOE refrigerated warehouse template was used to model average PDCs in different locations (NREL 2012). The refrigerated warehouse template was available in the EnergyPlus building simulation software (NREL 2012). The DOE provides commercial reference building models of the national building stock based on the national 2003 Commercial Buildings Energy

Consumption Survey (CBECS) data (CBECS 2015; Deru et al. 2011). The EnergyPlus refrigerated warehouses template for chilled and frozen perishable food was based on a benchmarking DEO study (Prakash and Singh 2008; California Energy Commission 2008; Hong 2009). The template included heat transfer through the insulated walls, infiltration of air through doors, people activity, food properties, included refrigeration systems, lights, evaporator fans, and defrosters. The energy consumption of PDCs was electricity used in the vapor-compression refrigeration. Air coil and refrigeration compressor characteristics were based on product handbooks (Baltimore Aircoil Company 2007; Bitzer 2009).

Supermarket input files are based on ASHRAE 90.1-2004 and 62-1999 standards (ASHRAE 2000; ASHRAE 2004). Thus, the EnergyPlus whole building energy simulation program was used to calculate energy demand of DCs and supermarkets in each state using the TMY3 annual weather data (Wilcox and Marion 2008), as reported in Appendix, Table A3. EnergyPlus input files included meters for each zone in the refrigerated warehouse (Figure 1), and provided electricity consumption for lights, medium and low temperature refrigeration, standard refrigeration, equipment, and HVAC. Figure 3 shows summary results of annual energy demand for each food storage zone and divided dock (MJ/m^2) in different states. In the building energy simulation input file, the dock area was metered as one zone. Dock allocation to food storage zones was done using area calculated by multiplying width of the zone and the length from the zone to dock doors as shown in Figure 1 (denoted by stripes). Frozen fish, refrigerated fruit, and frozen fruit occupied the largest volumes and had the highest energy demand. Food storage energy demand is reported in Appendix, Figures A1. Because dock had the highest energy demand (80% of total) and required an allocation to food storage zones, the dock energy demand and energy allocated to each food storage zone is shown in Appendix, Figure A2.

Individual energy demand of sub-metered equipment in coolers, freezers, and dock are reported in the Appendix, Figures A3, A4, and A5. The dock has the highest energy demand of over 10,000 MJ/m^2 due to refrigeration required to maintain the temperature close to freezing. Refrigerated fruit storage has the highest energy demand (~1,400 MJ/m^2) followed by frozen fish (~800 MJ/m^2).

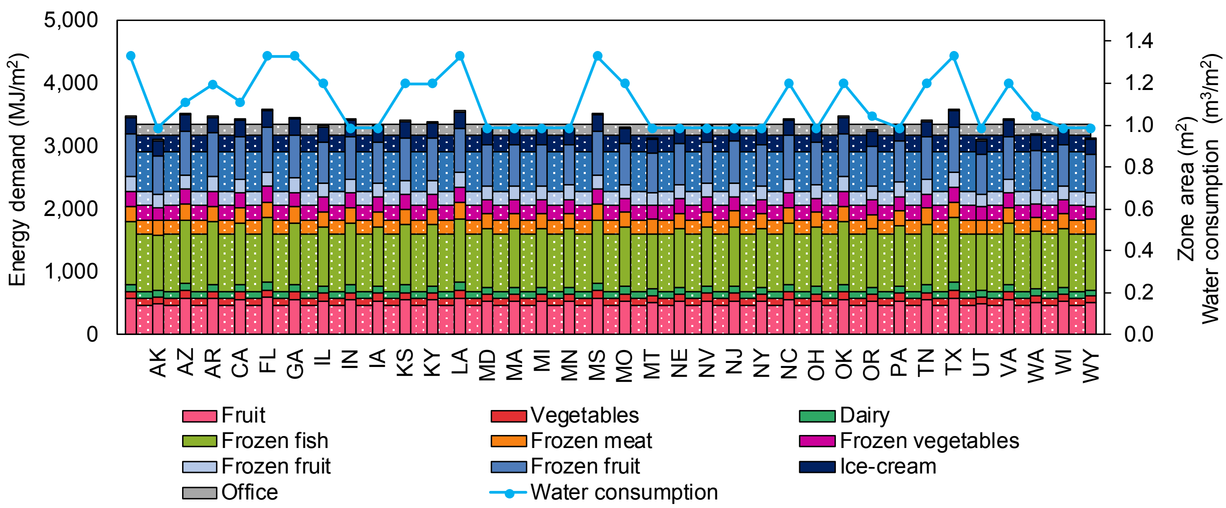


Figure 6. Distribution center zone areas (m^2), energy demand of each storage zone and dock, and total distribution center water consumption (m^3/m^2). Stacked area (dot pattern) represents combined food storage zone areas (m^2) and allocated dock area, stacked columns show total energy demand for storage and dock (MJ/m^2) of each food category, and a blue line shows total water consumption of food storages and dock (m^3/m^2).

The EnergyPlus supermarket output file provided separate electricity use for lights, standard refrigeration, and equipment in each supermarket zone in Figure 2. We reported bakery, deli, dry storage, office, produce, and sales equipment energy consumption in Appendix, Figure A6. Medium and low temperature refrigeration, HVAC, and natural gas result was provided only for the whole supermarket, as shown in the Appendix, Figure A7. To calculate the environmental impact of food categories, medium temperature refrigeration was allocated between produce and sales, low temperature refrigeration was allocated to sales where all frozen food is stored, natural gas was allocated to the bakery, and refrigerant emissions due to losses were allocated between produce, bakery, sales, and deli. The allocation was based on length and type of refrigeration cases including walk-in and cases provided by the supermarket EnergyPlus input file, as shown in the Appendix, Table A5. The HVAC electricity consumption was allocated between all zones based on their area. Energy demand for different supermarket zones without allocation is reported in the Appendix, Figure A5 and Appendix, Table A4.

3.4.10. Supermarket departments energy consumption

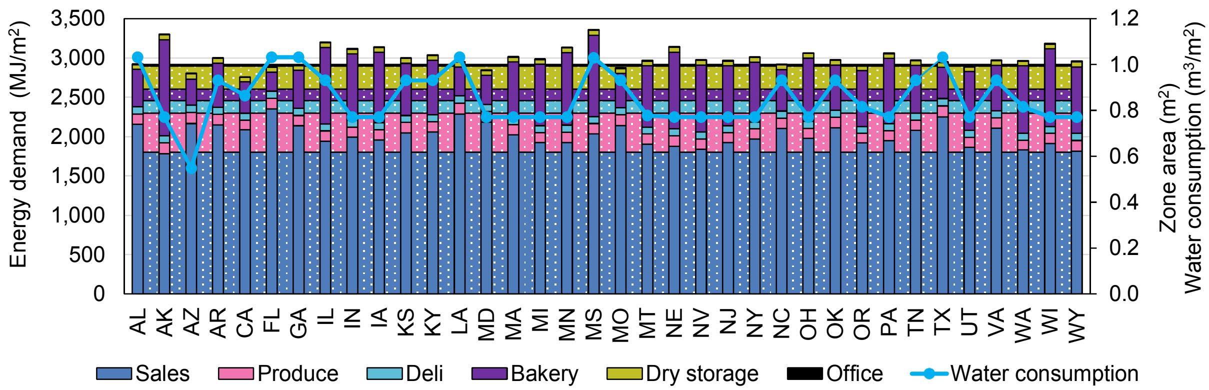


Figure 7. Supermarket zone areas (m^2) (dotted multi-color background), energy demand for each zone (MJ/m^2), and total water consumption (m^3/m^2). Stacked area represents supermarket zone areas (m^2), stacked columns show total energy demand supermarket zone (MJ/m^2), and a blue line shows total water consumption of supermarket (m^3/m^2).

3.4.10.1. Detailed state electric power generation life cycle inventory (LCI)

Refrigeration system and equipment of the PDCs was powered by electricity (Prakash and Singh 2008). Regional and state-level differences in environmental characteristic and greenhouse gas (GHG) emissions exist in electricity production in the United States (US EPA 2014). The electricity generation energy source mix of each state is composed of specific sub-regions defined in the Emissions and Generation Resource Integrated Database (eGRID) and North American Electric Reliability Corporation (NERC) (North American Electric Reliability Corporation 2016; US EPA 2014). We used electricity production, distribution, and imports

DataSmart LCI (LTS 2016) models, which included the U.S energy consumption, (U.S. Energy Information Administration 2015) eGRID sub-region emissions (US EPA 2014), and annual imports from Mexico and Canada (U.S. Energy Information Administration 2016).

3.4.10.2. Water consumption and water scarcity in different climate zones and locations

Water consumption was not modeled in the EnergyPlus refrigerated warehouse input file. Supermarket input file included water use at bakery and deli heat exchanger. CBECS included commercial building water consumption in different climate zones and provides average water use in refrigeration equipment (Energy Information Administration (EIA) 2016). Because the average warehouse water consumption included both non-refrigerated and refrigerated warehouses, we used water use in refrigeration equipment for DCs and supermarkets. A list of refrigeration equipment (walk-in units, cases, cabinets, and large cold storage areas) is provided in refrigerated warehouse and supermarket EnergyPlus input files. Water scarcity is a regional problem, thus we calculated water consumption for climate zones based on median water consumption values in each region (Energy Information Administration (EIA) 2016). Water consumption in different climate zones and for different equipment is reported in Appendix, Table A5. Total building water consumption for DCs and supermarkets is shown in Figures 3 and 4, respectively. The intensity of electricity use for building consumption and wastewater differs on a regional basis, but was excluded from the research because it is a data gap (Tidwell, Moreland, and Zemlick 2014). The average energy intensity of public water supplies is at 0.607 and 0.873 kWh per cubic meter (U.S. Department of Energy 2012a).

3.4.10.3. Refrigerant consumption, losses, and GHG emissions

DCs used ammonia as a refrigerant (Burek and Nutter 2018d). In supermarkets, typical refrigerant used are R-134a (stand-alone retail) and R404A (walk-in refrigerators) (EPA 2016).

Because R404A is coming under greater scrutiny due to its high Global Warming Potential (GWP), we chose and alternative R407A as the main refrigerant at supermarkets. Amount of refrigerant in the system (charge) and refrigerant losses based on refrigerant capacity were not included in EnergyPlus input files. Ammonia is not a direct GHG and effects on other impact categories is reported in previous work (Burek and Nutter 2018d). R407A is a mixture not available in current LCI databases, but its components difluoromethane (20%), R125 (40%), and R134A (40%) are. Thus, emissions for each of the components were calculated first and then combined into the R407A model based on proportions by a mass of each chemical in a mixture (J. A. Evans and Foster 2015). Refrigerant charge size in the United States is 1,360 kg per unit of equipment and 2.5 units of equipment are in a typical supermarket (5,574 m^2) (US EPA 2016). Based on literature data for refrigerant charge of 2.4 kg/m for R134a and total length of display cabinets of 389 m we calculated 933 kg charge for the modeled supermarket (J. A. Evans and Foster 2015). Annual emissions from installation, operation due to 15% loss, and disposal of R407A refrigerant components was calculated based on default emission factors, as shown in Appendix, Table A6 (EPA 2016). For operation, literature refrigerant capacity of 0.323 kg/m^2 yields annual refrigerant loss of 0.048 kg/m^2. Because modelled supermarket is smaller and has a lower charge than literature, we adjusted the refrigerant capacity to 0.093 kg/m^2 for the charge, which yields annual refrigerant loss of 0.014 kg/m^2.

3.4.10.4. Building envelope and insulation material

DC building envelope and insulation material modeling was described in previous research (Burek and Nutter 2018d). Athena Impact Estimator LCI data were used for supermarkets (Athena Sustainable Materials Institute 2017b).

3.4.10.5. National and state-level environmental impact of food distribution in the United States

To calculate national impact of the food storage and retailing, we connected the state-level freezers and coolers network and all state-level refrigerated supermarket zones into the national food distribution network.

Annual cold storage data were collected for food products stored for 30 days or more including frozen fruit, juice concentrate, dairy, frozen vegetables, and frozen poultry and red meat (USDA NASS 2018). Cold storage data is not reported for frozen fish (USDA NASS 2018). Fresh produce was summed into the total commodities in the coolers. Because dairy had a 4% share in total commodities in coolers, it was assumed 96% of commodities were produce. Monthly stock values reported in the USDA NASS (2018) were averaged. The summary of regional and national average monthly stocks in cold storage is provided in the Appendix, Table A7.

Fresh poultry, meat, and fish products are transported directly from the slaughterhouse to supermarket due to food safety requirements (Nychas et al. 2008; The Meat We Eat 2017). Processed meat products are transported from the meat processing manufacturer to supermarket (The Meat We Eat 2017). Frozen meat can be distributed all over the world, and thus products can be transported to PDCs first and then to supermarkets. According to the NREL (2012), the average PDCs do not include frozen or refrigerated bakery and deli items, thus, products are directly transported from the processing plant to the supermarket.

Perishables had the highest share (60%) in the national supermarkets sales in 2015 (Food Marketing Institute 2015b). Dry grocery had 34.6%, health/beauty/pharmacy 6%, and general merchandise 4.4%, as shown in Appendix, Table A9. These shares can vary for different supermarkets. According to one grocery store study, the largest share of total space in 2015 pertained to dry grocery (33%), perishables (26%), and general merchandise (24%) (Bishop 2015). We can conclude that perishables have the highest retailing speed. Perishables departments have much higher gross margins but also have much higher labor costs, capital expenditures (for refrigerated cases), energy costs, and transportation costs compared to packaged dry goods.

A model to calculate national environmental impact of chilled and frozen food included all cooler and freezer capacity and total commodities. The national dairy product environmental impact included annual operation of cooler 3 and capacity and annual stocks of dairy products, which was calculated by multiplying the average monthly stocks and 12 months. National produce was calculated using total chilled food in storage minus dairy. Allocation to raw fruit and vegetables was based on percent volume capacities of cooler 1 and 2, with 68% was allocated to fruit and 32% to vegetables. To calculate national frozen fruit and vegetable environmental impact all freezers 4 and 5 capacity and total frozen fruit and annual vegetable commodities were included. Total storage of frozen red meat and frozen poultry were assumed to be all freezer 2 capacity.

For supermarkets, national sales data by department and size of the cases and walk-in units was used to calculate environmental impact of cheese, fresh produce, and frozen food, and bakery and deli food items (Food Marketing Institute 2015b). The length of walk-in units and cases is provided in Appendix, Table A8, and width of the cases was assumed to be 1.5 m. Supermarket sales, average price, and amount of food in each supermarket zone for national assessment is reported in Appendix, Table A9. The produce section included refrigerated and non-refrigerated fruits and vegetable. We assumed half of the produce is refrigerated fruit and vegetables.

3.4.10.6. Method to calculate environmental impact of post-processing food storage and retailing

One study provided summary formulae to calculate environmental impact of food production from cradle-to-processing plant gate (Sanjuán, Stoessel, and Hellweg 2014). The national DC and supermarket network analysis was used to provide formulae to calculate specific food storage and supermarket environmental impacts. For food stored at DCs, the formulae included storage volume, stock availability, and duration of storage. All environmental impact coefficients in the formulae are provided in the Appendix, Table A10, A11, A12, A13, A14, A15, and A16. Other coefficients can be adapted to reflect specific volume and area for the DC or supermarket, supermarket sales, and food throughput.

Annual calculation of chilled and frozen food at supermarkets was more complex due to supermarket zone results, which included both refrigerated and non-refrigerated areas. Produce zone included refrigerated and non-refrigerated fruit and vegetables. Sales' perimeter department included dairy, packaged meat, and fresh meat aisles. Sales' frozen food included ice cream, frozen fruits and vegetables, frozen ready meals, frozen meat, frozen seafood and fish, frozen potatoes. In addition, sales included dry grocery, non-food section, pharmacy, and health and beauty. Thus, allocation between refrigerated and non-refrigerated aisles was necessary within the produce and sales departments. Supermarkets do not report stock change, thus, we used national sales information to calculate how much food is in each section, as shown in Appendix, Table A9 (Food Marketing Institute 2015b). Raw fruit and vegetables and frozen fruit and vegetables are reported together, thus we assumed 50% of total sales of either frozen or raw produce is fruit and 50% vegetables (Food Marketing Institute 2015b). Ice cream is stored in single-level open case, fresh meat in multi-deck meat cases, and frozen meat in meat walk-in freezer, as shown in Appendix, Table A8 (NREL 2012). We assumed dairy and packaged meat shares other multi-deck cases 50/50. Frozen fruit and vegetables, frozen ready meal, frozen seafood and fish, frozen potatoes, and other frozen food were assumed to evenly occupy remaining walk-in freezers and glass door reach-in cases. Average food prices were used as a conversion factor from $ to kg was used to obtain physical value, i.e. functional unit (kg) (USDA CNPP 2008; USDA CNPP 2004). For average food prices see Appendix, Table A9.

3.4.11. Life cycle impact assessment (LCIA) methods

ISO standards provide LCA principles and framework(ISO 2006a) and requirements and guidelines,(ISO 2006b) but no consensus or specific rule exists for choosing impact methods. The main environmental impacts in refrigerated DCs and supermarkets stem from electricity generation (Burek and Nutter 2018d). The environmental impacts depend on energy demand in specific climate zones and electricity generation source in different states. This research focuses on non-renewable fossil energy resource use and global warming impact. Regional whole building water use was assessed using the latest characterization model for water scarcity footprints, the available water remaining (AWARE) method (Boulay et al. 2017). The AWARE method meets the ISO standard on calculating water scarcity footprints (ISO 2014b). The characterization factor is based on the difference between availability and demand and it included ecosystems water requirements (Boulay et al. 2017). Regional water scarcity reference values for each state were extracted using GoogleEarth location number called FID, which corresponded to the FID number in water scarcity characterization factors provided in an online database (WULCA 2017). To be consistent with building energy modeling, a typical meteorological year (TMY3) location was used to find characterization factors for building water consumption. State-level AWARE method water scarcity characterization factors are reported in Appendix, Table A3. A factor Y in state X means that there is Y times less water in this state than in the world average location (Boulay et al. 2017).

3.5. Results and discussion

3.5.1. Environmental impact of the U.S. PDC network

The environmental impact assessment of DCs is shown in Figure 5 and Appendix, Figure A8 and A9. The size of circles shows environmental impacts per one cubic meter of the DC. Pie chart slices show a contribution of refrigerated food storage zones. Spatially explicit mapping of DCs allows to calculate total environmental impacts coming from DCs in one state. Choropleth maps show total environmental impact of all DCs in different states based on the USDA freezer and cooler capacities provided in Appendix, Table A1.

Figure 5. shows DC network global warming impact. The top three cold storage networks, California (14.4%), Florida (7.2%), and Texas (6.4%), have the highest GHG, followed by Wisconsin and Alabama. The highest global warming impact per storage capacity is Indiana, a state with the highest electricity global warming impact of 0.32 kg CO_2-eq/MJ. The lowest GHG emissions are for Washington.

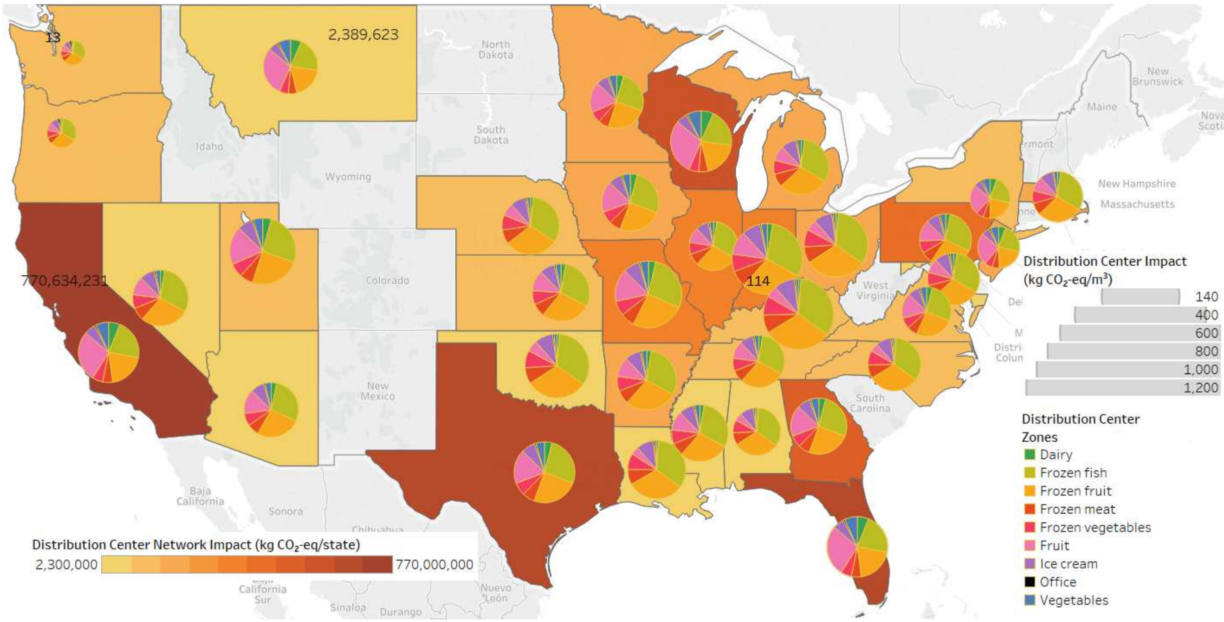


Figure 8. Pie charts in a choropleth geographical map show DC global warming impact. The size of circles shows DC GHG emissions (kg CO_2-eq/m^3).Gray bars on the right show variation of DC impact GHG emission (kg CO_2-eq/m^3). # shows number of DCs with similar GHG emissions. Multi-color pie charts show percent contribution of each DC zone to GHG emissions. Zones are defined by color in the legend on the right. The choropleth map shows state-level GHG emissions (kg CO_2-eq /state). Numeric values show minimum and maximum values for state-level results and per m^2.

DC choropleth maps for non-fossil energy and water scarcity are provided in Appendix, Figures A8 and A9. California, the largest distribution network, has the highest fossil energy use, followed by Florida, Georgia, Pennsylvania, and Texas, as shown in Figure 6. Montana has the lowest cold storage capacity and the lowest fossil energy use. Washington and Oregon have 8% share in total cold storage capacity, but have low fossil energy use due to hydropower electric energy supply. The states with the lowest and highest fossil energy use per volume are Oregon and Louisiana, respectively. The reduction from other states in Oregon is due to hydropower. The increase in Louisiana is due to hot-humid climate zone. Overall, frozen food has the largest share in total environmental impact (>50%). In most states, frozen fish and frozen fruit have the largest environmental impact. The refrigerated fruit has the largest impact in California, Wisconsin, Montana, Florida, and New Jersey where cooled storage capacity is almost as big as the frozen capacity.

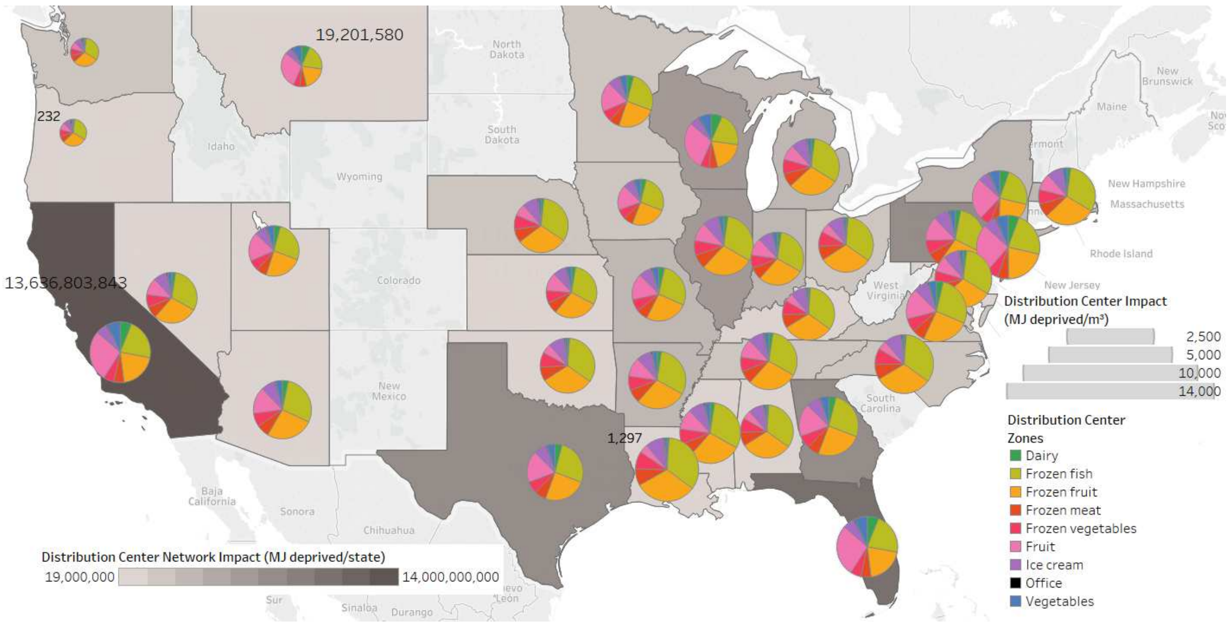


Figure 9. Pie charts in a choropleth geographical map show DC fossil energy use. The size of circles shows DC fossil energy use (MJ deprived/m^3). Gray bars on the right show variation of DC fossil energy use (MJ deprived/m^3). # shows number of DCs with similar fossil energy use. Multi-color pie charts show percent contribution of each DC zone to fossil energy use. Zones are defined by color in the legend on the right. The choropleth map shows state-level fossil energy use (MJ deprived/state). Numeric values show minimum and maximum values for state-level results and per m^2.

California, Utah, Nebraska, and Florida have the highest water impact, as shown in Figure 7. The differences shown here might be higher if DataSmart LCI data had regional water factors attributed to power production instead of the U.S. average water scarcity factors. The highest potential to deprive another user when using water is Arizona. Arizona water scarcity characterization factor is 100 m^3/m^3, based on the data given in Appendix, Table A3. The factor of 100 m^3/m^3 is the maximum, belonging to the scarcest regions, meaning there is 100 times less water in Arizona compared to the world average location. Arizona has a cumulative (building and background electricity water consumption) result of 157 m^3 deprived/m^2. The building consumption of 1.1 m^3 is equivalent to 110 m^3 consumed in the world average location. All other water consumption such as electricity production is equivalent to 47 m^3 consumed at the world average location. The building consumption at Arizona location contributes 55% to total water impact. Water scarcity was less than 1% for several states including Indiana, Louisiana, Maryland, Michigan, New Jersey, New York, Ohio, and Tennessee. For Arkansas, Georgia, Illinois, Iowa, Kansas, Kentucky, Minnesota, Mississippi, Missouri, Nebraska, North Carolina, Oklahoma, Oregon, Pennsylvania, Texas, Virginia, Washington and Wisconsin water scarcity was between 1% and 7.4%. Missouri and California building consumption contributes 14% and 13.4% to total water impact. Massachusetts, Nevada, and Utah building consumption contributed 37%, 26%, and 52%, respectively. Refrigerant loss contribution to total impacts is 30%. The dominant energy use in GDCs and PDCs was refrigeration (80%), with dock contributing two thirds of total energy consumption. Thus, in the future, it is important to include dock in the assessment since in the whole-building assessment dock is the main contributor to environmental impact. Improving energy efficiency of refrigerated dock will require complex analysis and innovative design solutions.

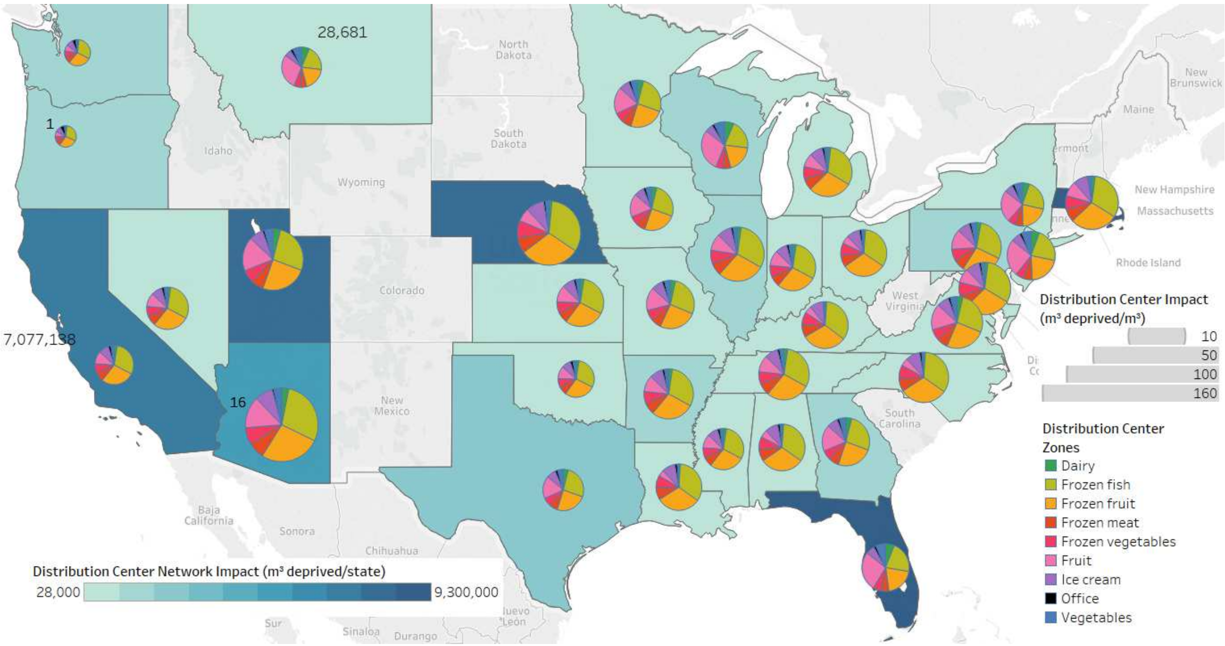


Figure 10. Pie charts in a choropleth geographical map show DC water impact of water consumption based on available water remaining. The size of circles shows DC water impact (m^3 deprived /m^3). Gray bars on the right show variation of DC impact water consumption (m^3 deprived /m^3). # shows number of DCs with similar water consumption. Multi-color pie charts show percent contribution of each DC zone to water impact. The choropleth map shows state-level water impact (m^3 deprived/state). Numeric values show minimum and maximum values for state-level results and per m^2.

3.5.2. Environmental impact of the U.S. supermarket network

Supermarket choropleth maps for global warming impact, non-fossil energy, and water scarcity are provided in Appendix, Figures A10, A11, and A12. The results in choropleth maps for fossil energy use and global warming impact are comparable to results for DCs. California, the largest distribution network, has the highest fossil energy use, followed by Florida, Georgia, Pennsylvania, and Texas (Appendix, Figure A11). Montana has the lowest cold storage capacity and the lowest fossil energy use. Washington and Oregon have 8% share in total cold storage capacity but have low fossil energy use due to hydropower electric energy supply. The states with the lowest and highest fossil energy use per volume are Oregon and Louisiana, respectively. The reduction from other states in Oregon is due to hydropower. The increase in Louisiana is due to hot-humid climate zone. Overall, frozen food has the largest share in total environmental impact (>50%). In most states, frozen fish and frozen fruit have the largest environmental impact. The refrigerated fruit has the largest impact in California, Wisconsin, Montana, Florida, and New Jersey where cooled storage capacity is almost as big as the frozen capacity.

Sales area has the largest contribution to global warming and water scarcity (Appendix, Table A10 and A12) because it includes all frozen food section for which low temperature refrigeration is required. In addition, dairy also belongs to the sales section and these cases have apportioned medium temperature refrigeration. The other part of medium temperature refrigeration is allocated to produce (refrigerated fruit and vegetables). Bakery and deli is the second largest contributor to impact due to natural gas use for food preparation and produce is the third.

In PDCs the main impact driver is refrigeration (>90%) (Burek and Nutter 2018d). In supermarkets, the main impact driver is refrigeration (60-70%), followed by natural gas (5-10%), interior and exterior lights (5-12%), and equipment (3-8%). Refrigerant loss accounts for 15% of total supermarket GHG emissions.

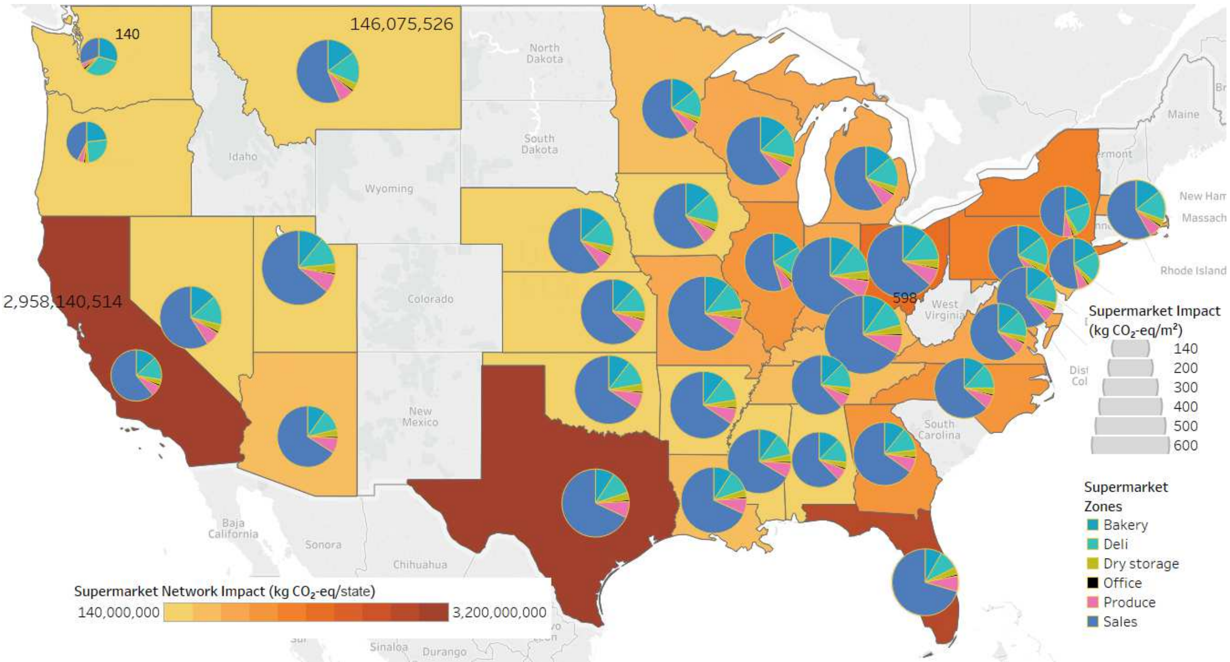


Figure 11. Pie charts in a choropleth geographical map show supermarket global warming impact. The size of circles shows supermarket GHG emissions (kg CO_2-eq/m^2). Gray bars on the right show variation of supermarket impact GHG emission (kg CO_2-eq/m^3). # shows number of supermarkets with similar GHG emissions. Multi-color pie charts show percent contribution of each supermarket zone to GHG emissions. Zones are defined by color in the legend on the right. The choropleth map shows state-level GHG emissions (kg CO_2-eq /state). Numeric values show minimum and maximum values for state-level results and per m^2.

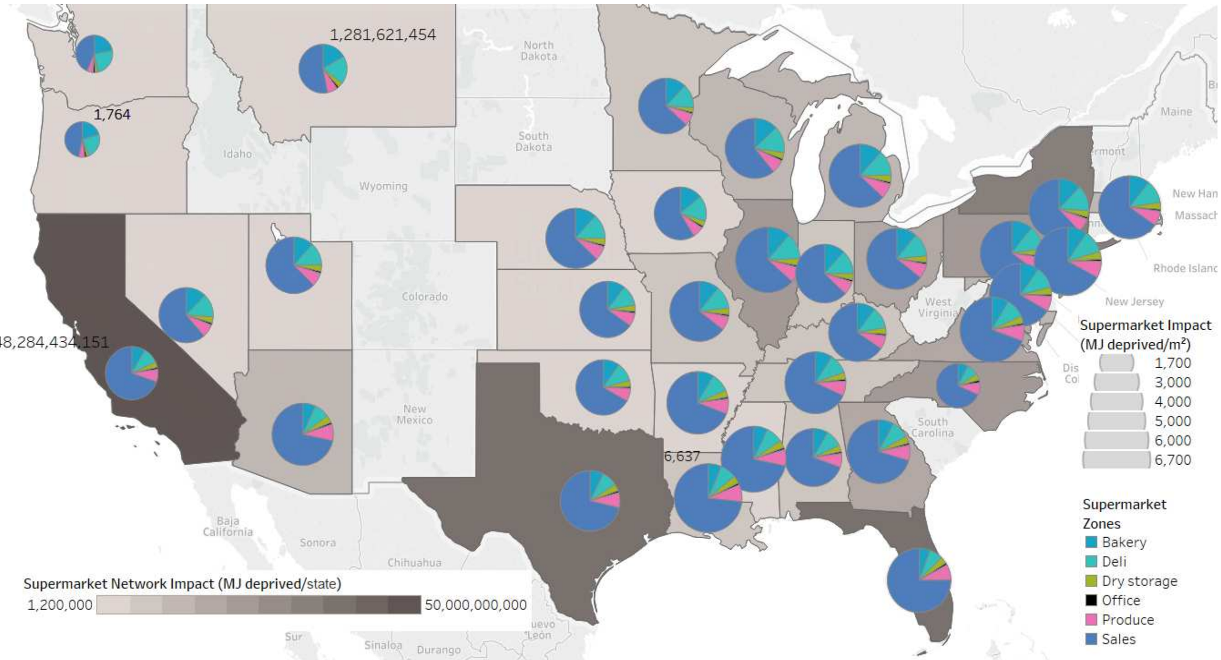


Figure 10. Pie charts in a choropleth geographical map show supermarket fossil energy use. The size of circles shows supermarket fossil energy use (MJ deprived/m^2). Gray bars on the right show variation of supermarket impact fossil energy use (MJ deprived/m^3). # shows number of supermarkets with similar fossil energy use. Multi-color pie charts show percent contribution of each supermarket zone to fossil energy use. Zones are defined by color in the legend on the right. The choropleth map shows state-level fossil energy use (MJ deprived/state). Numeric values show minimum and maximum values for state-level results and per m^2.

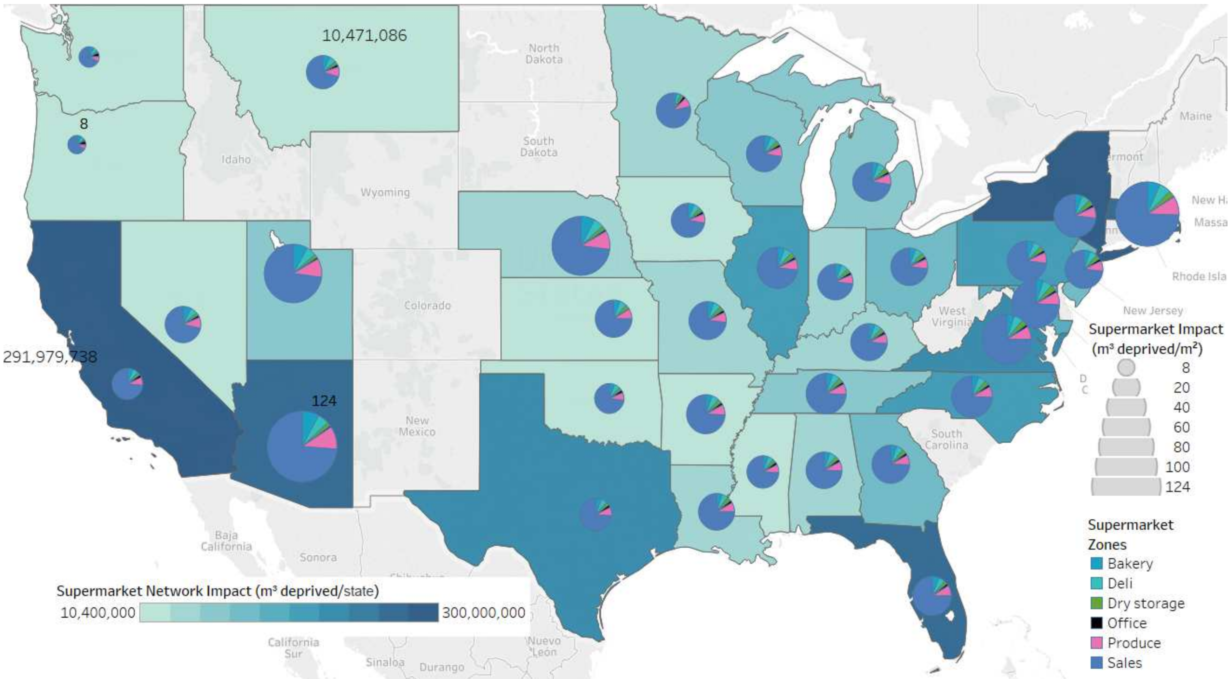


Figure 12. Pie charts in a choropleth geographical map show supermarket water impact of water consumption based on available water remaining. The size of circles shows supermarket water impact (m^3 deprived /m^2).). Gray bars on the right show variation of supermarket impact water consumption (m^3 deprived /m^3). # shows number of supermarkets with similar water consumption. Multi-color pie charts show percent contribution of each supermarket zone to water impact. Zones are defined by color in the legend on the right. The choropleth map shows state-level water impact (m^3 deprived/state). Numeric values show minimum and maximum values for state-level results and per m^2.

These results can be used to improve the existing DC and supermarkets. Further discussion will focus on using these models to calculate environmental impacts of food category. The DC and supermarket network analysis was expanded to include cold and frozen supply chain of food storage at DCs and supermarkets. The environmental impact results for each food category is a national assessment (including whole cold food supply network), but the resulting formulae allow calculating fossil energy use, global warming, and water impact of regional and alternative scenarios.

3.5.3. National environmental impact of food post-processing storing and retailing

Table 5 shows U.S. national average environmental impact of different food categories at PDCs and supermarkets in the United States. The environmental impact of storing based on the USDA assumption that food items at freezers and coolers remained in storage for at least one month, as shown in Table 5, columns 3, 4, and 5. Columns 6, 7, and 8 (Table 5) show retailing impact of different food items. How long each food item stays at the supermarket it is not known, thus, we used assumed length of stay at the supermarket reported in Table 4, which was calculated using average shelf-life of the product and divided by two. It was assumed that the majority of products will stay in a distribution system before the end of their shelf-life and the food items must have enough shelf-life to be stored at the consumer. In case of storing food at PDCs, the most notable difference in environmental impacts were shown between storing of frozen and raw vegetables (6% higher global warming impact of frozen vegetables) due to lower storing temperature. Frozen meat and frozen vegetables have lower storing environmental impact than raw food items, which can be attributed to higher amount of food items per m^3 (Figure 3).

More variation is shown in food retailing. Frozen meat and seafood have the largest global warming potential as shown in Table 5. Raw fish (2.25 days), raw meat (4 days), and chilled fruit such as berries and grapes (1.75 days) have the lowest global warming, as shown in Table 5. Dairy has wide range of shelf-life. Assumed length of stay for milk and yogurt was 10 days and 46 days for cheese.

To show potential additional impact of food distribution, a cradle-to-processing plant gate global warming impact results were collected from literature including U.S. Open-IO and DataSmart LCI databases (Suh and Huppes 2002; LTS 2016), as shown in Table 5, column 1 (LTS 2016; Suh and Huppes 2002). The results show different environmental impact between different food items. Average monthly food stocks already take into consideration that these food items were stored at the warehouse for at least a month (USDA NASS 2018).

At PDC, chilled and frozen fruit have similar global warming, non-renewable energy use, and water scarcity. Raw vegetables have the lowest impact, which could indicate that vegetable storage can hold more quantities of vegetables than fruit storage quantities of fruits, which may be due to different decomposition and food safety requirements.

Because the result depends on the area, sales, and price, it can be assumed that the difference stems from the type of product and throughput. At the supermarket, raw fruit and vegetables have a similar result because of the underlying assumptions that half of the fruit and vegetables are refrigerated and half non-refrigerated and because the refrigerated space is equally occupied by fruits and vegetables. Frozen ready meals have the largest supermarket impact, which may be attributed to an assumption that frozen ready meals, frozen meat, potatoes, frozen vegetables and fruits, and other occupy equally available space in the supermarket, but annual sales and prices vary.

Table 5. Cradle-to-processing plant gate literature results (column 1) and modelled U.S. national average yearly environmental impact of different food categories at PDCs and supermarkets.

	Cradle-to-processing plant gate LCA (literature)	PDC Assumption: all food items were stored for 1 month			Supermarket Assumption: food items have different length of stay at supermarket (Table 4)		
Impact category	Global warming	Global warming	Fossil energy	AWARE	Global warming	Fossil energy	AWARE
Unit	kg CO_2-eq/kg	kg CO_2-eq/kg	$MJ_{deprived}$/kg	$m^3_{deprived}$/kg	kg CO_2-eq/kg	$MJ_{deprived}$/kg	$m^3_{deprived}$/kg
Storage/zone			Cooler 1		Produce zone		
Raw fruit	0.308[a]	0.016	0.239	0.001	0.027	0.276	0.003
Storage/zone			Cooler 2		Produce zone		
Raw vegetables	0.177[b]	1.9E-04	0.003	1.8E-05	0.064	0.649	0.006
Storage/zone			Cooler 3		Sales zone		
Dairy	13.6[c]	0.012	0.181	0.001	0.063* 0.014**	0.726* 0.157**	0.007* 0.001**
Storage/zone					Sales		
Raw meat	5.4-18.2[d]		Not stored at PDC		0.003	0.040	3.7E-04
Storage/zone					Sales		
Raw fish and seafood	NA[e]		Not stored at PDC		0.002	0.025	2.3E-04
Storage/zone			Sub-freezer		Sales zone		
Ice cream	6.05[f]		No capacity data		0.384	4.40	0.001
Storage/zone			Freezer 4 and 5		Sales zone		
Frozen fruit	3.03[g]	0.016	0.227	0.002	3.33	38.2	0.012
Storage/zone			Freezer 3		Sales zone		
Frozen vegetables	2.26[h]	0.003	0.041	2.7E-04	2.61	29.9	0.009
Storage/zone			Freezer 2		Sales zone		
Frozen meat	NA[i]	0.006	0.089	0.001	6.24	71.5	0.022
Storage/zone			Freezer 1		Sales zone		
Frozen fish	2.21[j]		No capacity data		2.36	27.1	0.008
Storage/zone			Freezer 1		Sales zone		
Frozen seafood	2.21[k]		No capacity data		8.12	93.1	0.028
Storage/zone					Sales zone		
Frozen breakfast	2.34[l]		Not stored at PDC		0.987	11.3	0.003
Storage/zone					Sales zone		
Frozen pizza	2.34[m]		Not stored at PDC		0.697	7.98	0.002
Storage/zone					Sales zone		
Frozen snack	2.34[n]		Not stored at PDC		0.616	7.06	0.002

NA – not available, *cheese/eggs, *milk/yogurt

[a] Strawberries processed post-harvest in California from the DataSmart LCI database (LTS 2016).

[b] Potatoes at farm from the DataSmart LCI database (LTS 2016).

[c] Average fluid milk and cheese manufacturing from the Open IO LCI database: 2.57 kgCO_2-eq/\$ x 5.28 \$/kg (Suh and Huppes 2002).

[d] Average poultry and animal processing from the Open IO LCI database: 2.47 kgCO_2-eq/\$ x 6.99 \$/kg (Suh and Huppes 2002).

[e] NA

[f] Ice cream and frozen dessert from the Open IO LCI database: 1.39 kgCO_2-eq/\$ x 4.35 \$/kg (Suh and Huppes 2002).

[g, h] Frozen fruits, fruit juices, and vegetables from the Open IO LCI database: 0.742 kgCO_2-eq/\$ x 4.09 \$/kg (fruit) and 0.742 kgCO_2-eq/\$ x 3.04 \$/kg (vegetables) (Suh and Huppes 2002).

[i] NA

[j,k] Prepared fresh or frozen fish and seafood: 0.196 kgCO_2-eq/\$ x 11.3 \$/kg (Suh and Huppes 2002).

[l,m] Frozen specialties (frozen dinner and pizza) from the Open IO LCI database: 0.335 kgCO_2-eq/\$ x 7.00 \$/kg (Suh and Huppes 2002).

[n] Sausages and other prepared meat products from the Open IO LCI database: 0.611 kgCO_2-eq/\$ x 8.57 \$/kg (Suh and Huppes 2002).

Factors that impact shelf-life are time-temperature tolerance, processing, and packaging factors (Man and Jones 2000). Time-temperature tolerance concept defined shelf-life curves for different frozen foods, and defined quality loss as being proportional to the reciprocal of the storage temperature (Man and Jones 2000). Data presented in Table 5are representative for PDCs because the assessment accounted only food items, which are stored at least for a month. A study about frozen food quality showed that some foods were as old as 840 days in the distribution system (Man and Jones 2000). Large chain stores have faster turnover, some food items may have a faster turnover, and many PDCs use cross-docking and just-in-time logistics, which shorten the length of food items in storage and supermarkets (Bartholdi and Hankman 2011). Despite this, food waste due to expiration date, loss of quality, and damaged packaging at PDCs and supermarkets is high. Dairy, fresh fruits, vegetables, and meat and seafood food retail losses were on average 12% (milk, yogurt, cheese), 3.8 (cherry) 50% (papaya), 5.1 (celery) 42.5% (kale), and 4.5%, respectively (Kim et al. 2013; Burek et al. 2017a; Xue et al. 2017; Buzby et al. 2011). Figures 12, 13, 14, and 15 show environmental impacts of chilled and frozen food items with varying lengths of stay at supermarkets and distribution centers. The maximum length of stay of chilled and frozen food items at PDCs was assumed one year, except for dairy which has a maximum of 6 months of shelf-life. Produce such as apples could be a year old (refrigerated storage) before they are sold at supermarkets. Frozen vegetables, fruits, and meat have a shelf-life as long as 24 months. Freezing extends shelf-life of food items and reduces food losses. According to Buzby et al. (2011), frozen berries had 6% loss, frozen vegetables have between 5.8% (frozen carrots) and 6% (frozen potatoes) retail loss. Current results show only designed storage temperature, which is still not equal to maximum allowed (on average 18 degrees Celsius). One way to increase even more the shelf-life of frozen foods is to reduce storage temperature to -24 degrees Celsius, but the trade-off is increase in refrigeration energy and refrigerant losses for processing, transporting, storing, and longer stay in a distribution system.

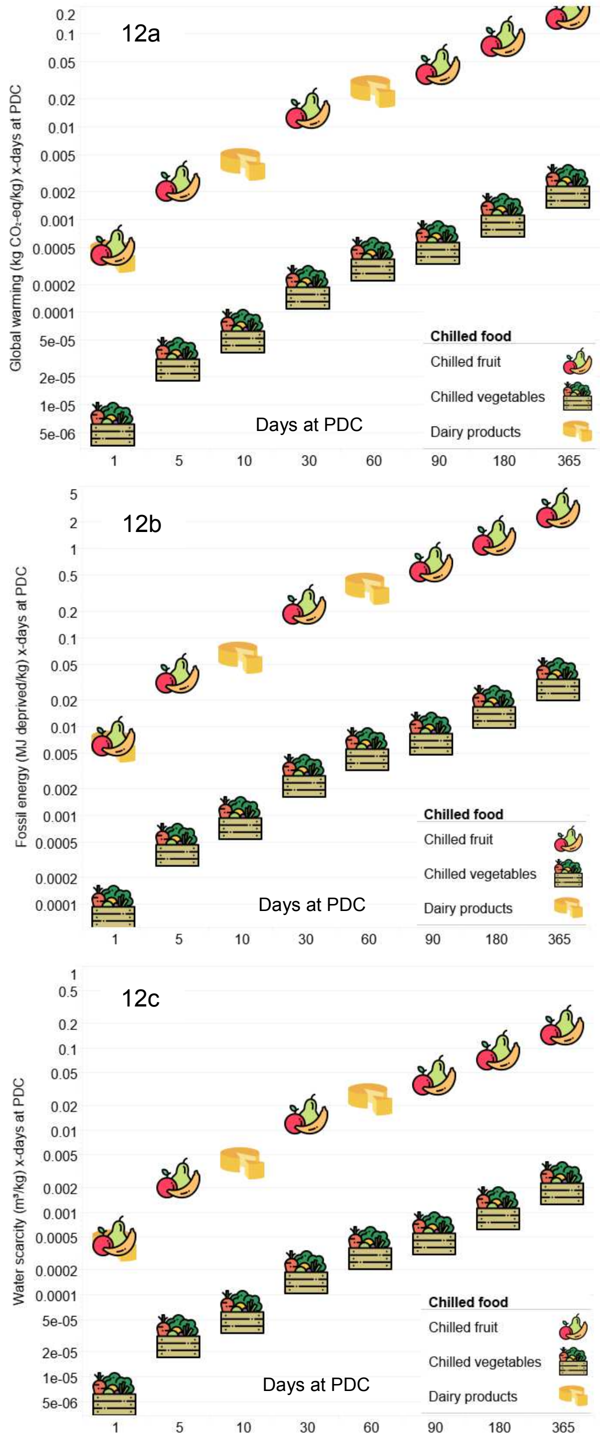


Figure 12. Chilled food global warming, fossil energy use, and water scarcity in relation to days spent at the PDC. Dairy and fruit results overlap so they were shown as alternating.

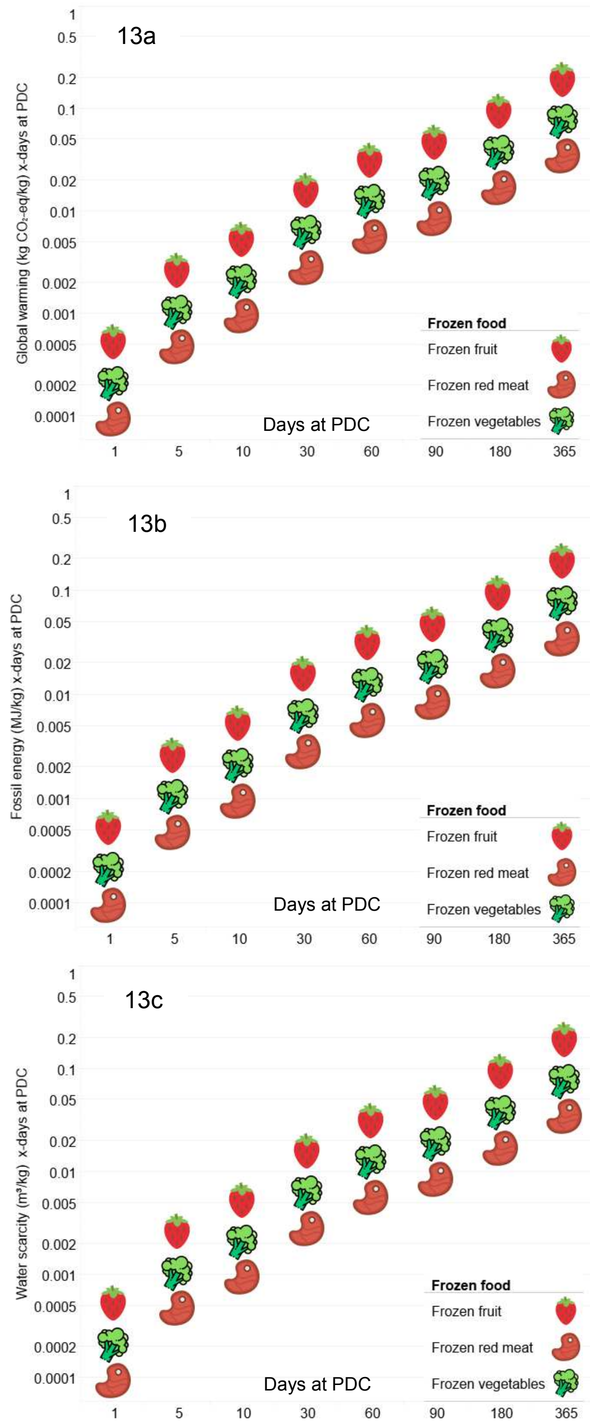


Figure 13. Frozen food global warming, fossil energy use, and water scarcity in relation to days spent at the PDC.

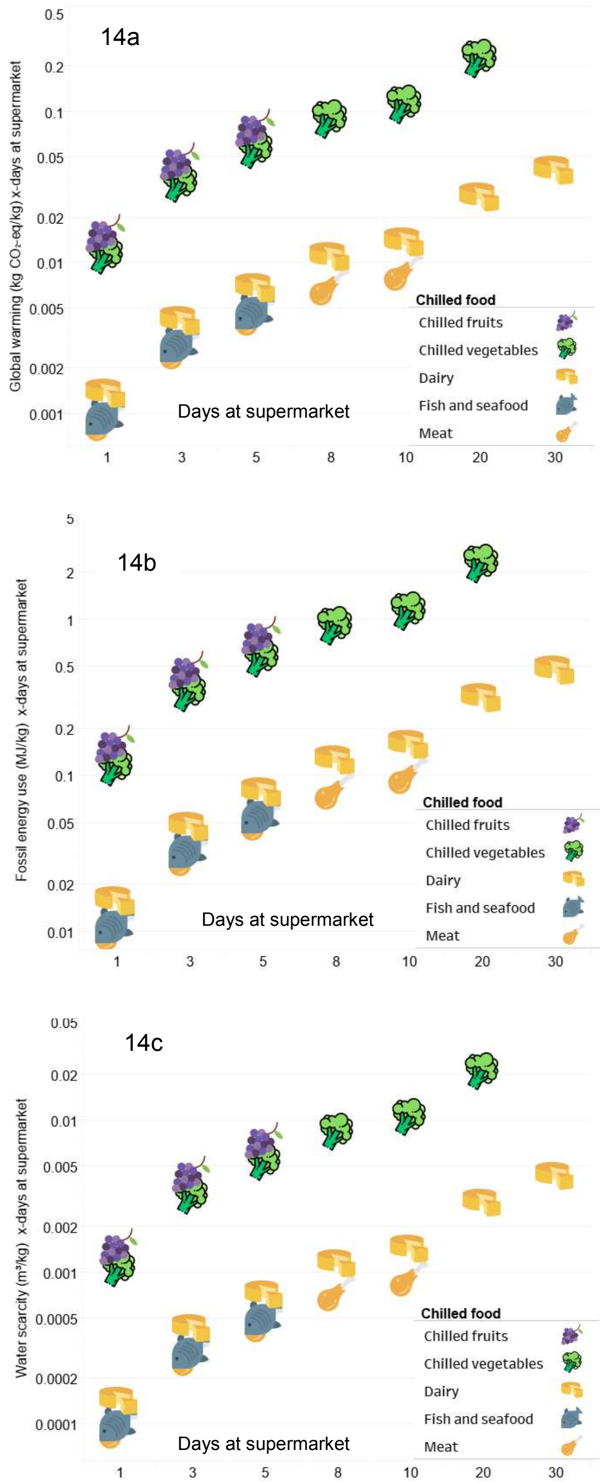


Figure 14. Chilled food global warming impact in relation to days spent at the supermarket.

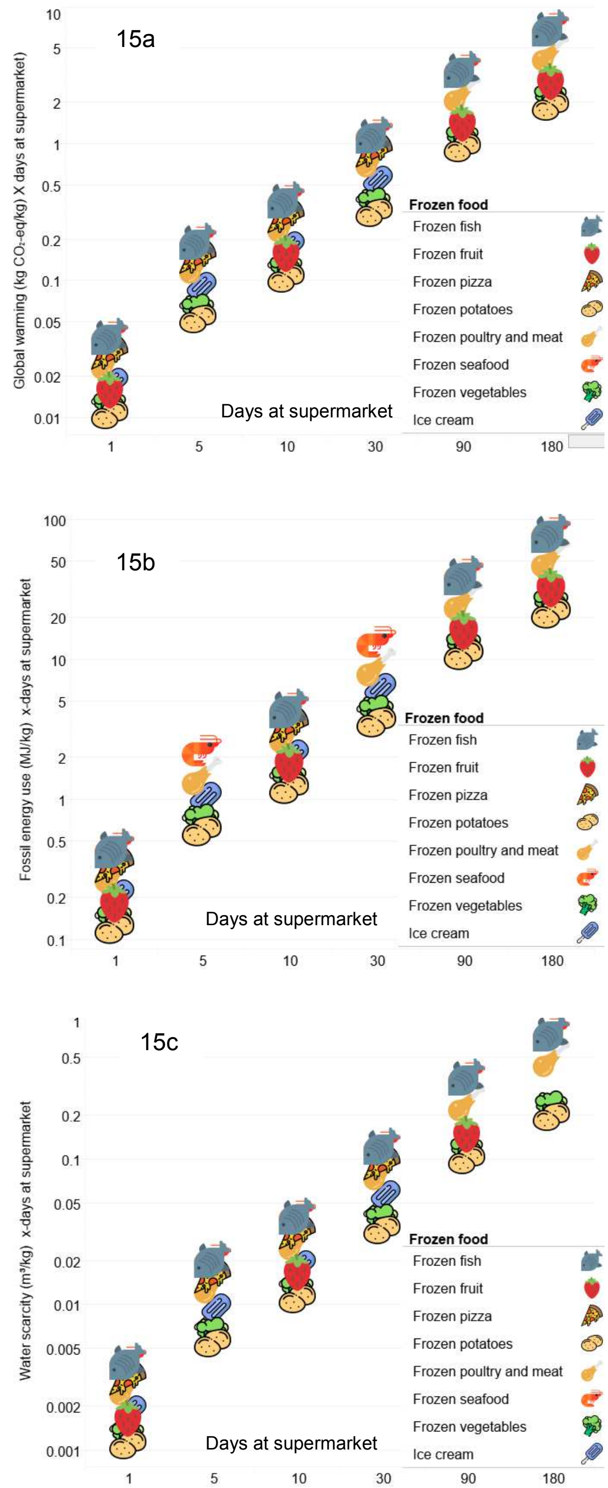


Figure 15. Frozen food environmental impact in relation to days spent at the supermarket.

Due to the dependency of data on fixed inherent factors such as size of zones at DCs, zone temperature, supermarket department size and refrigerated space within the department, and auxiliary factors such as capacity of frozen food at the DCs, sales and prices, and length of stay, which are variable, the reported results are not accurate per se, but show one of many possible results and the range of the DC and supermarket impacts on food. To enable broader usability for the industry and LCA community, we developed formulas, which based on the information available allow to calculate for specific DC and supermarket in a specific region.

3.5.4. Discussion about the food-energy-water nexus

Innovations in integrated management of food-energy-water nexus is vital to achieving sustainable development (Helmstedt et al. 2018). Often, food, energy, and water are disconnected spatially. PDCs and supermarkets are hubs for selling food and where food, energy, and water are spatially connected. Energy and water use data in PDCs and supermarkets is often proprietary (Mcgrane et al. 2018) and their role in wider nexus is not well understood. Policy is often focused on environmental sustainability of food production (Agovino, Cerciello, and Gatto 2018; Biggs et al. 2015), while less is done in retailers environmental accountability of their own practice.

3.5.5. From national to state-level environmental impacts of food post-processing storing and retailing

The LCIA results were presented only for average PDC and supermarket, but both PDCs and supermarkets come in different sizes and store different products. To make this research broadly applicable, we derived formulae to calculate fossil energy use, global warming impact, and water use for different food types. The equations for all unknown coefficients are provided in the Appendix, Table A10 to A16. The meaning of each variable is listed in the abbreviation list under each table in Appendix. Equation 1 calculates total environmental impact i of the frozen food DC and supermarket. Coefficients $freeze_{ff_{iDC}}$and $sales_{ff_{iRC}}$ are state level or national frozen food DC freezer environmental impacts per m^3 and sales zone total walk in, reach in displays environmental impacts per m^2. The user can specify volume of the freezer ($V_{ff_{DC}}$), time ($t_{ff_{DC}}$) at the warehouse, and average capacity ($avgCap_{ff_{DC}}$). For supermarkets, the user can define frozen food area (A_{ff_S}), time at the supermarket (t_{ff_S}), and total sales (P_{ff_S}), and average price of the item ($avgP_{ff_S}$).

$$ff_i\left(\frac{Unit}{kg}\right) = \frac{freeze_{ff_{iDC}}\left(\frac{Unit}{m^3 * yr}\right) \times V_{ff_{DC}}(m^3) \times t_{ff_{DC}}(yr)}{avgCap_{ff_{DC}}(kg)} + \frac{sales_{ff_{iS}}\left(\frac{Unit}{m^2 * yr}\right) \times A_{ff_S}(m^2) \times t_{ff_S}(yr)}{P_{ff_S}(\$)} \times avgP_{ff_S}\left(\frac{\$}{kg}\right) \qquad (1)$$

Equation 2 calculates total environmental impact i of fruit at DC and supermarket. Factors $cool1_{iDC}$ and $produce_{iS}$ are state level or national frozen food DC freezer environmental impacts per m^3 and sales zone total walk in, reach in displays environmental impacts per m^2. The user can specify volume of the cooler ($V_{cool1_{DC}}$), time ($t_{cool1_{DC}}$) at the warehouse, and average capacity ($avgCap_{fruitDC}$). For supermarkets, the user can define fruit refrigerated area (A_{fruitS}), time at the supermarket (t_{fruitS}), and total fruit sales (P_{fruitS}), and average price of the item ($avgP_{fruitS}$).

$$ref_{ifruit}\left(\frac{Unit}{kg}\right) = \frac{cool1_{iDC}\left(\frac{Unit}{m^3 * yr}\right) \times V_{cool1_{DC}}(m^3) \times t_{cool1_{DC}}(yr)}{avgCap_{fruitDC}(kg)} + \frac{produce_{iS}\left(\frac{Unit}{m^2 * yr}\right) \times A_{fruitS}(m^2) \times t_{fruitS}(yr)}{P_{fruitS}(\$)} \times avgP_{fruitS}\left(\frac{\$}{kg}\right) \qquad (2)$$

Equation 3 calculates total environmental impact i of fruit at DC and supermarket. The meaning of each variable is as in Equation 2, but for vegetables.

$$ref_{ivegetables}\left(\frac{Unit}{kg}\right) = \frac{cool2_{iDC}\left(\frac{Unit}{m^3 * yr}\right) \times V_{cool2_{DC}}(m^3) \times t_{cool2_{DC}}(yr)}{avgCap_{vegetablesDC}(kg)} + \frac{produce_{iS}\left(\frac{Unit}{m^2 * yr}\right) \times A_{vegetablesS}(m^2) \times t_{vegetablesS}(yr)}{P_{vegetablesRC}(\$)} \times avgP_{vegetablesS}\left(\frac{\$}{kg}\right) \quad (3)$$

Equation 4 calculates total environmental impact i of dairy at DC and supermarket. The meaning of each variable is as in Equation 2, but for dairy products.

$$ref_{idairy}\left(\frac{Unit}{kg}\right) = \frac{cool3_{iDC}\left(\frac{Unit}{m^3 * yr}\right) \times V_{cool3_{DC}}(m^3) \times t_{cool3_{DC}}(yr)}{avgCap_{dairyDC}(kg)} + \frac{sales_{idyS}\left(\frac{Unit}{m^2 * yr}\right) \times A_{dairyS}(m^2) \times t_{dairyS}(yr)}{P_{dairyS}(\$)} \times avgP_{dairyS}\left(\frac{\$}{kg}\right) \quad (4)$$

Equation 5 calculates total environmental impact i of fresh meat at supermarket.

$$ref_{imeat}\left(\frac{Unit}{kg}\right) = \frac{sales_{imeatS}\left(\frac{Unit}{m^2 * yr}\right) \times A_{meatS}(m^2) \times t_{meatS}(yr)}{P_{meatS}(\$)} \times avgP_{meatS}\left(\frac{\$}{kg}\right) \quad (5)$$

For supermarkets, instead of sales and price, the user can use food item capacity at the supermarket which will be consistent with the DC. An example calculation is given in Appendix, Example 1. Example allocation for dairy, fresh meat, packaged meat, and frozen food sections in sales supermarket zone is provided in Table A17. While the calculation for the DC is representative, supermarket results shown in Appendix, Example 1 should not be used to make any comparative assertions due to food allocation, sales, and price assumptions.

3.6. Conclusions, recommendation, and future research

The results presented here are an improvement over existing estimates because they include regional assessments and PDCs included dock food unloading and handling. Initiatives to reduce energy use in the food supply system should go beyond agricultural production practices (DTU 2016). PDCs and supermarkets have a strong dependence on energy inputs due to refrigeration. With policies to reduce fossil energy use, PDCs and supermarkets will become vulnerable. Historically, the decision for distribution center location was based on delivery to supermarkets at lowest cost. This research may inform policy makers and researchers to account for location-based effects of energy use and environmental impacts.

Some authors proposed a local box-scheme distribution system for raw vegetables (Markussen et al. 2014). According to Markussen et al. (2014), a local box-scheme distribution system was three times more efficient compared to a supermarket distribution system for vegetables. However, if the impacts of the local food production were significantly higher, the benefits of box-scheme were lost.

Refrigeration load is dependent upon infiltration rates. Reducing air changes per hour (ACH) from 2 to 1 for dock reduces energy consumption by 1.86%. Decreasing dock air infiltration to 0.5 ACH results in 3.2% energy use reduction. Products brought in at higher than storage temperature can increase the energy consumption up to 60% (Prakash and Singh 2008). Keeping most products at lowest possible temperature reduces electricity use of the refrigerated storage.

Among the key research challenge identified by food scientist is to reduce food loss and waste (NAS 2018). In the United States, food loos and waste has the lowest efficiency because their policies fail to discourage food waste (Agovino, Cerciello, and Gatto 2018). Waste food from PDCs and supermarkets to produce bioenergy (heat and power), which can be used in food processing plant (Lee and Tongarlak 2017) or converting food into a byproducts before end of shelf-life.

Extending shelf-life of food products is possible by freezing, but it comes with the increase of environmental impacts throughout the cold supply chain due to additional requirements for refrigeration. Lower storage temperature increases the shelf-life of frozen products, for example lowering frozen fruits temperature from -12 degrees Celsius to -24 degrees Celsius increased shelf-life from 3-4 months to more than 24 months.

Food properties also affects the refrigeration loads including storage temperature and incoming food temperature. Energy use increases linearly when storage temperature is decreased (Prakash and Singh 2008). It is not known how many products are brought to storage at different temperature from storage, but keeping temperature difference at minimum would reduce annual energy use (Prakash and Singh 2008).

More often carbon dioxide is used as refrigerant in display cabinets in supermarkets. We showed, if current supermarket refrigerant was replaced by carbon dioxide it could reduce GHG emissions by 18% and ozone depletion by 60%. However, supermarkets operate 24 hours and a risk high pressures at standstill, which may cause carbon dioxide to be blown off (J. A. Evans and Foster 2015).

Thus, to achieve reduction in the food-water-energy nexus, solutions to different problems must be applied as one integrated system of interconnected inputs, outputs, and processes (Helmstedt et al. 2018). This will also help highlight tradeoffs across the food-water-energy nexus. In addition, the solutions come at cost and require incentives, which will potentially increase the price of food distribution and consumer price.

Energy use for refrigeration (food storing and retailing) and refrigerant emissions (food retailing) are the major sources of GHG emissions of PDCs and supermarkets. PDCs and supermarkets must store and retail food in a more sustainable way. Energy management in PDCs and supermarkets, and low GHG building design are important measures in reducing environmental impacts of food storing and retailing. Energy efficiency improvements and the use wind and solar energy is considered an uncontested policy measure to reduce GHGs, which can reduce environmental impact of food storing and retailing (Dorward 2012). We proposed cost-effective strategies to reduce GHG emissions using solar and wind energy in PDCs in different states and found zero energy PDCs (Burek and Nutter 2018d). Because maximum solar energy potential from the roofs was 15%, the remaining energy was wind for zero energy PDCs.

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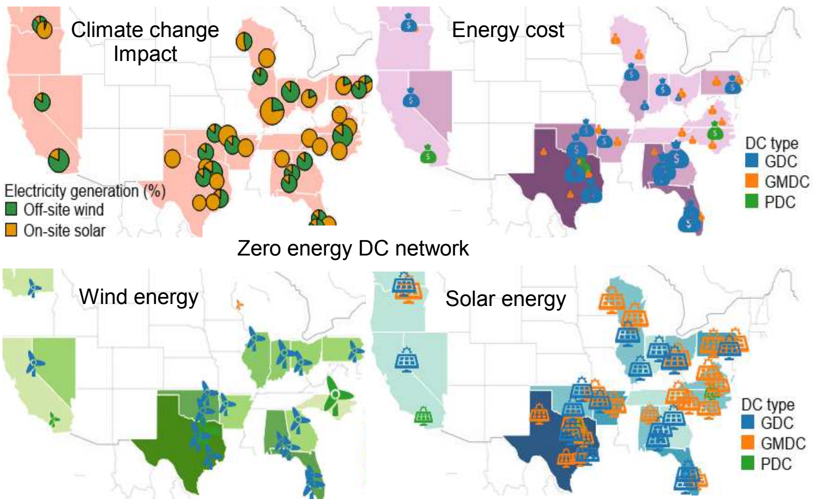
4. An life cycle assessment-based multi-objective optimization of the electricity mix for the grocery, perishable, and general merchandise multi-facility distribution center network

Burek, J., Nutter, D., (in review). Life Cycle Assessment-Based Multi-Objective Optimization of the Electricity Mix for the Grocery, Perishable, and General Merchandise Multi-Facility Distribution Center Network

4.1. Graphical abstract



4.2. Abstract

Walmart Stores Inc., the largest U.S. grocery retailer, owns a perishables, grocery, and general merchandise distribution center network, which stores and distributes refrigerated and non-refrigerated food in the United States. Finding cost-effective strategies to implement solar energy in distribution centers is the central objective of this research. Whereas in distribution centers that produced insufficient solar energy, nearby off-site wind energy generation was considered. The effects and tradeoffs of increasing renewable energy in distribution centers on cost and climate change were studied. In this research, we combined the life cycle assessment and quantitative methods including Monte Carlo uncertainty analysis and multi-objective optimization. A life cycle assessment-based multi-objective optimization model was built to find cost-effective strategies to minimize fossil energy use and mitigate impact of climate change for

the Walmart Stores Inc. distribution center network. The bi-objective and the triple-objective optimization included combinations of minimal cost, non-renewable fossil energy, and climate change criteria. The results of the multi-objective optimizations were Pareto-optimal solutions obtained by weighing importance of chosen criteria from the baseline to the zero energy scenarios. A selection of the Pareto-optimal solutions included the good, the better, and the zero energy building scenarios. A better building was a Pareto-optimal set of buildings, which demonstrated superiority from the life cycle assessment perspective. The superiority of Pareto-optimal solutions was evaluated using the Monte Carlo pairwise comparison. The good distribution centers were characterized by Pareto-optimal solutions between the baseline and the better distribution centers. Finally, zero energy general merchandise distribution centers were Pareto-optimal solutions with a maximal share of solar energy, but grocery and perishables distribution centers were combination of solar and supplemental wind energy because refrigerated warehouses are energy intensive. The study provided the benchmark for a tool that may improve distribution centers and other buildings and provided a framework to test environmental and renewable energy policies in buildings.

4.3. Introduction

In the United States, 30% of commercial building energy is used inefficiently or unnecessarily, for example, due to overcooling (Derrible and Reeder 2015). Energy savings are the most important metrics of buildings' sustainability because operational energy use is a primary cost and an environmental impact driver (Ibn-Mohammed et al. 2013). Maximizing building energy efficiency, finding strategies to cut electricity consumption, and reducing system costs is necessary in an ongoing effort to improve the energy use in buildings (B. Wang, Xia, and Zhang 2014). In literature, the cold energy storage was viewed as a prominent technology to reduce electricity consumption in refrigerated warehouses (K. Zhu et al. 2018). The cold energy storage could reduce the electricity consumption by 4.4% and operational cost by 20.5% in refrigerated warehouses (K. Zhu et al. 2018). An alternative option to improve refrigerated warehouse sustainability is by using renewable energy (Reindl, Claas, and Denison 2018). In their research, Fikiin et al. (Fikiin et al. 2017) argued there were promising solutions to include renewable energy in refrigerated warehouses in combination with the energy storage. Results of one case study showed that the photovoltaic installation can lead to both yearly total cost and energy savings (Meneghetti, Dal Magro, and Simeoni 2018). However, these studies did not include the life cycle assessment, and thus, the reported reductions over the entire life cycle might be lower.

Recent studies demonstrated that finding cost-effective optimum solutions for energy efficiency (Fan and Xia 2017) and renewable energy use (Safaei, Freire, and Henggeler Antunes 2015) in buildings were often solved using the single-objective and multi-objective optimization (Jing et al. 2017). In addition, lowering stress on the environment by encouraging energy and resource-efficient buildings has become a part of green building certification programs such as Leadership in Energy and Environmental Design (LEED) (U.S. Green Building Council 2013). Thus, to make informed choices and determine the best course of action towards green buildings, one needs to consider multiple criteria (Carreras et al. 2016). Often, the criteria are conflicting, for example, achieving the zero energy building may increase the building's cost (NREL 2015), and vice versa, increase in building products environmental impacts may decrease operational energy (Miller, Gregory, and Kirchain 2016). Thus, potential tradeoffs between sustainability, efficiency, and cost need to be considered and evaluated (Ostermeyer, Wallbaum, and Reuter 2013).

The multi-objective optimization is a method that can solve problems involving several competing objectives simultaneously. Authors used multi-objective optimization (1) to retrofit existing building envelope and achieve improved energy efficiency (Fan and Xia 2017), (2) to optimize the addition of solar panels (Antipova et al. 2014) and the battery storage in commercial buildings (Mariaud et al. 2017), (3) to optimize biomass gasification in the building's cooling, heating, and power systems (CHPSs) (J. J. Wang et al. 2014), (4) to optimize solid oxide fuel cells for combined CHPSs, (5) to provide alternative building designs (Carreras et al. 2016), (6) to evaluate cogeneration and solar energy in a mix of buildings' energy suppliers (Safaei, Freire, and Henggeler Antunes 2015), and to (7) improve the energy efficiency of the buildings (Jing et al. 2017).

The objectives focused on minimizing buildings' energy consumption and cost. One research minimized electricity consumption, retrofitting cost of the building envelope, and capital costs of photovoltaics (Fan and Xia 2017). Other authors maximized energy savings and cost-effectiveness and minimized payback period of retrofitting (B. Wang, Xia, and Zhang 2014). Some authors focused only on minimizing costs of photovoltaic and battery storage systems (Mariaud et al. 2017). In some cases, authors included objective functions that minimized daylight factors and thermal requirements for building cost-effective energy optimization in the early design stage (Negendahl and Nielsen 2015). In addition to economic objectives, some authors included environmental impacts, for example, one study minimized building's total cost and annual carbon emissions of the combined CHPS (Jing et al. 2017). The multi-objective optimization criterion was also the aggregated total environmental impact potential of building (Carreras et al. 2016). One author analyzed tradeoffs of minimizing different types of impacts including the non-renewable cumulative energy demand, greenhouse gas (GHG) emissions, acidification, and eutrophication (Safaei, Freire, and Henggeler Antunes 2015).

The technology used to improve the building target objectives included (1) a wall and roof insulation and solar panels (Fan and Xia 2017), (2) solid oxide fuel cells (Jing et al. 2017) (4) cogeneration (Charitopoulos and Dua 2017), (5) biomass gasification (J. J. Wang et al. 2014), and (6) lighting, air-conditioning, and geyser interventions (B. Wang, Xia, and Zhang 2014).

In recent years, the building optimization problems combined the life cycle assessment (LCA) method and the multi-objective optimization. Noteworthy examples of this research included the LCA multi-objective optimization of (1) building retrofitting (B. Wang, Xia, and Zhang 2014; Antipova et al. 2014), (2) a solar-assisted hybrid combined CHPS (J. Wang et al. 2015), and (3) the biomass CHPS (J. J. Wang et al. 2014). The LCA method was used in single-optimization problems (1) to reduce the environmental impacts of a building's hybrid combined CHPS (J. Wang et al. 2015) and (2) to evaluate effectiveness of CO_2 reduction strategies in the building sector (Karan, Mohammadpour, and Asadi 2016). In multi-objective problems the LCA methods was used (1) to increase renewable energy in building CHPSs (J. J. Wang et al. 2014; J. Wang et al. 2015), and (2) to improve building's energy efficiency through retrofitting (Antipova et al. 2014).

Authors of previous research used the multi-objective optimization to analyze sustainable food distribution, which minimized the post-processing transportation greenhouse gas (GHG) emissions and the total cost of the food distribution supply chain; this optimization model found feasible transportation routes (Validi, Bhattacharya, and Byrne 2014a). However, the research did not include distribution centers (DCs) and retail centers (RCs), which also played a significant role in the environmental performance of the food post-processing distribution (Burek and Nutter 2018a).

Even though the published building and LCA review papers showed a broadening of the LCA research in the building and construction sector, as shown in compressive reviews written by Chau et al. (Chau, Leung, and Ng 2015), Abd Rashid et al. (Abd Rashid and Yusoff 2015), and Cabeza et al. (Cabeza et al. 2014); not much LCA research has been done on DCs and supermarkets in the United States (Richman, Pasqualini, and Kirsh 2009). In the research published by Richman, Pasqualini, and Kirsh (2009), the authors used the LCA to evaluate improvements in cold storage warehouses by defining the best roof insulation materials for each climate zone. This research did not include refrigerated and non-refrigerated food distribution centers (2009).

In literature, one particular case of buildings, for which the use of renewable energy was evaluated using the LCA method, was zero energy buildings. Zero energy buildings combine both energy efficiency and renewable energy generation. The examples of the research that discussed zero energy buildings included the techno-economic analysis of hybrid zero emission building (Cao and Alanne 2018), development of nearly zero energy buildings (Weißenberger, Jensch, and Lang 2014), and discussion on steps to achieve zero energy buildings (Hernandez and Kenny 2010). Because of the low operational energy use in the residential sector, zero energy buildings can be achieved using photovoltaic (Weißenberger, Jensch, and Lang 2014). However, the concept of zero energy warehouses is relatively new (Brinks, Kornadt, and Oly 2016). Refrigerated warehouses are energy intensive buildings and installing photovoltaic is not enough to achieve zero energy targets (Meneghetti, Dal Magro, and Simeoni 2018).

This research extends to authors' studies about the environmental impacts of the Walmart Stores Inc. DC network and environmental impacts of the food post-processing storing and retailing (Burek and Nutter 2018b; Burek and Nutter 2018a). DCs are warehouses used for (1) receiving bulk shipments from processors and manufacturers, (2) temporary storage, (3) grouping customized retail orders, and (4) distribution of goods from DCs to a point-of-sale. Refrigerated and non-refrigerated DCs are among the highest energy use facilities in the United States. Refrigeration in commercial buildings accounted for the largest share of annual electricity consumption (14%), followed by ventilation (11.2%), lighting (10.6%), and space cooling (10.6%) (US EIA 2017b). In 2012, the construction of RCs and warehouses accounted for 43% of the total commercial building revenue, and warehouses alone used 300,000 TJ of energy (Alegria 2012). This was about 7% of total energy use of all commercial buildings (US EIA 2016). The top 75 North American food retailers have more than 49,890 RCs and 533 DCs with an estimated total area of 26,060,045 m^2 (MWPVL International 2010). The food supply chain consists of network of the suppliers (farmers), manufacturers, distributors, retailers, and end customers (Chan and Chan 2005). Thus, all DCs and RCs owned by a certain business are considered to be a distribution-retail network. The Walmart Stores Inc. is the largest retailer in the world and operates 173 DCs including 36 grocery DCs (GDCs), 6 perishables DCs (PDCs), and 42 general merchandise DCs (GMDCs) (MWPVL International 2010).

GDCs, PDCs, and GMDCs, and RCs are primary food distribution components (MWPVL International 2010), and have an important role in food distribution and sustainability. Food distribution includes processes that occur between producers, retailers, and customers from packaging, transport, and storage to delivery to the consumer. GDCs distribute refrigerated perishable food and dry food, PDCs only refrigerated perishable food, and GMDCs non-food and dry food (MWPVL International 2010). The largest are GMDCs (11,000,000 – 17,000,000 m^2) with mechanized conveyors, which can be up to 39 km long (MWPVL International 2010). GDCs are typically in the range from 9,000,000 to 11,000,000 m^2, and PDCs are in the range from 4,300,000 to 5,000,000 m^2.

In previous research, we assessed the environmental impacts of PDCs, GDCs, and GMDCs using the LCA method (Burek and Nutter 2018b). We included a state-level resolution of the life cycle inventory (LCI) and used the regional life cycle impact assessment (LCIA) method (Burek and Nutter 2018b). This study was a comprehensive whole-building LCA assessment. The study focused on full range of impact categories and analyzed environmental impacts of buildings' individual operation systems including lights, refrigeration, HVAC, conveyor systems, equipment, and building material and construction (Burek and Nutter 2018b). Previous study tested hypotheses that climate conditions, the year of the building's construction, building materials, state-level sources of electrical power, energy demand for refrigerated and non-refrigerated spaces, and conveyor lengths change the magnitude of environmental impacts across the U.S. First, the research identified similarities and differences between environmental impacts among the DCs. Second, the research investigated relationships between climate zones, energy demands, energy sources, building materials, and the environmental impacts of individual DCs (Burek and Nutter 2018b). Authors used the EnergyPlus building simulation to obtain the energy consumption data for existing DCs' LCA models (Burek and Nutter 2018b; U.S. Department of Energy 2012b). Results from previous research have shown that GDCs and PDCs have higher environmental impacts than GMDCs because the dominant building operation in GDCs and PDCs is refrigeration. GDCs and PDCs used 950–982 MJ/m^2 per year and 1.3–17 m^3/m^2 of natural gas per year, whereas, GMDCs used 56–185 MJ/m^2 and 1.5–16 m^3/m^2 of natural gas per year. Both refrigeration and conveyors are energy intensive, but their energy consumption is largely independent of climate zones (Burek and Nutter 2018b). The study concluded that differences in state-level purchased electricity energy mix affected differences in climate change impact more than the climate zone, as shown in Figure 1 (Burek and Nutter 2018b). Locations of buildings, type of buildings, and climate change impact (kg CO_2-eq/m^2) for the baseline scenario is shown in Figure 1.

A broad discussion about the Wal-Mart Stores, Inc. DC network, the LCA method used, input data, EnergyPlus modeling, and comprehensive LCIA results was described in detail by Burek and Nutter (Burek and Nutter 2018b). The subsequent study about food storing and retailing had a different scope because it focused on the cold food supply chain relationships to refrigerated distribution center storages and on the supermarket departments' cold zones, and allocated storing and retailing impact to different food categories (Burek and Nutter 2018a). Previous studies did not include the Monte Carlo uncertainty analysis (Burek and Nutter 2018b; Burek and Nutter 2018a).

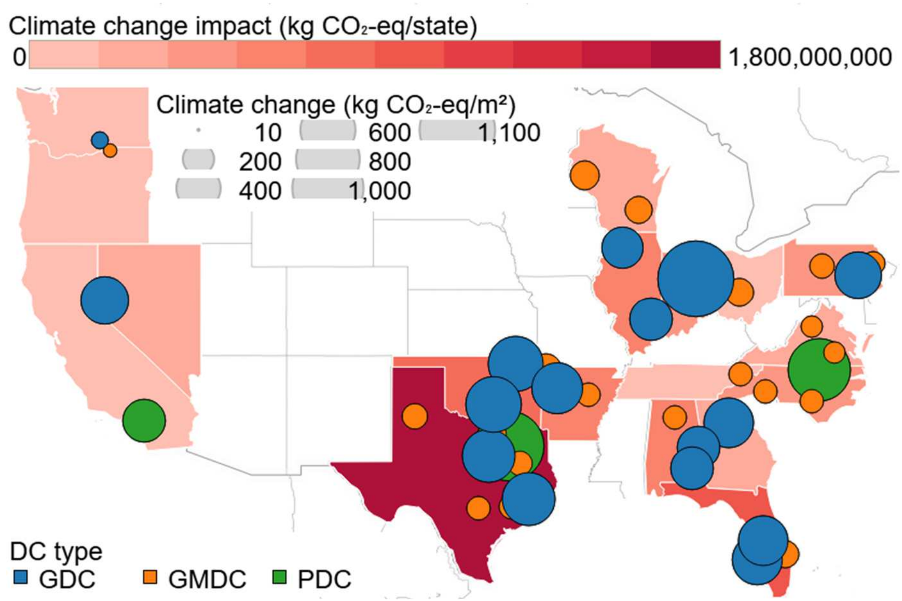


Figure 1. The Walmart Stores Inc. GDCs, GMDCs, and PDCs locations. The size of circles shows the climate change impact of each building (kg CO_2-eq/m^2). The choropleth gradient map shows the total climate change impact per state (kg CO_2-eq/state).

This study took the models from Burek and Nutter and combined the LCA modeling with the Monte Carlo uncertainty analysis and the multi-objective optimization, as shown in Figure 2 (Burek and Nutter 2018b). This study starts where the previous ended. The focus was not anymore on particular operation within the building, but on the overall environmental performance of buildings and optimal strategies to reduce their environmental impacts. The results presented in Burek and Nutter were used as a baseline scenario and as an input data to multi-objective optimization models (Burek and Nutter 2018b). We examined strategies to reduce the environmental impacts of the Walmart Stores Inc. DC network and examined pathways to achieve the zero energy DC network using the multi-objective optimization. The technologies to reduce environmental impacts and to obtain the zero energy DC network involved installing new solar panels and wind turbines, i.e., DCs were shifted from energy consumers to energy producers. We introduced wind turbines because solar panels were not a sufficient energy source for refrigerated warehouse to achieve zero energy due to their energy intensive operation (Meneghetti, Dal Magro, and Simeoni 2018). Primary benefits of solar and wind energy use are reducing dependency on fossil energy sources and climate change. The subject of inquiry was to find the most cost-effective way to mitigate the impact of climate change for DCs in different locations and to achieve the zero energy DC network.

The manuscript should be of interest to readers in the areas of building sustainability, sustainability of food and distribution, LCA experts, multi-objective optimization experts, and to readers interested in the complex system analysis. The research will also interest retail industry such as supply chain managers and may help DCs retrofitting or future DC planning.

4.3.1. Goal and scope

The scope of the study included the LCA of the local, regional, and global DC network owned by the Wal-Mart Stores, Inc., which is the same as in Burek and Nutter for the baseline scenario (Burek and Nutter 2018b). Several buildings were excluded because of missing cost data for optimization models. We started this study with the Monte Carlo uncertainty analysis and concluded that the largest uncertainties stemmed from the electricity generation. Then, we performed the Monte Carlo pairwise comparison to see if there were already buildings that perform better than the others in the network in terms of the life cycle fossil energy use.

The primary goals of this study were (1) to compare the environmental performance of the existing DC in one state to an existing DC of the same type in another state using the Monte Carlo pairwise comparison, which would enable finding and prioritizing improvements for locations that currently perform the worst, (2) to find tradeoffs between the building's energy consumption and on-site energy production in a spatial LCA-based multi-objective optimization model, which included economic (energy costs) and environmental outcomes (the non-renewable fossil energy use and the climate change impact) of the building's energy consumption and production, (3) to find the LCA-based cost-effective strategies to reduce the impact of climate change and fossil energy resource use by installing flat roof solar panels at existing DCs, and/or by purchasing off-site wind energy, (4) to compare current building's energy use and optimum solutions using the LCA-based Monte Carlo pairwise comparisons, (5) to find the least-costly DC network, which was superior to the existing DC network, and (6) to find the optimal zero energy DC network.

4.4. Materials and methods

The primary approaches used in this research were the LCA-based Monte Carlo pairwise comparison and the LCA-based multi-objective optimization. The LCA is a standard method to assess environmental impacts of products, processes, services, and whole buildings holistically, over the entire life cycle (i.e., from cradle-to-grave). Principles, requirements, and guidelines to perform LCA are given in International Standards: ISO 14040:2006, ISO 14044:2006, and ISO 14046:2014 (ISO 2006a; ISO 2006b; ISO 2014b). Based on the previous research and discussion, we used attributional LCA framework and process chain analysis. The attributional LCA is a system modeling approach in which environmental impacts are divided among products based on the functional unit and according to allocation principles (mass, energy, or economic). The process chain analysis includes itemized inputs and outputs for each LCA stage, as described in our previous work (Burek and Nutter 2018b).

Figure 2 shows a flow chart with data sources and methods used to perform this research. Columns 1, 2, 3, and 4 show data sources and steps necessary to perform the multi-objective optimization. Primary sources of data about DC locations, LCIA results, and baseline DC LCA models for the Monte Carlo uncertainty analysis and multi-objective optimization were taken from previous research, as shown in Figure 2, column 1 (Burek and Nutter 2018b). Cost data for purchased grid electricity, solar energy, and wind energy were obtained from literature, as shown in column 1. Column 2 shows the input data (i.e., cost, non-renewable fossil energy, and climate change) for the multi-objective optimization, column 3 shows objectives (i.e., cost, non-renewable fossil energy, and climate change) and constraints (i.e., source energy demand) used in multi-objective optimization, and column 4 shows a simplified bi- and triple-objective optimization model flow chart and selected solutions (i.e., Pareto-optimal bi- and triple-solutions' and associated purchased grid, wind, and solar energy mixes). The Matlab code was included in Appendix and was submitted to Mendeley data. Column 5 shows steps to perform the LCA-based Monte Carlo uncertainty analysis and the LCA-based Monte Carlo pairwise comparison. An overview of the uncertainty in the input data of LCA models and Monte Carlo uncertainty analyses was performed first followed by a comparative study of the baseline DCs using the Monte Carlo pairwise comparisons. A Monte Carlo pairwise comparison between the baseline DCs was used to assess whether there are superior DCs in the existing GDC, PDC, and GMDC networks. Column 6 shows the results of the multi-objective optimization and the Monte Carlo pairwise comparison, which were used for tradeoff analyses. Following the uncertainty analysis, a multi-objective optimization of GDC, PDC, and GMDC networks was performed. The results of the multi-objective optimization were further analyzed using the Monte Carlo pairwise comparison between the baseline DCs and the optimum results to find the good and the better DC networks, as shown in Figure 2. In addition, the optimal zero energy DC network was selected, as shown in Figure 2.

4.4.1. Previous life cycle assessment research of the Wal-Mart Stores, Inc. multi-facility PDC, GDC, and GMDC network

This research is connected to our previous work about environmental sustainability of PDCs, GDCs, and GMDCs owned by the Wal-Mart Stores Inc. (Burek and Nutter 2018b). Our previous research presented a broad discussion about the environmental impacts of GDCs, PDCs, and GMDCs and laid groundwork for this research (Burek and Nutter 2018b). For the purpose of this research, baseline process-LCA models for Wal-Mart Stores Inc. GDC, PDC, and GMDC networks were taken from previous work without modification and are available via Mendeley data (Burek and Nutter 2018b). Process-LCA models were built using the Simapro© 8.4. software, which has the ability to perform LCIA, Monte Carlo uncertainty analysis, and Monte Carlo pairwise comparison (PRé Consultants 2015). The system boundary for the whole-building LCA included the building operation (i.e., refrigeration, refrigerant loss, lights, HVAC, machinery, and water consumption) and infrastructure (i.e., construction material production (envelope and insulation), building construction, and the end of the building life (building demolition and material disposal)). The functional unit of 1 m^2 of DC floor space was also adopted from the previous work (Burek and Nutter 2018b). Results of the LCA for non-renewable fossil energy use and climate change impact results (per functional unit of 1 m^2 floor area) were adopted from previous work and were reported in the Appendix, Table A1 and in the Appendix, Excel document "Input data for multi-objective optimization.xlxs".

The number of DCs included in this study did not change significantly. The difficulty to find reliable renewable energy cost data for Arizona, Missouri, Mississippi, Wyoming, Nebraska led to a decision to exclude those DC locations from the research. The LCIA results adopted in this study were the climate change impact and the non-renewable fossil energy use. For most

DCs, there was a correlation between the non-renewable energy use and the impact of climate change including Arkansas, Alabama, Arizona, Florida, Illinois, Nebraska, North Carolina, Oklahoma, Ohio, Oregon, Texas, Washington, and Wisconsin (Burek and Nutter 2018b). Replacing purchased grid electricity with renewable energy will simultaneously mitigate the non-renewable fossil energy use and the impacts of climate change. Thus, we expect the bi-objective results for a minimal cost and climate change optimization and a minimal cost and non-renewable fossil energy optimization to be similar.

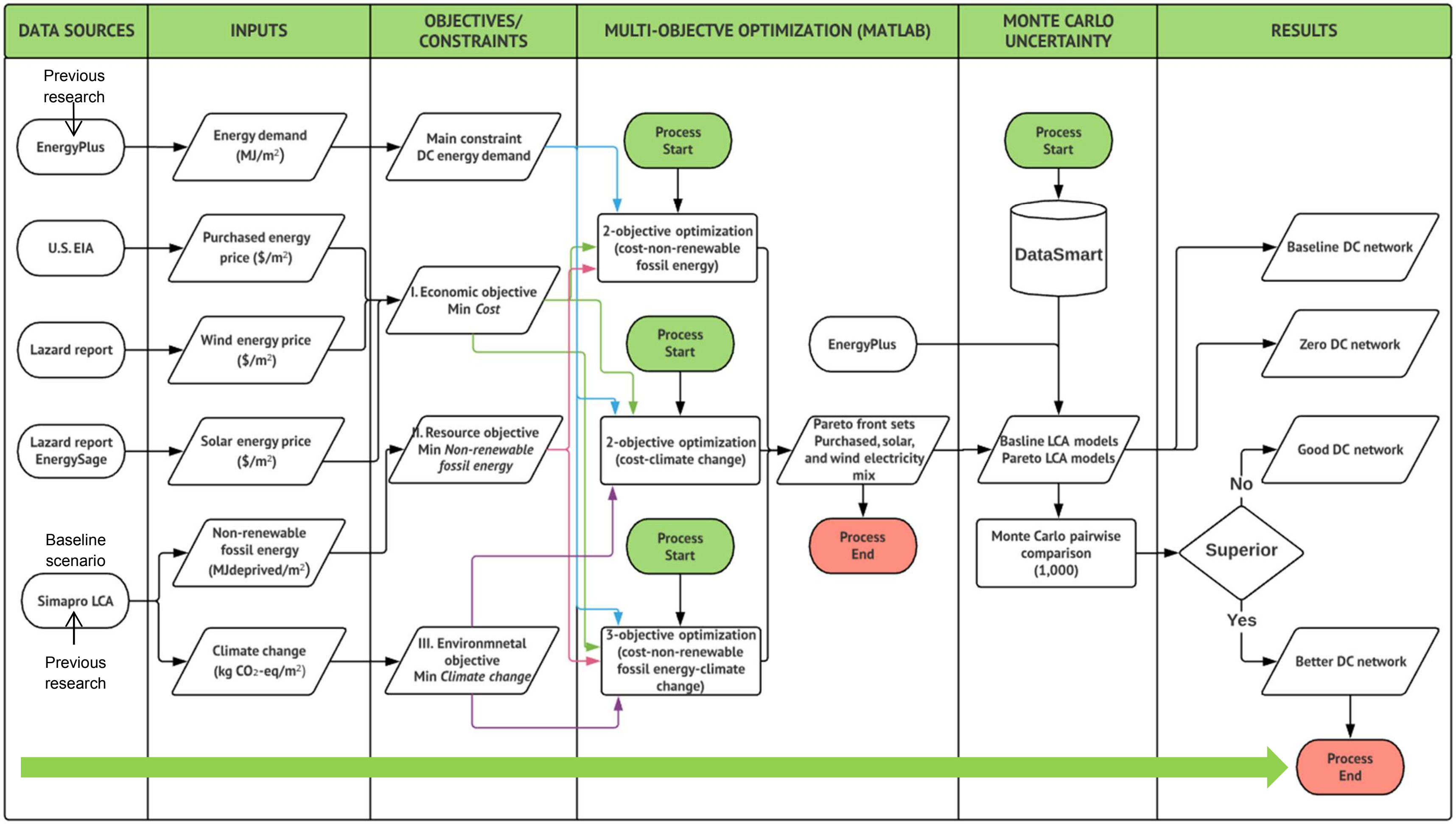


Figure 2. The multi-objective optimization, the Monte Carlo uncertainty, and the Monte Carlo pairwise comparison flow diagram.

4.4.2. The multi-objective optimization method

Multi-objective optimization methods were used previously for solving building's energy and environmental impact reduction problems using a mixed-integer linear programming (Karan, Mohammadpour, and Asadi 2016), a weighted sum method (Fan and Xia 2017), a non-linear programming (Hu and Cho 2014), a stochastic and numerical multi-objective optimization (Jing et al. 2017), and a differential evolution algorithm (H. Wang and Zhai 2016). In most cases, the multi-objective problem was transformed into and solved as a single-objective optimization problem (J. Wang et al. 2015).

We decided to perform the multi-objective optimization using the goal programming called the goal attainment method. The advantages of the goal attainment method are: (1) it is easier to implement than physical programming, (2) it is easier to code and is often used to solve practical cases, and (3) it is dependent on goal values chosen. The goal attainment problem involved reducing the value of a linear or non-linear function in order to attain the a priori specified vector which included goal values. A weight vector was used to indicate the relative importance of the goals. In addition, the goal attainment problem was subjected to linear and nonlinear constraints. In Matlab, the function used to solve the goal attainment problem is called fgoalattain. We used fgoalattain function to obtain our bi-optimization and triple-optimization results. The bi-optimization was performed at a minimal cost and minimal non-renewable fossil energy use criteria and at a minimal cost and minimal climate change impact. The triple-optimization was performed at a minimal cost, non-renewable fossil energy use, and climate change impact. The results of bi- and triple-optimization were Pareto frontiers. Pareto frontier was a set of Pareto-optimal results. Pareto-optimal result was a solution of the multi-objective optimization which cannot be improved without degrading the other objective value.

The multi-objective model finds a minimum of the problem specified by:

$$\underbrace{minimize}_{x,\gamma}\ \gamma \qquad such\ that \begin{cases} F(x) - weight \cdot \gamma \le goal \\ A \cdot x \le b \\ Aeq \cdot x = beq \\ lb \le x \le ub \end{cases}$$

(1), where $F(x)$ was the objective function, the weight was the relevance of the objectives, the goal was a target value for each objective. $A \cdot x \le b$ and $Aeq \cdot x = beq$ were linear constraints, and lb and ub were lower and upper bounds, respectively.

4.4.3. Objective functions

Primary objective functions used in bi-objective and triple-objective optimization models were cost, non-renewable fossil energy use, and climate change. These functions were chosen because the main goal of the study was to increase renewable energy in DCs. Replacing purchased grid electricity with renewable energy will simultaneously mitigate the non-renewable fossil energy and climate change impact, but potentially increase costs.

The minimum cost objective function shown in equation 2 calculated how much of the electricity was purchased from the grid and how much was generated from on-site solar panels and nearby wind farms at the lowest cost.

$$\underbrace{min}_{x} C_{total} = C_{mix(in)} \cdot x_1 + C_{PV(out)} \cdot x_2 + C_{wind} \cdot x_3$$

(2), where $\underbrace{min}_{x} C_{total}$ was the total purchased grid and renewable energy cost that needs to be minimized and x_1, x_2, and x_3 were variables representing shares of purchased grid, solar, and wind electricity, respectively. X_1, x_2, and x_3 variables were calculated using the multi-objective optimization. $C_{mix(in)}$, $C_{PV(out)}$, and $C_{wind(in)}$ were cost coefficients, as shown in Appendix, Table A1.

Costs of purchased grid ($C_{mix(in)}$), solar ($C_{PV(out)}$), and wind ($C_{wind(in)}$) energy were obtained from the U.S. Energy Information Administration (EIA) and the Lazard report, as shown in Figure 2 (U.S. Energy Infromation Administration 2016; Lazard 2017). In addition, state-level solar panel installation capital costs were obtained from the EnergySage report (EnergySage 2018). Costs coefficients ($C_{mix(in)}$) were based on the state electricity profiles for each location (U.S. Energy Infromation Administration 2016). Washington state had the lowest retail price of electricity (0.077 \$/kWh) and California had the highest (0.152 \$/kWh). Electricity prices were multiplied by the DC's total electricity purchased grid (kWh/year) and divided by the building area (m^2). Non-refrigerated buildings had lower electricity consumption and lower electricity cost per whole building area. Refrigerated DCs' purchased grid electricity cost was between 81.5 \$/m^2 (Washington) and 147 \$/m^2 (California). Non-refrigerated DCs had electricity costs between 28 \$/m^2 (Wisconsin) and 6 \$/m^2 (Texas). $C_{mix(in)}$ calculation data and results are provided in Appendix, Table A2.

Cost coefficients of solar energy ($C_{PV(out)}$) included the capital cost of installation of solar panels and the levelized solar electricity production cost. The Lazard report calculated the average U.S. comparative "levelized cost of energy" analysis for various technologies on a \$/MWh basis, including subsidies, fuel costs, geography, and cost of capital (Lazard 2017). Only average levelized costs of solar electricity production were taken from the Lazard report (Lazard 2017). Because capital costs of solar panel installation vary in different states and for different powers, we used data reported by EnergySage (EnergySage 2018). EnergySage reported minimum and maximum costs for 6kW and 10 kW solar panels, after the Federal Investment Tax Credit was taken into account for 2018 in different states (EnergySage 2018). We assumed a 10 kW solar system and calculated the average cost for each state. For some locations, data was not available, thus, the average cost of reported states was used for Alabama, Arkansas, North Carolina, Nevada, Oklahoma, Tennessee, and Wisconsin. Capital cost prices (\$/kW) were divided by a 25 year solar panel lifetime (Lazard 2017). The average solar power per panel square meter of 0.161 (kW/m^2) was multiplied by the total roof area available for installation of solar panels. The result was the installation capacity (kW) for each DC (Solar Power Rocks 2018a). Flat roofs are ideal for solar panels, but available space is less than the total building roof area. According to fire regulation IFC 605.11.3.3.1, 1.8 m space around the perimeter wall is necessary for buildings larger than 76.2 m to allow firefighters access to the roof (Solar Power Rocks 2018b). In addition IFC 605.11.3.3.2 and 605.11.3.3.3 require a 1.22 and 2.44 m pathway access. Commercial rooftop solar arrays cannot be greater than 46 by 46 m. Thus, the total roof area available for installation of solar panels was assumed to be 75% of building area (Interstate Renewable Energy Council 2008). In addition, building's flat roof will typically contain mechanical equipment, such as HVAC, refrigeration, and more.

The Project Sunroof estimated the amount of sun hitting a rooftop using 3D models derived from aerial imagery. The 3D models allowed estimation of shading for every point on a roof, for each possible position of the sun in the sky. The 3D models also enabled the estimation of the amount of available space for solar panels, including the pitch and azimuth of each roof plane. However, the 3D models did not provide data about the available space for solar panels for DC locations used in our models (Google Ink. 2017).

The Project Sunroof currently covers roughly 60M buildings in portions of 50 states and Washington DC (Google Ink. 2017). The online Project Sunroof tool provided data on energy production from panels placed in the viable roof space, which was calculated based on the typical weather data at the location. A solar installation capacity (kW) was multiplied by the average solar electricity price per kW, which provided the total solar panel cost for each location. Then, a total solar panel cost for each location was divided by total potential of solar electricity at each location. The total potential of solar electricity at each location was equal to a product of sun hours per year, solar potential area available, solar power per area, and DC to AC conversion losses. Wiring losses for DC to AC conversion were 78% (Mission et al. 2018). Sun hours per year for each location were obtained from the Project Sunroof (Google Ink. 2017). The sum of capital cost and levelized production cost was multiplied by the total electricity purchased (kWh/year) and divided by the DC area (m^2). The solar electricity cost and calculation data and results are provided in the Appendix, Table A3.

A cost coefficient for wind electricity ($C_{wind(in)}$) was calculated as a sum of wind turbine capital cost and a levelized wind electricity production cost. The capital cost for an on-shore wind turbine was between 1,200 and 1,650 $/kW and for an off-shore between 2,360 and 4,500 $/kW. We used average values of 1,425 $/kW for on-shore and 3,430 $/kW for off-shore capital costs (Lazard 2017). Total wind hours were calculated as a ratio of the annual potential electricity generation from wind and the installed wind capacity in each state. The highest on-shore wind capital cost was 0.393 $/kWh (Texas) and the highest off-shore wind capital cost was 2.36 $/kWh (Virginia). This value was multiplied by the total electricity purchased (kWh/year) and divided by the building area (m^2). Wind electricity calculation data and results are provided in Appendix, Table A4.

The minimum non-renewable fossil energy use objective function shown in equation 3 calculated how much of the electricity was purchased from the grid and how much was generated from on-site solar panels, and nearby wind farms at the lowest total fossil energy used. $\underbrace{min}_{x} FE_{total} = FE_{mix(in)} \cdot x_1 + FE_{PV(out)} \cdot x_2 + FE_{wind(in)} \cdot x_3$ (3), where $\underbrace{min}_{x} FE_{total}$ is the total non-renewable fossil energy use. X_1, x_2, and x_3 were variables, which were calculated using the multi-objective optimization and represent share of grid, solar, and wind energy. $FE_{mix(in)}$,

$FE_{PV(out)}$, and $FE_{wind(in)}$ were non-renewable fossil energy coefficients (MJ/m^2) for grid, solar, and wind electricity from the cradle-to-gate LCA, as shown in Appendix, Table A1.

The minimum climate change impact objective function is shown in equation 4.

$\underbrace{min}_{x} CC_{total} = CC_{mix(in)} \cdot x_1 + CC_{PV(out)} \cdot x_2 + CC_{wind} \cdot x_3$ (4), where $\underbrace{min}_{x} CC_{total}$ was the total climate change impact, which showed how much of the purchased grid electricity and electricity generated from on-site solar and nearby wind farm was necessary to buy/produce to obtain the minimal climate change impact. X_1, x_2, and x_3 were variables, which were calculated using the multi-objective optimization, and represent shares of grid, solar, and wind energy. $CC_{mix(in)}$, $CC_{PV(out)}$, and $CC_{wind(in)}$ were coefficients for climate change impact of grid, solar, and wind electricity from the cradle-to-gate LCA, as shown in Appendix, Table A1.

4.4.4. Linear constraints

Bi-optimization and triple-optimization models had the only one linear inequality constraint, i.e. the source energy demand (E_{demand}) for each DC at different locations, as shown in the equation (5). The site and source energy for purchased grid electricity for each building were obtained from the EnergyPlus building simulation report. The site to source energy conversion factor depended on the energy mix in electricity generation and varied from 1.74 (Washington) to 3.63 (Texas). A conversion factor for the renewable electricity produced on-site was 1.1.

$E_{mix(in)} \left[\frac{MJ}{m^2}\right] \cdot x_1 + E_{PV(out)} \left[\frac{MJ}{m^2}\right] \cdot x_2 + E_{wind(in)} \left[\frac{MJ}{m^2}\right] \cdot x_3 \geq E_{demand}$ (5), where $E_{mix(in)}$, $E_{PV(out)}$, and $E_{wind(in)}$ were coefficients set to be equal or higher than defined source energy demand (E_{demand}). A source energy demand required by each DC in different locations was obtained from the building energy simulation tool EnergyPlus. The assumption was that there was sufficient source energy from the electricity grid, wind, or solar electricity, and each can be potentially a single source of electricity.

4.4.5. Lower and upper bounds

Lower bounds for a purchased grid, solar, and wind electricity expressed on the basis of the source energy were set to 0, as shown in equations 6, 7, and 8. Upper bounds for purchased grid electricity were 100%, i.e., equal to source energy demand, as shown in the equation 6. For solar electricity, upper bounds were chosen to be the maximum available source solar energy at the location, as shown in the equation 7. Finally, wind electricity upper bounds were an additional renewable energy necessary to achieve a zero energy building, as shown in equation 8. In case the DCs' solar energy can hypothetically replace 100% of purchased grid electricity, the wind electricity upper bound was set to 0. Calculations of site and source energy potential for solar and wind electricity are shown in the Appendix, Tables A2, A4, A5, and A6.

$$0 \le E_{mix(in)} \le E_{demand} \quad (6)$$

$$0 \le E_{PV(out)} \le \underbrace{E_{PV}}_{max} \quad (7)$$

$$0 \le E_{wind(in)} \le 100 - \underbrace{E_{PV}}_{max} = \underbrace{E_{wind}}_{max} \quad (8)$$

4.4.6. Goals

The goal attainment problem involves reducing the value objective function in order to attain the goal values given in a goal vector. Thus, instead of minimizing the cost and environmental objectives, we provided a target value for each objective. Target values for optimization were the minimal cost, minimal non-renewable energy, and minimal climate change impact for each location, as shown in the Appendix, Table A9. The Pareto-optimal solution also depended on the goal value; for example, if the cost of wind energy was lower compared to cost of purchased electricity from the grid, the Pareto-frontier showed a different behavior than whenever the cost of wind energy was higher than purchased from the grid.

4.4.7. Weights

In most real-life problems, defined goals are not achievable. In the goal optimization each objective needs to be weighted. An appropriate set of weights (w_1 and w_2 for bi-objective, and w_1, w_2, w_3 for triple-objective optimization) needed to be defined for each objective. Weights provided a Pareto-optimal set of solutions that reflected the most desirable tradeoffs between the two and three objectives. We defined 50 arbitrary points and weights for the bi-objective optimization and 10 arbitrary points and weights combinations for the triple-optimization model. The weight vectors for the bi-objective and triple-objective optimization were defined in equations 9 and 10, respectively. The number of Pareto-optimal results was ≤ 50 for the bi-objective and ≤ 10 for triple-objective optimization. This was because not all solutions were Pareto-optimal. Also, duplicate results may have appeared for multiple weights. Duplicate results for different weights were excluded from charts. Each Pareto-optimal solution represented a mix of purchased grid, solar, and wind energy. The percent values were used to build Pareto LCA models. The assigned DC uncertainty was equal to the baseline. The Pareto LCA models were compared to the baseline LCA model using the Monte Carlo pairwise comparison to find the cost-effective and superior Pareto-optimal solution.

$\sum_{i=0}^{2} w_i = 1, w_i \geq 0$ (9)

Weight = [w_{cost}, $w_{non\text{-}renewable\ fossil}$]= [$w_{cost}$, $w_{climate\ change}$] [1]

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[1] [0.02, 0.98; 0.04, 0.96; 0.06, 0.94; 0.08, 0.92; 0.1, 0.9; 0.12, 0.88; 0.14, 0.86; 0.18, 0.82; 0.16, 0.84; 0.2, 0.8; 0.22, 0.78; 0.24, 0.76; 0.26, 0.74; 0.28, 0.72; 0.3, 0.7; 0.32, 0.68; 0.34, 0.66; 0.36, 0.64; 0.38, 0.62; 0.4, 0.6; 0.42, 0.58; 0.44, 0.56; 0.46, 0.54; 0.48, 0.52; 0.5, 0.5; 0.52, 0.48; 0.54, 0.46; 0.56, 0.44; 0.58, 0.42; 0.6, 0.4; 0.62, 0.38; 0.64, 0.36; 0.66, 0.34; 0.68, 0.32; 0.7, 0.3; 0.72, 0.28; 0.74, 0.26; 0.76, 0.24;

$\sum_{i=0}^{3} w_i = 1, w_i \geq 0$ (10)

Weight = [w_{cost}, $w_{non\text{-}renewable\ fossil}$, $w_{climate\ change}$] [2]

Bi-optimization and triple-optimization Matlab codes are reported in the Appendix. Also, Matlab input files were submitted to Mendeley data.

4.4.8. Life cycle impact assessment method

The non-renewable fossil energy use was calculated using upper heating values of fossil fuel resources. Characterization factors for the non-renewable fossil energy use are reported in the Cumulative Energy Demand (CED) method (M. a J. Huijbregts et al. 2006; Hischier et al. 2010). By definition, the non-renewable fossil energy use includes lifecycle direct and indirect fossil energy and energy consumed during the extraction, manufacturing, and disposal of the raw and auxiliary materials. The Intergovernmental Panel on Climate Change (IPCC) climate change characterization factors with a timeframe of 100 years were used to calculate the climate change impact (Hodnebrog et al. 2013).

4.4.9. Monte Carlo uncertainty analysis

Relative differences in environmental impacts result between DCs were not enough to support informed decision making due to uncertainty in LCIA results. Uncertainty in environmnetal impacts can overpower the relative difference between different DCs. Quantification of uncertainties in LCI input data supports informed decision making. LCIA results depend on input parameters including LCI input data and characterization factors. Both LCI input data and characterization factors had a degree of uncertainty, which may be due to

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0.78, 0.22; 0.8, 0.2; 0.82, 0.18; 0.84, 0.16; 0.86, 0.14; 0.88, 0.12; 0.9, 0.1; 0.92, 0.08; 0.94, 0.06; 0.96, 0.04; 0.98, 0.02]

[2] [0.25,0.25,0.5; 0.25,0.5,0.25; 0.5, 0.25, 0.25; 0.2,0.2,0.6; 0.2,0.6,0.2; 0.6,0.2,0.2; 0.1,0.1,0.8; 0.1,0.8,0.1; 0.8,0.1,0.1]

lack of knowledge regarding input data or due to inherent variability of the data. Both can be described by a probability distribution. Because of uncertainty in input data, there was not a single number to represent the potential environmental impacts of DCs. At present, the uncertainty analysis helps us understand to what extent results of an LCA were affected by uncertainty of input parameters. Uncertainty of characterization factors is not yet implemented in the SimaPro© 8.4 software (PRé Consultants 2015). Thus, we can only show a distribution of LCA results due to uncertainty of LCI input parameters. A typical method to calculate uncertainty of the LCIA results due to input parameters is the Monte Carlo uncertainty analysis. The Monte Carlo uncertainty analysis randomly samples the input data space.

The LCI of electricity generation in different states in building models originated from the DataSmart database, which was described in our previous work (Burek and Nutter 2018b; LTS 2016). The US-EI database is a modified Ecoinvent v2.2 databases with most European electricity unit processes replaced by the U.S. electricity mix. DataSmart database added state-level electricity production LCA models and uncertainty analysis based on the national statistics and approximation with the Ecoinvent 2 database (LTS 2016).

For input parameters originated from the EnergyPlus building simulation model (Burek and Nutter 2018b), the uncertainty was based on the published work (Eisenhower et al. 2011). EnergyPlus building simulations contain 1,000s parameters, which can be a source of uncertainties (Eisenhower et al. 2011). Authors studied the influence of 1,000 input parameters on output results in EnergyPlus models. The input parameters were varied ± 20% of their modeling value. The research identified which internal or intermediate processes transmit the most uncertainty to the final output (Eisenhower et al. 2011). Authors used quasi-random sampling and a uniform distribution for all nonzero parameters, and exponential distribution for parameters with zero nominal values (Eisenhower et al. 2011). The standard deviations in annual consumption (%) were used to calculate minimum and maximum uncertainty values of the LCI input data including HVAC, lighting, equipment, and refrigeration (Eisenhower et al. 2011). Uniform distribution was adopted as in Eisenhower et al. (2011) (Eisenhower et al. 2011).

We calculated a distribution range for other LCI input parameters including conveyor, size of the building, refrigerant loss, and water consumption. For the size of the building and the length of conveyor, we used the range reported for the Walmart Inc. Stores DC network. For the envelope material, the LCI uncertainty was calculated using the guidance on quantitative inventory uncertainty (Greenhouse Gas Protocol 2007). We kept the shape and orientation of the DC constant in accordance to research published by Eisenhower et al. (2011) (Eisenhower et al. 2011). The uncertainty values for input LCI parameters are reported in Table 1.

Table 1. Uncertainty assigned to LCI input data.

LCI input data	Reference	Distribution	Standard deviation (SD^2)
DataSmart			
Electricity mix	National statistics	Lognormal	1.5
Transmission	(Frischknecht et al. 2007)	Lognormal	2.0
Solar energy (flat roof panels)	(Frischknecht et al. 2007)	Lognormal	1.1
Wind energy (onshore)	(Frischknecht et al. 2007)	Lognormal	1.3
Wind energy (offshore)	(Frischknecht et al. 2007)	Lognormal	1.3
EnergyPlus			Relative standard deviation (%)
HVAC (GJ)	(Eisenhower et al. 2011)	Uniform	12%
Electricity (GJ)	(Eisenhower et al. 2011)	Uniform	7.5%
Heating (GJ)	(Eisenhower et al. 2011)	Uniform	10%
Interior equipment (GJ)	(Eisenhower et al. 2011)	Uniform	5.0%
Interior lights (GJ)	(Eisenhower et al. 2011)	Uniform	6.5%
Cooling (GJ)	(Eisenhower et al. 2011)	Uniform	22%
Pumps (GJ)	(Eisenhower et al. 2011)	Uniform	10%
Fans (GJ)	(Eisenhower et al. 2011)	Uniform	12%
Refrigeration (GJ)	(Eisenhower et al. 2011)	Uniform	16%
Other			
Conveyor (km)	calculated[1]	Uniform	23%
Conveyor energy use (kWh/km)	assumed	Uniform	20%
Envelope material (kg)	assumed	Uniform	20%
Refrigerant loss (kg)	assumed	Uniform	20%
Water consumption (m^3)	calculated[2]	Uniform	5.7%

[1]Relative standard deviation– standard deviation of the conveyor sample divided by the mean
[2]Relative standard deviation – standard deviation of the water consumption of walk-in units, cases, and dock divided by the mean

4.4.10. Monte Carlo pairwise comparison

The scope of this work also included comparative assertions based on a) the Monte Carlo pairwise comparison between the baseline DC network and b) the Monte Carlo pairwise comparison between the baseline DC and the Pareto optimal set of results for the same DC. The Monte Carlo pairwise comparison considered a cradle-to-grave LCA, which accounted for the electricity production uncertainty and the EnergyPlus model uncertainty (Eisenhower et al. 2011). Requirements to perform a pairwise Monte Carlo comparison and to provide comparative assertions were fulfilled (Weidema 1997). Comparative assertions were justifiable because (1) there were no data gaps in models, (2) the choice of environmental categories was appropriate in relation to the goal of the study to reduce fossil energy consumption and climate change impact, (3) modelled data was precise compared to the database, (4) data were complete and representative, (5) LCA models were consistent, (6) input data collected, data treatment, and results were reproducible. These data properties and models guaranteed that the comparison was fair and equivalent for building alternatives.

Because of uncertainty in the LCA models, the building with lower environmental impacts does not guarantee that it is better than the building with higher environmental impacts. In other words, they might not be statistically different due to uncertainty in input data. To prove, (1) that one building in a state is statistically different, i.e., superior, to others in the same state or in different states and (2) that baseline building is statistically different than its alternative solution; we used the Monte Carlo pairwise comparison. The Monte Carlo pairwise comparison compared all 1 to X number of solutions under uncertainty for pairs (1) or (2) under consideration, which enabled a true comparison and finding alternatives that are superior, and thus, considered better from the environmental impact perspective. One LCA model can have

7,000 processes with assigned uncertainties. All processes, typically the background process such as electricity generation, which pairs share, are fixed to same value during the comparison. As a rule of thumb, we choose X to be 1,000 Monte Carlo comparisons. In each run, the baseline or alternative LCA model may have higher or lower environmental impacts. They can also have lower environmental impact in one impact category and higher in others. The model counts how many times the baseline building has lower environmental impacts and how many times the alternative for each impact category. If 90% of time out of 100%, the baseline building has higher environmental impacts than alternative, we can say with 90% confidence that the alternative system is superior to the baseline for those impact categories. If the result is less than 90% for either of buildings, we say it is inconclusive or buildings are not different in terms of their environmental impacts even though one may have lower impact in the LCIA step of the analysis.

4.4.11. The Monte Carlo comparison of GMDCs, PDCs, and GDCs

First the Monte Carlo pairwise comparison was performed between each pair of baseline scenario. GMDCs were compared to other GMDCs, GDCs were compared to other GDCs, and PDCs were compared to other PDCs. The purpose of the Monte Carlo pairwise comparisons of the baseline DCs was to find DC locations for which reduction in environmental impacts should be a priority. The Monte Carlo pairwise comparison provided information if one DC had a statistically different environmental impact compared to other DCs in the network. For example, did the DC A in one state had a statistically lower climate change impact from the DC B, which was the same type of DC located in the same or a different state. The Monte Carlo pairwise analysis was run 1,000 times. If the DC A had 90% out of 1,000 runs of the time a lower LCIA result than the DC B, then DC A was superior to DC B. If the DC A had 90% out of 1,000 runs of the time higher LCIA result than DC B, then the DC A was inferior to the DC B.

4.4.12. The Monte Carlo comparison of baseline and alternative solutions

The multi-objective optimization provided 10 to 20 alternative solutions for each building. After obtaining Pareto optimal solutions for each building, the baseline scenario was compared to Pareto-optimal solutions to find the closest alternative optimal solution, which is superior to the baseline. This process was iterative until a superior Pareto-optimal solution was found for each DC.

4.4.13. The good, the better, and the zero DC network

A further analysis of Pareto-optimal results was necessary to narrow down results to two different DC solutions from the Pareto frontier, which abide to two criteria. We used the better building and the zero energy building criteria to find the best individual DCs and identify tradeoffs of those solutions. The better building criterion was an LCA-based criterion for superiority of one building over another.

Relative differences in environmental impacts between the baseline DC and Pareto-optimal alternatives were not enough to support informed decision making. Monte Carlo pairwise comparisons of baseline DCs and Pareto-optimal solutions support informed decision making. To find the better DCs, a Monte Carlo pairwise comparison of the baseline DC and Pareto DC models were used. Pareto-optimal DCs based on bi-objective and triple-objective optimization were compared to the baseline DC starting from the Pareto-optimal solution which yielded the lowest cost to assure that the selected better building was also cost-effective. The better DC was the first Pareto-optimal DC building that showed superiority in both climate change impact and non-renewable fossil energy use when a Pareto LCA model was compared to a baseline LCA model via Monte Carlo pairwise comparison.

The term zero energy building has been used for over 20 years, but no common definition had been established. The U.S. Department of Energy (DOE) evaluated current definitions and solicited industry input to formulate a common definition and nomenclature for zero energy buildings (Peterson, Taylor, and Grant 2016). According to the DOE, the zero energy building was defined as an energy-efficient building where, on a source energy basis, the actual annual delivered energy was less than or equal to the on-site renewable exported energy (Peterson, Taylor, and Grant 2016). Different renewable energy combinations can be used to achieve zero energy targets in buildings. However, we were interested in solutions that will have the minimal cost, minimal non-renewable energy, and minimal climate change impact. Thus, we expanded upon the DOE definition and evaluated only zero energy results obtained by the multi-objective optimization, i.e., the Pareto-optimal zero energy building.

The authors propose two other definitions: the better building and the good building. The better building was a Pareto-optimal set of buildings, which showed demonstrated superiority compared to the baseline building from the LCA perspective. The superiority in the LCA assessment was defined by a comparative assertion, an environmental claim regarding the superiority or equivalence of one product versus a competing product that performs the same function. In the LCA, the superiority of the one LCA model in one or more impact categories was evaluated by Monte Carlo pairwise comparison. The good DCs were characterized by Pareto-optimal solutions between baseline and better buildings. Thus, the results of the bi- and triple-objective optimization were Pareto-optimal solutions obtained by weighting importance of criteria; i.e., from the baseline DC network, the good DC network, the better DC network, to the zero energy DC network.

4.5. Results and discussion

4.5.1. The Monte Carlo uncertainty analysis

We used 1,000 Monte Carlo uncertainty runs to calculate environmental impacts' distribution and 95% confidence interval of the LCIA results. Individual box-and-whisker plots in Figure 3 show Monte Carlo uncertainty results for baseline cradle-to-grave LCIA results of GDCs, GMDCs, and PDCs. The box plot shows the first and third quartile also called the 25th and 75th percentile. The thick black line of contact of two quartiles is the mean value. The interval between the upper and lower whisker shows the maximum extent of the Monte Carlo uncertainty results for each DC type. The size of the box-and-whisker plots was similar across different states and DC type.

The mean value in Figure 3 shows that GDCs, GMDCs, and PDCs, have different climate change impact. This is because GMDCs, PDCs, and GDCs have different operations: GMDCs are non-refrigerated buildings with conveyors, GDCs are in part refrigerated and in part non-refrigerated, and PDCs are only refrigerated. Refrigerated PDCs and GDCs have a higher climate change impact than GMDCs (Burek and Nutter 2018b). Within the same type of DCs, mean values also showed a different climate change impact (Burek and Nutter 2018b), as shown in Figure 3. The state-level differences originated largely in the energy mix used to generate electricity in each state. Other differences were due to different lengths of conveyor, climate zone, and building age (Burek and Nutter 2018b). Some DCs showed overlapping or similar range of the climate change impact, for example, GDCs in Bartsville, Oklahoma and Clarksville, Arkansas, others showed different range, for example, the GDC in Grandview, Washington, as shown in Figure 3. However, this was not enough to make a comparative assertion about the superiority of the GDC in Grandview, Washington. The Monte Carlo pairwise comparison was needed to reaffirm that Grandview, Washington was statistically different, and thus, superior to other GDCs. The LCIA results for other impact categories were discussed in Burek and Nutter (Burek and Nutter 2018b).

The primary uncertainty in LCIA results originated from uncertainty in input parameters used in electricity generation and not from the uncertainty originated in EnergyPlus models. The GDC in Washington and the GMDC in Oregon had the lowest impact to climate change, which was linked (1) to 36% - 70% natural gas and 4% hydropower in electricity generation fuel profile (2) and was to a lower energy demand due to cold climate zone. The minimum and maximum values (whiskers) for climate change impact of GDCs and PDCs were 25 and 4,554 kg CO_2-eq/m^2, respectively, as shown in Figures 3a and 3b. For GMDCs, the range of climate change impact was from 14 to 996 kg CO_2-eq/m^2, as shown in Figure 3c.

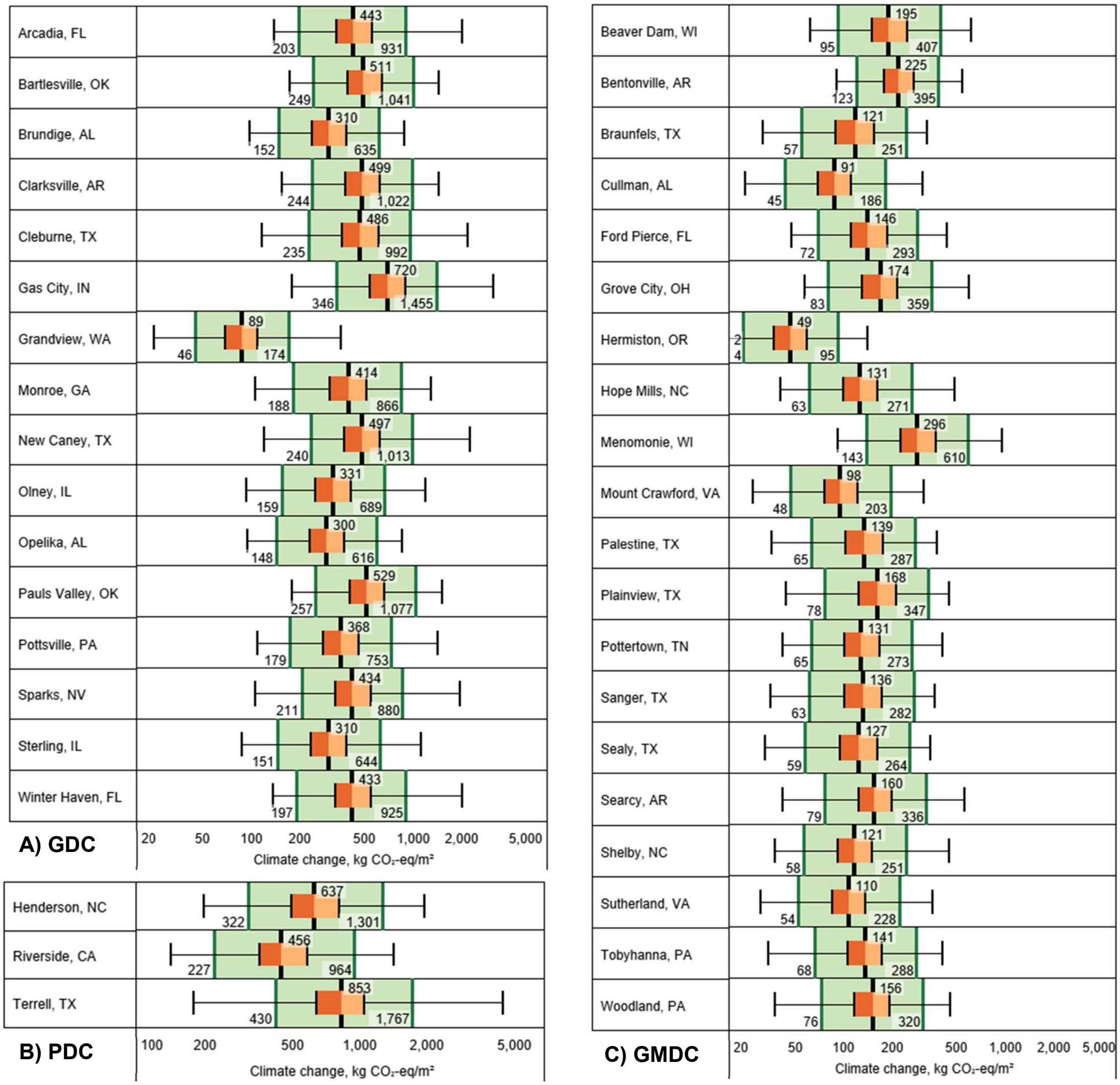


Figure 3. Box-and-whisker plot cradle-to-grave LCIA results uncertainty analysis results for baseline A) GDCs, B) GMDCs, and C) PDCs, based on distribution range in Table 1. A thick black line is the mean value. Lower and upper whiskers are the maximum extent of the Monte Carlo results. The green area is the width of the 95% confidence interval bounded by the 5th (2.5%) and 95th (97.5%) percentile. The box plot shows the first and third quartile also called the 25th (dark orange) and 75th percentile (light orange). The x-axis is in logarithmic scale.

4.5.2. The Monte Carlo pairwise comparison

The results of Monte Carlo pairwise comparisons for the climate change impact category are shown in Tables 2 and 3. Pairs for the Monte Carlo comparison were all taken from the baseline scenarios for PDCs, GMDCs, and GDCs, and thus, the Monte Carlo pairwise comparison was conducted between the baseline whole-building LCA model for one location and the baseline LCA model of the building located in the same state or in a different state. The results of Monte Carlo comparisons proved or dismissed differences in the climate change impact observed in Figure 3. Also, it identified buildings that perform worse than others in the network and needed to be improved first. We choose only one impact category because reducing climate change impact will reduce other environmental impacts. The main impact driver in all impact categories was electricity, which we showed in the previous study (Burek and Nutter 2018b).

All DCs in rows (A) were compared to DCs in columns (B), as shown in Tables 2 and 3. The result of each Monte Carlo comparison was reported in non-diagonal boxes. The Monte Carlo comparison of the GDC in Brundidge, Alabama was statistically different and had a lower climate change impact compared to the GDC in Park Way, Indiana, which was highlighted by a green color and annotated with the less than (<) symbol in the Table 2. Also, the GDC in Brundidge, Alabama was statistically different and had a higher climate change impact compared to the GDC in Grandview, Washington, which was highlighted by the red color and annotated with the greater than (>) symbol. A summary of pairwise comparisons was given in diagonal squares. Squares' color and symbols showed whether a DC in the row A was superior, inferior or equal to a DC in the column B. The green square and less than (<) symbol meant that the climate change impact of the DC in the row A was 90% of time less than impact of the DC in the column B. The red square and greater than (>) symbol meant that the climate change impact of the DC in the row A was 90% of the time higher than the impact of the DC in the column B. Orange squares and = symbols meant that the impact of the DC in row A was not statistically different from the DC in column B. Colored diagonal squares showed the dominant and conclusive characteristic (superior, inferior, and equal) of the DC in the row A. Numbers in black framed squares showed how many times the DC in the row A was superior, inferior or both compared to the DC in the column B.

The results of Monte Carlo pairwise comparison of baseline DCs in different states proved with the 90% confidence that the GDC in Washington was superior to other GDCs and the GMDC in Oregon was superior to other GMDCs, as shown in Table 2 and Table 3, respectively. The GDC in Indiana had statistically higher impact compared to GDCs in Alabama, Pennsylvania, Illinois, and Washington. The PDC in California was superior compared to the PDC in Missouri. Arkansas, Ohio, and Wisconsin. In Texas, the GMDC in Plainview was inferior to GMDCs in Braunfels and Sealy. Other results were inconclusive, i.e., the LCIA impact of DC A was not statistically different from DC B, as shown by the prevalence of orange and = symbol squares. Thus, primary efforts to reduce climate change impact should focus on DC locations in Arkansas, Indiana, Ohio, and Wisconsin.

Table 2. LCA-based Monte Carlo pairwise comparison between baseline GDCs in different states.

GDCs A - rows B - columns	Brundidge, AL	Opelika, AL	Clarksville, AR	Arcadia, FL	Winter Haven, FL	Monroe, GA	Olney, IL	Sterling IL	Gas City, IN	Sparks, NV	Bartlesville, OK	Pauls Valley, OK	Pottsville, PA	Cleburne, TX	New Caney, TX	Grandview, WA
Brundidge, AL	**1/1**	=	=	=	=	=	=	=	<	=	=	=	=	=	=	>
Opelika, AL	=	**1/1**	=	=	=	=	=	=	<	=	=	=	=	=	=	>
Clarksville, AR	=	=	**1**	=	=	=	=	=	=	=	=	=	=	=	=	>
Arcadia, FL	=	=	=	**1**	=	=	=	=	=	=	=	=	=	=	=	>
Winter Haven, FL	=	=	=	=	**1**	=	=	=	=	=	=	=	=	=	=	>
Monroe, GA	=	=	=	=	=	**1**	=	=	=	=	=	=	=	=	=	>
Olney, IL	=	=	=	=	=	=	**1/1**	=	<	=	=	=	=	=	=	>
Sterling IL	=	=	=	=	=	=	=	**1/1**	<	=	=	=	=	=	=	>
Gas City, IN	>	>	=	=	=	=	>	>	**6**	=	=	=	>	=	=	>
Sparks, NV	=	=	=	=	=	=	=	=	=	**1**	=	=	=	=	=	>
Bartlesville, OK	=	=	=	=	=	=	=	=	=	=	**1**	=	=	=	=	>
Pauls Valley, OK	=	=	=	=	=	=	=	=	=	=	=	**1**	=	=	=	>
Pottsville, PA	=	=	=	=	=	=	=	=	<	=	=	=	**1/1**	=	=	>
Cleburne, TX	=	=	=	=	=	=	=	=	=	=	=	=	=	**1**	=	>
New Caney, TX	=	=	=	=	=	=	=	=	=	=	=	=	=	=	**1**	>
Grandview, WA	<	<	<	<	<	<	<	<	<	<	<	<	<	<	<	**15**

< A has statistically significant lower impact than B in climate change impact category. More than 90% of the time A result has a lower impact than B. Thus, A is superior to B

>A has statistically significant higher impact than B in climate change impact category. More than 90% of time A result has higher climate change impact than B. Thus, A is inferior compared to B.

= Inconclusive. A is not environmentally superior to B in climate change impact category.

Color legend: red – inferior, yellow – equal/inconclusive, and green – superior.

Numbers in diagonals show how many times certain building is superior (green) and inferior (red), mostly superior (green/red), equal (yellow) to other buildings.

Table 3. LCA-based Monte Carlo pairwise comparison between baseline GMDCs in different states.

GMDCs A - rows B - columns	Cullman, AL	Bentonville, AR	Searcy, AR	Ford Pierce, FL	Shelby, NC	Hope Mills, NC	Grove City, OH	Hermiston, OR	Woodland, PA	Tobyhanna, PA	Pottertown, TN	Braunfels, TX	Palestine, TX	Plainview, TX	Sanger, TX	Sealy, TX	Mount Crawford, VA	Sutherland, VA	Beaver Dam, WI	Menomonie, WI
Cullman, AL	**4/1**	<	=	=	=	=	<	>	=	=	=	=	=	=	=	=	=	=	<	<
Bentonville, AR	>	**6**	=	=	>	=	=	>	=	=	=	>	=	=	=	=	>	>	=	=
Searcy, AR	=	=	**1**	=	=	=	=	>	=	=	=	=	=	=	=	=	=	=	=	=
Ford Pierce, FL	=	=	=	**1/1**	=	=	=	>	=	=	=	=	=	=	=	=	=	=	=	<
Shelby, NC	=	<	=	=	**2/1**	=	=	>	=	=	=	=	=	=	=	=	=	=	=	<
Hope Mills, NC	=	=	=	=	=	**1/1**	=	>	=	=	=	=	=	=	=	=	=	=	=	<
Grove City, OH	>	=	=	=	=	=	**2**	>	=	=	=	=	=	=	=	=	=	=	=	=
Hermiston, OR	<	<	<	<	<	<	<	**19**	<	<	<	<	<	<	<	<	<	<	<	<
Woodland, PA	=	=	=	=	=	=	=	>	**1**	=	=	=	=	=	=	=	=	=	=	=
Tobyhanna, PA	=	=	=	=	=	=	=	>	=	**1/1**	=	=	=	=	=	=	=	=	=	<
Pottertown, TN	=	=	=	=	=	=	=	>	=	=	**1/1**	=	=	=	=	=	=	=	=	<
Braunfels, TX	=	<	=	=	=	=	=	>	=	=	=	**3/1**	=	<	=	=	=	=	=	<
Palestine, TX	=	=	=	=	=	=	=	>	=	=	=	=	**1/1**	=	=	=	=	=	=	<
Plainview, TX	=	=	=	=	=	=	=	>	=	=	=	>	=	**3**	=	>	=	=	=	=
Sanger, TX	=	=	=	=	=	=	=	>	=	=	=	=	=	=	**1/1**	=	=	=	=	<
Sealy, TX	=	=	=	=	=	=	=	>	=	=	=	=	=	<	=	**2/1**	=	=	=	<
Mount Crawford, VA	=	<	=	=	=	=	=	>	=	=	=	=	=	=	=	=	**3/1**	=	<	<
Sutherland, VA	=	<	=	=	=	=	=	>	=	=	=	=	=	=	=	=	=	**2/1**	=	<
Beaver Dam, WI	>	=	=	=	=	=	=	>	=	=	=	=	=	=	=	=	>	=	**3/1**	<
Menomonie, WI	>	=	=	>	>	>	=	>	=	>	>	>	>	=	>	>	>	>	>	**1 4**

< A has statistically significant lower impact than B in climate change impact category. More than 90% of the time A result has a lower impact than B. Thus, A is superior to B
>A has statistically significant higher impact than B in climate change impact category. More than 90% of time A result has higher climate change impact than B. Thus, A is inferior compared to B.
= Inconclusive. A is not environmentally superior to B in climate change impact category.
Color legend: red – inferior, yellow – equal/inconclusive, and green – superior.
Numbers in diagonals show how many times certain building is superior (green) and inferior (red), mostly superior (green/red), equal (yellow) to other buildings.

4.5.3. The good, the better, and the zero energy distribution center network

Pareto-optimal sets were results obtained by weighting objectives' importance. The model was designed to give a set of 50 results, but the actual results were less than 50. Summary results of bi-objective and triple-objective optimization were presented in the 2D Pareto front chart in Figure 4. A Pareto front was annotated with the arrow going through the center of a pie, as shown in the Figure 4a. The size of the pie does not show any particular metric in the Figure 4. One pie was larger to highlight the firs Pareto-optimal solution for which the improved building is better than the baseline. All subsequent pies to the right are also better, but the highlighted one has the lowest cost, as shown in Figure 4a. The x-axis shows costs ($\$/m^2$) of each Pareto-optimal solution, and the y-axis shows climate change impact (CO_2-eq/m^2). Weighting was given for 50 points, but some weighting combinations did not yield a Pareto-optimal result. The bi-objective (cost and non-renewable fossil energy use) optimization and triple-objective (cost, non-renewable fossil energy, and climate change) optimization results were plotted in the bi-objective (cost climate change impact) chart due to results similarity, as shown, in Figure 4. However, the bi-objective cost and non-renewable optimization results and triple-objective optimization results were less dense than the bi-objective cost and climate change impact results (i.e., the number of Pareto-optimal results was lower than for bi-objective cost and climate change optimization), as shown in the Appendix, Figures A10 and A11. Numerical results for the individual bi-optimization (cost and non-renewable fossil energy and cost and climate change) and the triple-optimization (cost, non-renewable fossil energy, and climate change) are shown in the Appendix, Excel document "Pareto front numerical results.xlsx".

Pie slices show shares of energy sources (purchased grid, solar, and wind) for different objectives' weighting combinations, which satisfy energy demand of DCs in different locations. The areas of the pies in the Figure 4 do not show any particular metric, but one pie was bigger than all other to highlight the first Pareto solution, which compared to the baseline was 90% of times superior (better) according to the result of the Monte Carlo pairwise comparison. The baseline solution in most cases was an optimal result for a single-objective optimization with 100% purchased grid electricity, in which the objective was only to minimize cost. For several locations including Brundidge (AL), Clarksville (AR), Riverside (CA), Winter Haven (FL), Sterling (IL), Olney (IL), Gas City (IN), Grove City (OH), Bartlesville (OK), Pottsville (PA), Woodland (PA), Tobyhanna (PA), Terrell (TX), and Menomonie (WI), the baseline solution was not a part of the optimal result because the purchased grid electricity ($\$/m^2$) had a higher cost than the purchased off-site wind electricity, as shown in the Appendix, Table A1. Thus, baseline solutions were added to the Pareto-optimal results in Figures 4b, 4d, 4b, and 4d.

Highlighted pies in Figure 4a with a diameter bigger than other pies show the better DC result, which has combined properties of a Pareto-optimality and LCA-based Monte Carlo superiority. The last pie to the right is the Pareto-optimal result for zero energy DC, as shown in Figure 4a. All pies between the better DC and the zero energy DC had properties of the better DC, but the solution was more expensive, as shown in Figure 4a. Finally, because of the better DC definition, another set of DCs were the good DCs, which were Pareto-optimal cost-effective solutions, but which were not superior compared to the baseline DC, as shown in Figure 3a. Thus, the environmental performance and energy reduction achieved is not statistically different than the baseline building.

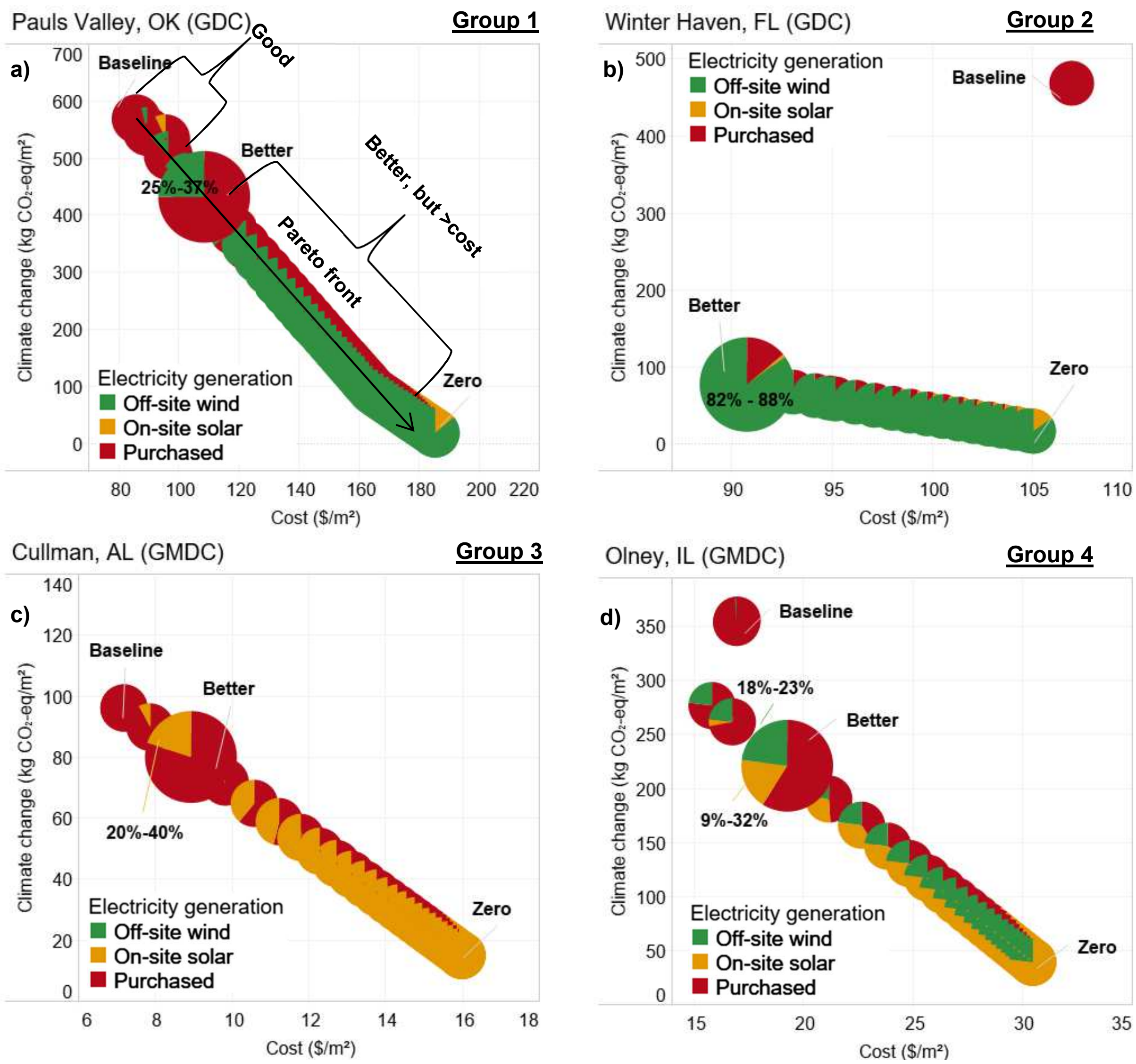
Results in Figures 4a, 4b, 4c, and 4d were for a single DC as annotated in the figure title, but similar Pareto-results were found for multiple buildings, and thus, this result was representative for multiple buildings annotated as Group 1, Group 2, Group 3, and Group 4. Individual Pareto-front results for DCs are reported in Appendix, Figures A1, A2, A3, A4, A5, A6, A7, A8, and A9. Results in Figures 5a, 5b, 5c, and 5d are for single DCs.

Group 1 showed uniform distribution of Pareto-optimal results for cost and climate change impact optimization. The results for the triple-objective optimization started at a cost value higher than 177 $\$/m^2$ and overlapped with results of the bi-objective optimization. This was due to a result gap for cost range starting from 110$\$/m^2$ to 130$\$/m^2$, for which the non-renewable fossil energy criteria was not calculated. Single results for Opelika (AL), Monroe (GA), New Caney (TX), Cleburne (TX), and Pauls Valley (OK) of Group 1 are shown in Appendix, Figures A1 and A2. Numerical results are presented in Appendix, Excel document "Pareto front numerical results.xlsx". The highlighted pie in Group 1 shows the better DC result. The better DCs in Group 1 was achieved by purchasing 25-37% of off-site wind energy from the nearest location. The Pareto-optimal zero energy DCs included more than 86% wind energy and 14% solar, which was at the maximal solar energy potential that GDCs in Group 1 can produce via on-site roof panels. Arcadia (FL) GMD had a similar Pareto-pies distribution and an equal zero DC profile to Group 1, but a better building included 10% solar and 13% wind energy, as shown in Figure 5a. For Sparks (NV), Grandview (WA), and Henderson (NC) same conclusions were valid as for Group 1, but the Pareto-front distribution was steeper than for DCs in Group 1, as shown in Appendix, Figure A1 and A2.

In Group 2, all GDCs and PDCs locations had a lower wind energy cost than the purchased grid electricity. Thus, the Pareto-optimal better DC was also the lowest cost option in which 82-88% electricity was supplied by wind farms. The zero energy DCs had a maximal available energy from solar panels and remaining energy from wind. For GDCs in Winter Haven (FL), Sterling (IL), and Gas City (IN) and PDC in Riverside (CA), the Pareto-optimal zero energy solution had a lower cost compared to the baseline. Individual results for GDCs and PDCs are shown in Appendix, Table A3 and A4.

All solutions for GMDCs in Group 3 produced enough electricity from solar panels to become zero energy DCs. The zero energy DC solution assumed between 64% and 93% of solar energy installation capacity. If maximum solar capacity was installed, GMDCs in Group 3 could export between 7.2% (Cullman, AL) and 92% (Searcy, AR) electricity to the energy grid, which would reduce the cost of the zero energy DC. The better DCs must have at least 20% (Cullman, AL) up to 40% (Bentonville, AR) energy coming from solar panels. Individual results are provided in the Appendix, Figures A5 and A6. The GMDC in Midway (TN) had an equal zero energy DC profile compared to the Group 3 (i.e., 100% energy was from solar panels). However, the better building in Midway (TN) required only 5% energy from solar panels, as shown in Figure 5d.

GMDCs in Group 4 did not produce enough solar energy to reach the zero energy building. The better DCs had between 5% (Woodland, PA) and 32% (Grove City, Ohio) of the on-site solar energy production and from 18% (Tobyhanna, PA) to 23% (Olney, IL) of off-site wind energy, which resulted in \$1 to \$2 increase in cost, as shown in the Appendix, Figure A7. The zero energy DCs had between 77% and 82% electricity produced from the maximum potential energy from solar panels and the remaining electricity was supplied by wind farms. The better GMDC at Menomonie (WI) required more than 50% renewable energy, i.e., 47% from wind and 6% from solar energy. The maximum solar energy potential was higher than 50% of the total source energy demand, and thus, the zero energy building had solar energy at the maximum value. The better GMDC in Hermiston (OR) had 32% energy supplied by solar panels and 6% by wind. Again, the zero energy DC profile was equal to the maximum solar energy potential of 94%, as shown in Figure 5c.



Group1: GDCs in Opelika (AL), Arcadia (FL), Monroe (GA), Sparks (NV), Pauls Valley (OK), New Caney (TX), Cleburne (TX), and Grandview (WA) and a PDC in Henderson (NC).
Group 2: GDCs in Brundidge (AL), Clarksville (AR), Winter Haven (FL), Sterling (IL), Gas City (IN), Henderson (NC), Sparks (NV), Bartlesville (OK), Pottsville (PA), and Grandview (WA) and PDCs in Riverside (CA) and Terrell (TX)
Group 3: GMDCs in Bentonville (AR), Cullman (AL), Searcy (AR), Fort Pierce (FL), Hope Mills (NC), Mount Crawford (VA), Sutherland (VA), New Braunfels (TX), Palestine (TX), Plainview (TX), Shelby (TX), Sanger (TX), Sealy (TX), Beaver Dam (WI)
Group 4: Olney (IL), Grove City (OH), and Tobyhanna (PA), Woodland (PA)

Figure 4. Combined bi-objective and triple-objective optimization Pareto-optimal results for GDCs, PDCs, and GMDCs. The 2-objective optimization included cost ($/m^2) on x-axis and climate change impact (kg CO_2-eq/m^2) on y-axis. The 3-objective optimization included cost ($/m^2), climate change impact (kg CO_2-eq/m^2), and non-renewable fossil energy ($MJ_{deprived}$/m^2), but is plotted as a projection in a 2D cost-climate change chart. Highlighted pies are Pareto-optimal better DCs results. The last pies on the right are Pareto-optimal zero energy DCs.

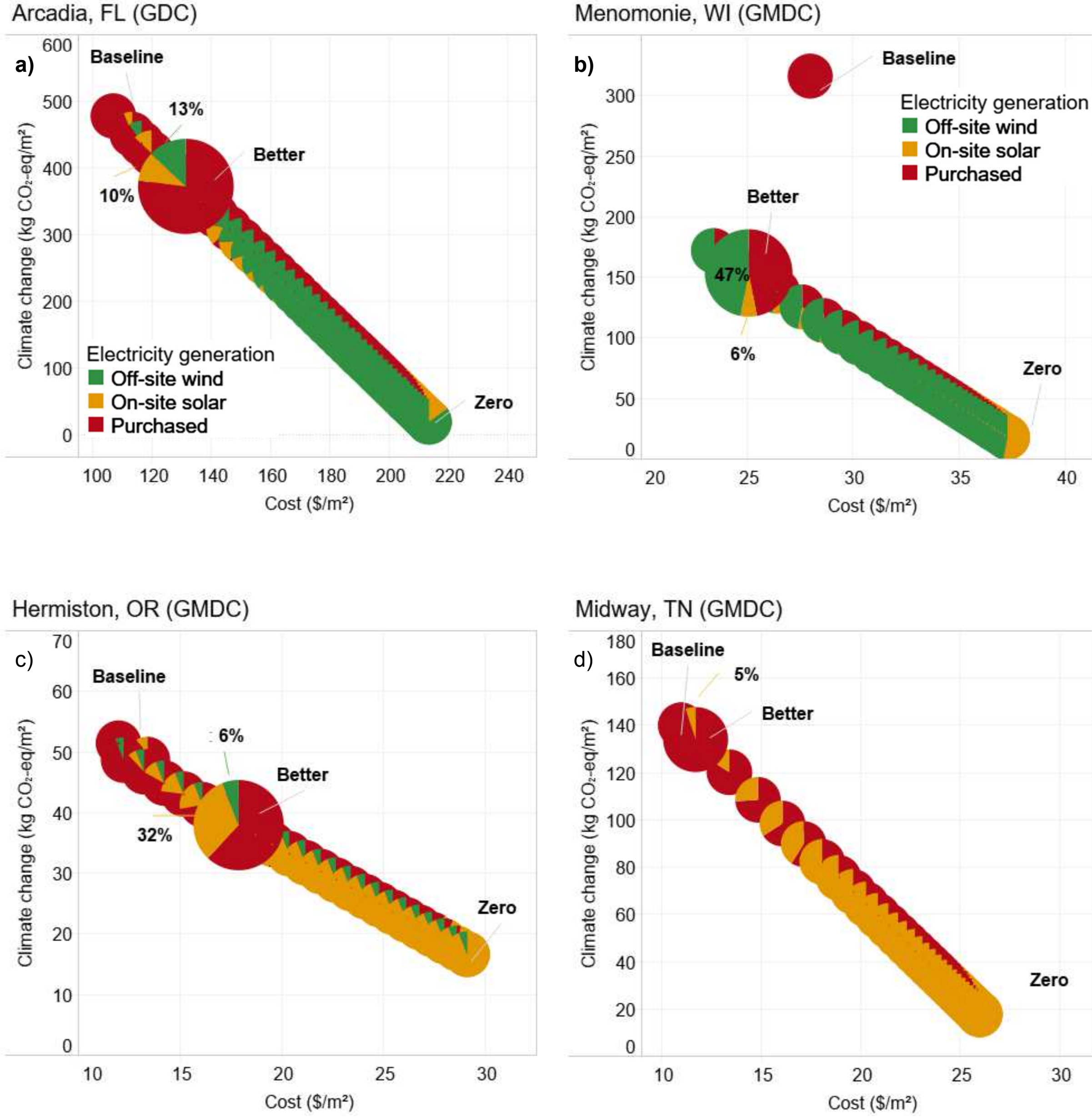


Figure 5. Combined bi-objective and triple-objective optimization Pareto-optimal results for GDCs, PDCs, and GMDCs. The 2-objective optimization included cost ($/m^2) on x-axis and climate change impact (kg CO_2-eq/m^2) on y-axis. The 3-objective optimization included cost ($/m^2), climate change impact (kg CO_2-eq/m^2), and non-renewable fossil energy ($MJ_{deprived}$/m^2), but is plotted as a projection in a 2D cost-climate change chart. Highlighted pies are Pareto-optimal better DCs results. The last pies on the right are Pareto-optimal zero energy DCs.

4.5.4. Tradeoff analysis of the better, and the zero energy distribution center network

In the tradeoff analysis, we focused only on three Pareto-optimal solutions: the good, the better, and the zero DC network. First, we analyzed tradeoffs between (1) climate change impact reductions achieved by introduction of solar and wind energy and (2) total energy cost, as shown in Figures 6a, 6b, 6c, 6d, 6e, and 6f.

A summary of climate change impact results for each state (kg CO_2-eq/state) is presented in gradient choropleth geographical, on top of which we showed results for each location in circles (kg CO_2-eq/m^2). A summary of energy costs for each state ($/state) is presented in gradient choropleth geographical, on top of which we showed relative results for each location using circles and numerical annotations ($/$m^2$). The combination chart was named chorobag because of bag symbol.

The choropies in Figure 6a show the baseline climate change impact which is fully dependent on purchased grid electricity. Figures 6b and 6c show state-level and individual DCs' reductions in climate change impact for two Pareto-optimal networks: the better, and the zero DC network. The pies in Figures 6b and 6c show relative increase in renewable energy for each scenario, and circle size shows relative reductions in climate change impact. Overall, state-level climate change impact shows reduction from baseline and better to zero energy network, while energy cost in some states increased and in others decreased. The better DC network showed an increase in wind and solar energy, reaching the maximum of 40% solar energy (GMDC in Arkansas) and between 30% to 90% wind energy, as shown in Figure 6b. Cost of DCs that were adversely affected by an increase of renewable energy increased in Texas, North Carolina, and Florida, as shown in Figure 4e and 4f. DCs' locations where the cost decreased due to introduction of renewable energy were for (1) GDCs in Alabama, Arkansas, Florida, Indiana, (2) GMDC in Wisconsin, and (3) PDC in California and Texas, as shown in Figure 6e. The range of decrease in cost was between 6.5% (GDC in Arkansas) and 34.4% (PDC in California). The average cost increase was 27.3%. The minimal cost increase of 1.4% was observed for a GDC in Nevada and maximum 91% for a GMDC in Florida.

Zero energy DCs had 5 times lower climate change impact compared to baseline, as shown in graduated choropleth shades Figures 6a and 6c. The size of the circle in the zero energy DC network solution shows the minimal climate change impact, which is not equal to zero because it includes construction material and renewable energy infrastructure and energy production burdens. Despite the 3-4 times higher energy demand for PDCs and GDCs compared to GMDCs, and statistically proven differences between their climate change impact (Figure 6a), in the zero energy DC solutions the climate change impact results fell within the narrow range for all buildings, as shown in Figure 6c. In the zero energy solution, most GMDCs had only solar energy, because solar energy potential was sufficient to replace purchased grid energy. The reduction in climate change impact for GMDCs that served as energy producers and perform at the zero energy DC solar energy capacity may be higher if we installed the maximum number of panels and exported solar energy. However, this research was limited to attributing and satisfying energy demand for the given network and omitting the consequences of solar energy export. Numerical results are reported in Appendix, Excel document "Numerical results for the good the better and the zero DCs.xlxs".

The majority of the zero energy DCs showed relative increase in cost compared to the baseline, as shown in Figure 6f. On average, zero energy buildings increased cost by 44.7%. The minimum cost increase was for the zero energy PDC in Terrel, Texas (2.4%), and the maximum was for the two GMDCs in Searcy and Bentonville, Arkansas (63%). The highest reduction in cost was found for the PDC in California 28% compared to the baseline. Only three other locations showed a reduction in building energy cost due to the cheaper wind energy including GDCs in Gas City, Indiana by 7%, Sterling, Illinois by 13%, and Winter Haven, Florida by 2%. At those locations, the absence of solar energy suggests a cost-effective zero energy building. Based on these results, the best candidates for zero energy buildings were (1) GDCs that showed a cost decrease due to cheaper wind energy and (2) GDCs and PDCs with a maximum of 10% increase in cost, such as Brundidge (AL), Bartlesville (OK), and Terrell (TX). Numerical results are presented in Appendix, Excel document "Numerical results for the good the better and the zero DCs.xlxs".

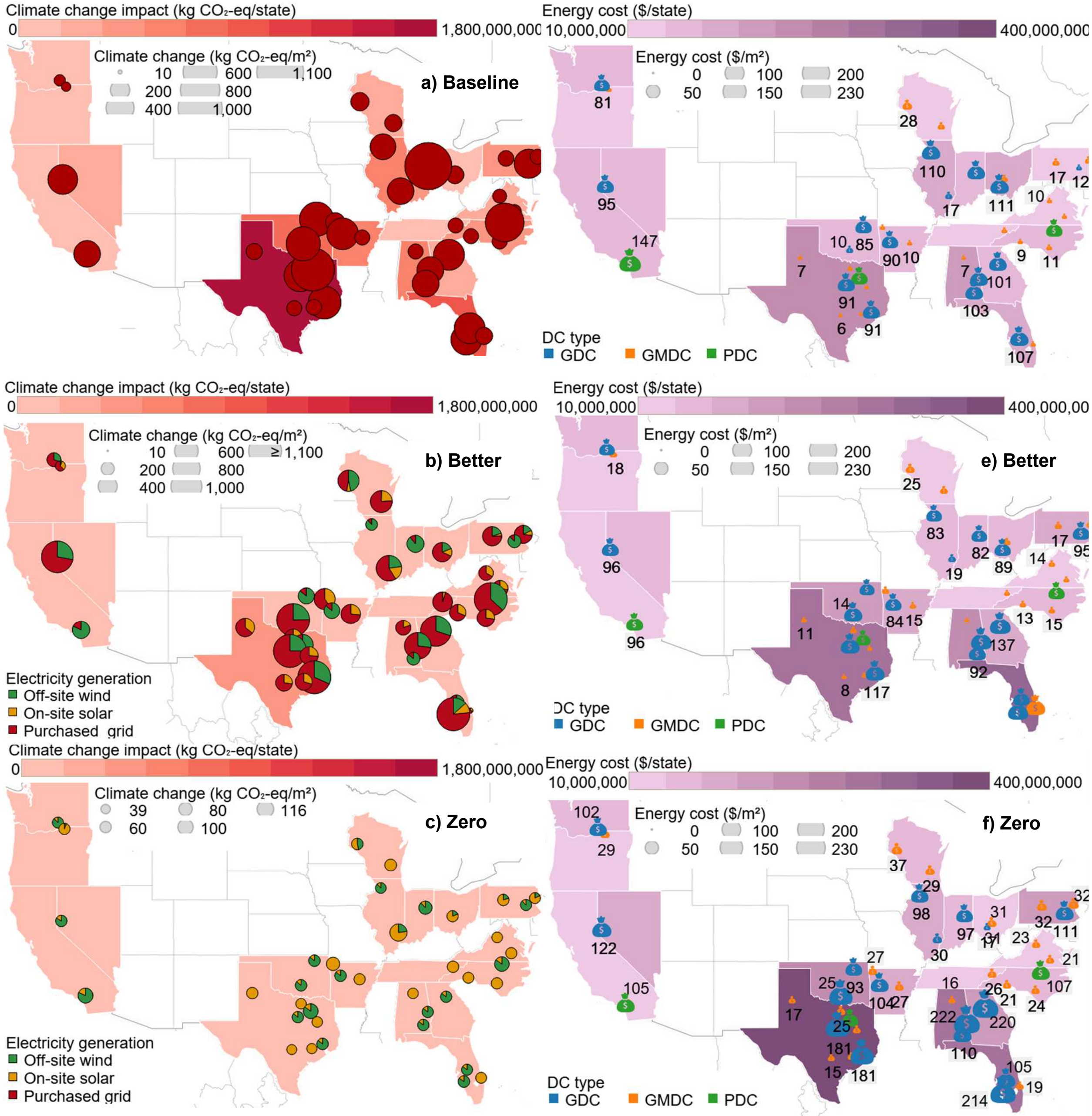


Figure 6. ChoroPie plots for the baseline, the better and the zero energy DC network. The size of the pies shows the DCs' climate change impact for each scenario ($/m^2). The multi-color pies show a share of purchased grid, on-site solar, and off-site wind energy in the better and the zero solutions. Choropleth maps with gradient color show combined climate change impact of all DCs in one state (kg CO_2-eq/state). ChoroBag plots shows cost tradeoffs in the f) better, and g) zero energy DCs compared to e) baseline due to increase of renewable energy. Dollar bag color shows DC type. Symbol size shows relative magnitude of total energy cost per area ($/m^2). Annotations below show individual DC's cost ($/m^2). Graduated choropleth maps show relative cost for all buildings in one state ($/state).

4.5.5. Wind turbine and solar panel capacity needed to achieve the better, and the zero energy scenarios

Geographical maps with a wind turbine symbol (ChoroWind) and annotation show the number of wind turbines necessary for the whole building to achieve the better and the zero energy DC scenarios, as shown in Figures 7a and 7b. Annotations below the number of wind turbines show installation capacities (2 MW, 4 MW, 14MW, and 16MW) specific to each location. Third annotation shows a power curve for onshore wind turbines and offshore wind farms. The power curve is the steady power delivered by the turbine as a function of steady wind speed between the cut-in and cut-out speeds. Installation capacities, power curve, choice of onshore and offshore wind farms were based on the National Renewable Energy Laboratory (NREL) recommendation for current and near future wind farms, which were the closest to DC locations (NREL 2014). For most wind farm locations, the NREL assumed 16 MW wind turbines. The size of wind turbines affected the number of wind turbines necessary. PDCs and GDCs needed between 2 and 7 of 16 MW wind turbines for the better building scenario, and up to 8 of 16 MW wind turbines for the zero energy. The choropleth map gradient color shows the total electricity produced from wind energy in each state. Under the zero energy scenarios, Florida, Texas, and Alabama produced the highest amount of wind energy, as shown in Figure 7b.

Geographical maps with a solar panel symbols (ChoroSolar) show solar panel installation power for each location and building type for better and zero energy scenarios, as shown in Figure 7c and 7d. Second annotations show the total solar panel area estimated for better and zero energy scenarios. PDCs are the most energy intensive buildings and the absence of solar energy in PDCs located in California, North Carolina, and Texas in the better building scenario was because wind energy was cheaper in those locations. Some GMDCs that are able to satisfy electricity demand only from solar panels can potentially produce more electricity and export it to the electricity grid. GMDCs that can export solar electricity are: Cullman, Alabama, Searcy, Arkansas, Bentonville, Arkansas, Fort Pierce, Florida, Gas City, Indiana, Hope Mills, North Carolina, Shelby, North Carolina, Pottertown, Tennessee, Palestine, Plain View, Sanger, and New Braunfels in Texas, and Mount Crawford and Sutherland, Virginia. That potential depended on the energy demand and of solar days. The range of electricity produced beyond the building demand was estimated between 134 MJ/m^2 (Searcy, Arkansas) and 2,242 MJ/m^2 (Sealy, Texas), in other words, each building can produce 10% and up to 2.3 times more energy than required. Numerical results are presented in Appendix, Excel document "Numerical results for the good the better and the zero DCs.xlxs".

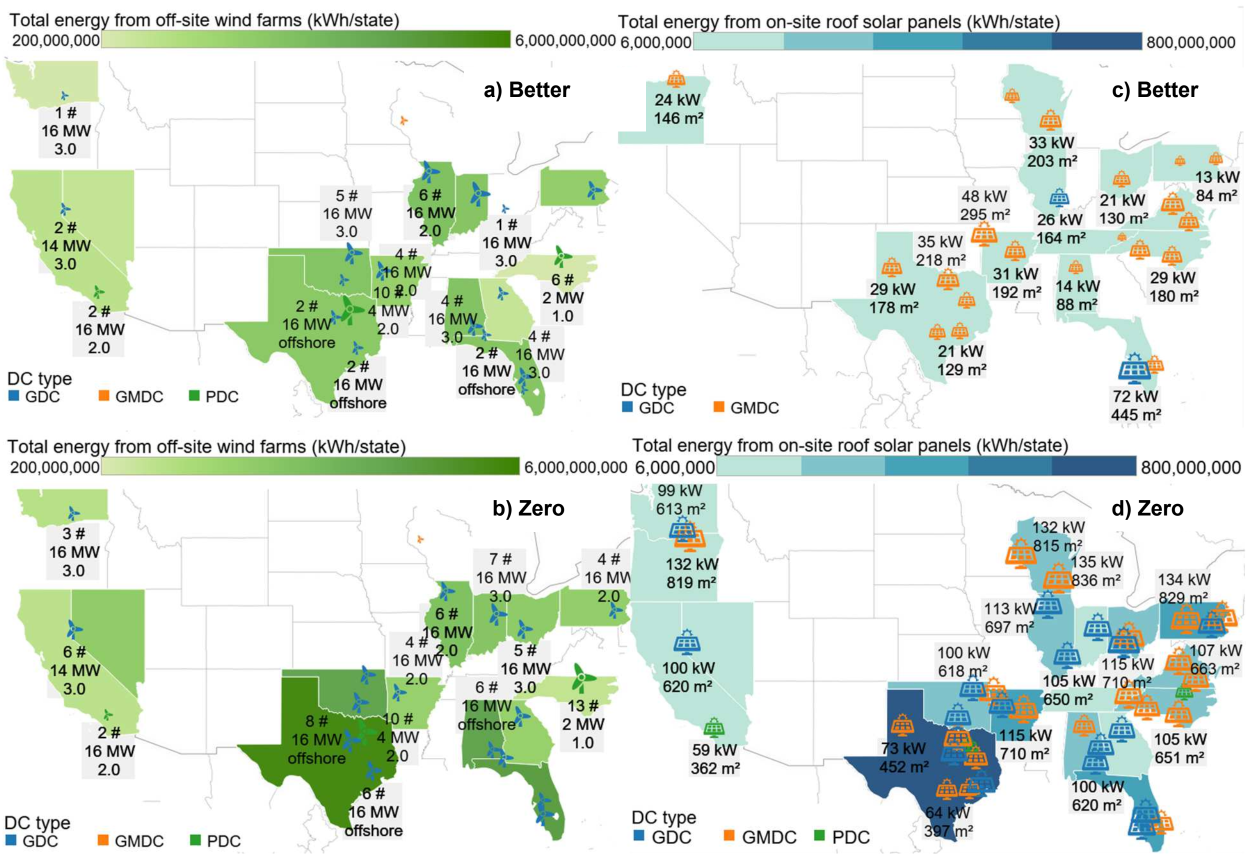


Figure 7. ChoroWind– a geographical map with a wind turbine symbol shows number of wind turbines that need to be installed for a) better DCs and b) zero energy DCs. Numerical values are annotated to each wind turbine. Wind turbine color shows DC type. Wind turbine size shows how many wind turbines is necessary to install for a) better DCs and b) zero energy DCs. Graduated choropleth maps show state-level wind electricity generation (kWh/state). ChoroSolar – a geographical map with a solar panel symbol shows kW of solar panels that need to be installed for c) better DCs and d) zero energy DCs. Numerical values for kW installed and total solar panel area (m^2) are annotated for each solar panel. Solar panel color shows DC type. Graduated choropleth maps show state-level solar electricity generation (kWh/state).

4.6. Conclusions

This research represents a first attempt at reducing environmental impacts of a large scale multi-facility distribution center network by installing solar and wind energy, and by finding the optimal zero energy distribution centers networks. The key novelty and contribution presented in this work was that the study provided systemic approach to improve the environmental sustainability of distribution centers. The study links the LCA and quantitative analysis including the Monte Carlo uncertainty analysis, Monte Carlo pairwise comparison, and multi-objective optimization. The uncertainty analysis provides additional confidence in the results and conclusions. The Monte Carlo pairwise comparison is frequently overlooked in the LCA research. LCA researchers tend to make conclusions and comparative assertions about superiority of one system over another based on differences in LCIA results, which according to ISO standard is omitted (ISO 2006a). This research is different and meets the requirements for the Monte Carlo comparison. Thus, the final selection of better buildings and zero buildings was based on quantitative analysis and statistical superiority of the Pareto-optimal solution. The advantage of this approach for decision making is that selected solutions are Pareto-optimal, their environmental performance is also statistically better, and are cost-effective compared to the baseline solution. The discussion presented here may have important implications for decision-makers, environmental policy, and building energy codes, who set targets based on percent reductions, which as we showed in this research do not guarantee that the building is better than the existing due to underlying uncertainties.

From results of this research the policy makers can make a more informed selection of the importance of criteria to achieve substantial improvements. Typically, these are based on expert judgment (Lippiatt et al. 2013). The predefined importance criteria may fail in reducing environmental impacts which will show improvement from the baseline. The importance of criteria may be different for different locations. For example, the policy maker may choose to give a climate change impact a relative importance of 30%. However, results show that for a non-refrigerated DC it is enough to have the climate change criteria set to 10% to achieve a better building. Cost and climate change impact should have equal importance if we want to achieve the zero energy building. For refrigerated buildings, the relative importance of the climate change criteria should be around 50%, but to achieve the zero energy, it should be 80%.

One application of this research is incorporating results into traditional mathematical procedures for selecting new DCs locations, which will include information about food market areas, location cost, zero energy, and minimal environmental impact of building. The models and procedures used in this study can also be applied to other types of buildings available in EnergyPlus.

The results presented here may be applicable to other buildings, for example buildings' located in Arkansas, Indiana, Ohio, and Wisconsin performed worse and will become vulnerable first with policies to reduce fossil energy use.

Businesses' decision-making is based on a number of factors, including cost. This research has provided conclusive evidence for potential of cost-effective implementation of renewable energy in distribution centers and provided optimal solutions to maximize renewable energy use in distribution centers. The research was based on real distribution center locations, energy simulations based on real data, real building types and sizes, real solar energy potentials, real wind energy locations and capacities, and real costs; thus, providing reliable and current information and solutions for retailer industry.

Lastly, DCs and supermarkets have an important role in environmental sustainability of food supply chains. In order to reduce a fossil energy dependency of buildings, the best solution was replacing fossil energy with optimal combination of wind and solar energy. Renewable energy sources were proved to be beneficial in building sustainability in certain locations. However, what worked for one location did not work for other location in terms of wind-to-solar energy ratio and their cost-effectiveness. The next step for decision makers would be to determine the probability of proposed solutions happening and consequences of their application using the consequential LCA.

The study has put forward a more precise definition of zero energy buildings, that is, that a zero energy building is a cost-effective life cycle assessment-based Pareto-optimal solution, which at the same time maximizes the on-site solar energy production. This underlines the importance that a building should neither depend on the available renewable energy at nearby locations nor depend solely on the on-site energy production. In addition, we provided two additional definitions, i.e., of the good and the better building. The better building is an intermediate, but the most feasible cost-effective and more sustainable solution, at present. The good building is a feasible, least-costly solution in cases where the increase in cost for the better building is too high.

Finally, the research provided new insights for understanding results of the life cycle assessment, how to interpret them and use for decision-making, and created a paradigm for future research. The research should be of interest to readers in the areas of building sustainability, sustainability of food and distribution, LCA, and complex system analysis. The research will also be of interest to retail industry such as supply chain managers and for future distribution center planning.

A barrier to implementing renewable energy was a higher cost of the zero energy distribution centers network compared to the baseline. The cost increase was from 1 to 11 times for the zero energy distribution centers Thus, the best candidates for zero energy distribution centers were Brundidge (AL), Bartlesville (OK), and Terrell (TX) with a cost increase of 10% or less. The multi-objective optimization pointed to cost savings in implementing renewable energy when potential wind energy was cheaper in some locations. We identified a number of distribution centers which showed cost reduction for the zero energy building network including Gas City (IN), Sterling (IL), Winter Haven (FL), and Riverside (CA), whereas some distribution centers showed potential to become solar energy producers and exporters. Further research is required in order to evaluate different solar panels and storage and wind turbine technologies. Practical implementation of solar panels needs to include solar storage, which was beyond the scope of this study. Cost of energy varies; thus, the results presented in the work are true as long as the prices are not too different. If, for example, wind energy in states for which the current price is lower than purchased grid becomes higher than purchased grid, the Pareto-frontier will change. While the goal of zero energy distribution center networks still remains remote, the proposed better distribution center network is achievable.

The variety of solutions underlines the importance of including location specific characteristics such as purchased grid and renewable energy costs, building energy demand, climate zone, electricity grid, solar production potential, and wind potential. The reductions presented here will have positive implications to food distribution sustainability. Because of location specific solutions, the research presented here may be of practical importance in further sustainable distribution center location decision-making and reducing food storage impact. However, other factors and possible tradeoffs need to be taken into account, such as food-miles, i.e., a new location needs to be such so that will not increase other food environmental impact.

Regional and global consequences of installing new roof solar panels and wind turbines on the energy market were not assessed in this research. The consequential life cycle assessment, which includes additional economic concepts like marginal production costs, markets, elasticity of supply and demand, and dynamic models, may provide additional insight into what happens with energy markets when the demand for solar energy and wind energy increases. However, the state-level electricity generation consequential life cycle assessment models were not available, and thus, consequential life cycle assessment was beyond the scope of this research.

The findings presented here provide a starting point for further examination of other warehouses and implementation of other renewable energy sources and/or building efficiency improvements. A number of the conclusions of the study may be valid for other warehouses in the United States. The optimization and life cycle impact models presented here can also be adapted to optimize renewable energy in other warehouses and commercial buildings.

The key factors presented here provide the benchmark and framework for a tool that may help improve the existing distribution and retail center network in the United States and to test environmental and renewable energy policies in place and decision making. This research also contributes to several Sustainability Development Goals including

The models originating from this research are comprehensive process-based LCA models, which include accurate and reproducible building energy data. The models can be adapted for any other cold supply chain in the world. They allow performing scenario analysis including the indirect factors, such as a change in technology and supply chain effects, and external factors, such as refrigerator choice and energy efficiency. Other energy efficiency practices in warehousing that could be used in the multi-objective optimization are: just in time technique (excluding DC storage), skylights, energy storage systems, ground source heat pumps, energy efficient light systems with motion sensor, rainwater harvesting, low water use appliances, sustainable building materials, choice of insulation material, thickness of insulation material, and green roofs. However, only the shift to renewable energy can make commercial buildings zero energy and with minimal GHG impact. In addition to wind and solar energy, we may consider bioenergy produced from food waste, which will need acquired knowledge about food waste availability in different regions.

The results of this study suggest a number of new avenues for research. One potential area of research not discussed in this manuscript is improvements in dock at grocery and perishables distribution centers' and conveyor at general merchandise distribution center's energy efficiency.

The zero energy building will become more feasible if multiple solutions are offered, which will provide synergic effect. Regional and global consequences of installing new roof solar panels and wind turbines on the energy market were not assessed in this research. The consequential LCA, which includes additional economic concepts like marginal production costs, markets, elasticity of supply and demand, and dynamic models, may provide additional insight into what happens with energy markets when the demand for solar energy and wind energy increases.

Other future work may focus on analysis of different refrigeration systems and refrigerants, which will reduce energy use, climate change impact, and water footprint. For example, one could use the models to examine the nationwide effect of using more energy-efficient conveyor and refrigeration systems or compare the effects of an energy design measures and policy regulations across several building types in different climate zones. Finally, the models could also integrate climate models to assess DCs energy consumption of future.

In the future, we plan to expand the multi-objective model to include energy efficiency such as existing and emerging technologies for insulating buildings, cold storages for refrigerated DCs, efficient heating, cooling, and ventilation, efficient refrigeration in storage and dock areas, conveyor efficiency, reductions in infiltration rates due to unloading, and other options which may reduce costs of the proposed zero energy DC network. The biggest challenge is to find life cycle inventories for emerging insulation materials, cold storages, and conveyor. One objective that has gained more attention in recent research about buildings and energy is water consumption and water scarcity. Refrigerated buildings use more water, but the challenge is to quantify water losses from different refrigeration system. Food refrigeration requirements also affect the refrigeration loads. Refrigerated food may enter at higher temperature to refrigerated warehouses, which can increase energy consumption. Adding water and food reductions will contribute in advancing the food-energy-water nexus. The hypotheses tested in that research will be that multi-dimensional optimization model, which will optimize reductions in food, energy, and water nexus can be used to find zero energy and minimal environmental impact at lower cost than proposed.

The model can also include indoor air quality, daylight, acoustic, and use of space. Accessibility of the models via Mendeley data and reproducibility of results guaranties continuation of the discussion presented here.

Future work will extend this research further on supermarkets. Additional, objectives considered for supermarkets will include refrigerant. Again, the challenge is to find reliable life cycle inventories of refrigerants.

Inter-disciplinary and cross-disciplinary research is necessary to open a pathway towards environmental sustainability. For example, to improve food environmental performance we must connect it to other problems such as economy, energy, climate, and water. Analyzing the whole system will ensure food, energy, and water resource resilience. Although, the solutions proposed in this research show dramatic reductions, these are not the only solutions that should be highly taken into consideration. The environmental impacts of each food category depended also on food properties: frozen or chilled; food category: fruits, vegetables, dairy, and meat; length of stay; and storing and retailing. Because of the results presented in this thesis, it is also important to find reductions for each food category. On a building level, cross docking and on time delivery were not examined, which have a potential to reduce environmental impacts of food as well as food waste. There are other feasible options and it is expected that the final solutions will be a plethora of improvements, in food, building, and energy sectors. The overall reductions and zero energy and minimal GHG emission can be obtained by adding up multiple solutions.

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5. Summary and conclusion

The analysis presented is a valuable contribution to the scientific literature on an understudied topic, i.e., the food post-processing storing in distribution centers (DCs) and retailing at supermarkets. The main goal of this study was to present new research results about (1) energy use in DCs and supermarkets and their environmental impact, (2) allocation of energy and water consumption to food (food-energy-water nexus) and cold food storing and retailing environmental impact, and (3) finding optimal solutions to reduce DCs dependency on fossil energy and have minimal environmental impact.

Major findings included:

- new research results about energy and water use in distribution centers and supermarkets
- environmental impact depended on building type, location, and equipment
- optimal use of solar energy poses opportunity to reduce environmental impact of non-refrigerated distribution centers
- optimal use of wind and solar energy poses opportunity to reduce environmental impacts of refrigerated distribution centers
- frozen food storing and retailing has higher impact than chilled food, but it is highly dependent on how long the food stays at the storage or at the supermarket.

The proposed solutions will consequently mitigate the environmental impacts of food storing and retailing. Our findings indicated that the optimal use of renewable energy poses opportunity to reduce environmental impacts of refrigerated and non-refrigerated DCs and may be a leading solution in transition to zero energy buildings.

5.1. Summary of chapter 2

First, the study provided scientific understanding of food DC networks' environmental impacts in the United States. The research examined environmental impacts of PDCs, GDCs, and GMDCs. DCs were characterized by building type, location, climate zones, typical meteorological year (TMY3), energy source for electricity production, and equipment. The environmental impacts of the largest multi-facility DC network in the United States were assessed. Materials (LCI data) and methods (LCIA methods) included global and regional resolution. The regional resolution was adopted in LCIs' input data for specific DCs locations and different climate zones, which was reflected in location-based energy and water consumption and state-level based electricity generation and distribution. In addition, results also show regional resolution due to use of LCIA methods such as World Impact + and the water footprint method AWARE. The global resolution of the LCA was presented through climate change impact.

Chapter 2 drawn a number of conclusions: (1) the primary energy use in PDCs and GDCs was refrigeration (80%) and in GMDCs there were conveyor systems (50%); (2) the dock area, where food is loaded and unloaded, used 80% of energy in PDCs; (3) environmental impacts depended on building mechanical systems, envelope material, location, age, type, size, and electricity generation, (4) location-specific provenance of electricity from fossil fuels such as coal affected the primary sources and magnitude of the environmental impacts of life cycle energy, climate change, water, and land impacts. In addition, building material and lighting became relevant for non-refrigerated spaces and in low-energy impact states. The research showed explicit links of energy and water use in buildings, i.e., refrigerated buildings used more water, but water impact was dependent on energy sources and local water availability. To achieve sustainability in food systems, policy measures need to include food production, distribution, retailing, and consumption. Thus, this study is a new contribution to the food sustainability issues because post-processing food distribution has long been a data gap in LCAs of food.

5.2. Summary of chapter 3

The role of DCs and supermarkets is to move or store food and other products. More research was necessary to understand the effects of increasing global cold food supply chain. The research assessed the cold food supply chain in the United States and identified which food has the highest and lowest storage and retailing impacts. This research evaluated the post-processing cold food supply chain and calculated the environmental impact of food storing and retailing. The key questions addressed were: What is the environmental impact of DCs' freezers and coolers and supermarket refrigerated zones in sales and perishables departments? What is the environmental impact of different chilled and frozen food?

The required knowledge included modelling zone-level refrigerated storage facility and supermarkets and collecting data on different food storage capacity, supermarket sales, and average food prices. The case study was based on the national U.S. cold food supply DC and supermarket network. The regional aspect was expanded and included regional food stocks. Including the food aspect placed this research in the food-water-energy nexus. The research went from the whole-building LCAs, DC's freezers and coolers and supermarket department LCAs to food storing and retailing LCAs, which were focused on cold food supply chain. Our research illustrated effects of state-level perishable food storing and retailing, included current cold storage capacities, and average monthly amount of food in the storage. Building location has the biggest role in magnitude of environmental impacts due to fixed choice of electric grid fossil fuel mix. However, amount of food stored in different locations and cooler-freezer ratio varied, which also affected the environmental impacts. Finally, through network analysis and broad discussion about environmental impact of PDCs' freezers and coolers and supermarkets' cold zones, this research provided a national benchmark about the environmental impact of food. Flexible and adaptive formulae, procedures, and data provided can be used to assess environmental impact of food storage and retailing in any state. As the cold food supply chain expands, this research may inform future DC and retail center retrofitting and planning, food traceability, and strategic management. One application of results presented in Chapter 4 is incorporating results into traditional mathematical procedures for selecting DCs locations, which will target food market area, least-cost locations, and minimal environmental impact of building.

5.3. Summary of chapter 4

Finally, to improve DCs' network environmental performance, multi-objective optimization of the DC network with the least-fossil energy, least-cost, and least-impact objectives was performed. This part of the research provided (1) a new insight into optimal use of solar and wind energy in DCs, (2) cost-effective and environmentally sustainable strategies to mitigate climate change impact and use of non-renewable fossil energy resources in DCs, and (3) an adaptable and flexible LCA-based multi-objective optimization model. The required knowledge included collecting data on energy prices and calculating solar and wind energy potential for different locations. In this research, LCA and quantitative methods were combined such as the Monte Carlo uncertainty analysis and multi-objective optimization. Climate zones had little effect on energy demand because the primary impact contributors were refrigeration for GDCs and PDCs and conveyors in GMDCs. Both refrigeration and conveyors are energy intensive, but their energy consumption is largely independent of climate zones. While energy efficiency remained one of the most important ways to reduce environmental impacts of buildings, using renewable energy has the highest environmental impact reductions. This research has provided conclusive support towards potential cost-effective implementation of renewable energy in DCs and provided optimal solutions to maximize renewable energy use. Chapter 4 draws several applicable solutions for building-energy sector and its main goal to reach zero energy and minimal GHG emissions. This research recommended a more precise definition of zero energy and provided two additional definitions, i.e., of the good and the better building. The results included tailored optimal solutions for fossil energy and climate change mitigation of PDCs, GDCs, and GMDCs in different locations. The tradeoffs of the good, better and zero energy DC networks were discussed.

Lastly, DCs and supermarkets have an important role in environmental sustainability of food supply chains. Intrinsic and variable factors identified by this research for buildings, food, water, and energy contributed to the magnitude of environmental impacts. To reduce fossil energy dependency of buildings, the best solution was replacing fossil energy with optimal combination of wind and solar energy. Renewable energy sources were proved to be beneficial in building sustainability in certain locations. However, what worked for one location did not work for other location in terms of wind-to-solar energy ratio and their cost-effectiveness. The next step for decision makers would be to determine the probability of proposed solutions happening and consequences of their application. The study provided new insights for understanding commercial buildings that are part of food distribution supply chain and created a paradigm for future studies in food distribution. The research should be of interest to readers in the areas of building sustainability, sustainability of food and distribution, LCA, and complex system analysis. The research will also be of interest to retail industry such as supply chain managers and for future distribution center planning.

5.4. Conclusion

This study established procedures to calculate environmental impacts of DCs and RCs, provided benchmark results of their environmental impacts, bridged the data gap of cold food storing and retailing environmental impact, and found optimal cost-effective solutions to increase renewable energy in commercial buildings and begin transition to zero energy buildings. Overall, this research contributed to three scientific areas: food, buildings, water, and energy. The summary of topics covered in this research included: (1) spatially explicit energy demand and water use in existing GDCs, PDCs, and GMDCs and their environmental performance in different locations; a (2) discussion about environmental impacts of current management practices in food storing and retailing; and (3) tradeoffs of storing and retailing of chilled vs. frozen food. In addition, the research included (1) analysis and optimization of energy systems toward sustainable energy systems; (2) application of solar and wind energy sources in buildings; (3) optimal solutions of both fossil and renewable energy systems, which are economically feasible and have lower or minor impact on the environment; (4) environmental and economic impacts of renewable energy use in DCs; and (5) optimal solutions for zero energy and minimal GHG emission DC multi-facility networks. The results will serve as benchmark to improve sustainability of distribution centers, and consequently, food storing.

In conclusion, the results of this research are important in supporting:

- further development of DC and supermarket building codes such as LEEDs,
- sustainable cold food supply chain,
- increase of renewable energy in buildings,

- policy makers in setting environmental criteria for better and zero energy buildings,
- developments in the food-water-energy nexus,
- food policy
- Sustainable Development Goals (SDGs).

5.5. Future research

The future work will include, but will not be limited to the following areas:

- find least-cost strategies to reduce the environmental impact of the national supermarket network using the multi-objective optimization
- examine regional and global consequences of installing new roof solar panels and wind turbines
- include other energy efficiency practices in warehousing in the multi-objective optimization model
- evaluate other renewable sources such as bioenergy from food waste
- perform optimization of food storing and retailing
- reduce water consumption in buildings
- model future building energy consumption based on projected climate models.

Inter-disciplinary and cross-disciplinary research is necessary to open a pathway towards environmental sustainability. For example, to improve food environmental performance one must connect it to other problems such as economy, energy, climate, and water. Analyzing the whole system will ensure food, energy, and water resource resilience. Although, the solutions proposed in this research show dramatic reductions, these are not the only solutions that should be highly taken into consideration. The environmental impacts of each food category depended also on food properties: frozen or chilled; food category: fruits, vegetables, dairy, and meat;

length of stay; and storing and retailing. Because of the results presented in this study, it is also important to find reductions for each food category. On a building level, cross docking and on time delivery were not examined, which have a potential to reduce environmental impacts of food as well as food waste. There are other feasible options and it is expected that the final solutions will be a plethora of improvements, in food, building, and energy sectors. The overall reductions and zero energy and minimal GHG emission can be obtained by adding up multiple solutions.

The models originating from this research are comprehensive process-based LCA models, which include accurate and reproducible building energy data. The models can be adapted for any other cold supply chain in the world. They allow performing scenario analysis including the indirect factors, such as a change in technology and supply chain effects, and external factors, such as refrigerator choice and energy efficiency. Other energy efficiency practices in warehousing that could be used in the multi-objective optimization are: just in time technique (excluding DC storage), skylights, ground source heat pumps, energy efficient light systems with motion sensor, rainwater harvesting, low water use appliances, sustainable building materials, choice of insulation material, thickness of insulation material, and green roofs. However, only the shift to renewable energy can make commercial buildings zero energy and minimal GHG impact. In addition to wind and solar energy, one may consider bioenergy produced from food waste, which will need acquired knowledge about food waste availability in different regions. This will also help understanding whether some DCs and supermarkets have more food waste than others.

Regional and global consequences of installing new roof solar panels and wind turbines on the energy market were not assessed in this research. The consequential LCA, which includes additional economic concepts like marginal production costs, markets, elasticity of supply and demand, and dynamic models, may provide additional insight into what happens with energy markets when the demand for solar energy and wind energy increases.

Finally, other future work may focus on analysis of different refrigeration systems and refrigerants, which will reduce energy use, climate change impact, and water footprint. For example, one could use the models to examine the nationwide effect of using more energy-efficient conveyor and refrigeration systems or compare the effects of an energy design measures and policy regulations across several building types in different climate zones. The models could also integrate climate models to assess DCs and supermarket energy consumption of future.