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A Picture of Hartford's Community Food Environment: An Image Recognition Approach

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Abstract

The rise in recent years of research dedicated to community food environments has produced valuable insights but has focused primarily on one dimension of access to healthy food: availability. This study expands the current research and utilizes an innovative approach in generating a food environment index by focusing on consumer choice in restaurants. Using food images crowdsourced from Google Place (n=19,907) and TripAdvisor (n=3,252) in restaurants (n=487) of the Greater Hartford Area, we employed a deep-learning based food-image-recognition technique to identify the food type and nutrition information from these food images, which were also validated by manual coding. We then generated a community food environment index by aggregating the deep-learned nutrition information from each restaurant on the census-tract level and explored this index's relationships with each neighborhood's socio-demographic characteristics and two established food environment indices, namely the USDA's Food Access measure and the mRFEI. Our results showed that deep learning results were reasonably accurate (75% accuracy when compared with manual coding), and the resulting food environment index was significantly correlated with the share of single parent households ($p<0.05$) and people living in group quarters ($p<0.01$) in each census tract. We also observed moderate consistency and weak correlations between our food environment index and both established indices. This pilot study shows that a deep-learning based food-image-recognition approach has the potential to map out local food environment and complement other food environment indices by accounting for food environment-diet relationship and portraying the individual's choices in built food environments.

Keywords: restaurant, nutrition, community foodscape, food environment index, deep learning, food image recognition, crowdsource

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The terminology of food environments has become a part of household dialogue in recent years. This is in part due to their popularization in mainstream media outlets, the surge of diet-related chronic diseases, and the rise in visualization tools, such as ArcGIS mapping technology and Tableau. The term "food environment" refers to the human-built and social environments within a community that impacts the accessibility, availability, and adequacy of food (Rideout et. al., 2015). The U.S. Department of Agriculture has declared Hartford, CT a "food desert" based on the poverty rate of city residents and residential proximity to supermarkets (NBC Connecticut, 2015). Since 2011, the city of Hartford has not seen a single supermarket from a large food retailer open its doors. However, the built food environment is not limited to grocery stores or supermarkets. It extends to convenience stores, restaurants, farmer's markets, food pantries, soup kitchens, etc. This paper focuses on restaurants as an indicator of the built food environment. This narrowing in on restaurants is justified by the increased presence of restaurants in daily life due to the cultural shift in food consumption and meal sharing. As data shows, Americans are spending more to eat out rather than to cook at home due to fast-paced lifestyles and the workday extending to dinner at the office and happy hour with colleagues. The USDA, Economic Research Service (ERS) Food Expenditure Series (2020) measures the U.S. food system. According to this report, the total sales of food prepared outside of the home surpassed that prepared inside the home for the first time in 2014. In 2019, the expenditures for sales of home-prepared food were approximately $799,404 million, while the total expenditure for food prepared outside the home, including that sold in restaurant settings, exceeded $969,350 million (ERS, 2020). While some established food environment indices incorporate restaurants in their delineation of healthy and obesogenic food environments, they do not incorporate consumer choice. This research study aims to fill this gap by providing a picture of actual restaurant food consumption in the Greater Hartford Area foodscape to portray individual choices in a food environment index.

Review of Literature

Much of the previous literature surrounding Connecticut's food environment has centered around large cities as "food deserts", however, the Greater Hartford Area has varying degrees of diversity and economic vitality, making it an optimal population to research the multifaceted nature of food environments and determine possible predictors of healthy food access.

Community Food Environments. According to the conceptual definition of "access" proposed by Penchansky and Thomas (1981), there are five dimensions of access: availability, accessibility, affordability, accommodation, and acceptability. Much of the previous literature has focused on a singular dimension of food access. This research has been dedicated to understanding environmental determinants on the availability of healthy food. Beginning in the 1970s, much of the literature pertaining to the built food environments has been dominated by measuring and evaluating "food deserts" as a large proportion of urban America was classified as such. "Food deserts" are defined as areas with limited access to affordable and healthy food, primarily measured by proximity to the nearest supermarket (Dutko et. al., 2012). In recent years, there has been a shift in focus away from "food deserts" and toward "food swamps". Cooksey-Stowers et.al describe a "food swamp" environment as an area with a high-density of food service establishments serving high-calorie fast food and junk food (2017).

Food environments as a concept have interested public health practitioners as well as other environmental and public health professionals because they serve a predictor of population risk for obesity and other diet-related chronic diseases. As early as the 1990s, researchers recognized the role food environments play in individual health outcomes. According to Hill and Peters (1998), large portion size and availability to high-fat diets promote overeating and increase obesity risk, both of which are characteristics of one's food environment. The heightened attention to "food swamps" is primarily from research findings demonstrating it to be a better predictor of obesity compared with the "food desert" classification (Cooksey-Stowers, et. al., 2017). The severity of "food swamps" has also been found to be related to higher hospitalization rates of diabetic adults (Phillips & Rodriguez, 2020).

Other food environment research has centered on the neighborhood characteristics as predictors of poor food environments and their relationships with health disparities. In a study which included the 6,500 "food desert" tracts identified by the USDA's Economic Research Service, researchers found that census tracts with greater rates of poverty in more populated areas had a higher likelihood of a "food desert" classification (Dutko et. al., 2012). An analysis of 54 relevant studies published between 1895 and 2008 found that residents of neighborhoods that had ample access to supermarkets and limited access to convenience stores tended to have healthier diets and lower levels of obesity (Larson, et. al., 2008). This review also found that studies from across the U.S. suggested that low-income and minority neighborhoods have increased access to fast-food restaurants and calorie-dense foods, characteristic of "food swamps", and are most affected by the lack of accessibility to supermarkets and healthy food options. A study which investigated the correlations between community food environment and neighborhood racial/ethnic and socioeconomic composition in North Carolina, Maryland and New York found that predominantly minority and racially mixed neighborhoods had more than twice as many grocery stores and half as many supermarkets compared to predominantly white neighborhoods (Moore et. al., 2008). This study also found fewer fruit and vegetable markets, bakeries, specialty stores, and natural food stores in poorer and non-White areas. A multivariate analysis examining the associations between commercial food store outlet data across 28,050 zip codes and Census 2000 data came to similar conclusions (Powell et. al., 2007). They found fewer chain supermarkets in low-income neighborhoods, overall. In African American neighborhoods, there were 52% fewer chain supermarkets compared to white neighborhoods and in Hispanic neighborhoods, only 32% of that in non-Hispanic neighborhoods.

These studies demonstrably show the disparities in access to nutritious food, however, gaps in the literature remain. Since “food deserts” and “food swamps” only address the accessibility dimension of “access”, further research is needed on the food environment-diet relationship and its associations with neighborhood characteristics and effects on diet-related chronic diseases. The multitude of factors that go into the decision-making process of choosing what to eat has not yet been widely studied, due to issues of psychometrics and the sheer volume of influences (Lytle, 2009). For instance, Cheadle, et. al. (2011) distinguished shelf space in relation to four product areas, fresh produce, meat, milk, and bread, as a measure to assess the availability of healthy foods, along with purchasing and consumption behavior. Further research is needed to attain accurate measures for assessing influences and characteristics of individual dietary behavior.

In addition, scarce research has been employed to discover the best practices for measuring and evaluating food environments. A literature analysis was conducted on 137 peer-reviewed articles published between January 1990 and August 2007 that measured food environments on the community-level (McKinnon, et. al., 2009). The researchers found various instruments and methodologies to measure food environments, including market baskets, inventories, and analyses of geography, sales, or nutrients, with the most common being geographic analysis. The review concluded that more research needs to be done to adequately measure food environments with a greater focus on reliability and validity.

The most established food environment measures are the USDA's Food Access Research Atlas or the corresponding Food Environment Atlas, and the CDC's maps of the Modified Retail Food Environment Index (mRFEI). The Food Access Research Atlas is a census tract overview of food access utilizing measures and indicators of supermarket accessibility, designating tracts with low access as "food deserts". Similar to the Food Access Research Atlas, the Food Environment Atlas from the USDA uses a broader approach to determine food access through variables such as restaurant proximity, food prices, and nutrition assistance programs. The mRFEI combines the concepts of "food deserts" and "food swamps" calculating the percentage of food retailers considered healthy in each census tract. These measures prioritize indirect spatial metrics, such as distance to a restaurant, in place of direct nutrition information of food consumption.

Food Image Recognition. Measures of nutrition components derived from food image recognition provide an alternative to spatial metrics and deliver firsthand observations of individual consumption. Food image recognition was first explored in a study done by Williamson et. al. (2004), which involved the comparison of digital photography and visual estimations for food selections, plate waste and portion size. This pilot study yielded digital photography to be a viable alternative to estimating food intake via direct observation. In 2008, this method was coined the Remote Food Photography Method (RFPM) and researchers reaffirmed its accuracy in measuring an individual's energy intake by cross validating the results with those from directly weighing foods (Martin et. al., 2008). Martin et. al. (2008) cited the rate of error for RFPM was comparable to self-report methods. Technological advancements in deep learning models have revolutionized food image recognition and has had a dramatic impact on the efficiency and accuracy of food capturing and interpretation (Kawano & Yanai, 2014). Food image recognition technology has been popularized by location-based services through the optimization of mobile capabilities which produce accurate nutrition estimations in real-time through consumer-captured images. These images are uploaded and analyzed by deep learning-based image classification apps, such as CalorieMama. While food image recognition has the potential to inform dietary decisions and advance public nutrition knowledge, this method has not been applied in a large-scale manner. The labor and temporal difficulties in obtaining individual dietary data may be attributing factors to this gap in research. In contrast to extracting data from an individual device, mental recall, and activity patterns, crowdsourcing from an application programming interface has been shown to be an alternative to traditional methods (Zhao, 2017). This crowdsourcing approach has been shown to adequately assess food choices influenced by local food environments by web-scraping food-related tweets (Chen & Yang, 2014). To our knowledge, no previous studies have employed crowdsourced food images to reveal patterns of health inequality. This study employs this method to harvest the nutrient information gathered from user-uploaded food images on Google Place and TripAdvisor to gain insight on the Greater Hartford Area’s local food environment.

Research Aims

Both the USDA’s Food Access Research Atlas and the mRFEI lack the centrality of consumer choice as a critical part of community interaction with built food environments, which this paper intends to investigate. Our research study creates a food environment index based on calorie averages for restaurants in the Greater Hartford Area aggregated by census tract from crowdsourced food images and nutrition information obtained through a food image recognition deep learning model. The first question we will resolve in this paper is how well the deep-learned results align with manually coded results for nutrition information, which will determine the validity of our instrument. The second research question we wish to answer revolves around the relationships that exist between our food environment index and neighborhood socio-demographic characteristics. The third question we will investigate is whether our deep-learning generated food environment index aligns with other established food environment indices.

Methodology and Data

We conducted a multimethod research study aimed at determining the relationships between restaurant nutrition, neighborhood characteristics and the community food environment of Hartford County, CT. Hartford County has a racially and economically diverse population estimated to be 891,720 as of 2019 with similar demographics to the national average (Census Bureau). Located in Hartford County, the city of Hartford is the fourth most populous city in Connecticut, serving as a cultural destination and food hub for much of central and eastern Connecticut.

Data Sets and Preparation

Primary Data. We utilized two primary data sets: the spatial data of all restaurants in Hartford County and web-scraped food images from each restaurant located in the geographic boundaries. The restaurant data was generated from requests for businesses from the Yelp API under the food category. In combination with a Python program, this produced the required result queries and data for businesses related to food within our predetermined geographic boundaries (n=937). The data was then cleaned and cross-validated with Google Place, purging any unidentified restaurants and other business related to food, i.e., supermarkets, convenience stores, etc. (n=532). Restaurants which were permanently closed, according to Google Place, were also filtered out of the data set, along with restaurants that lacked any food images. Each restaurant was assigned an index before the food images were collected to ensure anonymity. Of all the restaurants found within the geographic area, 487 restaurants fit the inclusion criteria and composed the final data set.

Our second primary data set consisted of crowdsourced food images uploaded by customers, which better depict the reality of customer orders compared to using all menu items supplied by restaurant owners or retail food companies. The food images were manually scraped from Google Place for each restaurant using a simple mass downloader extension (n=19,907). Food images were also acquired from TripAdvisor, an online travel company with user-generated reviews, to cross-validate the Google Place data (n= 3,252) (there were significant number of restaurants (n=239) without user uploaded images). Since our objective was to collect images of food ordered and consumed by customers, food images were excluded from the data set if the image was determined to have been staged or part of an advertisement. Drink images and restaurant-focused images, such as, a photo of the interior of restaurant that featured a food item, were also excluded. Our final sample included 16,216 images from 487 restaurants across 66 census tracts. Each image was standardized to 544x544 pixels to be processed by the deep learning model. From the collected food images, data on identification of food type, macro-nutrition estimations, and portion size were collected.

Secondary Data. Data was collected for select demographic characteristics and nutrition-related health outcomes on the census-tract level. To assess community diversity and economic vitality, comparable data was collected from the CDC’s 2018 Social Vulnerability Index (SVI) for each census tract within the geographic boundary of the sample in this study. SVI utilizes American Community Survey’s (ACS) 5-year estimates to determine the relative vulnerability status of each census tract. Variables included in SVI's are related to socioeconomic status, household composition and disability, minority status and language, and housing type and transportation.

Data was also collected from two well-established food environment indices to validate our deep learning model. The 2015 U.S. Food Access Research Atlas provided data to recognize census tracts which are considered "food deserts". The modified retail food environment index (mRFEI) represents the percentage of healthy food retailers on census-tract level.

Measures and Procedures

Two quantitative methods were administered to collect the data associated with the food images. First, the food images were run through a Food AI API, CalorieMama, which outputted a highly detailed food profile, including food name, calories for 1000g of food, along with other nutritional information via image identification. The CalorieMama API utilizes machine learning techniques and deep learning food image recognition models to recognize a variety of cuisines and preparation styles. Second, 281 of the crowdsourced images randomly selected from 20 restaurants were manually coded, 75 of which were coded twice, by two independent raters for identification of food type, nutrition information and portion size based on Food and Nutrient Database for Dietary Studies (Montville et. al., 2013).

To determine the neighborhood socio-demographic characteristics, we obtained the following variables in each census tract from the 2018 SVI data set:

(a) Percentage of persons below poverty estimate,

(b) Unemployment rate estimate; per capita income estimate,

(c) Percentage of persons without a high school diploma (age 25+) estimate,

(d) Percentage of persons aged 65 and older estimate, 2014-2019 ACS,

(e) Percentage of persons aged 17 and younger estimate, 2014-2019 ACS,

(f) Percentage of civilian noninstitutionalized population with a disability estimate, 2014-2018, ACS,

(g) Percentage of single parent household with children under 18, 2014-2018 ACS,

(h) Percentage of minority (all persons except white, non-Hispanic) estimate, 2014-2018 ACS,

(i) Percentage of persons (age 5+) who speak English “less than well” estimate, 2014-2018 ACS,

(j) Percentage of housing structures with 10 or more units estimate,

(k) Percentage of mobile homes estimate,

(l) Percentage of occupied housing units with more people than rooms estimate,

(m) Percentage of households with no vehicle available estimate, and

(n) Percentage of persons in group quarters estimate, 2014-2018 ACS

These variables represent the overall vulnerability in terms of socioeconomic status, household composition, disability, minority status, language, housing type and transportation. We further obtained two established food environment indices in each census tract, namely the USDA Food Access Research Atlas percentage of population with low access and mRFEI scores. The Food Access Research Atlas uses 2015 data to find the share of population that is beyond one mile from a supermarket for census tracts within urban areas and vehicle availability for all tracts. mRFEI scores are calculated for each census tract by dividing the number of healthy food retailers by the number of healthy food retailers and the number of less healthy food retailers, multiplied by 100. Supermarkets, larger grocery stores, supercenters, and produce stores within census tracts or a half mile from the tract boundary are considered healthy food retailers. Less healthy food retailers use the same measures of proximity, but include fast food restaurants, grocery stores with three or fewer employees, and convenience stores.

Statistical Approach

Food Image Analysis. To answer my first research question, determining the validity of the CalorieMama API calorie estimations, the API's analysis was cross validated with the manually coded results. Specifically, two independent coders identified the food name and nutrition information of 281 food images (75 were double coded to ensure validity) from 20 randomly selected restaurants in our sample based on Food and Nutrient Database for Dietary Studies (U.S. Department of Agriculture, 2020), and compared that with the most likely food name and nutrition information identified by the API.

Analysis by Census Tract. To answer my second research question, determining which neighborhood characteristics may be associated with nutrition information, a correlation analysis was conducted. The outcome analyzed was the average calorie estimation on the census-tract level. To find this, we first took the average of the calories for all food images within each restaurant (i.e. average calories for 1000g food in each restaurant), and then aggregated the average restaurant calorie information by census tract (n=66). The average calorie estimations were derived from all food images identified by the CalorieMama API for each restaurant. The socio-demographic variables we assessed were derived from the SVI data (listed above and in Table 1).

To answer my third research question, how well our deep-learning based community food environment index aligns with other established community food indices, i.e., USDA food access and the mRFEI, we used the aggregated average calorie information in each census tract (derived from deep learning) and investigated its correlation with mRFEI and USDA food access measure. In addition, the resulting data was also used to create a series of census-tract level food environment maps using ArcGIS, which were then used to compare the differences among our deep-learning generated food environment index, USDA Food Access measure and mRFEI.

Results

Food Image Analysis

Out of the 281 images assessed through manual coding using FNDDS food codes, we found that the CalorieMama API correctly identified 211 food images, reaching approximately 75% accuracy[1]. The CalorieMama API had more specific and accurate food labels for 24 images, mostly since the FNDDS food code database has limited ethnic food identifiers, specifically for Korean dishes and less so for Mexican, Italian, and Chinese dishes. However, the API had more inaccurate identifications for images with multiple food items, where it could only identify one of the food items present in the image. Comparatively, the results from manual coding were able to identify all food items pictured. CalorieMama also identified most sandwiches and burgers as “beef burger”, while many were not. It also classified many salads as “Caesar Salad” when there was greater variability of salad type.

When determining portion size, we found that CalorieMama’s deep learning model was insufficient -- the CalorieMama API did not produce accurate assessments and was unable to predict portion size from the web-scraped food images. The FNDDS database calculation was more accurate than CalorieMama’s assessment. In correspondence, we used the calories for 1000g of each food as the basis for our analysis.

Analysis by Census Tract

[1] Additionally, four images were incorrectly identified by both human coding and the deep learning model due to poor photograph quality.

Associations with Socio-Demographic Data

The correlation analysis for average calorie estimations on the census-tract level and socio-demographic variables is shown in Table 1. Average calorie estimates were positively correlated with the ACS's "Percentage of person with no high school diploma (age 25+) estimate" at a significance level of 0.1. The ACS's "Percentage of persons aged 17 and younger estimate, 2014-2018" was significantly, negatively correlated with average calorie estimates at the census-tract level ($p<0.1$). It was also found that the rate of single parent households and percentage of people residing in group quarters had a positive correlation with the outcome of interest at a significance level of 0.05 and 0.01, respectively. All other socio-demographic variables had no significant correlation with the aggregated average calorie estimations.

Table 1.

CORRELATION BETWEEN SOCIO-DEMOGRAPHIC VARIABLES AND AVERAGE CALORIES OF THE RESTAURANTS ON CENSUS-TRACT LEVEL (N=66)

VARIABLE	MEAN (SD)	MIN/MAX	CORRELATION
Percentage of persons below poverty estimate	17.44776 (13.38573)	0/49.2	0.03
Unemployment rate estimate	9.167164 (5.704527)	0/23.3	-0.04
Per capita income estimate, 2014 - 2018 ACS	32691.94 (16646.26)	5509/68705	-0.18
Percentage of persons with no high school diploma (age 25+) estimate	17.19254 (12.65109)	0.3/49	0.23*
Percentage of persons aged 65 and older estimate, 2014-2019 ACS	14.76119 (6.322733)	1.6/28.7	-0.06
Percentage of persons aged 17 and younger estimate, 2014-2018, ACS	21.54179 (6.766767)	2.1/39.3	-0.21*
Percentage of civilian noninstitutionalized population with a disability estimate, 2014-2018 ACS	13.01791 (4.425098)	0/25.4	-0.03
Percentage of single parent household with children under 18 estimate, 2014-2018 ACS	13.8806 (14.18879)	0.5/100	0.27**
Percentage of minority (all persons except white, non-Hispanic) estimate, 2014-2018 ACS	60.94925 (30.78525)	9/100	-0.01
Percentage of persons (age 5+) who speak English "less than well" estimate, 2014-2018 ACS	7.441791 (6.804792)	0/25.1	0.04
Percentage of housing structures with 10 or more units estimate	20.29552 (20.56323)	0/87.3	-0.09
Percentage of mobile homes estimate	0.7761194 (3.600425)	0/25.5	0.15
Percentage of occupied housing units with more people than rooms estimate	3.020896 (2.958067)	0/10.3	-0.05
Percentage of households with no vehicle available estimate	18.89104 (14.54787)	0/60.4	-0.03

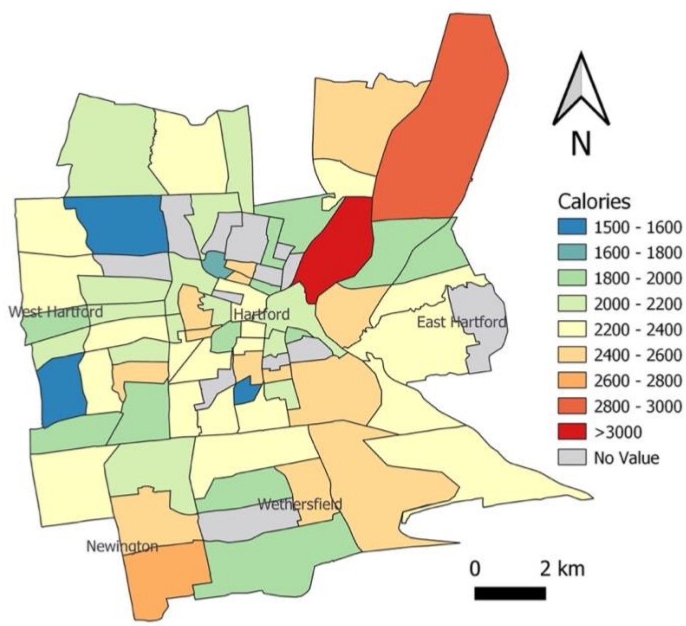
Percentage of persons in group quarters estimate, 2014-2018 ACS	3.941791 (12.37788)	0/93.4	0.37***
**** p<0.01, ** p<0.05, * p<0.1*			

Deep Learning Model with Mainstream Food Environment Indices

Figure 1a shows our deep-learning nutrition information measure mapped for the Greater Hartford Area. This map demonstrates our food environment index through the aggregated average calorie estimates for each census tract (Mean=2214.92, SD=276.98, Min=1500, Max=3028.88). Census tracts with the highest average restaurant calories were found to be in the northeast end of Hartford, while the lowest were congregated in the West Hartford area.

Figure 1a.

Average Calorie by Census-Tract Level in Greater Hartford area.



We then compared our food environment index with two widely used food environment indices, USDA's Food Access and the mRFEI shown in Figure 1b and Figure 1c, respectively.

The correlation between our index and the USDA Food Access (Mean=.07, SD=.18, Min=0, Max=.99) was 0.121 (p=0.33), demonstrating that lower food access weakly correlated with higher average calories. Consistent with our index, census tracts with the lowest access were found to be in the northeast end of Hartford, while the highest were on the west side of Hartford. When comparing our food environment index with the mRFEI (Mean= 8.20, SD=7.55, Min= 0, Max=33.33), the correlation was found to be -0.141 (p=0.28). This trend represents higher mRFEI weakly correlated with lower average calories. Consistent with our index, census tracts with the lowest mRFEI scores (least healthy) were found to be in the east and northeast end of Hartford, while the highest (most healthy) were on the west side Hartford. Therefore, we found moderate consistency and observed weak correlations between our index and both mainstream food environment indices but found no statistical significance in either correlation analysis. Note that this may be due in part to the small sample size.

Figure 1b.

USDA Food Access on Census-Tract Level in the Greater Hartford Area.

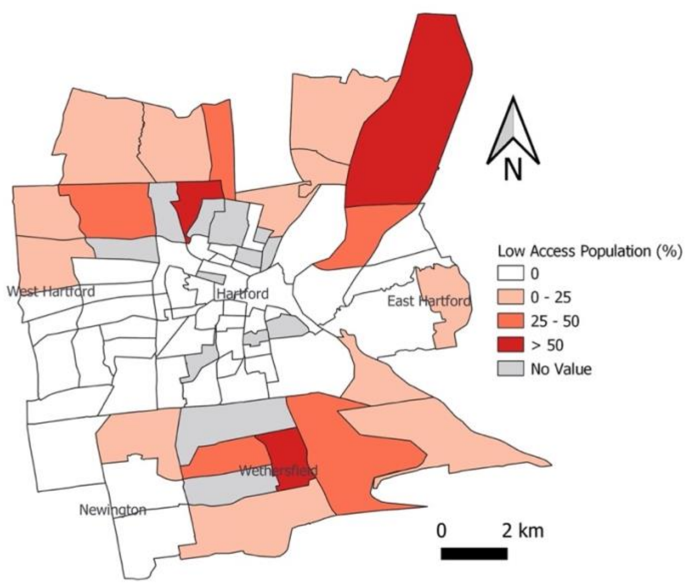
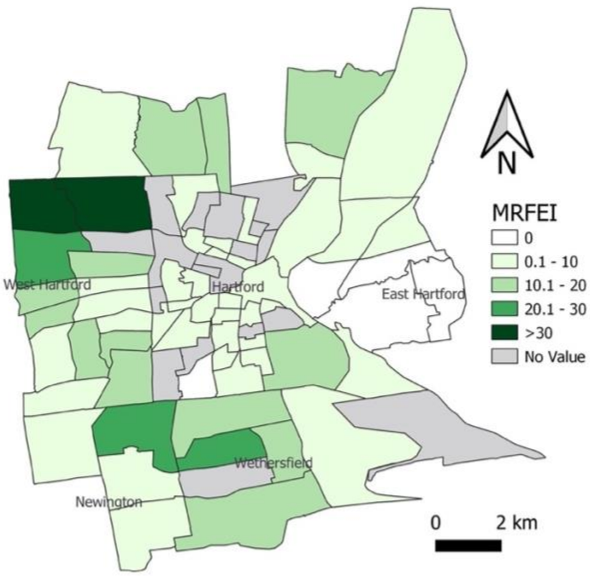


Figure 1c.

mRFEI on Census-Tract Level in the Greater Hartford Area.



Discussion

Through a deep learning-based food image recognition model, this study was able to calculate calorie estimations for crowdsourced restaurant food images and develop a community food environment index for the Greater Hartford Area. Our results shed light onto the validity of our methodology, and the correlations between our generated food environment index with socio-demographic variables as well as some established food environment indices on the census-tract level.

Model Validation

Our method of acquiring data from the deep learning model provided a new and unique consumer-based approach to researching community food environments through the employment of crowd-sourced food images. The validity of this measure was critical in making comparisons with other food environment indices and determining the relevance of ours. According to our results, the CalorieMama API sufficiently identified food images and provided accurate calorie estimations for the majority of images. This suggests that our method of collecting nutritional data through the deep learning model accurately measured what it was intended to. In the analysis of peer-reviewed articles that involved community food environments, researchers McKinnon, et. al. determined that validity was one area that was often neglected. The manually coded randomly selected portion of food images from the sample aptly determined the deep learning result's accuracy in assessing calorie information per food image. In doing so, it also ensured the validity of the primary method and the resulting food environment index.

Measuring Socio-demographic Correlators

Extensive research has been dedicated to discovering the predictors of poor food environments and their relationships with health disparities. Previous studies have found neighborhoods with lower socio-economic status and higher diversity vitality correlated with "food deserts" and "food swamps". Our correlation analysis involving socio-demographic variables adds to the growing literature that demonstrates the associations between poor food environments and lower socio-economic characteristics. Our index was positively correlated with three variables that may indicate low socio-economic neighborhood status, namely the variables for those without a high school diploma, single parent households, and those living in group quarters.

Measuring Consumption over Availability

Unlike most food environment indices, our technique is able to measure and study the food environment-diet relationship. The use of deep learning-based food image recognition allows for wider representation of the lived food environment by utilizing crowdsourced food images. Previous literature has shown that predicting consumption is complicated by the complexities of the decision-making process, which has many distinct factors and influences (Lytle, 2009). Still, what is consumed is an important consideration in developing food environment indices. We filled the gap of predicting consumption by deriving data from food images taken after the decision-making process has occurred.

The USDA's Food Access Research Atlas classifies "food deserts" by measuring supermarket accessibility. The mRFEI is more comprehensive than the atlas since it utilizes "food deserts" and "food swamps" in calculating a census tract's food environment score. However, these established indices focus solely on availability and accessibility. In contrast, our food environment index derives itself directly from consumer images and focuses entirely on direct consumption rather than indirect spatial availability. The directions of the correlations of our index with the USDA Food Access measure and the mRFEI demonstrate theoretical consistency, but our index may be measuring different constructs (i.e. consumption from restaurants). These differences in constructs as well as the small sample size on the census-tract level (n=66) may explain the lack of statistical significance in our correlation analysis of food environment indices.

Implications for Public Health

This study enriches the growing body of literature dedicated to food environment indices. The primary impact is providing highly effective methodology and an accurate visualization tool to explore the food environment-diet relationship. With the popularization of GIS technology, public health officials have stressed mapping the spatial foodscape. This approach may lack the food and quality measures within the food environment-diet relationship, while overemphasizing the proximity or density of certain types of food establishments within communities (Widener 2018). Thus, the immediate implications of this study are to inform public policy makers and health experts of the landscape of the restaurants in each neighborhood, while providing critical insight into consumer choice.

Additionally, the crowdsourced food image recognition deep learning method developed in this study is widely applicable and scalable. Food environments have been touted for their correlations with obesity and diabetes, but this approach may offer a deeper understanding in investigations of the effects of consumer choice on diet-related diseases (Cooksey-Stowers, et al. 2017; Phillips & Rodriguez, 2020). In addition, nutrition-based deep-learning instruments will offer an alternative to traditional assessments, such as food frequency questionnaires or food records, and alleviate associated issues with time, labor, and cost. It can also be applied to a larger geographical scale. Moreover, this tool has the potential to clarify sociocultural aspects of nutrition science and eliminate misconceptions surrounding health effects of ethnic food cultures or regional cuisines through accurate nutrition assessments.

Limitations

There are several stipulations worth mentioning before employing crowdsourced deep learning models to additional research on food environments. First, the primary data set was constrained by the crowdsourced images found on Google Place and TripAdvisor, excluding nutrition information from restaurants that lacked user-uploaded food images. Also, our methodology for the acquisition of data may not discover true neighborhood food choice, since it is likely that some of the food images were taken by individuals traveling from outside the community. Second, the data was acquired before the COVID-19 pandemic which drastically altered the urban foodscape. Thus, our food environment index retrospectively includes restaurants that have closed due to hardship from the pandemic. Third, in our tests of validity, CalorieMama only had 75% accuracy for food image identification and was inaccurate in terms of calculating portion sizes. The deep learning model may need to be adjusted for food items that have similar appearances and poorer photo quality.

Conclusion

This study examines the food environment in the Greater Hartford Area through a deep learning-based food recognition model. Our food environment index was developed from the nutrition information derived from crowdsourced food images, which was manually cross validated with FNDDS calorie information. Our results found associations between the food environment index derived from the deep learning model with socio-demographic variables, including single-parent households and those living in group quarters, and weak correlations with two established food environment indices. Deep-learned nutrition information can shed light on the food environment-diet relationship, but further research should incorporate location-based food tracking activity to ensure representativeness of the community. Further research should also be conducted to determine trends with crowd-sourced nutrition information with diet-related chronic diseases.

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