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Visualizing the food landscape of Durham, North Carolina

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Abstract

In partnership with community leaders of Durham, North Carolina, the Duke World Food Policy Center is creating a Durham Food Justice Plan (DFJP) for envisioning an equitable food system. The Food Justice plan serves to incorporate Durhams local food history in terms of combating historical and present injustices in the food system. We propose creating an integrative, interactive visual for DFJP to view the food landscape of Durham, which will be utilized to study its relationships with the people living in the area where these establishments reside. We created a food landscape platform in Tableau using multisource data including Durhams food vendor data from North Carolinas Department of Commerce and census data for demographic data, neighborhood labels, and street and highways. We incorporated the Google Geocoding API and the aggregated information based on census blocks and tracts in visualization. We produced a variety of maps and graphs to highlight diverse relationships. The food landscape visualization allows us to see interactive patterns among food vendors and demographic data in Durham. We expect to utilize the developed landscape visual for insightful statistical analysis on food inequity issues.

KEYWORDS

data visualization, food vendor data, geocoding, Durham County, food insecurity, Tableau

1 | INTRODUCTION

According to the Economic Research Service of the U.S. Department of Agriculture (USDA), 11.1% of the U.S. population experienced food insecurity, where "their access to adequate food for active, healthy living is limited by lack of money and other resources" (USDA, 2019). Additionally, 4.3% experienced a more serious form of food insecurity, "where food intake of one or more members is reduced and normal eating patterns are disrupted" (USDA, 2019). According to the Food Bank of Central and Eastern North Carolina, approximately 15% of Durham County is food insecure; 20% of children under the age of 18 are food insecure; and around 34% of Durham County children are receiving reduced/free school meals (Food Bank, 2019). Nationally, fast food chains, liquor stores, and smaller grocery stores tend to have higher prevalence in low income and minority areas than they do in high-income neighborhoods (New York Law School Racial Justice Project, 2012). Areas with this phenomenon are known as food swamps.

The Duke World Food Policy Center (WFPC) is part of Duke's Sanford School of Public Policy. The WFPC aims to develop a food policy that addresses equity for all in terms of food systems. They also focus on outreach to educate the public on food systems and food security issues (Duke World Food Policy Center, 2020). To envision a different and more equitable food system in Durham, the WFPC is working with Durham's community leaders to develop the Durham Food Justice Plan (DFJP). The DFJP is a series of short-term and long-term projects dedicated to turning Durham into an "equitable food community" (Duke World Food Policy Center, 2019). A key Durham Food Justice Plan project the creation of a visual reference to Durham's food landscape. The purpose is to establish a deep understanding of Durham's food history and its current food system. We contributed to the food landscape project via data visualization of relevant data, to communicate food-related trends and highlight new relationships for researchers to explore.

Data visualization is the interactive, visual representation of abstract data. Visualization allows for converting raw data into spatial data, which serves to illuminate new relationships with which researchers can pursue new lines of inquiry and to communicate research results to the public. Visualization follows along four key research goals: determining the kind of information to visualize, determining the visualization techniques appropriate for communicating information, determining how users interact with the visualization, and determining the effectiveness of these displays. Furthermore, visualization also addresses how to integrate multiple data sources in a way that new trends in the data emerge, without misinformation or distortion.

2 | RESEARCH OBJECTIVES

We are interested in demonstrating the effectiveness of the visualization to analyze the state of food deserts and food swamps in Durham, North Carolina, along with understanding the market shares of vendors. Along these principles, we decided to focus on visualizing data on food access points. An access point refers to places where people can purchase and consume food. Access points include grocery stores, restaurants, convenience stores, department, and dollar stores. Product wholesales and bulk level vendors like Sysco are not considered access points. We collected data from North Carolina's Department of Commerce, which consists of food vendors by category with information on their addresses, business description, sales, and year established. Additionally, we collected data from the Durham Neighborhood Compass (DNC), which contains a variety of data on Durham, particularly socioeconomic data. For techniques, we use the data analytics platform Tableau to aggregate different variables to display various relationships. The ideal product will be flexible, as the City of Durham has grown by approximately 16 square miles between 2000 and 2016, and its population has grown by approximately 35% (The City of Durham, n.d.-a). The Tableau product allows for multiple sheets of data, including a variety of graphs and map displays with a variety of built-in map layers. Standard graphs between variables of interest, maps, word clouds, mosaics, and map layers are the primary visualization techniques used to demonstrate potential relationships. Tableau is naturally interactive and for purposes of communication will be readily exportable to relevant parties. We determine effectiveness by examining which visual patterns in the data emerge through visualization of the food vendor data. Therefore, we also strive to integrate these multiple data sources together to create visualizations using all these data sources.

3 | METHODS

3.1 | Data collection

Data on food vendors in North Carolina is readily available through North Carolina's Department of Commerce's online Business Search feature (North Carolina Department of Commerce, 2019). The feature allows collecting data through a variety of filters, including the NAICS code, city, county, and specific company names. NAICS stands for the North American Industry Classification System, grouping business for statistical analysis (U.S. Census Bureau, n.d.-b). Initially, we collected data by the first four digits of the primary NAICS code, which is a six-digit number, in order to obtain food vendors classified as grocery stores and as restaurants. The grocery store category's prefix is 4451. This category includes standard retail stores (Food Lion, Harris Teeter, Gmart) and convenience stores (Circle K, Sheetz). These subcategories are specified by the last two digits. Notably Walmart, Target, and dollar stores are not in this category. The restaurant category (NAICS 7225) is more diverse, containing fast food vendors, full-service restaurants, delicatessens, and miscellaneous categories. The data are organized as multiple pages, with uniform variables, and the data are downloadable in the form of an Excel spreadsheet. However, for each page, a separate Excel spreadsheet is created. Therefore, data processing is necessary for proper visualization. Notable variables include Street Address, Contact Name, Contact Title, Annual Sales, and Year Established (NC Department of Commerce). The grocery and restaurant store data amount to 810 records as of March 2019. Additionally, we downloaded vendor data under the Department Store and Generalized Merchandise categories. These categories include stores that do not provide food, so further processing is necessary. However, data are only available for vendors currently active, meaning that without the closed vendors, we do not have a complete picture of Durham's food landscape.

The second primary data source is the United States Census Bureau. The Census Bureau provides "geographic base files known as TIGER (Topologically Integrated Geographic Encoding and Referencing)" files which delineate "physical features and census tract boundaries of every county in the United States" (Rizzardi, Mohr, Merrill, & Selvin, 2019). We downloaded the shapefiles for North Carolina from the Census Bureau's official website to visualize these boundaries in Tableau (Shen, 2016; U.S. Census Bureau, 2019). The key variables used from the Census Bureau are Geometry, geoid10, and countyfp10. Geometry depicts the shape of a census block region, which in turn is used to plot the census regions in Tableau. The geoid10 variable is a 15-digit numeric string indicating the state, county, census tract, and census block in order. The shapefiles also have separate variables for each region, including the countyfp10. As Durham, North Carolina, is entirely within Durham County, the value of countyfp10 is "063," which will ease computation cost with Tableau. Of note, the census tract portion of geoid10 is a padded six-digit numeric string.

For intersecting the food vendor data with demographic data, we use DNC. The DNC is a community resource continuously updating data about Durham, maintained by DataWorks NC. The data set is an accumulation of national and local data sources, including the U.S. Census Bureau and the Health Indicators Project (DataWorks NC, 2020). Variables include topics related demographics, health, safety, and housing. The DNC data are available at both block group and tract level, with the observations being the geographic regions at each level. A census block group is a collection of census blocks within a single census tract. Block groups are determined by the first digit of the census block number. Both data sets have a formatted Geography Label and Geography ID variable to identify a specific region. The Geography Label on the tract level has the format "Tract 1.01," a number with two decimal places and at most six total digits. For the block group level data, the Geography Label has the format "Tract 1.01, Block Group 2" with the tract portion having the same format from the tract-level data, and Y is an integer. Issues arise with the Geography ID variable. This variable is a subset of the geoid10 variable from the U.S. Census data. The Geography ID variable from the tract level data is an 11-digit numeric string variable, and the variable from the block group level data is a 12-digit string variable. However, when downloading the data, the census block group Geography ID variable truncated the values, leaving the same number for every observation. Therefore, we needed to reconstruct the Geography ID variable for the block group level data using the Geography Label variable.

3.2 | Data processing and cleaning

Downloading the NC Commerce data provided three grocery store files, 14 restaurant files, one department store file, and one generalized merchandise file. Each file downloaded from the website provides a disclaimer within the sheet. Therefore, it was necessary to merge and clean the data prior to using Tableau. Additionally, in order to utilize Tableau's map feature, we needed to determine the latitudinal and longitudinal coordinates of the food vendors. We therefore used Tableau Prep Builder to clean and process the data from NC Commerce. First, from "Connections" section, select the plus sign, which allows for adding a new connection to a data source. We used this button to add all the spreadsheets to a Prep Builder workspace. Rudimentarily, the union feature allows merging data in a single sheet.

As all the data came from the same site, the variables were uniform, reducing complications in the process. Select a data source within the Prep Builder and drag it onto another data source, particularly the "Union" box that appears. A separate Union box will appear that displays the joined data. Additional data sources can be added by dragging those sources to that union box; however, at most, seven data sources can be joined together per union function. Therefore, one will have to combine these Union boxes through the same process to obtain a single data set.

When data sources are initialized, variable types (strings, integers, decimals) are assigned automatically to each variable. However, there are variables with number values that are not quantitative variables, including the NAICS label and phone numbers. Also, merging the data adds new variables indicating the original data source of an observation, which are not relevant. Therefore, we select Union boxes that merge a cluster of observations to efficiently fix these issues. We modify variables by right clicking them. In this case, we deleted the irrelevant variables: "Table Names" and "Table Names-1." Above each variable is an icon indicating its classification. Clicking on that icon allows us to change the variables related to zip code, phone numbers, and NAICS to string variables. We assigned geographic roles to relevant variables (city, state, address, and county), and appropriate variables were assigned string variable types (phone number, NAICS). Furthermore, in each basic NAICS code, 4451 and 7225, there are subcategories that match the variable Business Descriptions based on the full primary NAICS number. As an example, 445110 and 445120 within grocery stores, respectively, represent the values "Convenience Store" and "Retail Stores." Using this observation, we created a new variable called "Business Category," a string variable with four values: Grocery Store, Convenience Store, Restaurant, and Variety (generalized merchandise and department stores) to obtain a simplified view of Durham's food landscape.

We obtained the latitude and longitude coordinates for each address through geocoding. To set up this process, we created three calculated fields within Tableau Prep Builder: Latitude, Longitude, and Accuracy, giving each observation a default value to initialize the variables. Accuracy refers to whether the geocoding process obtained precise coordinates or approximated the coordinates for a vendor. A Google Geocoding API Key was obtained to accomplish this task. The API functions by submitting a URL containing the API Key and the desired address, which then returns the latitude and longitude coordinates. In order, to efficiently obtain these coordinates for the entries, we adapted a Python script that runs the API Key for each entry (Battersby, 2019). We modified the script slightly to account for pound signs that appeared in some addresses. To link the script to Tableau Prep Builder, we installed TabPy, an application that combines the software language Python with Tableau. We used the platform Anaconda to run Python and install TabPy.

Using the Anaconda Prompt, for each geocoding session, we start the TabPy server, which allows for running Python scripts. Therefore, Tableau Prep Builder runs a flow that obtained the latitude and longitude coordinates for each address and then runs that data into a fixed output, allowing for using the data without repeatedly geocoding, which has a monetary cost. There were two notable geocoding outliers from incorrectly entered addresses. These addresses were temporarily removed from the extract after the script icon through the filtering command. The data were exported as both a CSV file and a Tableau Extract file.

In order to combine the food vendor data and DNC data for separate analysis, we used Tableau Prep Builder again to condense the vendor data following a similar process above. The key difference in this step was taking its geoid10 variable and creating a specific substring up to the block group variable for combining with the DNC data set. The "LEFT" function within Tableau software applications constructed this new variable "geoblockid." Furthermore, we used the "Aggregate" feature of Prep Builder to add the Annual Sales values by the census block group variable. Aggregation effectively switched the observation variable from the "Company Name" to the geoblockid, meaning that we needed two outputs for processing.

In R, we imported the two outputs along with the fixed DNC data set, along with the Tidyverse library. Census block groups are the most detailed DNC level data available, allowing more observations for potential statistical analysis. Also, although the NC Commerce data provided zip codes of the vendors, zip code boundaries are not determined by the streets, roads, and geographic boundaries of an area. Therefore, any data groupings by zip codes neither accurately nor meaningfully visualize the data. Census delineated regions are the proper geographic regions to use. The ideal level would be census blocks to generate large numbers of observations to run deeper statistical algorithms; however, the smallest level available through DNC is the block group level. Therefore, our goal was to collect both the total number of food vendors in a census block group and the number of vendors in each category under the Business Category variable we created. We then tallied the number of vendors grouped by the census block group and separately tallied the data by Business Category within the geoblockid variable. In order to create variables that tallied each separate category, we used Tidyverse's "pivot_wider" function, which widens the data set, and successfully created the separate categories. "Null" values did appear as a result; however, due to the definition of these variables, replacing null values with zero was intuitively sound. Finally, we added these new data onto the DNC data using a left join. The left join was necessary because there are census block groups that have zero food vendors in them. An inner join would erase those block groups and potentially crucial data involving them. Moreover, we took the opportunity to create a variable called "Block_Food_Market_Share," which is the percentage of the total Annual Sales of food vendors a block group contains.

4 | RESULTS

4.1 | Visualizing with Tableau

We use two data sources to start the process of visualizing the data. The merged and cleaned data of Durham's food vendors is the first source. The second source is the downloaded shapefiles of North Carolina. In the data source section of a new Tableau workbook, these two sources are added and combined with a full outer join, which adds all variables and observations from each source. However, a condition is needed on this join, as both data files have latitude and longitude coordinates, and we wish to create a map based on the latitude and longitude coordinates. Therefore, we use the built-in "makepoint" function, which sets the latitude and longitude of a vendor to intersect with the geometry variable from the shapefiles (Marten, 2019). This join condition links the latitude and longitude of the vendors to the appropriate census tract and census block. With the data source initialized, we were able to create multiple sheets to display different visualizations. We focused on graphs and maps to demonstrate the effectiveness of visualizing food vendor data with Tableau (Tableau, n.d.-a, n.d.-b, n.d.-c, n.d.-d).

Figure 1 shows two mosaic images visualizing the distribution of vendors by NC Commerce data's "Business Description" variable. The left image shows the distribution of vendors established in the 80s, and the right image shows vendors established in the 2010s. Mosaics can use the

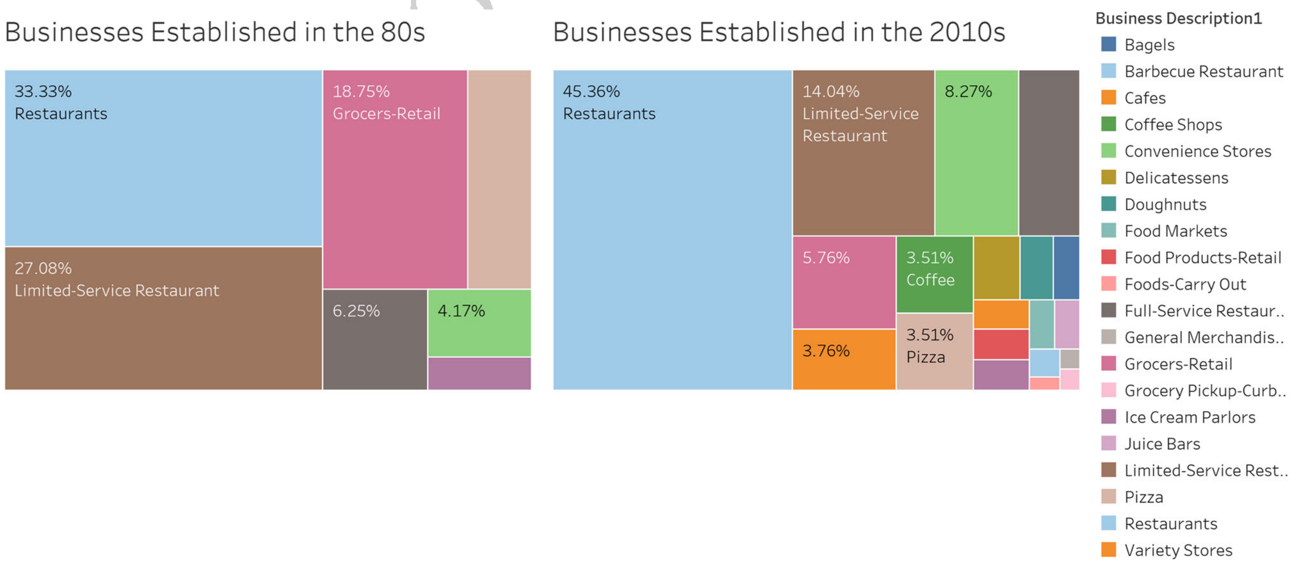

FIGURE 1 Side by side comparison of mosaic plots depicting business distribution of food vendors in the eighties and 2010s

specific number or the percentage. In both images, over half of the vendors established in each decade are restaurants. However, the diversity of food vendor businesses increased tremendously. The 2010s mosaic shows more specialized food vendors. Similar mosaics can be created with the annual sales variable to display the proportion of sales of each food vendor category.

Regarding TIGER files, the most detailed level available from the Census Bureau is state level. There are over a thousand census blocks in North Carolina, making processing speed very slow when viewing a map sheet. For usability, we take advantage of TIGER data's Countyfp10 variable. Using the filter feature, we can keep only TIGER data located inside Durham County, and we can zoom into regions of interest quickly (U.S. Census Bureau, n.d.-a). Using the built-in map layers, we created a variety of maps displaying the potential of viewing regions of interest. Moreover, Tableau has built-in map layers, which add streets, terrain, and some demographic data.

The following figure display the food landscape using built-in Tableau demographic map layers. Figure 2 uses the 2018 Population Data layer and the Business Category variables to color code variables in downtown Durham. Furthermore, the streets and highways are included in the map layer settings to show that this area is delineated by US-70, US-147, and I-85. Intuitively, the visual confirms a high number of restaurants in the downtown area.

Currently, we have not found a way to visualize both the DNC data in the form of map layers within Tableau. However, we did create a separate worksheet using the merged DNC and condensed food vendor data. Figure 3 displays the number of food vendors in each census tract, segmented by census blockgroup. We used the "geotractid" variable created when fixing the DNC-block group level data. In addition, we could assign the geoblockid as a label to create the segmented bars, which shows the extent to which block groups contribute to the vendor count within each census tract. Of note, in the interface, we can highlight each segment to view the specific block number. Therefore, even for block segments without a label (due to being too small), the block group can be found within Tableau. From the diagram, Census tracts 20.21, 4.02, 20.27, 20.28, and 22.00 have the highest number of food vendors. In each tract, a single blockgroup has a majority of the tracts food vendors. A similar diagram can be created using the market share variable to display which tracts contribute to the annual food sales.

5 | DISCUSSION

With the visualization, we produced a variety of maps to highlight diverse relationships and to make observations to inspire future research. Figure 2 shows the downtown Durham area (bounded by Interstate 85, U.S. 70, and U.S. 98). With initial observations, we can see that low population tracts have more grocery stores than high population tracts. In Figure 2, we note the high prevalence of restaurants in Durham. However, there are key improvements to make with the visual and data.

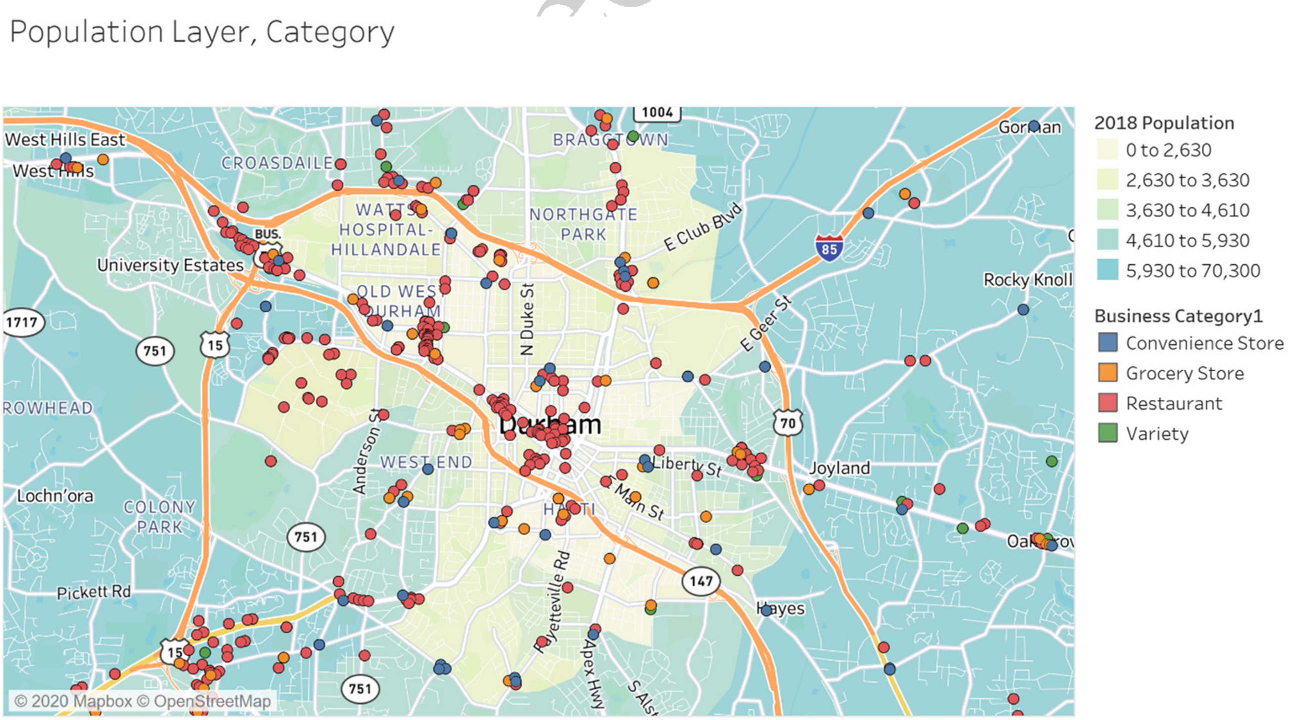

FIGURE 2 Built-in map layer of 2016 U.S. Population, with coordinates of food vendors. The main area is downtown Durham, delineated by U.S. 70, U.S. 147, and I-85

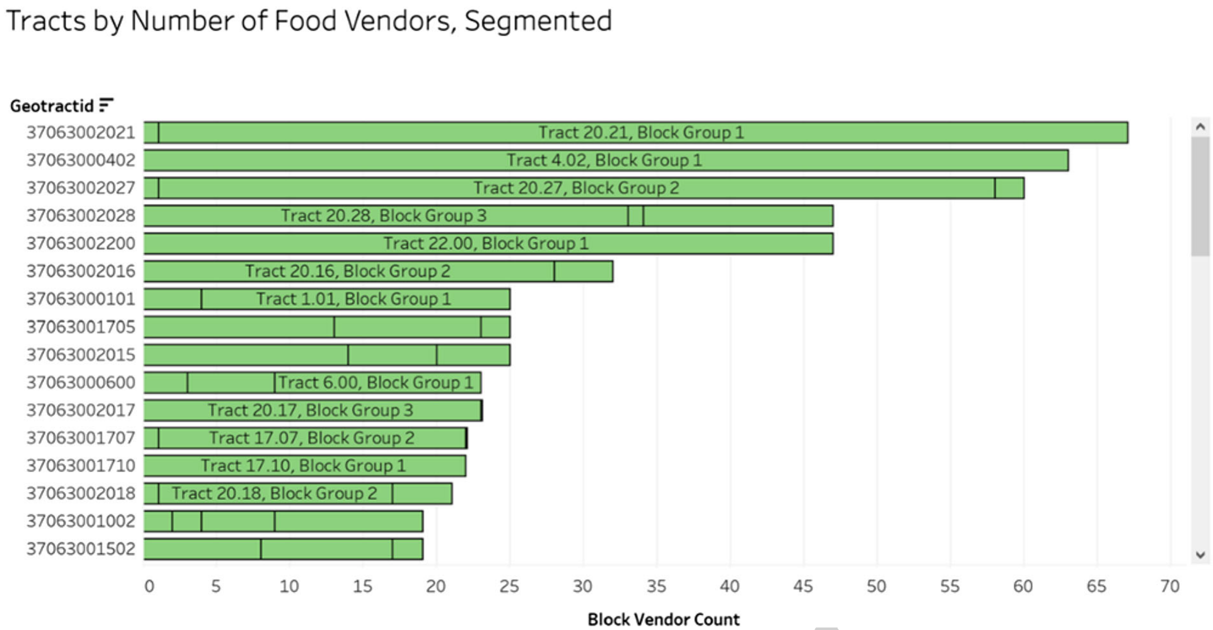

FIGURE 3 Portion of number of food vendors in each census tract, descending

Simplifying the Business Description categories to basic four categories fits the data visualization principle of simplification, utilizing the dashboard feature of Tableau. The dashboard feature allows viewing multiple sheets for comparison purposes. The left image of Figure 4 shows the high prevalence of restaurants in downtown Durham, with a small number of Grocery and Convenience Stores. However, the right image complicates the visual. Although we have more details, observing coffee shops, retail stores, and even barbecue restaurants, we are forced to look at

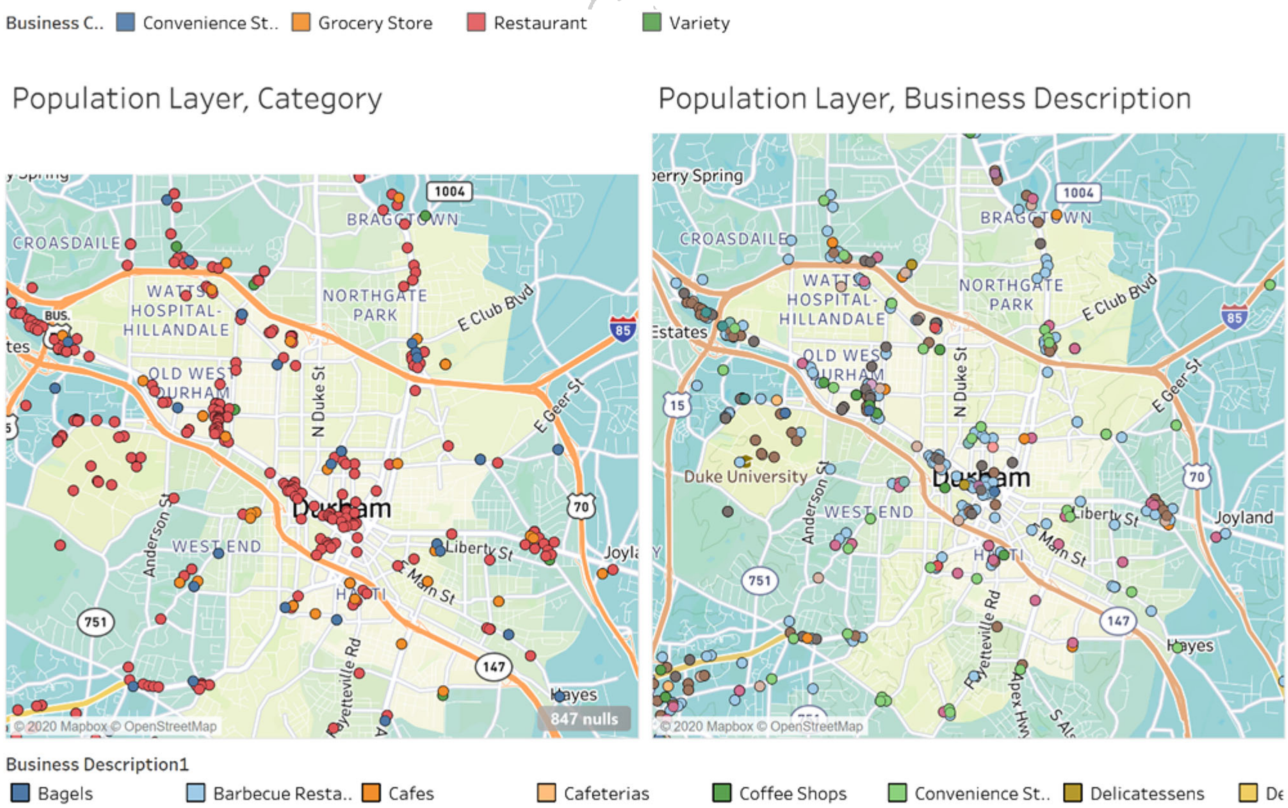

FIGURE 4 Side by side comparison of Business Category versus Business Description variable

over 15 categories in the legend in order to decipher the visual information. Therefore, we can conclude the constructed Business Category variable is effective at simplifying the food landscape such that someone viewing the image can notice the general profile of food-providing services in downtown Durham.

From observing Figure 2, we note that the population numbers are heavily imbalanced, based on national trends rather than relative to Durham. Furthermore, demographic data are in the form of raw numbers rather than proportions. We cannot properly determine which areas are minority communities without proportional data, necessitating the need for U.S. Census data of Durham. The DNC data are promising sources to create custom map layers within Tableau, as it contains percentage demographics between 2014 and 2018. However, we have not currently found methods to integrate these layers with map visualizations of the food vendors. The visualized data using DNC data consist of aggregated food vendor data. Therefore, there is a risk of losing information in the current format of two separate Tableau workbooks. A potential avenue is using ggplot in R and potentially linking those graphs with Tableau with RServe, which functions similarly to TabPy. This format uses a Census API Key in order to collect ACS data and variables of interest (Walker, 2020).

Furthermore, we do not have data on closed vendors. At the minimum, because the NC Commerce data are updated annually, we can begin tracking closed vendors as of March 2019 with the visual. Finally, we have noted some incorrectly labeled vendors by their primary NAICS code. The data do not provide an accurate reflection of the diversity of food vendors within a single category. For example, within the NAICS code 445120, both Food Lion and local grocery stores are listed. As a result, any analysis that attempts to find trends over time will be inherently underfitted. In addition, there are very clear outliers in the food vendor data. Walmart has about $76 million in annual sales, which heavily skews any visualizations relying on market share and annual sales. Additionally, stores that have a significant share of nonfood-related goods (Target, Walmart) may not have accurate sales values. For future research, we are considering using rough estimates of the proportion of food revenue to determine their annual sales. Such changes should improve trend lines and outliers when using any visualization using the annual sales and market share variable.

We expect to perform more sophisticated statistical analysis with the integrated data, potentially looking into kaggling and time-series analysis once we obtain access of data from previous years. In addition, we are interested in making a dynamic visualization and an interactive web application for researchers, so that they will be able to filter and edit visualizations based on their research objectives.

Finally, we are interested in exploring new variables not available in the NC Commerce data. Ownership of vendors is an important characteristic for understanding the food landscape, as food security is often tied to national chains versus local ownership. Furthermore, with the goal of obtaining racial equity in food systems, determining the ethnicity of food owners in Durham is an important characteristic. Some inferences are possible using the contact names; however, such a method is not completely reliable. In order to establish future research along these lines, we have, in partnership with the WFPC, inspected a sample of grocery store data to track potential errors in the data, including the store's current status, errors in the store's classification, and whether the store is local or part of a regional or (inter)national chain. We observe that there are vendors that should be convenience stores, which are now closed, and another vendor identified as being a local company selling international-themed food. There is potential for expanding this inspection to the whole data set.

6 | CONCLUSION

We were successful in obtaining data of food vendors in Durham using the NC Commerce Data. With the software Tableau Prep Builder, we combined the multiple sheets of collected data into a single data set for visualization, and we created new variables using these data, primarily Business Category. The business category variable proved to be effective in simplifying the classifications of business descriptions in a way that communicated potential trends of interest throughout map visualizations of Durham. Furthermore, with the use of data form the U.S. Census Bureau, we created map visualizations using geometric delineations of census tracts and blocks, which will be effective in visualizing data from the DNC.

The food landscape visualization allows us to see interactive patterns among food vendors and demographic data in Durham with a wide variety of visualization techniques. The visualizations confirmed trends we expected, including high concentrations of vendors around high traffic highways and roads. We expect the visualizations to improve in effectiveness when incorporating NC Commerce data from previous years, primarily to demonstrate how Durham's food landscape has changed through time.

We expect to utilize the developed landscape visual for insightful statistical analysis on food inequity issues. Topics include ownership of vendors based on ethnicity, presence of local vendors versus (inter)national vendors, money flow of annual sales, and dietary quality of the food vendors. We expect to make a more comprehensive visualization using more complex data sets, including the Behavioral Risk Factor Surveillance System data. Being able to visualize this information effectively will allow an interactive web tool for researchers to use for both communication and studying Durham's food landscape.

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DATA ACCESSIBILITY STATEMENT

The data that support the findings of this study are available at the following resources: Durham Neighborhood Compass at compass.durhamnc.gov/en/about (DataWorks NC, 2020); North Carolina Department of Commerce at https://accessnc.nccommerce.com/business/business_custom_search_infogroup.html (North Carolina Department of Commerce, 2019); and the U.S. Census Bureau at https://www.census.gov/programs-surveys/geography.html (U.S. Census Bureau, 2019

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