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Integrating Environmental Barriers into Food Desert Maps:
Improving measurement of resource access inequities

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Abstract

Background: Current definitions of food deserts mainly use distance to supermarkets as a proxy for food access. In urban environments, residents rely heavily on active transportation (e.g., walking, biking). Compared to healthy young adults, vulnerable populations, including older adults and individuals with chronic health or disability conditions, are more susceptible to experiencing environmental factors as barriers to moving through the environment via active transportation. Individuals with asthma may have an asthma attack while walking along a road with poor air quality from heavy car traffic; individuals with autism may experience sensory overload from noise and light stimulation walking down that same road; older adults may suffer heat stroke while walking on a road with no tree shade on a hot summer day. All of these may occur while these individuals are traversing what looks like a short distance to get the groceries they need. Current methods likely overestimate food access for these vulnerable populations in many parts of the city.

Objectives: In this work, we propose and implement an example of a new approach to mapping food deserts that accounts for environmental barriers experienced by vulnerable populations. We focus on the elevated risk of heat stroke among older adults on a hot summer day in Chicago, identifying temperature, humidity, and heat index as highly impactful environmental variables.

Hypothesis: We hypothesize that accounting for environmental barriers posed to older adults by temperature, humidity, and heat index on a hot summer day in Chicago will reveal that de facto access to food is overestimated by standard measures of access for many older adults during times when the city is experiencing hot summer weather.

Methods: To implement, we: (1) calculate and map average raw distance to the nearest grocery store per census tract, (2) calculate and map temperature, humidity, and heat index on a typical summer afternoon in Chicago per census tract, (3) propose a simple distance-penalty formula (with a penalty multiplier per measured environmental variable value) for older adults, (4) use measured environmental variable values and the distance-penalty formula to convert raw distance to food source per census tract to 'Real Feel' distance for older adults, and (5) map 'Real Feel' distance for older adults per census tract.

Results: Using one km as a cutoff for 'walkable', we find that, of the approximately 340,000 older adults living in Chicago, 150,000 live in census tracts where the average distance to a grocery store is un-walkable even under ideal environmental conditions (i.e., based on raw distance). On a typical hot summer afternoon, non-ideal environmental conditions convert the raw distance to a longer 'Real Feel' distance, and an additional 100,000 older adults live in a census tract where the average distance to a grocery store is un-walkable. Many of these additional older adults live on the edges and south side of the city; 60 percent are non-white, 35 percent live alone, and 15 percent have income below poverty.

Policy Implications: Adding in de facto environmental barriers to food access allows us to map food access inequities more accurately, identify localized populations where access to food is overestimated

in some circumstances, and highlight environmental barriers as critical intervention points that policy makers can address to improve access. Here, we assessed food access for older adults in Chicago. We can also use this approach to assess access to resources and public goods other than food, for other vulnerable populations, in other cities. Interactive tools incorporating this approach — also with increased geographic and temporal resolution — may prove useful for policymakers, and for residents making daily destination and route decisions.

We provide an accounting of limitations of the current example implementation and provide some exposition on potential future directions.

Background

Access to fresh, healthy, culturally appropriate food is one of the essential social determinants of health. Access is impacted not only by ability to afford food, but by the physical accessibility of places to purchase or otherwise obtain food.[1,2] In urban areas, the USDA considers a census tract to have low physical access to food if a substantial portion of the population must travel over half a mile (0.8 kilometers) to reach a grocery store. In rural areas, the reference distance is 10 miles (16 kilometers). The USDA considers a census tract to be a food desert if it is both low access AND low income (based on poverty rate and median income). As of a 2017 USDA report, over 80 million people in the U.S. live in a census tract classified as both low access AND low income (a food desert) based on these standards; nearly 40 million people do if the urban/rural reference distances are increased to one mile/20 miles (1.6 kilometers/32 kilometers).[3,4]

There are several reasons why this type of analysis, which bases assessment of physical access to food on raw distance to food source, may overestimate access for many individuals and populations.[20] In this work, we specifically propose that:

- Environmental factors (e.g., poor air quality, extreme temperature and humidity, lack of tree shade) can act as barriers to moving through the environment, especially for individuals who rely solely, or largely, on active transportation (e.g., walking, biking).
- Environmental factors have a disproportionate impact on the health and mobility of some vulnerable populations, like older adults, children, and individuals with chronic health conditions.
- These vulnerable populations are unequally distributed geographically throughout cities, with vulnerable populations often concentrated in low-income census tracts.
- Environmental factors are also unequally distributed throughout cities, with non-ideal environmental conditions often concentrated in low-income census tracts.
- Using status quo methods of measuring physical access to food sources fails to account for the outsize impact environmental barriers have on the mobility and de facto access of vulnerable

populations, and likely overestimates the physical access to food for these populations. [5,6,7,8,9,10,11,12,13,14]

We propose a new approach to mapping food deserts that accounts for environmental barriers experienced by these vulnerable populations. This will allow us to map inequities in access to food more accurately, make explicit the connections between environmental barriers and de facto access, or lack of access, to food, and highlight environmental barriers as possible critical points of intervention to improve access.

Approach

In this work, we outline a new approach to mapping food deserts that accounts for environmental barriers experienced by vulnerable populations, and we implement an example of this approach. In this approach, instead of simply calculating raw distance to food source, we use (1) raw distance, plus (2) measurements of local, relevant environmental variables at the time of travel, and (3) a 'distance-penalty' formula that quantifies the impact of environmental variables on the ability of a specific vulnerable population to move through the environment, to calculate 'Real Feel' distance to the closest food source for individuals in the specific vulnerability group.

In our example implementation, we focus on older adults who live in the urban setting of Chicago, and who rely on foot transport to get to food sources, as our vulnerable population of interest. We further focus on the elevated risk of heat stroke in this population as it is a risk experienced universally by older adults with clear environmental inputs, and clear impacts on the ability of older adults to move through their environment; we identify temperature, humidity, and heat index as highly impactful environmental variables in this context.

For the example, we also limit our scope temporally, to focus on summer afternoons when the risk of heat stroke is highest. Further, because the COVID-19 pandemic substantially impacted status quo traffic patterns (and potentially local temperature, air quality, and other environmental conditions) in 2020 and 2021, we chose to use data from a hot summer day in July of 2019 to inform the example.

In order to calculate the 'Real Feel' distance to food source for a specific vulnerability condition, we need four elements:

- Raw distance to food source, per census tract
- Values of environmental variables that impact the mobility of individuals with the at-risk condition, again, per census tract
- Quantification of the impact that each of these environmental variables has on the mobility of, and felt distance for, individuals with that at-risk condition

- A 'penalty formula' that takes all of these elements as input to convert raw distance to 'Real Feel' distance for individuals with the at-risk condition, at the time of travel, per census tract

Data & Methods

Food Source Locations

We used the search term "grocery" on the Chicago Data Portal free text search bar to find three relevant data sets:

- Grocery Store Status: A list of grocery stores in Chicago and last known status (open or closed); last updated June 2020
- Nearby Cook Country Grocery Store Chains: A list of grocery stores that are part of a multi-store chain and are located at or within one mile (1.6 kilometers) of Chicago's city limits; last updated April 2019
- Nearby Independent Cook County Grocery Stores: A list of independently owned- and operated grocery stores located at or within one mile (1.6 kilometers) of Chicago's city; last update July 2018

From these datasets we extracted the longitude and latitude points for all grocery stores in the City of Chicago, and in a buffer of one mile (1.6 kilometers) surrounding the City of Chicago limits. We include grocery stores outside of the city to account for cases where a grocery store just outside the city may be the closest food source for individuals living near the edge of the city.

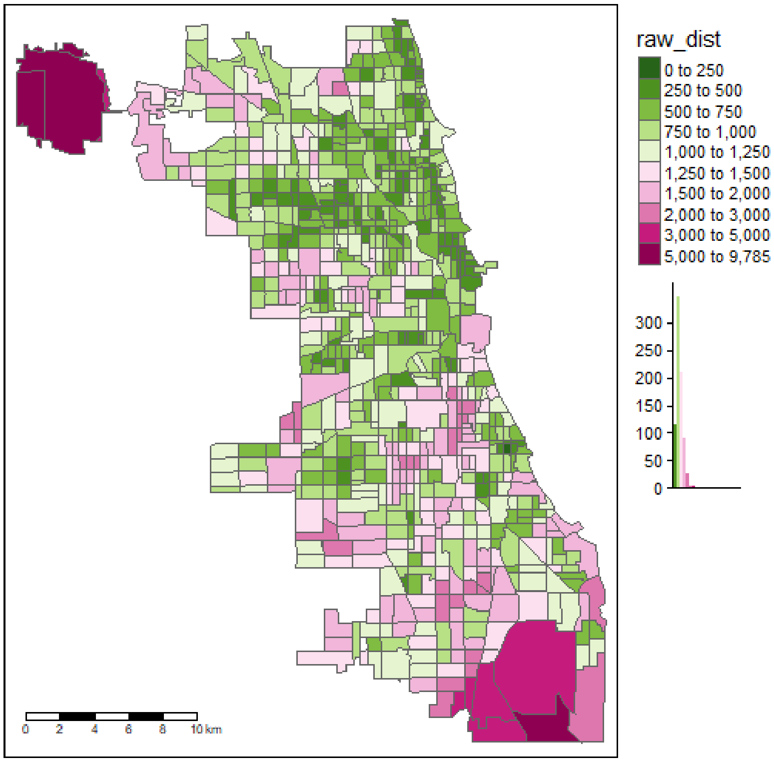
Raw Distance to Food Source

A typical approach to calculating average distance to a food source per census tract is to pick a single centroid point per census tract, calculate "as the crow flies" distance between that point and surrounding grocery stores, and then choose the shortest route available. We take a more realistic approach in a few ways.

First, instead of calculating distance "as the crow flies," we calculate distance to surrounding grocery stores along the existing street network. Second, when choosing the shortest route available, we incorporate penalties for streets that are less desirable for walking (e.g., a busy arterial street or highway) so that we favor walk-friendly routes.

Finally, instead of calculating distance for a single centroid point per census tract, we calculate distance for 100m-spaced starting points covering the full area of the census tract and average shortest path length across all these starting points to get the average distance to food source for the census tract. This accounts for the fact that people live all over the tract, not just at the center, and head out from different points to walk to the grocery store.

Figure 1: Raw Distance to Food Source per Census Tract - Measured in Meters



Environmental Variable Values

We first identified environmental variable values that would highly impact the mobility and felt distance for older adults. We specifically thought about the elevated risk of heat stroke among older adults on a hot summer afternoon in Chicago, and identified temperature, humidity, and heat index as highly impactful environmental variables.

Our overall hypothesis is that differential micro-climate factors on a scale even smaller than census tracts impact human health, mobility, and felt-distance. Therefore, our goal was to obtain climate/environmental variable values at as high spatial resolution as possible. While in future work, we hope to implement similar analyses at higher resolution, for this first proof of concept analysis, we set out to make calculations at the census tract level. Therefore, we looked for data sources that provide measures of these climactic/environmental variable values at census tract or higher geographic resolution.

We purchased climate raster data from the PRISM Climate Group at Oregon State University. These data are based on measurements from a variety of government- and non-government- run monitoring stations, and application of a climate model to interpolate across values measured at each physical monitoring station to obtain climate values at 800m spatial resolution for the whole of the continental U.S. Climate metrics available from this dataset are listed in ***Table 1***.

Table 1: Climate Metrics Available at 800m Spatial Resolution from PRISM Climate Group

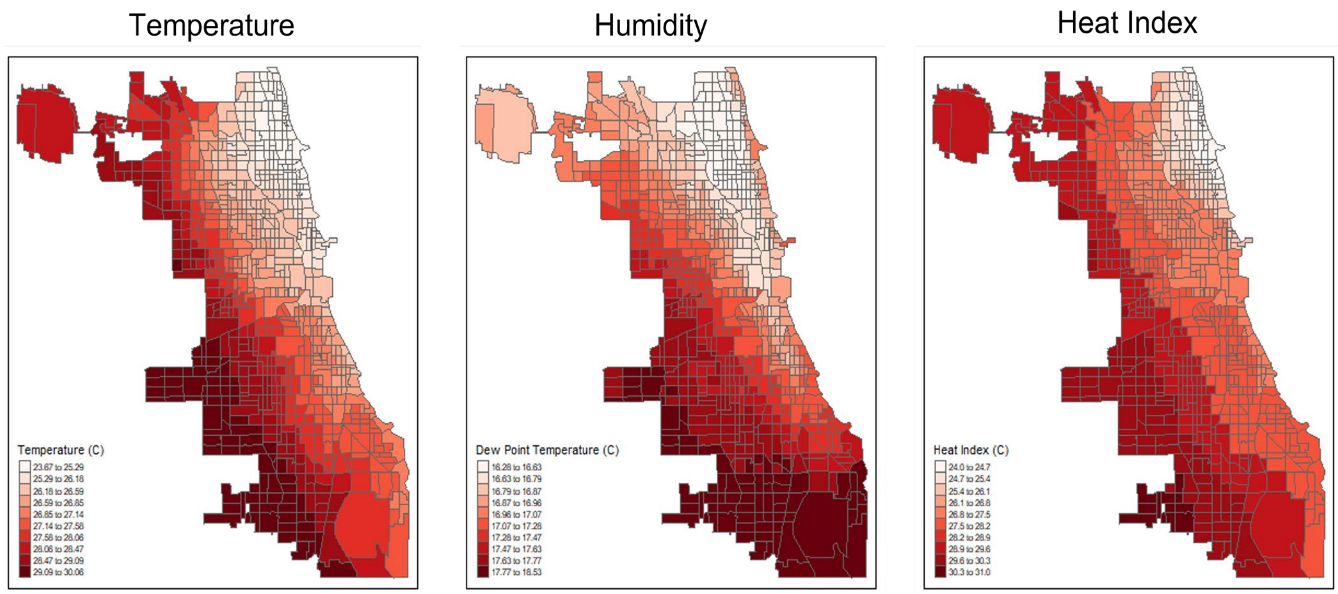
Parameter Name	Description
Tmean	Mean temperature
Tmax	Maximum temperature
Tmin	Minimum temperature
Tdmean	Mean dew point temperature
Pp	Total precipitation (rain and snow)
Vpdmin	Daily minimum vapor pressure deficit
vpdmax	Daily maximum vapor pressure deficit

Highest available time resolution is daily. We use the Tmax (Maximum temperature) metric and the Tdmean (Mean dew point temperature) metric as best available approximations of the temperature and humidity in the afternoon on a hot summer day. We use the heat.index function from the weathermetrics R package to calculate Heat Index from Tmax and Tdmean. This gives us access to Temperature, Humidity, and Heat Index data at high geographic resolution.

Multiple rasters generally overlap each census tract boundary; an average temperature, humidity, or heat index value for the census tract was calculated by taking an area weighted average of those rasters.

We calculated average temperature, humidity, and heat index per census tract for every day in July 2019, and chose to focus on values for July 7, 2019. We chose to focus on July 7 since that day had one of the largest ranges of heat index across census tracts in the city, as well as a minimum census tract heat index below 27 C/80 F (the heat index reference value, and the first value at which caution is recommended) and a maximum census tract heat index well above 27 C/80 F (Figure 2).

Figure 2: Environmental Variable Values per Census Tract - Measured in Degrees Celsius



Penalty Formula

We proposed a simple structure for the penalty formula (Figure 3) using a few assumptions.

- Raw distance is equal to the 'Real Feel' distance for a healthy young adult under ideal environmental conditions.
- Certain vulnerability conditions may impact mobility and felt distance even under ideal environmental conditions (see Figure 3A, second term).
- We assume values for each environmental variable that represent 'ideal' or 'reference' conditions with respect to that variable (e.g., we assume that ideal temperature is equal to 21 C/70 F, ideal dew point temperature is 13 C/55 F; we assume 27 C/80 F as the reference temperature for heat index, as this is the lowest heat index at which even mild exposure warnings begin to take effect, and older adults are advised to take precautions against heat illness when the temperature climbs above 27 C/80 F – see ref and ref). (see Figure 3B)
- We assume a linear relationship between departure of an environmental variable from the ideal or reference value and impact on mobility or felt distance (e.g., in the case of temperature's impact on felt distance, every degree above the ideal of 21 C/70 F increases the felt distance for older adults by the same amount). (see Figure 3B, terms 3-5)
- We assume that certain environmental variables may have adverse impacts on mobility and felt distance for certain vulnerability groups when the variable climbs above OR below a certain ideal or reference value or range of values. Therefore, we implement dummy variables to allow specific modifier terms to impact calculation of 'Real Feel' distance only when relevant. For example, at least for some vulnerability conditions, temperature may impact felt distance both when the temperature

becomes very hot, and when temperature becomes very cold. For vulnerability conditions where this is relevant, we plan to implement two separate modifier terms for temperature, allowing for different magnitudes of impact for each of these terms, and for a different ideal or reference temperature. (See Figure 4A, terms 3-5 and Figure 4B, terms 3-7)

Figure 3: Basic Structure of Penalty Formula - Overview and Reference Values

A

Real Feel Distance (Older Adult) =

Raw Distance +
Raw Distance * Older Adult Impact +
Raw Distance * Environmental Variable Value Increment * Environmental Variable Impact

B

Real Feel Distance (Older Adult) =

Raw Distance +
Raw Distance * Older Adult Impact +
Raw Distance * Temperature Increment * Temperature Impact Multiplier +
Raw Distance * Humidity Increment * Humidity Impact Multiplier +
Raw Distance * Heat Index Increment * Heat Index Multiplier

Reference Temperature = 21°C (70°F)
Reference Humidity = 13°C (55°F)
Reference Heat Index = 27°C (80°F)

Figure 4: Basic Structure of Penalty Formula - Detail and Future Implementation

A

Real Feel Distance (Older Adult) =

Raw Distance +
Raw Distance * *Older Adult* Impact +
***Temp over 21C Dummy* * Raw Distance * (Temp – Reference Temp) * *Older Adult High* Temp Impact per Degree +**
***Dew Point over 13C Dummy* * Raw Distance * (Dew Point – Reference Dew Point) * *Older Adult High* Dew Point Impact per Degree +**
***Heat Index over 27C Dummy* * Raw Distance * (Heat Index – Reference Heat Index) * *Older Adult High* Heat Index Impact per Degree**

B

Real Feel Distance (Older Adult) =

Raw Distance +
Raw Distance * *Older Adult* Impact +
***Temp over 21C Dummy* * Raw Distance * (Temp – Reference Temp) * *Older Adult High* Temp Impact per Degree +**
***Dew Point over 13C Dummy* * Raw Distance * (Dew Point – Reference Dew Point) * *Older Adult High* Dew Point Impact per Degree +**
***Heat Index over 27C Dummy* * Raw Distance * (Heat Index – Reference Heat Index) * *Older Adult High* Heat Index Impact per Degree +**
***Temp under 16C Dummy* * Raw Distance * abs(Temp – Reference Temp) * Older Adult *Low* Temp Impact per Degree +**
***Dew Point under -1C Dummy* * Raw Distance * abs(Dew Point – Reference Dew Point) * Older Adult *Low* Dew Point Impact per Degree**

We did a deep-dive literature review to find empirical evidence upon which to base our estimates of environmental variable impact (see ***Appendix 2*** for Literature Review), and used this approach to estimate the impact of temperature, humidity and heat index on mobility and felt distance for older adults (Figure 5).

Temperature: Stotz et al. exposed groups of older adult women to temperatures of either 20 degrees Celsius or 30 degrees Celsius conditions for 30 minutes, holding humidity constant, and measured distance walked in six minutes following the exposure. The group exposed to the 20 degree temperature condition walked 602.1m on average; those exposed to the 30 degree temperature condition walked 572.8m on average: (572.8/602.1-1)/(30-20) 0.50% decrease in distance traveled per 1ºC increase in temperature.

Humidity: Stapleton et al. exposed groups of older adults to dew point temperatures of either 10 degrees Celsius or 28 degrees Celsius conditions for two hours, holding temperature constant at 36.5 degrees Celsius. Over the course of a two-hour resting exposure, the group exposed to the ten degree dew point temperature condition had a cumulative change in body heat content of 200kJ on average; those exposed to the 28 degree dew point temperature condition had a cumulative change in body heat content of 400kJ on average: (400/200-1)/(28-10) 5.5 percent increase in accumulated body heat content per 1ºC increase in dew point temperature.

Heat Index: A review by Kenney et al. cites several relevant statistics. Note that apparent temperature is a temperature index that combines the effects of air temperature, relative humidity and wind speed: "...temperatures above the 90th percentile in California were found to increase risk of excess mortality by 4.3% for every 5.6°C increase in apparent temperature (4)"; "In 15 European cities, an increase in apparent temperature of 1°C above a threshold temperature unique to each city was associated with a 3.12 % increase in mortality in Mediterranean cities and a 1.84 % increase in mortality in northern European cities (3)". These statistics lead us to find a range of 0.77 percent to 3.12 percent increase in mortality per 1ºC increase in apparent (heat index) temperature; we extrapolate a much larger impact on less severe outcomes such as lowering of mobility and increase in felt distance and estimate a 7.5 percent increase in felt distance per 1ºC increase in apparent (heat index) temperature.

Figure 5: Quantified Impact of Environmental Variables

Temperature

0.5% decrease in distance walked per 1C >> (0.5% increase in distance per 1C)

Stotz, Anja, et al. "Effect of a brief heat exposure on blood pressure and physical performance of older women living in the community—a pilot- study." International journal of environmental research and public health 11.12 (2014): 12623-12631.

Humidity

5.5% increase in body heat content per 1C >> (5.5% increase in distance per 1C)

Stapleton, Jill M., et al. "Do older adults experience greater thermal strain during heat waves?." *Applied Physiology, Nutrition, and Metabolism* 39.3 (2014): 292-298.

Heat Index

0.75-3.5% increase in mortality per 1C >> (7.5% increase in distance per 1C)

Kenney WL, Craighead DH, Alexander LM. Heat waves, aging, and human cardiovascular health. *Med Sci Sports Exerc.* 2014;46(10):1891-1899. doi:10.1249/MSS.0000000000000325

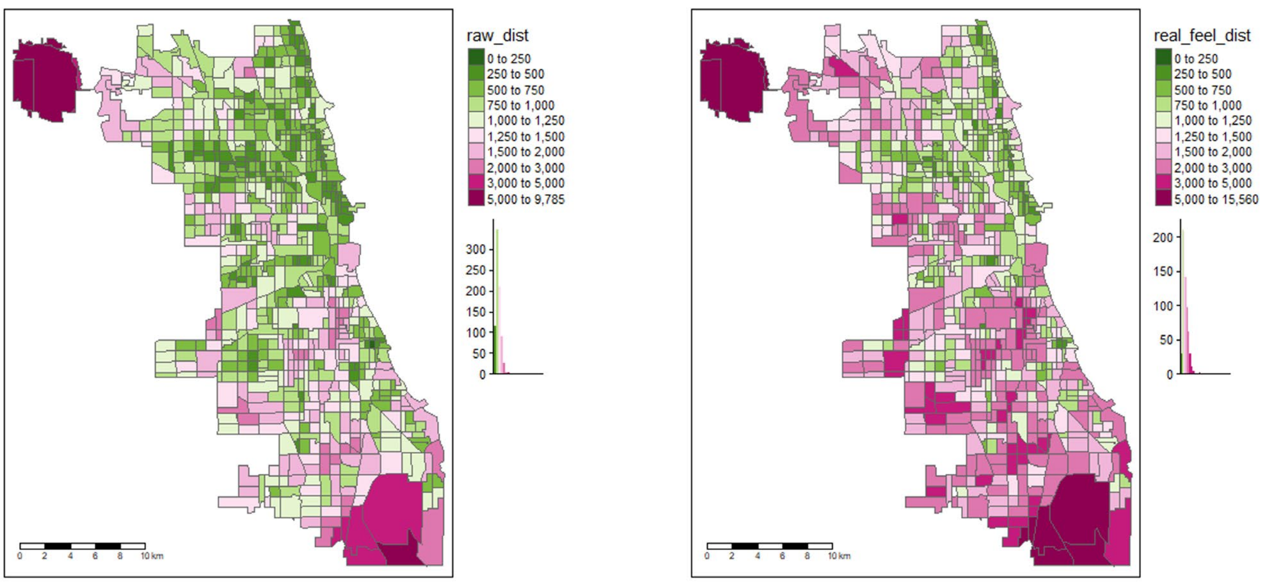
Code Repository

Analyses and code necessary to reproduce the analyses is original work of the paper authors; code has been made publicly available on GitHub by the authors at https://github.com/artinthetrees/real-feel-distance.

Results

Geographic Differences in Raw Distance to Food Source, Real Feel Distance to Food Source for Older Adults, and Concentration of Older Adults

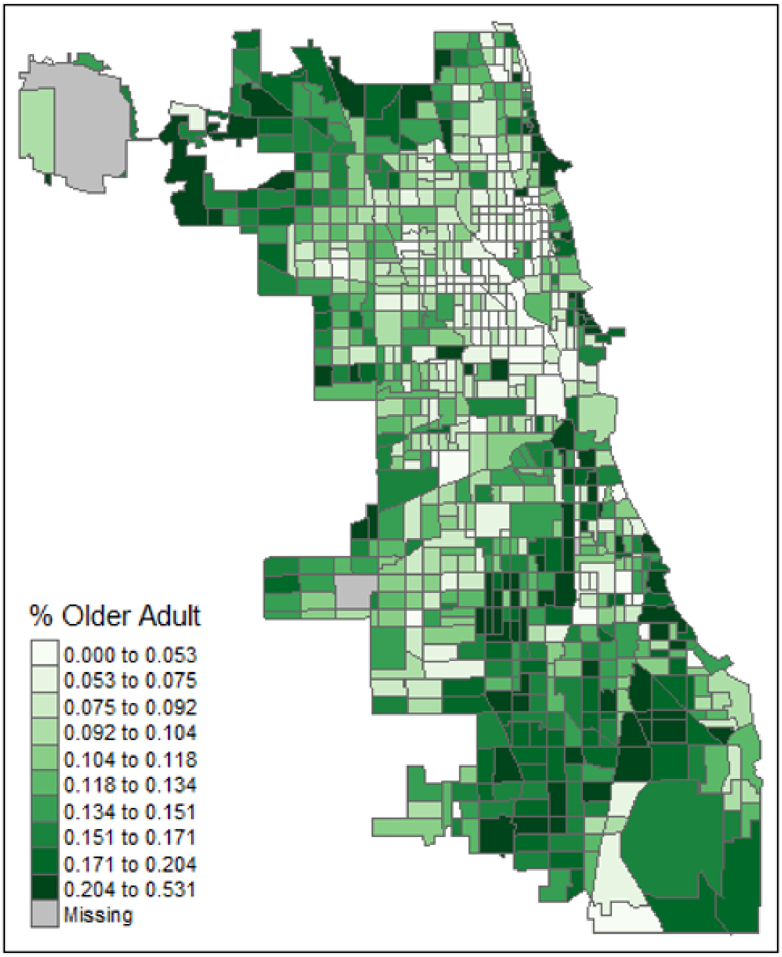
Figure 6: Raw and Real Feel Distance for Vulnerability Condition: Older Adults



Based on the USDA threshold of either 0.5 or one mile (0.8 or 1.6 kilometers) to a grocery store as determinative of low access to food in an urban context, as well as other literature, we assume that many people will avoid walking trips to get groceries if the distance is over one km, so we color our map of raw distance to food source accordingly (Figure 6, left panel).[15,16,17,18] Here, anything in a shade of green indicates an average distance of one km or less, with darkest green indicating shortest distances and lightest green indicating close to one km distance. Anything in a shade of pink indicates an average walking distance of over one km, with darker pink indicating longer distances to a food source.

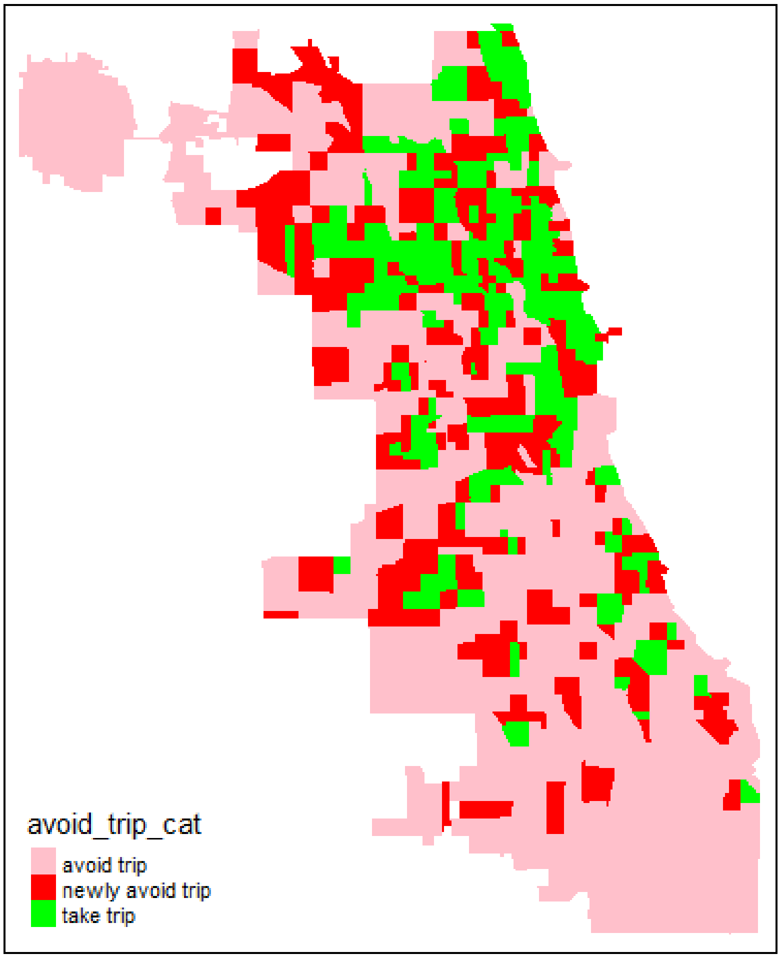
Comparing the map of raw distance to food source (Figure 6, left panel) and ‘Real Feel’ distance to food source for older adults (Figure 6, right panel), it is clear that many of the areas that are light green, or just on the edge of being walkable based on raw distance, flip to pink (or un-walkable) based on ‘Real Feel’ distance for older adults in those census tracts. Importantly, many of the areas that flip from walkable to un-walkable are those census tracts on the edges and south side of the city where there are also high concentrations of older adults (Figure 7).

Figure 7: Rate of Vulnerability Condition: Older Adults



Impact of 'Real Feel' Distance on Geographic Differences in Avoided Walking Trips to Food Sources for Older Adult

Figure 8: Raw versus Real Feel Distance, and avoided walking trips for Older Adults



We present another way to visualize how things change per census tract when we go from raw to 'Real Feel' distance in Figure 8. In pink are the tracts where distance to a food source is already over one km based on raw distance to a food source. In these tracts, anyone, including older adults, is likely to avoid walking trips to the grocery store, even under ideal environmental conditions. In red are the tracts where distance to food source is under one km based on raw distance, but over one km based on 'Real Feel' distance for older adults. In these red tracts, older adults are likely to avoid a walking trip to the grocery store on a typical hot summer day in Chicago, even though they might easily walk to the grocery store under ideal environmental conditions.

Implications of ‘Real Feel’ Distance for Older Adults in Chicago on a Hot Summer Day

From our map visualizations, it looks like many areas on the edges and south side of the city with high concentrations of older adults ‘flip’ from having a nearest food source that is walkable to having a nearest food source that is un-walkable when we consider how raw distance to food source actually ***feels*** for an older adult negotiating that distance in their specific home census tract on a typical hot summer day in Chicago. On a hot summer day in Chicago, typical methods of assessing food access overestimate the number of older adults with good food access. By how much?

We use ACS 2015-19 5-year estimates data[19] to get a sense of the magnitude of this overestimation. We find that of the 2.74M people in Chicago, 340,000 are older adults. Based on raw distance, there are already 150,000 older adults in Chicago with a nearest food source that is un-walkable. When we consider ‘Real Feel’ distance, we calculate that an additional 100,000 older adults have a nearest food source that, while likely walkable under ideal environmental conditions, is not walkable under environmental conditions typical on a hot summer day in Chicago. Many of these additional older adults (for whom food access is likely regularly overestimated) are exposed to additional vulnerabilities that also compromise their ability to access food; 60 percent are non-white, 35 percent live alone, and 15 percent have income below the poverty line.

Discussion

Policy Implications

Improved accuracy in identification and localization of populations with low food access: Adding in de facto environmental barriers to food access allows us to map food access inequities more accurately, and to identify localized populations where access to food is overestimated in some circumstances. This gives us a better sense of the magnitude of the problem of limited food access (How many people have low access to food?), which populations are most impacted, where, and when. This allows for the possibility of thinking about interventions that are place- and time- based or otherwise targeted to a specific population that has issues with low food access (e.g., Older adults may be targeted for an intervention through Medicare, partnering with the AARP, or by specific messaging campaigns calibrated to be appealing to older adults).

Environmental barriers as critical intervention points to improve food access: Adding in de facto environmental barriers to food access allows us to highlight environmental barriers as critical intervention points that policy makers can address to improve access. In this example where we see that temperature, humidity, and heat index have a dramatic impact on the level of true access older adults have to food in Chicago on a typical hot summer day, policy makers may think about how to modify not only where food sources are located (e.g., tax incentives to a grocery chain to open a new store - a traditional intervention approach), but also how to modify how hot and humid certain locations in the city get on a hot summer day (e.g., replacing absorptive road surfaces with more reflective surface materials, planting and maintaining trees in parkways and increasing green park-space) or how otherwise to modify the environment to make it easier for residents to deal with non-ideal, hot, humid environmental conditions (e.g., add benches with shade shelters and drinking fountains in parkways, increase size of parkways to better separate pedestrians from the heat generated by car traffic and the heat radiated from road asphalt).

Utility for Policymakers and Residents: Interactive tools incorporating this approach — also with increased geographic and temporal resolution — may prove useful for policymakers, and for residents making daily destination and route decisions. Some possible examples include:

For a policymaker, it may be useful to have an interactive tool that allows them to choose a vulnerability condition (e.g., “Older adult”) and a season, and then displays a map of Real-Feel distance to closest food source for individuals with that vulnerability condition in that season per census tract. This tool could also display a map of the concentration of individuals with that vulnerability condition per census tract alongside the Real Feel distance map for individuals with that vulnerability condition. This would allow for visual inspection and manual identification of census tracts/areas where many individuals with that vulnerability condition reside and where, at the same time, individuals with that vulnerability condition are particularly at risk of low food access. Policymakers might prioritize individuals with that vulnerability condition living in the identified census tracts for food access interventions. Automated comparisons and calculations built into such a tool could make this identification process easier and more automated.

For older adult residents, an interactive tool that allows them to choose their vulnerability condition (e.g., “Older adult”), the closest intersection to their residence, and the season, and displays both the raw and Real-Feel distance to the grocery store that is closest to them by raw distance, and/or identifies the closest grocery store for them based on Real Feel distance instead of raw distance might help that resident decide (1) that they should avoid a walking trip to the grocery store they usually think of as close to them because the Real- Feel distance is longer than raw distance and too much for them, and/or (2) that they will go to a different store than usual because, while the raw distance is longer than that to their usual store, the Real-Feel distance is shorter. Such a tool would be even more useful if real-time environmental variable data were available for use by the tool at high geographic resolution.

Generalizability: While we limited analysis in this work to consider only the impact of select environmental barriers on access to food in Chicago for older adults during a typical hot summer afternoon time period, in the future we hope to enlarge the scope to consider the impact of a wider variety of environmental conditions on access to other physically located public goods and resources (e.g., parks, public transportation, libraries, banks, etc.), in other cities, for individuals with vulnerability conditions other than older age, and at other times of day and/or year.

Current Limitations & Proposed Extensions

Environmental Variable Data: The PRISM Climate Group environmental variable data for the city of Chicago is an interpolation of actual measurement data from six measurement stations in the city. While sophisticated climate modeling is impressive and captures overall climate trends accurately enough for many applications, it is likely that this modeling approach does not capture variations in environmental variables at the micro-scale that might be most relevant to understanding variations in environmental experience of residents block-to-block in a city. Additionally, PRISM data are limited to temperature, humidity, and precipitation data and do not cover items such as noise, vibration, light, air quality, etc.

It would be ideal to obtain a wider set of actual environmental variable measurements at much higher geographic and temporal resolution throughout the city. In fact, our original intent in this work was to leverage data from the "Array of Things" (AoT) project in Chicago. The AoT consists of a network of sensor nodes distributed throughout the city of Chicago, measuring environmental data such as temperature, humidity, light, noise, and air quality, and presumably providing measurements of these variables at high temporal and relatively high spatial resolution. Unfortunately, in our own analysis of the available data, we found the AoT data to be much sparser than expected and we were unable to leverage the AoT data for this work.

Some potential avenues to obtain environmental variable datasets with a greater variety of environmental measures, and at higher spatial and temporal resolution, may include: (1) use and expand data source review (see ***Appendix 1*** for Data Source Review) to find and access existing data sources that give us access to environmental data other than temperature, humidity, and heat index, and/or that may include actual monitor measurements at higher geographic resolution than is available via the six area monitors used for PRISM modeling in the Chicago area, (2) collaborate with the Array of Things team to obtain funding and buy-in of the city administration to strategically expand AoT nodes and data collection, (3) plug into and work with the growing community developing strategies for monitoring urban micro-climates using mobile monitoring stations attached to cars or bikes, such as MIT Senseable City Lab (see here for a recent review).

Improving penalty formula: Currently, the penalty formula for older adults includes terms only for temperature, humidity and heat index impact on mobility and felt distance for older adults, specifically focusing on the impact with respect to risk for heat stroke. Additionally, for the moment, each impact parameter is generally based on data from a single experiment/publication. There are several ways we may improve this approach: (1) expand the scope of the literature review (see ***Appendix 2*** for Literature Review) to include risks to mobility that older adults face other than differential risk of heat stroke, (2) expand the literature review to find multiple sources to inform each impact parameter we already include in the penalty formula, (3) perform a sensitivity analysis exploring potentially large ranges for each impact parameter we already include in the penalty formula to understand how much the exact value and magnitude of each parameter impacts our conclusions. Finally, we may also think about sourcing the data necessary to implement observational studies using high-resolution environmental variable data and GPS walking trip data tied to demographics to: (1) look at impact of environmental conditions on how long trips take and on how many trips are avoided ('deficit trips'), and (2) empirically determine and/or confirm some of these parameters.

Increased resolution: Currently, we aggregate all distance to food source and environmental variable calculations up to the census tract level. For example, while we first generate the shortest path to a food source for regularly spaced grid points at 100m resolution within each census tract, we end up averaging the lengths of these paths to generate an average shortest distance to a food source at the census tract level which we then assume is the shortest distance to a food source for everyone in that tract. We say that all individuals/older adults in a census tract have a walkable food source based on raw distance, or they all do NOT have a walkable food source. This often hides a substantial amount of variability in shortest distance to food source for people living in the same census tract.

To improve on this, we can start by making our calculation of how many people have a walkable or un-walkable food source based on raw distance at the 100m grid point level instead of at the census tract level; Specifically, instead of attributing the whole population of the census tract to walkable or un-walkable based on the average shortest distance to a food source for the whole census tract, we can divide the whole population of the census tract by the number of 100m grid points we place in the census tract. This gives us one "grid-point-sub-population" per 100m grid point; we can then assign each grid-point sub-population as having a walkable or un-walkable food source based on whether the 100m grid point that population is assigned to has a shortest distance to a food source that is walkable or un-walkable.

This approach likely gives us a better estimate of how many individuals/older adults have a nearest food source that is walkable or un-walkable based on raw distance than our current approach. However, this approach divides population per census tract uniformly among each 100m grid point within that census tract, essentially assuming that population is evenly distributed across the land area of each census tract. An even more accurate approach that accounts for non-uniform distribution of population across the land area of each census tract would be to use high geographic resolution estimates of population size to estimate what portion of the total population of a census tract should be assigned to each 100m grid point placed in a census tract. In fact, high geographic resolution estimates of population size for the whole earth do exist and have advanced greatly in sophistication of their estimation procedures in recent years. Currently, the High Resolution Settlement Layer (HSLR) provides population distribution estimates at a resolution of one arc-second (approximately 30m) for over 140 countries, including the U.S.; the currently available data is for 2015. The Facebook High Resolution Population Density Map also provides population distribution estimates at a resolution of one arc-second (approximately 30m); this resource may provide more updated population estimates as compared to the HSLR.

Additionally, we currently calculate an average value of each environmental variable across the whole census tract and apply these values in the penalty formula for a specific at-risk population to convert raw distance to 'Real-Feel' distance for all individuals in that at-risk population in the census tract. This is an imperfect approach in at least two ways: (1) this likely hides a substantial amount of variability in environmental variable values within the census tract; some people traveling the same distance within the same census tract may have very different environmental exposures (e.g., some streets in a census tract may be shady residential streets and others may be busy car-ways with no tree shading; some shortest routes to food source within the same census tract may be mainly along the former, and some routes may be mainly along the latter), and (2) we frequently see that the shortest path to a food source from many points in a specific census tract leads to a food source in a neighboring census tract, and a substantial portion of the route to that food source is through that neighboring census tract; in these cases it would likely be more accurate to apply the environmental variable values for the neighboring census tract (through which the individual must mainly travel to arrive at the nearest food source) instead of the environmental variable values for the census tract in which the individual resides.

To improve on this, we can start by calculating the ‘Real-Feel’ distance for each shortest raw distance path to food source in the census tract (one path per 100m grid point in the census tract). As suggested above for the case of raw distance, we may then estimate the number of people in the census tract with a walkable or un-walkable food source based on ‘Real-Feel’ distance by assuming a uniform population distribution throughout the census tract land area and assigning equal divisions of the total census tract population to each 100m grid point in the census tract, or by non-uniformly allocating divisions of the total census tract population to each 100m grid point in the census tract, based on high resolution population density maps such as the HSLR.

To account for the observation that the shortest path to a food source frequently requires travel through a neighboring census tract, in converting raw distance to ‘Real-Feel’ distance we may identify what fraction of each of these paths is through the “home” census tract, and what fraction is through a neighboring census tract, and apply the average environmental variable values for the “home” census tract only to the distance that is in the home census tract while applying the average environmental variable values for the neighboring census tract to the distance traveled in the neighboring census tract.

To account for travel in home and neighboring census tracts to get to the nearest food source and the variability in environmental exposure between “home” and neighboring census tracts, AND to account for variability in environmental exposures even within a single census tract, we can apply environmental variable values at the highest resolution possible given the resolution of our environmental variable data, instead of at the resolution of the census tract. For example, PRISM climate data are at 800m resolution, and several 800m rasters are often at least partially contained by a single census tract. In converting raw distance to ‘Real-Feel’ distance for a specific shortest path to food source we may identify what fraction of each of these paths is through each of the 800m PRISM rasters, and apply the environmental variable values for each raster the path traverses only to the path distance that goes through, or is contained by, that raster. The added value of this approach will be highest when the geographic resolution of the environmental variable data we can obtain is highest.

In a perfect world where we have extremely high geographic and temporal resolution environmental variable data, we can even envision that the combination of the data and this tool framework could provide a real-time tool for residents of the city to make daily decisions about which food source/grocery to go to and which route to take to minimize ‘Real-Feel’ distance given real time current environmental conditions. Instead of just identifying the single shortest path to food source for 100m grid points throughout the city based on raw distance, and then converting the raw distance just for that route to 'Real- Feel' distance (as we do in this stage of the project), the tool could be used to calculate the raw distance to any available surrounding food source option (not necessarily just the closest one), convert each of these raw distances to 'Real-Feel' distance, and choose the shortest route based on 'Real-Feel' distance. This might help avoid the "Google maps scenario," where Google always recommends the shortest/fastest route even though a more pleasant or easier route might be just a minute longer than the shortest/fastest route. And the food source recommended by the tool as the "closest" based on "Real-Feel" distance might be different for a person in one at-risk population at different times of day or year (because there will be different environmental exposures along different routes at different times of day or year), or for two people in different at-risk populations at the exact same time and starting from the exact same location (because the same environmental exposures along a route impact one at-risk population differently as compared to another). Finally, instead of determining the shortest route to each surrounding food source based on raw distance and then converting to "Real Feel" distance to determine a best route to take, this data and tool framework could inform a mechanism by which the shortest route to a food source could be directly calculated based on "Real- Feel" distance given real-time environmental data and the at-risk condition of interest; this aspiration recognizes that it may be possible to find a shorter "Real-Feel" distance to food source if the possibilities of routes are not initially constrained by first calculating shortest raw distance path to all surrounding food sources.

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