Sharing Air:

A Review and Application of Effective Methods of Communicating Temperature Data

Claire A. King

Department of Geography and the Environment, University of Richmond

Senior Capstone Project

Dr. Todd Lookingbill

April 25, 2022

Abstract

One's residence should not determine an individual's health or lifespan. Further, if the environment where someone lives is detrimental to one's health, that information ought to be shared with him or her. Surface heat exposure poses dangers to human health, and surface temperature is influenced by surrounding environmental factors. Surface temperature and related environmental data should be shared with communities in formats that best meet local needs. It is a matter of environmental and health justice. On July 15, 2021, a team of citizen scientists united under the Virginia Heat Watch project to collect surface temperature data in ten localities across Virginia. The current study aims to meet the communication, engagement, and analysis goals of the Virginia Heat Watch project through a community-based approach. Using Richmond, Virginia as a case study, web maps and communication methods were piloted before being presented to other localities. Four public web maps were created across the studied localities of Abingdon, Arlington, Petersburg, and Richmond, Virginia. Through computations of Pearson's r values, it was found that in Arlington and Richmond, tree canopy is negatively correlated with temperature and impervious surfaces are positively correlated with temperature. Regarding social variables in Arlington, temperature was positively correlated with the white percentage of the population and negatively related to median household income. In Richmond, however, temperature was negatively related to the white percentage of the population and positively related to median household income. These discrepancies between localities and their divergence from the expectations imposed by previous literature suggest that further research should be done. This study makes an important contribution to the work of the Virginia Heat Watch Project by displaying and analyzing their findings and communicating the findings of the current study based on locality needs. Future work should expand the mapping and communication of Heat Watch data to all ten Heat Watch localities.

Introduction

Temperature in the Community

Extreme heat has dangerous health consequences for exposed individuals and communities. Temporary heat waves see an influx of hospital visits, but those living in areas of prolonged exaggerated heat can develop long-term health challenges as well ("Temperature Extremes," 2020). Some of the direct health impacts of exposure to extreme heat are dehydration, heat stroke, cardiovascular disease, respiratory conditions, cerebrovascular disease, and death. The direct impacts of extreme heat conditions, however, are further compounded by indirect impacts such as exceeding the capacity of medical response teams, increased risk of injuries and work-related accidents, increased transmission of diseases, and possible disruptions to urban infrastructure ("Heat and Health," 2018). All of these compounding dangers of heat make it the leading cause of weather-related mortality in the U.S. (Luber and McGeehin, 2008). Due to environmental and structural factors, some areas are more prone to extreme heat, and thus the people within them face more extreme consequences.

Heat-concentrated areas are not distributed evenly across the landscape. Areas that experience higher temperatures than surrounding areas are called heat islands and most frequently occur in urban areas. Structural and environmental factors such as impervious surfaces and tree canopy influence where heat islands occur. It has been found that impervious surfaces- those that do not absorb moisture and are often dark, heat-absorbing colors- are related to increased daytime and nighttime surface temperatures (Ryu & Baik, 2012). Many urban building materials such as asphalt and roofing are heat-absorbing, impervious materials. They reflect little sunlight, instead absorbing the heat and releasing it slowly, maintaining higher surface temperatures even after the sun has set ("Learn About Heat Islands," 2014). In contrast, tree canopy and other forms of vegetation bring about daytime cooling through transpiration and reduce daytime urban heat especially when tree canopy is greater than 40% (Ziter et al., 2019). Evaporation, transpiration, and shade are all functions of trees and other vegetative surfaces that bring about cooler surface temperatures. In the urbanization of land, vegetative surfaces tend to be replaced by a high concentration of impervious built surfaces, thus significantly reducing the cooling potential of the land. The effects of heat islands are not felt evenly across the population, rather heat is often concentrated in neighborhoods that are impacted by other social and environmental factors that contribute to higher levels of social vulnerability (Popovich & Flavelle, 2019).

The U.S Center for Disease Control (CDC) defines social vulnerability as "the resilience of communities…when confronted by external stresses on human health." To calculate social vulnerability, the CDC considers population characteristics, housing type, and transportation access ("At a Glance," 2021). It was found that social vulnerability is positively related to heat-related mortality. Some of the population characteristics identified within socially vulnerable populations include low socioeconomic status, minority populations, and elderly or youth populations (Eisenman et al., 2016). Decades of racist and classist housing policies have created a concentration of minority and poor neighborhoods in urban areas with more affluent, white neighborhoods in the suburbs. Under the current temperature landscape, individuals' social vulnerability is compounded by their proximity to uneven heating. This environment puts their health and lives at risk, but many are not even aware of the disproportionate danger they are in because they are not given the information necessary to protect themselves or advocate for change.

Sharing Science

Barriers to and inaccessibility of data is a manifestation of colonial ideas of racism and classist structures (Dutta et al., 2021). Without equitable access to scientific knowledge, communities cannot make informed decisions about their habits or lifestyles, or advocate for the environmental and health justice that they are owed. Not only is data accessibility necessary, but also further communication of the findings and implications is needed. Even if data are shared, they are not useful to communities unless the data can be understood and their implications are clear. Education and access to knowledge is important in shaping the behaviors and values of communities. Climate work, in particular, stands to benefit from accessibility to all, as knowledge about the environment and environmental causes is positively correlated with behavior that benefits the environment (Liobikienė & Poškus, 2019). Involving affected community members in stages of the scientific process such as data collection or data communication can be an effective way of spreading accessibility.

Citizen science is a form of scientific collaboration that invites individuals and organizations to participate in the scientific process. The U.S. government recognizes the "unique benefits" of citizen science and has begun to encourage its use through legislative measures such as the 2017 Crowdsourcing and Citizen Science Act (Crowdsourcing and Citizen Science Act, 2017). Including community volunteers in citizen science projects is a cost-effective method for researchers to collect reliable data. Often, engaging volunteers can also allow researchers to expand the temporal and spatial scope of observations due to greater labor capacity. Additionally, citizen science projects bring community members into contact with science, thus making the findings more relevant to the individual and helping to spread interest in the works of the scientific community (Pocock et al., 2014).This type of community-academic partnership has been shown to allow included stakeholders to make valuable contributions to the work, but it requires all members to have a basic background knowledge of the topic (Rieckmann & Bokop, 2021). This finding reemphasizes the importance of the communication of scientific findings to community members.

The method of communication and the format of delivery is important to audience engagement and retention. Scientific communication can take many forms and not all are equal, so communication methods must be considered carefully before selection. Before selecting a format, the target audience should be considered, as environmental knowledge and values impact how information will be received and retained (Schneiderhan-Opel & Bogner, 2020). Thus, an audience-centered model that is aware of local values, climate experiences, and the general level of climate knowledge is necessary to reach audiences most effectively. Familiar communication formats and data visualization techniques should be used to avoid both confusion and taxing the viewer's memory (Franconeri et al., 2021). Regarding the effectiveness of different forms of communication, Putortì et al. (2020) found that viewers often preferred, and learned more from, a video communication than a text press release. Similarly, Dwyer et al. (2010) found that visual representations of data are more effective in audience memory uptake than a text-based presentation. Data visualizations transform raw data into illustrative figures, and they can take many forms such as charts, graphs, tables, infographics, and maps. Maps, also called geovisualizations, are effective in communicating complex data to audiences with various levels of expertise, but their design must still be carefully considered (Goudine, 2018).

Formatting data visualizations according to audience preferences is critical to effective communication. There are nuances in viewer preferences for the visual aids they receive, and evidence suggests that audience preferences can impact the way they interact with and receive the information (Ajani, 2021). Studies of audience preferences in maps reveal that viewers generally prefer simple maps over complex ones, and that decluttering visualization designs leads to higher clarity and memory uptake (Johannsen et al., 2018; Ajani, 2021). Further, audiences are more convinced of the urgency of communicated issues when the map's scale is directly relevant to the viewer's location (Johannsen et al., 2018). Geovisualizations can be created and hosted in various platforms, but research suggests that viewers prefer interactive tools over static maps (Bishop et al., 2013). Hosting a map in an interactive tool allows maps to remain interactive for viewers, and the map's extent as well as the information that it displays can be placed under viewer control. Geovisualization is a powerful visualization technique, but maps must be carefully crafted to best reach audiences.

Virginia Heat Watch

On July 15, 2021, groups from ten localities across Virginia gathered to collect surface temperature data. This collaboration between localities, facilitated through the Virginia Foundation for Independent Colleges and a partnership with CAPA Strategies, created the VA Heat Watch project. The group consisted of representatives from colleges and universities across the state in Abingdon, Arlington, Farmville, Harrisonburg, Lynchburg, Petersburg, Richmond, Salem, Virginia Beach, and Winchester, VA. Data was collected along multiple paths in each locality and at three times of day: morning, afternoon, and evening. There are three central goals of the VA Heat Watch project:

1. To describe and display the distribution of temperature and humidity.

2. To engage local communities to understand and address disproportionate extreme heat.

3. To better understand relationships between urban climates, infrastructure, and human well-being.

All of the goals of the project are valuable, however not all are being met. Despite being released in a report, the data are not yet accessible to all locality representatives in its current format (Heat Watch VFIC Report, 2021). Technology, software, GIS experience, and capacity barriers impede the use of the Heat Watch data in some localities, thus preventing some localities from further communicating the data to community members (Marymount University, personal communication, February 5, 2022). Additionally, barriers to the data impede the analysis of the data on a local level, so the findings cannot be used to their full potential.

Intent of Study

This study aims to use a community-based approach to support the goals of the Virginia Heat Watch Project by aiding in the creation of a series of interactive web maps for Virginia's

Heat Watch localities. The first goal of this project is to convey Heat Watch data in a format that is accessible and inspiring to community members, paying special attention to those who are disproportionately affected by heat. In order to best meet that goal, this project takes a community-based approach, engaging with community partners to meet the unique needs of each area. Each step of the project incorporates the preferences of the locality. The second goal of this project is to investigate the relationships between temperature and other environmental factors. It can be expected that community desires and need for GIS support vary. Additionally, communication formatting will be adjusted to meet the expressed needs of the respective locality. Relationships between environmental factors and temperature are expected to follow previous literature which suggests positive relationships between temperature and impervious surfaces and negative relationships between temperature and tree canopy. Flexibility in the community-based model will enable the project to best support the goals of the VA Heat Watch project and the Virginia communities experiencing urban heat.

Methods

Site Description

The Virginia Heat Watch project involves ten localities across the Commonwealth of Virginia. Localities include Abingdon, Arlington, Farmville, Harrisonburg, Lynchburg, Petersburg, Richmond City, Salem, Virginia Beach, and Winchester. Localities in the far northern, eastern, southern, and western reaches of the state are represented. The Heat Watch localities represent a wide range of cities, counties, and towns, spanning from towns like Farmville with populations of 8,216 to cities like Virginia Beach with populations of 459,470 (“Race,” 2020). Heat Watch data was collected for each of the above localities, but this study focused on localities that opted in to the creation of a web map to display their Heat Watch data.

Abingdon, Virginia is a town located in the south-western corner of the state within Washington County. The town has an area of 8.06 square miles and a population of 8,376. Racially, the town is 89.9% white (“Race,” 2020). In 2019, the median household income was $45,848 (“Median Income,” 2019). Abingdon has a median age of 46 years, with 18.2% of the population below 18 years of age and 23.4% of the population above 65 years of age (“Age and Sex,” 2019).

Arlington, Virginia is a 26 square mile county in northern Virginia with a population of 238,642. The county is 60.9% white (“Race,” 2020). In 2019, the county’s median household income was $120,071 (“Median Income,” 2019). Arlington has a median age of 34 years, with 17.8% of the population below 18 years of age and 10.5% of the population above 65 years of age (“Age and Sex,” 2019).

Petersburg, Virginia is 20 miles south of Richmond, VA, lying near the James River. The city has an area of 22.94 square miles. The city’s population is 33,458 and 16.2% white. The city has a large Black or African American population, representing 74.2% of all residents (“Race,” 2020). Based on the 2019 American Community Survey, the median household income was $38,679 (“Median Income,” 2019). Petersburg has a median age of 38.1 years, with 21.4% of the population below 18 years of age and 16.7% of the population above 65 years of age ("Age and Sex," 2019).

Richmond, Virginia is the Capital of Virginia, and it is built around the James River. The city spans an area of 62.57 square miles. The city has a population of 226,610 and is 43.3% white and 40.4% Black or African American ("Race," 2020). The 2019 American Community Survey reported that the median household income was $47,250 ("Median Income," 2019). Richmond has a median age of 34 years, with 17.6% of the population below 18 years of age and 12.8% of the population above 65 years of age ("Age and Sex," 2019).

Community-Based Approach

This project was designed to meet the expressed needs of each locality that was included. Points of contact for each locality were established based on representatives previously involved in the Virginia Heatwatch project. The research was guided by locality requests that were collected in the form of a survey.

Community Survey. A digital survey was developed to gauge interest in the creation of web maps that would display the Heat Watch data. The form began by stressing the importance of the Heat Watch data, outlining the current barriers to the data's use, and noting the benefits of a public mapping resource. The survey asked participants a series of seven questions including which locality they represented, if they were interested in the development of a web map to display their locality's Heat Watch data, their level of capacity to create the web map without support, and what additional layers they would want to see in the web map.

The survey was presented to community representatives at a Virginia Heat Watch meeting over Zoom in February 2022, following a brief presentation of a web map prototype and a description of the possibilities of web maps for other localities. All representatives were asked to respond to the survey. Seven of the ten localities were present on the call. All representatives who were surveyed were connected to a college or university in their respective locality.

Case Study. A community-based model required maintaining close contact with localities. Rather than managing communication with all participating localities, Richmond, Virginia was selected to be a case study in this research. It was the pilot location for the initial community survey, the web maps, and conversations about reaching community members with scientific findings. Two individuals were selected as Richmond-based guides for the shaping of the project. The first, Beth Zizzamia, is the GIS Operations Manager of the Spatial Analysis Lab at the University of Richmond. Mrs. Zizzamia is knowledgeable about surveys and mapping. She was consulted before the survey was administered, regarding what data should be included in the map, and for spatial analysis assistance throughout the research. The second community contact was Devin Jefferson, the Community Science Catalyst at the Science Museum of Virginia in Richmond. Mr. Jefferson is familiar with Richmond and works to involve community members in his work at the science museum. His knowledge was integral to the selection of the format by which community members would receive the research, and he informed which data layers would be included in the final product. Regular communication was maintained with these two individuals to inform the planning and implementation of the current project.

Maps

Maps were created for each locality that communicated interest via the community survey presented at the Virginia Heat Watch meeting in February 2022. Maps were created in ArcGIS Pro software and were moved to ArcGIS Online to be hosted as a web map. A web map platform was chosen to ensure that each locality could access its respective map. The web maps were created to be interactive, and the selection of included data was dictated by the requests made on the initial community survey. The first map was piloted with the Richmond community partners Beth Zizzamia and Devin Jefferson. Web maps were designed to encourage user exploration, so data layers were made relevant to different levels of geography such as neighborhoods and census blocks using the Zonal Statistics tool in ArcGIS Pro.

Data Analysis. ArcGIS Pro was also used to perform several statistical and spatial analyses to be communicated to representatives from Arlington and Richmond. Pearson's R values were computed in ArcGIS Pro for all relationships between variables including:

1. Temperature (Data from VA Heatwatch, 2021)
2. Tree canopy (Data from NLCD USFS Tree Canopy Cover (CONUS), 2016)
3. Impervious surfaces (NLCD Percent Developed Imperviousness (CONUS), 2019)
4. Percentage of the population that is white (U.S. Census Bureau, 2020)
5. Median household income (American Community Survey, 2020)

The Pearson's R value represents the correlational relationships between each pair of layers and is calculated using this formula:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

where

r = correlation coefficient

x_i = values of the x-variable in a sample

$\underline{x}$ = mean of the values of the x-variable

y_i = values of the y-variable in a sample

$\underline{y}$ = mean of the values of the y-variable

Additionally, the five hottest block groups in each locality were identified and demographic and landscape analyses were performed. To identify the hottest block groups, the Heat Watch data were summarized by mean temperature into block groups using the ArcGIS Pro zonal statistics to table tool. Resulting tables were then joined to the block group layer and block groups were sorted into descending average temperature values before the highest five were selected. Demographic variables of median income and race were reported for the identified block groups as well as the percent tree canopy cover and impervious surfaces. All values were compared to the locality average values. The afternoon surface temperature layer was always used to perform analyses.

Data Summary. The web maps display many data layers from various locations. Most of the data used in this research are spatial data that were collected from open source GIS data sources. The primary source of data was the data collected by the Virginia Heat Watch team in July 2021. Other data sources include the Richmond Geohub, Arlington's Open Source Data Portal, ArcGIS online, the National Land Cover Database, and the U.S. Census Bureau.

Results

Community Survey

The survey had six responses from Heat Watch locality representatives. Five localities were represented in the responses. There were two responses from Abingdon, one response from Arlington, one from Petersburg, one from Richmond, and one from Virginia Beach. 100% of respondents indicated that they were interested in the development of a web map to display their local Heat Watch 2021 data. Five respondents indicated that they either do not have GIS software or that they could use some help, and one respondent indicated that they had GIS capabilities and could make their own map. The four localities that requested a web map were Abingdon, Arlington, Petersburg, and Richmond. Six different types of data layers were requested, but the three most popular were tree canopy, demographic data, and impervious surfaces (Table 1).

Case Study

The Science Museum of Virginia's Community Science Catalyst, Devin Jefferson, was the primary community representative that shaped the design of the Richmond pilot study. He was in support of a web map platform to host the information, and stressed the importance of allowing users to drive their own exploratory learning and to "get them to start thinking about this for themselves" (Devin Jefferson, personal communication, April 8, 2022). Mr. Jefferson's request was that any additional analysis be left out of the web maps so users would interpret the maps on their own without being told what to look for. He requested that the Richmond map include the Heat Watch data, tree canopy, impervious surfaces, income, and green spaces. He also suggested that heat, tree canopy, and impervious surface data be summarized to different levels of geographies to allow viewers to make the data relevant to themselves (Devin Jefferson, personal communication, April 8, 2022).

Mr. Jefferson recommended that the web maps be displayed in a public space where community members will encounter them. Not only should they be hosted publicly online, but displayed in a public physical space as well. In Richmond, Mr. Jefferson suggested that maps could be tested for display on the Hyperwall at the Science Museum of Virginia (Devin Jefferson, personal communication, April 8, 2022).

Maps

Four web maps were created to display data for Abingdon, Arlington, Petersburg, and Richmond. The web maps are hosted publicly on ArcGIS Online. Each map includes different layers based on the locality's requests. The Richmond map includes temperature, tree canopy, impervious surfaces, median household income, and parks. Temperature, tree canopy, and impervious surfaces are computed on the cell, neighborhood, block group levels (Table 2).

Data Analysis

In Arlington, Pearson's R values range from -.88 to .67. Temperature was shown to be negatively correlated with median income and tree canopy, but positively correlated with impervious surfaces and percent white population. The correlation between temperature and percent white was 0.04, between temperature and income was -0.21, between temperature and impervious surfaces was 0.67, and between temperature and tree canopy was -0.6. Tree canopy was positively correlated with percent white and median income, and impervious surfaces were negatively correlated with tree canopy, percent white, and median income (Figure 1).

In Richmond, Pearson's R values range from -0.84 to .67. Temperature was shown to be negatively correlated with percent white, median income, and tree canopy, but positively correlated with impervious surfaces. The correlation between temperature and percent white was -0.12, between temperature and income was -0.34, between temperature and impervious surfaces was 0.67, and between temperature and tree canopy was -0.6. Tree canopy was positively correlated with percent white and median income, and impervious surfaces were negatively correlated with median income but positively correlated with percent white (Figure 2).

Arlington's five hottest block groups experienced average afternoon temperatures higher than the county average on July 15, 2021. The five hottest block groups all had below average tree canopy cover and above average impervious land cover for the county. White population percentages were higher in the five hottest block groups than would be representative of the county, and median household income ranged from $84,704 to $190,118 (Table 3 & Figure 3).

Richmond's hottest block groups experienced higher afternoon surface temperatures than the city average. Tree canopy cover in the hottest block groups is less than 5% compared to the city average, 26.18%. The impervious land cover in the five hottest block groups ranged from 62.67% to 87.42%, and the city average was 35.37%. The white population in the hottest block groups was higher than the city average, and the median income in the identified block groups ranged from $10,958 to $52,961 around the city median of $51,421 (Table 4 & Figure 4).

Discussion

Data Analysis

Arlington's hottest block groups are all concentrated in the center of the county (Figure 3). These block groups had above-average temperatures, with extremely low tree canopy rates and extremely high rates of impervious surfaces (Table 3). These block groups also align with districts categorized as for commercial use, “Limited Industrial District”, and some residential areas (“Zoning Polygons,” 2022). That means that community members work, or even live, in some of the hottest areas of the city. Frequenting hot areas of the city puts individuals at greater risk of heat-related dangers. Mitigation of the heat and communication to residents and work-based members of the community must occur in order to protect individuals from the dangers of high temperatures that they face.

The demographic makeup of Arlington’s hottest block groups did not align with previous research that would suggest non-white and low-income populations are most often exposed to higher temperatures in cities (Dialesandro et al., 2021). Rather, the five hottest block groups in Arlington all had whiter populations than would be expected based on the county average. Similarly, two of the hottest block groups boasted median household incomes more than $48,000 greater than the county average (Table 3). In Arlington, positive correlations were identified between temperature and white population, challenging what previous research would suggest. However, temperature and median household income were shown to have a negative correlation which aligns with previous research (Figure 1). Future research should investigate why Arlington’s heat landscape impacts different populations than would be expected.

Although surprising, the demographic makeup of Arlington’s hottest block groups is promising for web-based science communication. Science communication should reach the people who are most affected, and web-based communication can only work if the affected populations have internet access and technological literacy. Pew Research (2021) reports that broadband internet service is most common in white households that have an annual income above $75,000. Since residents in Arlington’s five hottest block groups were predominantly white and median household incomes were above $75,000, residents of the identified communities will more likely be able to access web-based communications including web maps (Table 3).

Richmond’s hottest block groups are spread through the city, with three block groups identified in the center of the city, one on the northern edge, and one along the southern edge of the James River (Figure 4). The identified block groups had above-average temperatures and, as expected, low rates of tree canopy and high rates of impervious surfaces (Table 4). These relationships are further shown in the correlation coefficients that demonstrate a negative correlation between temperature and tree canopy and a positive correlation between temperature and impervious surfaces. In Richmond, it was also demonstrated that whiteness and temperature were negatively correlated, but income and temperature had a positive correlation (Figure 2). It is surprising that income and temperature are positively correlated, not only because it challenges existing research, but also because in the current research, income and tree canopy were still positively correlated. Future research should investigate the factors that may contribute to a positive correlation between temperature and income in Richmond, VA.

It is important to note that in Arlington, lower income is an indicator of higher heat exposure and that in Richmond percent white is negatively related to temperature (Figure 1; Figure 2). These two statistics suggest that in Arlington, populations with lower household income are more frequently exposed to hotter temperatures and that in Richmond, people of color are more likely to live in hotter block groups. Both low income populations and non-white populations experience greater social vulnerability, so disproportionate exposure to heat puts them at even greater risk (Eisenman et al., 2016). For these reasons, future scientific communication regarding temperature in Arlington, Virginia and Richmond, Virginia ought to be targeted to the lower income and minority populations that are in the hottest block groups.

There were several challenges in the statistical and spatial analyses performed for the current research. The analyses required many datasets for each locality, and data accessibility varied. Accessibility varied by data topic and locality. One limitation of the study was that, due to accessibility, datasets from various years had to be used, including tree canopy data from 2016 which is likely outdated. Additionally, localities have unequal GIS data resources available. Arlington and Richmond have many datasets available for download, but Abingdon and Petersburg do not. This made searching for Abingdon and Petersburg's data layers more difficult, and that is reflected in the limited data available in their web maps. Future projects should work to support Abingdon and Petersburg in their GIS data accessibility and bolster the web maps put forth in the current work. Furthermore, this project should be expanded to include all Virginia Heat Watch localities to ensure that data is being communicated to all community members in the state.

Communication

The web map platform used in the current research has various strengths. Some of the benefits of the platform are its accessibility from any location with internet access and its simplicity for user-guided learning. Users may choose which layers to display by turning layers on or off. Importantly, maps can easily be edited to update old data layers or add new ones. This feature is promising for the prolonged relevance of the current research. Additionally, as suggested by previous research, it is optimal for maps to be displayed in an interactive tool, and web maps allow for that capability (Bishop et al., 2013). In the current research, the web map platform allowed for the inclusion of multiple layers based on a single dataset that was aggregated to different geography levels. Including these layers was suggested by Mr. Jefferson as a way to allow users to make the data relevant to themselves, and the web map platform enables that mission.

Displaying the data in a web map platform has a few drawbacks, however. Some layers, especially raster datasets, do not display well in ArcGIS Online. For all layers, symbology options are more limited in ArcGIS Online than they are in software editions of the program. If these symbology challenges are not addressed, the communicative powers of geovisualizations can be jeopardized. Another limitation of the web map platform is that the internet is required for access. This limits where maps can be displayed and creates accessibility obstacles for some populations. According to Pew Research Center (2021), of all races and incomes, white people and people with income over $75,000 use the internet most frequently, and of all ages, people over the age of 65 use the internet least frequently. Interestingly, populations with the lowest internet usage are also socially vulnerable populations (Pew Research Center, 2021; Eisenman et al., 2016). Internet access as a prerequisite for map access is most likely to remove socially vulnerable populations from the audience. This is in direct opposition to the goal of the current research to communicate scientific information to the populations who are most affected.

Community-Based Approach

The community survey that was administered at a Virginia Heat Watch meeting was important in guiding the current research based on community needs, but results were incomplete. Only seven of the ten Heat Watch localities were given the option to request a web map because three were not present at the meeting. Additionally, the layer request question could have been improved. Tree canopy was listed as an example of a possible additional layer to include, and six out of seven respondents requested it. That prevalence suggests that listing it as an example may have encouraged people to request it (Table 1). On the other hand, the layer request question was the survey's most important question to ensure that the created maps were based on expressed locality needs. That was crucial to the community-based approach.

Piloting the survey, maps, and communication strategies with representatives from Richmond was a helpful step in the community-based approach. Following the discipline of design thinking, working with two extreme users (Zizzamia and Jefferson) allowed the current research to better target the intended market/audience of the web maps and to effectively integrate layers into the web map platform (Brown & Katz, 2011). Piloting the study in Richmond allowed for an in-depth web map with significant local knowledge to inform some of the findings. Maps that were created for other localities lack the depth of the Richmond map. Additionally, using Richmond as the pilot study influenced decisions for maps of other localities whose needs may have been different. In future studies, researchers should maintain communication with every locality on the same level that this research communicated with representatives in Richmond.

Taking a community-based approach introduced different knowledge than would have been otherwise accessible. Identifying community representatives with whom close contact would be maintained brought insight from an expert in involving the community in science and a GIS expert. Additionally, they both offered knowledge of the local terrain by being familiar with their locality to a degree that research by an outsider would not attain. The community-based approach also presented some challenges. Communicating with community partners and waiting for correspondences that were necessary to inform the next steps of the project was time-consuming. It required time from both parties to set up meetings, to review progress, to offer feedback, and to redesign the project based on representative feedback. Despite this temporal burden, the results are far richer because each locality received the maps that would be most useful to it and its residents.

One contradiction to the community-based approach that this research presents is that analyses and maps were still performed and created by an outsider. A true community-based study would come from within, but that was not possible in the current study. Rather, community representatives from whom preferences were gathered stand as the local experts that supported the study. Despite this limitation, local input was valued and centered in the conduct of the current research.

Virginia Heat Watch

The current research effectively meets the three goals of the Virginia Heat Watch project in Abingdon, Arlington, Petersburg, and Richmond. The first goal- displaying the data- was addressed through the creation of a web map for each locality. All web maps display the locality's Heat Watch data, but the depth of additional layers in the map varies due to data accessibility and the case study design of the current project. The current research also addresses the second goal, which is to engage local communities. The second goal was met through the community-based approach taken in the current study. Heat Watch representatives were engaged, but more significantly, community experts in Richmond were deeply involved in the shaping of the project. Finally, analysis performed for Arlington and Richmond localities addresses the third Heat Watch goal which is to understand relationships between climates, infrastructure, and human well-being (Heat Watch VFIC Report, 2021). Meeting the Heat Watch goals in four localities is a great step forward, but it is only a start. Heat Watch mapping projects and analysis should be expanded to include all ten Virginia Heat Watch localities to ensure community members are receiving the information they need to make informed decisions.

Bibliography

Ajani, K., Lee, E., Xiong, C., Nussbaumer Knaflic, C., Kemper, W., & Franconeri, S. (2021). Declutter and focus: Empirically evaluating design guidelines for effective data communication. *IEEE Transactions on Visualization and Computer Graphics*, 1–1. https://doi.org/10.1109/TVCG.2021.3068337

American Community Survey [ACS] (2020). *Median household income in the past 12 months (in 2020 inflation-adjusted dollars* (ACS 5-year estimate; Table B19013) [Data set]. U.S. Census Bureau. https://data.census.gov/cedsci/table?t=Income%20and%20Poverty&g=0500000US51760,51760%241500000&tid=ACSDT5Y2020.B19013&moe=false

Arlington CO GISMC. (2022). *Zoning Polygons* [Data set]. Arlington County GIS Open Data Portal. https://gisdata-arlgis.opendata.arcgis.com/datasets/zoning-polygons/explore?location=38.880825%2C-77.102000%2C13.55

At a glance: Cdc/atsdr social vulnerability index. (2021, August 30). ATSDR; Center for Disease Control. https://www.atsdr.cdc.gov/placeandhealth/svi/at-a-glance_svi.html

Bishop, I. D., Pettit, C. J., Sheth, F., & Sharma, S. (2013). Evaluation of data visualisation options for land-use policy and decision making in response to climate change. *Environment and Planning B: Planning and Design*, *40*(2), 213–233. https://doi.org/10.1068/b38159

Brown, T., & Katz, B. (2011). Change by design: Change by design. *Journal of Product Innovation Management*, *28*(3), 381–383. https://doi.org/10.1111/j.1540-5885.2011.00806.x

Crowdsourcing and Citizen Science Act, 15 USC § 3724 (2017). http://uscode.house.gov/view.xhtml?req=granuleid:USC-prelim-title15-section3724)&num=0&edition=prelim#sourcecredit

Dialesandro, J., Brazil, N., Wheeler, S., & Abunnasr, Y. (2021). Dimensions of thermal inequity: Neighborhood social demographics and urban heat in the southwestern u. S. *International Journal of Environmental Research and Public Health*, *18*(3), 941. https://doi.org/10.3390/ijerph18030941

Dutta, M., Ramasubramanian, S., Barrett, M., Elers, C., Sarwatay, D., Raghunath, P., Kaur, S., Dutta, D., Jayan, P., Rahman, M., Tallam, E., Roy, S., Falnikar, A., Johnson, G. M., Mandal, I., Dutta, U., Basnyat, I., Soriano, C., Pavarala, V., … Zapata, D. (2021).

Decolonizing open science: Southern interventions. *Journal of Communication*, jqab027. https://doi.org/10.1093/joc/jqab027

Dwyer, C. P., Hogan, M. J., & Stewart, I. (2010). The evaluation of argument mapping as a learning tool: Comparing the effects of map reading versus text reading on comprehension and recall of arguments. *Thinking Skills and Creativity*, *5*(1), 16–22. https://doi.org/10.1016/j.tsc.2009.05.001

Eisenman, D. P., Wilhalme, H., Tseng, C.-H., Chester, M., English, P., Pincetl, S., Fraser, A., Vangala, S., & Dhaliwal, S. K. (2016). Heat Death Associations with the built environment, social vulnerability and their interactions with rising temperature. *Health & Place*, *41*, 89–99. https://doi.org/10.1016/j.healthplace.2016.08.007

Franconeri, S. L., Padilla, L. M., Shah, P., Zacks, J. M., & Hullman, J. (2021). The science of visual data communication: What works. *Psychological Science in the Public Interest*, *22*(3), 110–161. https://doi.org/10.1177/15291006211051956

Goudine, A. (2021). Geovisualization: A framework and case-study analysis for effective climate related visualization [MASTER OF SCIENCE, University of Victoria]. https://dspace.library.uvic.ca/bitstream/handle/1828/12948/Goudine_Alexei_MSc_2021.pdf?sequence=5&isAllowed=y

Heat and health. (2018, June 1). World Health Organization. https://www.who.int/news-room/fact-sheets/detail/climate-change-heat-and-health

Heat Watch Report. *Virginia Foundation for Independent Colleges*. (2021). https://osf.io/3xvmg/

Johannsen, I. M., Lassonde, K. A., Wilkerson, F., & Schaab, G. (2018). Communicating climate change: Reinforcing comprehension and personal ties to climate change through maps. *The Cartographic Journal*, *55*(1), 85–100. https://doi.org/10.1080/00087041.2017.1386834

Learn about heat islands. (2014, June 17). [Overviews and Factsheets]. Heat Islands; U.S. Environmental Protection Agency. https://www.epa.gov/heatislands/learn-about-heat-islands

Liobikienė, G., & Poškus, M. S. (2019). The importance of environmental knowledge for private and public sphere pro-environmental behavior: Modifying the value-belief-norm theory. *Sustainability*, *11*(12), 3324. https://doi.org/10.3390/su11123324

Luber, G., & McGeehin, M. (2008). Climate change and extreme heat events. *American Journal of Preventive Medicine*, *35*(5), 429–435. https://doi.org/10.1016/j.amepre.2008.08.021

National Land Cover Database [NLCD] (2016). *NLCD USFS tree canopy cover (CONUS)* [Data set]. MRLC. https://www.mrlc.gov/data/nlcd-2016-usfs-tree-canopy-cover-conus

National Land Cover Database [NLCD] (2019). *NLCD 2019 percent developed imperviousness (CONUS)* [Data set]. MRLC. https://www.mrlc.gov/data/nlcd-2019-percent-developed-imperviousness-conus

Pew Research Center. (2021, April 7). Internet/broadband fact sheet. *Pew Research Center: Internet, Science & Tech*. https://www.pewresearch.org/internet/fact-sheet/internet-broadband/

Pocock, M. J. O., Chapman, D. S., Sheppard, L. J., & Roy, H. E. (2014). *Choosing and using citizen science: A guide to when and how to use citizen science to monitor biodiversity and the environment*.

Popovich, N., & Flavelle, C. (2019, August 9). Summer in the city is hot, but some neighborhoods suffer more. *The New York Times*. https://www.nytimes.com/interactive/2019/08/09/climate/city-heat-islands.html

Putortì, E. S., Sciara, S., Larocca, N. U., Crippa, M. P., & Pantaleo, G. (2020). Communicating science effectively: When an optimised video communication enhances comprehension, pleasantness, and people's interest in knowing more about scientific findings. *Applied Psychology*, *69*(3), 1072–1091. https://doi.org/10.1111/apps.12193

Rieckmann, M., Hoff, H., & Bokop, K. (2021). Effective community-academic partnerships on climate change adaption and mitigation: Results of a european delphi study. *Sustainability and Climate Change*, *14*(2), 76–83. https://doi.org/10.1089/scc.2020.0061

Ryu, Y.-H., & Baik, J.-J. (2012). Quantitative analysis of factors contributing to urban heat island intensity. *Journal of Applied Meteorology and Climatology*, *51*(5), 842–854. https://doi.org/10.1175/JAMC-D-11-098.1

Schneiderhan-Opel, J., & Bogner, F. X. (2020). The relation between knowledge acquisition and environmental values within the scope of a biodiversity learning module. *Sustainability*, *12*(5), 2036. https://doi.org/10.3390/su12052036

Temperature extremes. (2020, December 21). Center for Disease Control. https://www.cdc.gov/climateandhealth/effects/temperature_extremes.htm

U.S. Census Bureau (2019). American Community Survey [ACS] 5-Year Estimates. Table S0101. *Age and sex*. Retrieved from https://data.census.gov/cedsci/table?t=Age%20and%20Sex&g=0500000US51013_1600000US5100148,5161832,5167000&tid=ACSST5Y2019.S0101&moe=false.

U.S. Census Bureau (2019). American Community Survey [ACS] 5-Year Estimates. Table S1903. *Median income in the past 12 months (in 2019 inflation-adjusted dollars*). Retrieved from https://data.census.gov/cedsci/table?t=Income%20and%20Poverty&g=0500000US51013_1600000US5100148,5161832,5167000&tid=ACSST5Y2019.S1903&moe=false.

U.S. Census Bureau (2020). *Race*. Decennial Census Redistricting Data. Table P1. Retrieved from https://data.census.gov/cedsci/table?g=0400000US51%240500000&tid=DECENNIALPL2020.P1.

Ziter, C. D., Pedersen, E. J., Kucharik, C. J., & Turner, M. G. (2019). Scale-dependent interactions between tree canopy cover and impervious surfaces reduce daytime urban heat during summer. *Proceedings of the National Academy of Sciences*, *116*(15), 7575–7580. https://doi.org/10.1073/pnas.1817561116

Figures & Tables

(Listed in order of appearance)

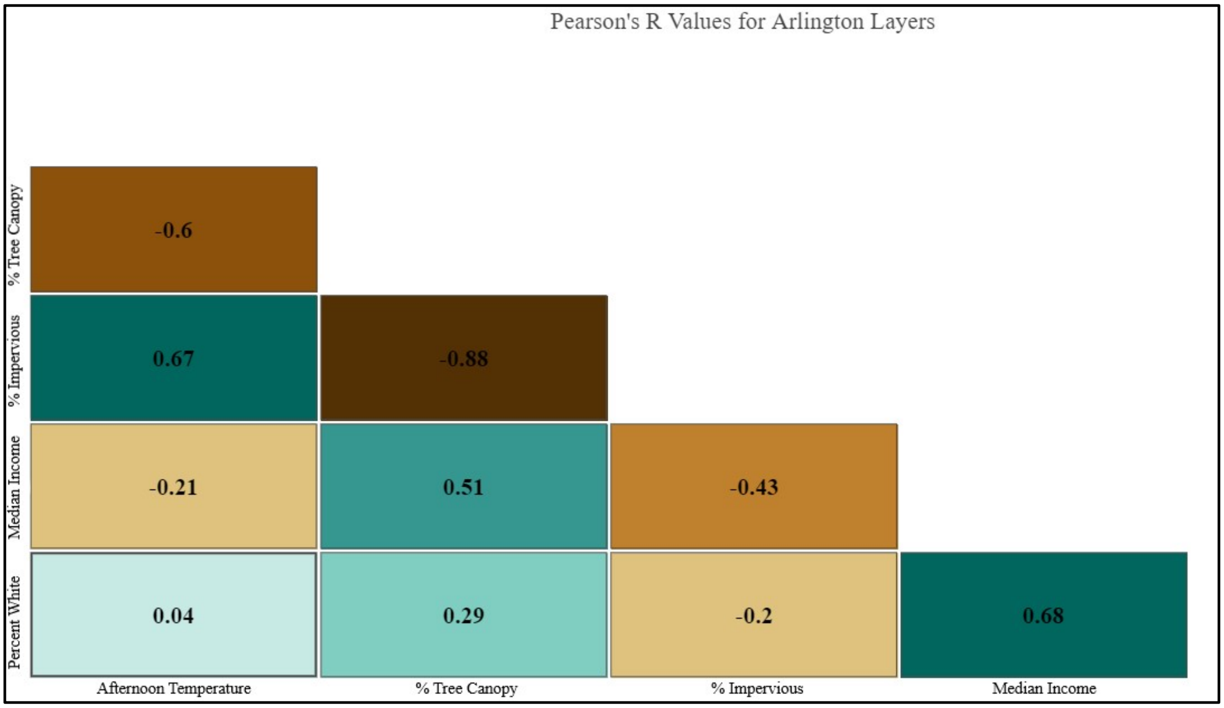

Figure 1. Correlations between temperature and other environmental and social variables in Arlington, Virginia. Data used in the computation was sourced from Virginia Heat Watch (2021), U.S. Census Bureau (2020), and the National Land Cover Database [NLCD] (2016, 2019). Note that temperature and white populations are positively correlated, while temperature and median household income are negatively correlated.

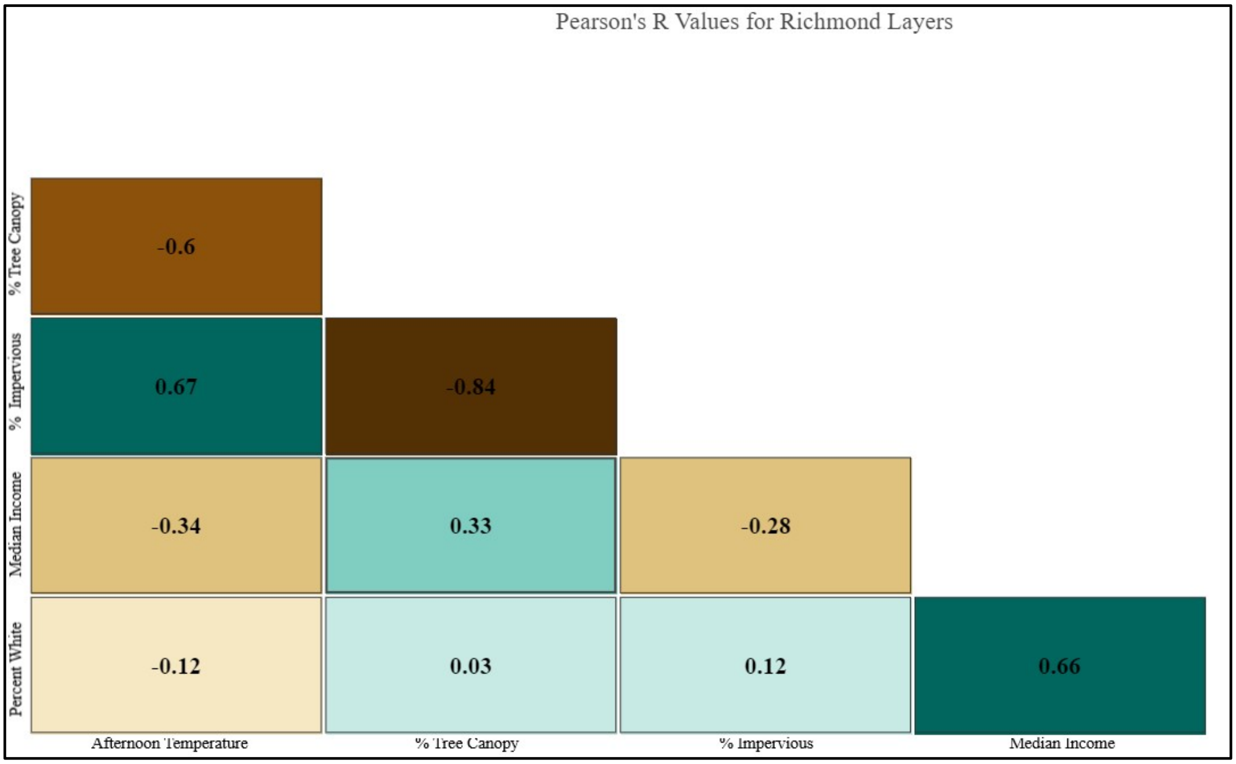

Figure 2. Correlations between temperature and other environmental and social variables in Richmond, Virginia. Data used in the computation was sourced from Virginia Heat Watch (2021), U.S. Census Bureau (2020), and the National Land Cover Database [NLCD] (2016, 2019). Note that temperature and white populations are negatively correlated, and temperature and median household income are negatively correlated.

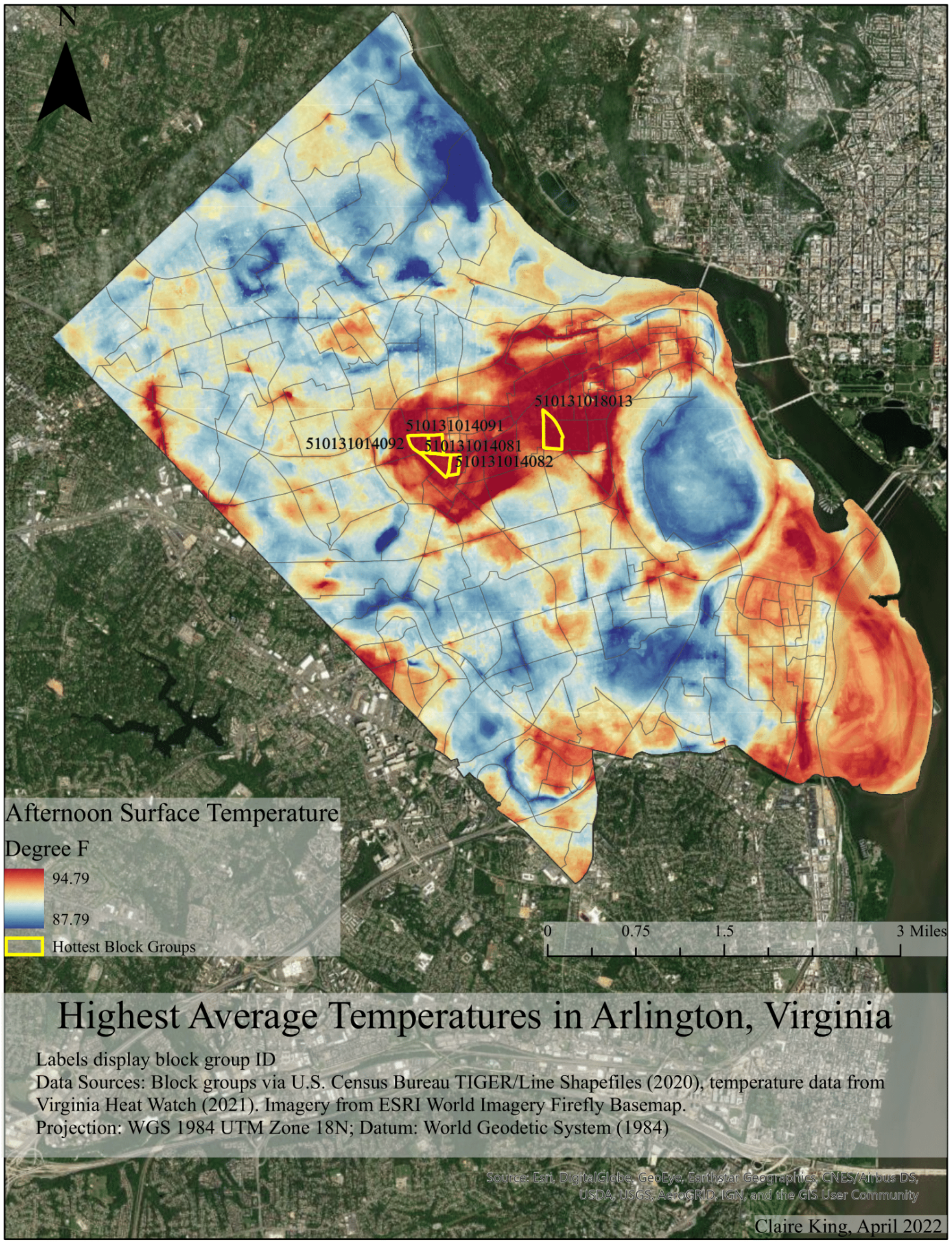

Figure 3. Highest average temperatures in Arlington, Virginia. This map identifies, in yellow, the five block groups with highest average temperature values in Arlington, Virginia. Identified block groups are labeled using block group IDs. The map displays, and selections are based on, the Virginia Heat Watch afternoon surface temperature data collected on July 15, 2021. Temperature values range from 87.79 - 94.79 degrees fahrenheit. Zonal statistics allowed for the aggregation of temperature values by block groups. Non-selected block group boundaries are also included in the map to contextualize the Heat Watch data. The imagery basemap further contextualizes the Heat Watch data by displaying surrounding land cover.

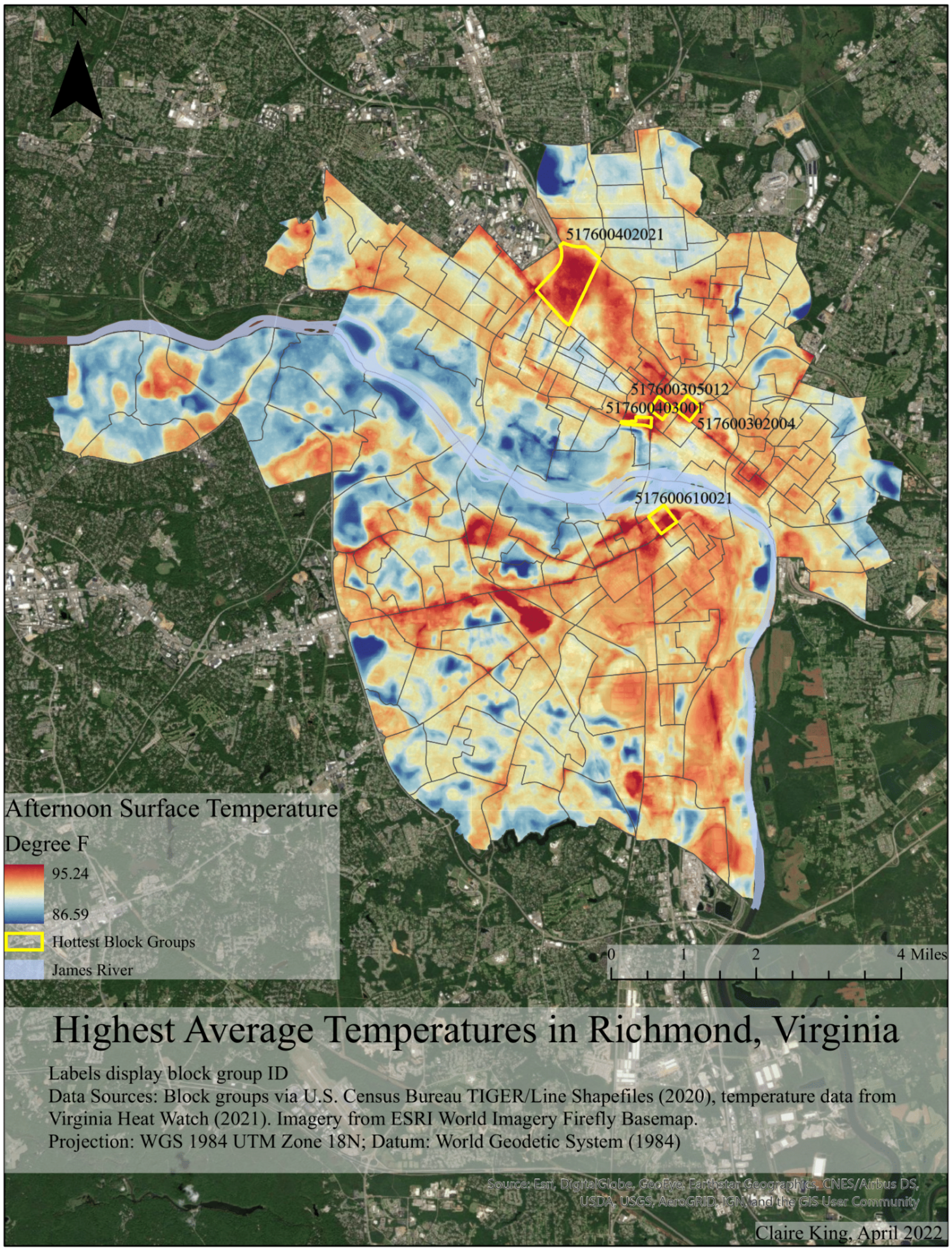

Figure 4. Highest average temperatures in Richmond, Virginia. This map identifies, in yellow, the five block groups with highest average temperature values in Richmond, Virginia. Identified block groups are labeled using block group IDs. The map displays, and selections are based on, the Virginia Heat Watch afternoon surface temperature data collected on July 15, 2021. Temperature values range from 86.59 - 95.24 degrees fahrenheit. Zonal statistics allowed for the aggregation of temperature values by block groups. Non-selected block group boundaries are also included in the map to contextualize the Heat Watch data. The imagery basemap further contextualizes the Heat Watch data by displaying surrounding land cover.

Table 1. Results from the community Heat Watch survey. Responding representatives were asked to provide their level of interest in a web map to display their local Heat Watch data, their capacity to create one, and the additional layers they would like to add to a map. These results guided the creation of each locality's web map.

Locality Represented	**Web Map Interest**	**GIS Capacity**	**Requested Layers**
Richmond City	Yes	I have some GIS but could use some help	Tree cover or canopy, CDC social vulnerability index, housing type
Abingdon	Yes	I have some GIS but could use some help	Tree cover, block-level demographic data (median household income, %nonwhite)
Abingdon	Yes	I don't have GIS and I am interested in a web map	Tree cover, surrounding water sources
Petersburg	Yes	I think we have GIS but I don't know how to use it.	Tree cover, impervious surfaces, socioeconomic factors
Arlington County	Yes	I don't have GIS and I am interested in a web map	Tree cover, housing type, income levels
Virginia Beach	Yes	I have GIS and I can make my own	Impermeable surfaces, a variety of demographic data

Table 2. Richmond, Virginia web map layers. A list of data layers included in the Richmond web map and their sources.

Layer Name	**Data Source**
Neighborhoods	Neighborhoods (2020). Richard Morton, City of Richmond, VA. Via Richmond Geohub.
Block Groups	U.S. Census Block Groups (2020). TIGER/Line Shapefiles via United States Census Bureau.
Afternoon Temperature	Afternoon Surface Temperature (2021). Richmond, Virginia Heat Watch data.
Afternoon Temperature by Neighborhood	Zonal statistics (by neighborhood) performed on Afternoon Surface Temperature.
Afternoon Temperature by Block Group	Zonal statistics (by block group) performed on Afternoon Surface Temperature.

Tree Canopy	NLCD USFS Tree Canopy Cover (CONUS) (2016). National Land Cover Database.
Tree Canopy by Neighborhood	Zonal statistics (by neighborhood) performed on tree canopy.
Tree Canopy by Block Group	Zonal statistics (by block group) performed on tree canopy.
Impervious Surfaces	NLCD Percent Developed Imperviousness (CONUS) (2019). National Land Cover Database.
Impervious Surfaces by Neighborhood	Zonal statistics (by neighborhood) performed on impervious surfaces.
Impervious Surfaces by Block Group	Zonal statistics (by block group) performed on impervious surfaces.
Median Household Income by Block Group	Median Household Income In The Past 12 Months (In 2020 Inflation-Adjusted Dollars) (2020). Table B19013. Via U.S. Census Bureau.
Parks	Parks (2020). City of Richmond, VA. Via Richmond Geohub.

Table 3. Arlington, Virginia's hottest census block groups and related environmental and social variables. The table includes the average afternoon temperatures of the five hottest census block groups in Arlington on July 15, 2021. Additionally, percent tree canopy cover, percent impervious land cover, population data, and median household income are reported.

Block Group ID	**Average Afternoon Temperature (F)**	**Percent Tree Canopy Cover**	**Percent Impervious Land Cover**	**Population Total**	**Population Percent White**	**Median Household Income (USD)**
510131014092	93.65	0.00	88.45	947	79.09	84,704
510131014081	93.50	0.00	92.76	338	70.71	190,118
510131014082	93.44	0.00	94.10	450	72.67	No Data
510131014091	93.33	0.00	89.55	1,173	69.05	119,853
510131018013	93.13	3.40	60.16	966	74.22	170,958
County Average	**91.05**	**20.41**	**40.39**	**238,643**	**60.88**	**122,604**

Table 4. Richmond, Virginia's hottest census block groups and related environmental and social variables. The table includes the average afternoon temperatures of the five hottest census block groups in Richmond on July 15, 2021. Additionally, percent tree canopy cover, percent impervious land cover, population data, and median household income are reported.

Block Group ID	**Average Afternoon Temperature (F)**	**Percent Tree Canopy Cover**	**Percent Impervious Land Cover**	**Population Total**	**Population Percent White**	**Median Household Income (USD)**
517600402021	92.93	1.40	86.85	1,766	79.28	52,961
517600305012	92.86	0.00	87.42	1,428	51.47	10,958
517600403001	92.78	0.67	71.56	608	59.7	11,250
517600302004	92.73	0.07	82.07	743	53.97	35,900
517600610021	92.71	4.78	62.67	1,304	52.68	50,458
City Average	**90.74**	**26.18**	**35.37**	**226,610**	**43.31**	**51,421**