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Mapping Temperature Deviation and Elderly Vulnerability using Open Source Technology: A One-Week Analysis of Manhattan, New York City

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Abstract

This paper outlines a research method for collecting, analyzing, and visualizing real-time temperature data for cities using open data and open source technology. The system collects temperature data for each census tract in Manhattan three times daily via the OpenWeather API and stores observations in a PostgreSQL/PostGIS database. A one-week pilot study (November 15-22, 2025) analyzed 8,990 temperature observations across Manhattan's 310 census tracts, revealing a borough-wide temperature range of 38.3°F to 55.2°F, including a mean of 45.4°F and standard deviation of 4.4°F. Census tract 263 (Washington Heights) recorded the coldest temperature (38.3°F), while tract 2.02 (Lower East Side) recorded the warmest (55.2°F). Tract 303 (Inwood) exhibited the highest internal temperature variability with a standard deviation of 4.6°F across the study period. A vulnerability index combining temperature deviation with elderly population density identified census tract 181 (Upper West Side) as having the highest risk during the study period. This approach establishes a scalable, replicable model for continuous climate monitoring to inform urban planning, design, and policy. Ongoing data collection and analysis are proposed in the paper. The active project is viewable at: https://terrestrialresearch.com/machinelearning/agetemp/tempage.html.

Keywords: urban heat island; open data; elderly vulnerability; real-time temperature monitoring; microclimate variability; climate adaptation planning

Research application website

https://terrestrialresearch.com/machinelearning/agetemp/tempage.html

Github repository

https://github.com/aurashak/manhattantemp

1. Introduction

It's been well-documented that researching the urban heat island effect is important for a wide range of activities within the fields of architecture, urban planning, urban design, energy production, public health, and more [1, 2]. In New York City alone, heat-related deaths have increased 370% from 2000-2022, causing 100+ annual deaths attributable to extreme heat. Heat mortality is projected to triple by 2050 under current emissions scenarios, including an additional 6-8 heat waves per year [3, 4, 5]. Among the most vulnerable are elderly populations (65+), which account for 70% of heat-related hospitalizations. Many of these are related to deeply systemic issues, as seen by low-income communities and communities of color experiencing temperatures 5-10°F hotter than wealthier neighborhoods [6].

The City and State of New York have major initiatives designed to combat cold and hot temperature extremes. Those range from infrastructure design programs such as Cool Roofs, Million Trees, Cool Pavement, improving building efficiency with programs like Local Law 97, and providing services like cooling centers and emergency medical care (extreme heat action plan), among others. One such mapping initiative is the NYC Department of Health and Mental Hygiene (DOHMH) Heat Vulnerability Index (HVI), which identifies the census tracts with highest heat vulnerability based on surface temperature, elderly populations, poverty, lack of air conditioning, and other factors [7, 8, 9]. Neighborhoods are scored from 1 (lowest risk) to 5 (highest risk). With this composite data, the HVI shows neighborhoods whose residents are more at risk of severe health impacts during and immediately following extreme heat [7].

This paper outlines an additional method for understanding urban temperature extremes. Unlike other UHI tools, this process updates in real-time to show current vulnerability risks and is replicable in other cities. In demonstration of this method, this paper conducts a sample analysis for studying temperature deviation in Manhattan. The sample analysis is a one-week temperature deviation study of all 310 census tracts in Manhattan, with a focus on the census tracts that contain elderly residents, for the week of November 15-22, 2025. Outlined in this study are which tracts were the coldest and hottest during the period, which areas deviated the most from the Manhattan-wide average temperature, and which tracts exhibited the most internal deviation across the week. The temperature deviation is then measured against the number of elderly residents in each census tract to determine which tract had the greatest at-risk population from temperature changes [10]. These results establish a baseline for understanding changes in small-scale temperature patterns and population vulnerabilities, while providing a method for long-term data collection and analysis [11].

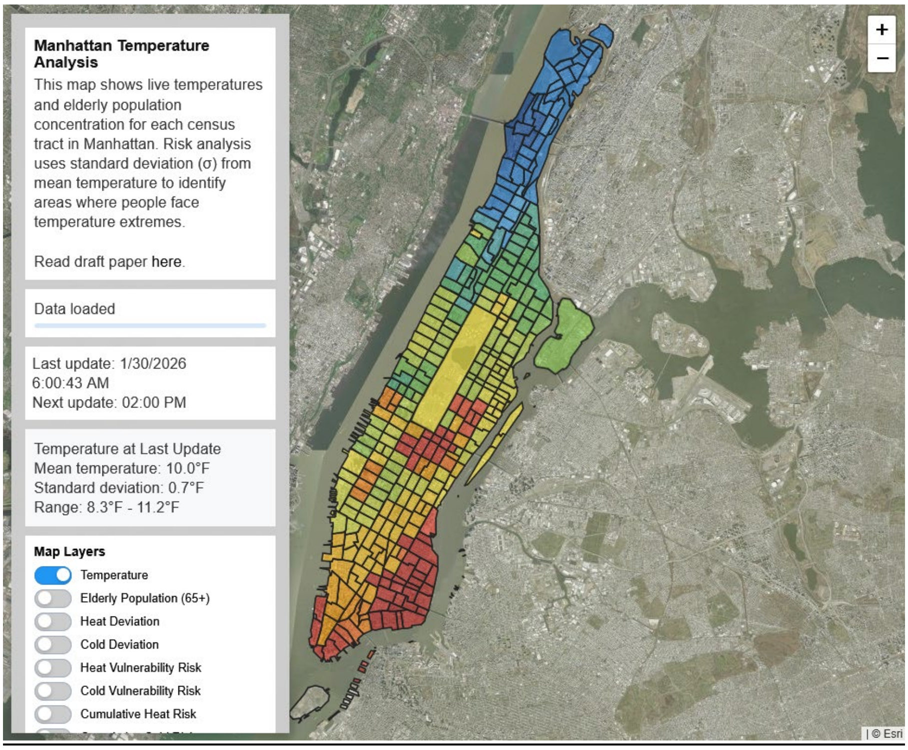

Fig 1. Interactive web-based map of Manhattan showing temperature deviations

Using this method, temperature measurements were recorded for each census tract in Manhattan (310) three times per day (06:00, 14:00, and 22:00 EST) via the OpenWeather API [12]. This generated a total of 8,990 observations over the eight-day period. The system uses JavaScript, HTML/CSS, Python, PHP, and PostgreSQL to collect, store, and analyze these temperature statistics, and to store and reference geographically coded demographic information, such as number of residents per census tract [13].

Of Manhattan's 310 total census tracts, **the weekly temperature range was 38.3°F to 55.2°F - a span of 16.9°F, and had an overall mean of 45.4°F. The standard deviation of this average temperature was 4.4°F [14]**. Among the 310 census tracts, only 193 contain residents - the others are non-residential monuments, parks, islands, and industrial areas. The 193 residential census tracts contain 170,998 elderly residents (aged 65+) [15].

The tract with the coldest weekly average was 271 in Washington Heights North, with a temperature of 44.5°F, and the hottest was 005 (Governors Island/Ellis Island/Liberty Island), with a temperature of 45.9°F. While tract 271 has residents, tract 005 does not. The tract with the weekly warmest average that had residents was 026.02 (East Village) with a similar temp of 45.9°F. The coldest temperature recorded was 38.3°F in tract 263 (Washington Heights South), while the warmest temperature recorded was 55.2°F in tract 2.02 (Lower East Side). Census tract 303 (Inwood) had the highest internal standard deviation for any census tract, with a high of 54.6°F and low of 39.1°F, giving it a range of 15.5°F and internal deviation of 4.6°F [14].

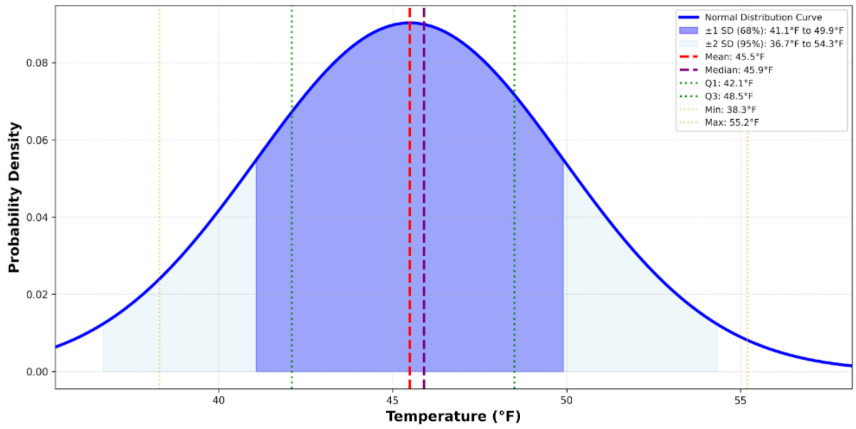

Fig 2. Distribution chart for temperatures the week of Nov 15-22, 2025

To assess social risk, temperature deviation metrics were combined with elderly population counts from census data [15]. Using z-scores, the study measures how many standard deviations each tract's temperature deviates from the Manhattan-wide mean at each observation time [14] [16]. The resulting one-week elderly vulnerability index combines these z-scores with normalized elderly population density to determine a vulnerability score for each tract. This identifies census tract 181 (Upper West Side Central) as having the highest combined temperature deviation and concentration of elderly residents (2,699 elderly residents, vulnerability score = 0.44), indicating the greatest weather-related risk for this specific period based on both temperature exposure and vulnerable population density [17].

Despite extensive documentation of UHI effects and their public health impacts [1, 2], existing UHI assessment tools face limitations in their scope and timing. Tools like the NYC Heat Vulnerability Index (HVI), rely on static annual snapshots, rather than analysis on a continuous basis [7]. Furthermore, most UHI monitoring systems require expensive proprietary infrastructure, which reduces methodological transparency and makes replication unlikely.

This methodology advances urban microclimate analysis in three ways. It provides real-time monitoring capabilities that can identify current risk conditions rather than relying on historical data or annual snapshots. Second, using open-source code, freely available APIs, census data, and standard database technologies, ensures replicability across location regardless of budget or technical resources. Third, by focusing on temperature deviation patterns and posting daily analysis results, this system potentially enables more responsive and targeted policy, design, and emergency services for vulnerable groups. While existing UHI tools like HVI excel at identifying chronic vulnerability through long-term analysis, this approach provides a fine-grained geographic and temporal approach necessary for immediate response.

Although this report focuses on one week of temperatures, data collection is ongoing. Results will be analyzed at one-year and two-year intervals, and the elderly-risk model will be updated when new demographic data becomes available. Over time, the growing dataset will support additional analysis and long-term planning for sustainability, public health, and emergency response [7]. This information is intended to support researchers and professional designers of urban systems, such as architects, planners, engineers, etc, and service providers of healthcare, emergency response, and more, to refine their approach for better outcomes [17].

This study develops and documents a complete workflow using open data sources [12, 15] and open-source technologies (PostgreSQL/PostGIS, JavaScript, Python, PHP) for continuous temperature data collection and analysis. Specific objectives include identifying census tracts experiencing extreme temperatures and greatest internal deviation and conducting vulnerability assessments using elderly population data. Additionally, this project verifies open data temperature predictions against ground-based measurements; and compares findings with NYC's existing Heat Vulnerability Index.

1.1 Research Objectives

- Methodological framework: Provide detailed documentation for developing a land classification method using open data designed for urban and suburban contexts. The utilization of open data and open source technology makes this approach replicable and accessible.
- Validation: Conduct two example analyses demonstrating the method's application and reliability.
- Technical assessment: Document challenges and opportunities related to data quality, resolution, and long-term system maintenance.

2. Methods

2.1. Study Area and Timeline

This study focused on Manhattan (New York County), New York City, which contained 310 census tracts in 2020 (the year from which the data was collected) [15]. The pilot study period ran from November 15-22, 2025, with temperature data collected three times daily at 06:00am, 2:00pm, and 10:00pm EST, generating 8,990 total observations. Data collection continues beyond this pilot period to support planned one-year (November 2026) and two-year (November 2027) analyses.

2.2. Temperature Data Collection

Temperature data are collected via the OpenWeather API, which returns estimates for each census tract (One Call API v3.0). OpenWeather's API allows web developers to pull current and historical weather data, including regularly updated forecasts for any geographic coordinate. Querying the API only 3 times per day per census tract, ensures the program does not exceed rate limits [12]. With a paid account, a greater number of queries could be implemented.

The temperature data provided by the OpenWeather API is derived using the organization's proprietary Numerical Weather Prediction (NWP) model. NWPs use complex differential equations based on atmospheric physics to process key datasets including wind velocity, air pressure, humidity, and temperature. The data are collected from ground-based weather stations, satellite thermal imaging, aircraft, balloons, ocean buoys, and radar. The data are fed into supercomputers, where complex differential equations using atmospheric physics can project the data into a spatial grid, called the "analysis", that can represent anywhere on earth. This process also converts the raw data into user-friendly outputs, such as the likelihood of rain or snow. In recent years, machine-learning approaches have emerged that expand on NWP and produce even more detailed and accurate short and long term forecasts [18, 19, 20].

The OpenWeather API allows for modeled temperature readings to occur at the centroid of any geographic area that is provided. This study utilizes a .GeoJSON file with geographic coordinates for each census tract in Manhattan, which allows OpenWeather to provide the temperature for the center of each census tract. This ensures consistent spatial representation across the study area [13, 22, 11, 2].

2.3. Demographic Data

Elderly population data (residents aged 65+) were obtained from the 2020 U.S. Census Bureau Decennial Census [15]. Of Manhattan's 310 total census tracts, 193 contain residents, all of which include elderly populations. The remaining 117 non-residential tracts represent parks, monuments, industrial zones, and infrastructure areas and were excluded from vulnerability analysis. The 193 residential census tracts contain 170,998 total elderly residents.

Elderly populations face disproportionate risk from temperature extremes due to physiological factors including higher rates of chronic illness, social isolation, and limited mobility [7, 6, 4, 3]. Heat-related deaths among NYC elderly residents increased 370% from 2000-2022 [7].

The census tract with the highest elderly population (65+) in 2020 was 175 in the Upper West Side, with 2,721 residents, while the lowest is census tract 009 with only 14 residents. The average number of elderly residents per census tract, among the 193 of Manhattan's 310 census tracts that have residents, is 886, with the median being 796. This right-skewed distribution (the mean being higher than the median) indicates some tracts with very high elderly populations are pulling the average up. The standard deviation from that average is 601.7, indicating a high range of variability per tract [14]. The largest group of census tracts, 46 tracts, or 24% or the total, falls in the 1,001-1,500 range. The 12 tracts in the Upper West Side and Upper East Side neighborhoods with 2,000+ elderly residents should be priority areas for heat emergency response [7].

Elderly populations have been proven to face disproportionate risk from temperature extremes due to physiological and social factors. They account for 70% of heat-related hospitalizations and experience significantly elevated mortality during both heat waves and cold snaps, including declines in thermoregulation, higher rates of chronic illness, social isolation, and limited mobility. Heat-related deaths among NYC elderly residents increased 370% from 2000-2022, with Northern Manhattan neighborhoods showing particularly high vulnerability [7, 6, 4]. Cold exposure similarly poses significant risk, as demonstrated by increased winter mortality rates [3].

2.4. Data Verification

OpenWeather NWP data were compared with field measurements from the National Weather Service (NWS) weather station located near Belvedere Castle in Central Park [22]. NWS data are published through the Cornell University and NOAA NOWData platform [23]. For the study period, OpenWeather data fell within the range of NWS measurements, demonstrating validity.

However, the Central Park station's location within verdant parkland, hundreds of meters from the dense urban environment, limits its relevance for understanding heat patterns across the borough [2]. Additional verification sources including New York State Mesonet (NYS-MET), NYC-Micronet, and NYC Urban Hydro-Meteorological Testbed (NY-uHMT) may provide archival data for future validation [24, 25]. Ground-based sensors following World Meteorological Organization (WMO) standards could be deployed across census tracts for comprehensive validation [26].

2.5. System Architecture and Software

The system demonstrated here integrates geographic information systems (GIS), automated data collection, statistical analysis, and interactive web visualization. The architecture combines programming and web development tools JavaScript version ES6. and HTML5 and CSS3 for user interface, PHP 8.1.12 for data collection and API access, PostgreSQL 15.3 with PostGIS 3.3.2 for data storage, and GeoJSON files for census data and geographic boundary data.

Geographic data preparation was conducted using QGIS 3.x for editing, merging, and processing census tract boundary files. Census tract shapefiles from the U.S. Census Bureau (2020) were merged with demographic data, validated for geometric accuracy, and exported as GeoJSON files for web visualization. The Leaflet.js library (version 1.9.x) renders interactive maps in the web interface, displaying census tract polygons, temperature data, and vulnerability classifications.

The frontend for the website, visible at terrestrialresearch.com, uses HTML, JavaScript, and the Leaflet.js mapping library to create an interactive map in the web browser. On the backend, PHP handles automated data collection and requests data using the API. Also on the backend, PostgreSQL with the PostGIS provides spatial database capabilities, storing both geographic polygons and temperature observations [13]. The GeoJSON files provide the geographic foundation, containing census tract boundaries and demographic data [15].

Python 3.11.2 provides computing for statistical analysis and visualization. The project uses several data analysis libraries: NumPy 1.24.3 for numerical array operations and mathematical functions; Pandas 2.0.2 for data structures and time-series analysis;

Psycopg2 2.9.6 as the connector between Python and PostgreSQL; and Matplotlib 3.7.1 for generating distribution charts. These libraries enable calculation of descriptive statistics, z-scores, and temporal patterns across the dataset.

A one-time setup process imported census tract geometries from the GeoJSON file and calculated their geographic centroids. This calculation happens only once during setup and the resulting coordinates are permanently stored as centroid_lat and centroid_lon. Once the geography is calculated, the system collects temperature data for each census tract centroid from the OpenWeather API, three times daily: 6:00 AM, 2:00 PM, and 10:00 PM Eastern Standard Time. This temperature data is stored in a PostgreSQL database containing two tables [13]. One table is static, containing 310 rows that represent each census tract in Manhattan. Each tract contains the unique GEOID, neighborhood name, elderly population count, and the pre-calculated geographic centers in the form of latitude and longitude [15, 22]. This table was populated once during initial setup and rarely changes. The second table, in contrast, grows continuously with each new temperature reading collected. This is creating a robust historical dataset [11]. Each row represents one observation for one census tract at one point in time. Key columns include GEOID, timestamp, temperature in Fahrenheit, and Celsius, humidity, and latitude/longitude points. For the week of this study, this table included over 8,900 observations.

Once data is collected, the program performs queries to calculate current and cumulative statistics and risk assessments. This includes calculating the range of temperatures, all-time minimum and maximum temperatures, the global average temperature, and the average of each census tract, and the global standard deviation and standard deviation of each tract [12]. This data powers both the visualization layers and the statistics panels on the website. This data provides a sophisticated real-time environmental monitoring system that is replicable for other cities.

2.6. LLM-assisted coding

The open source Large Language Model (LLM) qwen3-coder was used to assist with coding and debugging for Python, JavaScript, PHP, and PostgreSQL/PostGIS implementations [27]. Server infrastructure, online interface, mapping framework (Leaflet, QGIS, US Census), API connectivity (OpenWeather), and statistical analysis methods were developed by the author, while LLMs assisted with accessing open source coding language and debugging.

2.7. Statistical Analysis

Statistical analysis measures are applied to determine average temperatures, standard deviations, and vulnerability risks for Manhattan during the study period, and for a cumulative basis [14, 11]. Statistical analyses occur within three technology layers: PostgreSQL for historical analysis, PHP for collection-time processing, and JavaScript for real-time visualization.

2.7.1. Summary Statistics

Core statistical measures applied are:

- Mean Temperature (μ)
- Standard Deviation (σ)
- Z-score

The mean temperature (μ) represents the average temperature across all 310 census tracts in Manhattan [14]. The mean provides the baseline reference temperature for Manhattan at each measurement interval, against which individual tract temperatures are compared. Formula:

$$\mu = \frac{\Sigma\, T\_i}{n}$$

Where:

- T_i = temperature of census tract i
- n = number of census tracts (310)

The standard deviation (σ) quantifies the degree of temperature variability across all 310 census tracts in Manhattan at each measurement time [14]. Larger standard deviations indicate greater temperature difference across the borough [2]. Smaller standard deviations indicate more uniform temperature distribution. Formula:

$$\sigma = \surd\left[\frac{\Sigma(T\_i - \mu)^2}{n}\right]$$

Where:

- T_i = temperature of census tract i
- μ = mean temperature across all tracts
- n = number of census tracts (310)

To measure internal temperature fluctuation within each census tract across the one-week study period, the within-tract mean and standard deviation were calculated [14]. The within-tract mean represents the average temperature for an individual census tract over all observations during the week.

The z-score standardizes each census tract's temperature relative to the historic distribution, enabling identification of temperature anomalies [14, 16]. Formula:

$$Z = \frac{(T\_tract - \mu\_historic)}{n\sigma\_historic}$$

Where:

- T_tract = current or weekly average temperature of the specific census tract
- μ_historic = historic mean temperature across all observations

σ_historic = historic standard deviation

Interpretation:

Z = 0: tract temperature equals the historic mean
Z > 0: tract is warmer than historic average
Z < 0: tract is cooler than historic average
$|Z| \geq 1.0$: tract temperature deviates by at least 1 standard deviation
$|Z| \geq 2.0$: tract temperature is in the extreme tail of the distribution

2.7.2. Vulnerability Risk Classification System

The vulnerability risk index integrates temperature deviation with elderly population density to identify geographic areas where environmental heat or cold stress overlaps with demographically vulnerable populations [28, 10]. By incorporating the absolute value of temperature z-scores, the index ensures that both extreme heat and extreme cold conditions contribute meaningfully to vulnerability assessment. The weighting scheme assigns 60% to temperature deviation, reflecting its role as the primary and spatially dynamic environmental stressor [2], while elderly density receives 40% weight as a relatively stable demographic modifier of temperature-related health risk. This allocation prioritizes the identification of temperature extremes while ensuring adequate attention to areas with concentrated elderly populations.

Temperature deviations are classified into discrete risk levels based on z-score thresholds. These categories apply to both above-average (heat) and below-average (cold) conditions.

<u>Heat Risk Categories (Above Mean)</u>

Applied when $Z \geq 0.5$:

- Extreme: $Z \geq 2.0$ ($\geq 2\sigma$ above historic mean)
- Very High: $1.5 \leq Z < 2.0$ (1.5σ to 2σ above mean)
- High: $1.0 \leq Z < 1.5$ (1σ to 1.5σ above mean)
- Elevated: $0.5 \leq Z < 1.0$ (0.5σ to 1σ above mean)

<u>Cold Risk Categories (Below Mean)</u>

Applied when $Z \leq -0.5$:

- Extreme: $Z \leq -2.0$ ($\geq 2\sigma$ below historic mean)
- Very High: $-2.0 < Z \leq -1.5$ (1.5σ to 2σ below mean)
- High: $-1.5 < Z \leq -1.0$ (1σ to 1.5σ below mean)
- Elevated: $-1.0 < Z \leq -0.5$ (0.5σ to 1σ below mean)

Vulnerability Index

The combined vulnerability score consists of two weighted components:

Temperature Component (60% weight) formula:

$$\text{Temp\_component} = |\text{Z-Score}| \times 0.6$$

Elderly Density (40% weight) formula:

$$Density\_i = \frac{Elderly\_i}{max(Elderly\_all\ tracts)}$$

Where:

Elderly_i = number of residents aged 65+ in tract i
max(Elderly_all tracts) = maximum elderly population across all Manhattan residential tracts (2,721 in tract 175)

Apply weight formula:

$$Elderly\_component = Density\_i \times 0.4$$

The combined vulnerability score integrates temperature exposure and demographic vulnerability into a single continuous measure that enables risk classification across census tracts. Formula:

$$V\_score = (|Z\text{-}Score| \times 0.6) + (Normalized\ Elderly\ Density \times 0.4)$$

These thresholds categorize the combined vulnerability scores into discrete levels [10]:

- Extreme Vulnerability: V_score ≥ 1.5 - Indicates areas requiring immediate intervention and emergency response planning
- Very High Vulnerability: 1.2 ≤ V_score < 1.5 - Identifies locations with substantial combined risk warranting proactive public health measures
- High Vulnerability: 0.9 ≤ V_score < 1.2 - Designates areas with notable risk that should be prioritized for targeted interventions
- Elevated Vulnerability: 0.5 ≤ V_score < 0.9 - Flags areas with moderate combined risk suitable for enhanced monitoring

3. Results

3.1. Temperature Summary

During the one-week study period (November 15-22, 2025), Manhattan exhibited a borough-wide temperature range of 38.3°F to 55.2°F, spanning 16.9°F. The mean temperature across all 8,990 observations was 45.4°F with a standard deviation of 4.4°F.

Census tract 263 (Washington Heights) recorded the coldest single observation at 38.3°F, while census tract 2.02 (Lower East Side) recorded the warmest at 55.2°F. When averaged across the entire week, census tract 271 (Washington Heights North) had the coldest weekly mean temperature of 44.5°F, and census tract 005 (Governors Island/Ellis Island/Liberty Island) had the warmest weekly mean of 45.9°F. Among residential census tracts, tract 26.02 (East Village) recorded the highest weekly average temperature of 45.9°F.

Census tract 303 (Inwood) exhibited the highest internal temperature variability during the study period, with an internal standard deviation of 4.6°F. This tract experienced temperatures ranging from 39.1°F to 54.6°F, a span of 15.5°F.

3.2. Elderly Population Summary

Of Manhattan's 310 total census tracts, 193 contain residential populations, housing 170,998 elderly residents (aged 65+). Census tract 175 (Upper West Side) contained the highest elderly population with 2,721 residents, while census tract 009 had the lowest with 14 elderly residents. The mean elderly population per residential census tract was 886, with a median of 796 and standard deviation of 601.7. This right-skewed distribution indicates concentration of elderly populations in certain tracts. Forty-six census tracts contain between 1,001-1,500 elderly residents, representing the most common population range. Twelve census tracts in the Upper West Side and Upper East Side neighborhoods contain 2,000 or more elderly residents each.

3.3. Vulnerability Assessment

Census tract 181 (Upper West Side), with the highest vulnerability score (0.438), represents a clear target for public health interventions based on its exceptionally high elderly population (2,699). The top 10 vulnerability tracts contain 23,924 elderly residents, allowing focused outreach to a geographically concentrated high-risk group. These geographic clusters account for a disproportionate concentration of vulnerable populations and should receive prioritized resource allocation for [7]:

- Emergency cold-weather outreach
- Home heating assistance programs
- Wellness check-ins
- Emergency shelter information
- Utility disconnection prevention
- Heat wave preparedness (for future summer months)

4. Discussion

4.1. Comparison with Heat Vulnerability Index

The NYC Department of Health and Mental Hygiene's Heat Vulnerability Index (HVI) provides an established benchmark for comparison with this study's vulnerability assessment. The HVI ranks Manhattan census tracts from 1 (lowest risk) to 5 (highest risk) based on multiple variables including temperature, elderly populations, poverty, lack of air conditioning access, and social isolation [7].

The HVI identifies census tract 096 in East Harlem as the highest risk area in Manhattan, assigning it a risk level of 5 (extreme vulnerability). In contrast, this study's vulnerability assessment only includes elderly population as the demographic variable, and as a result identifies census tract 181 in the Upper West Side Central as the highest risk area. Both assessment methods provide valuable but complementary information. The HVI's multi-variable approach captures issues that reflect long-term socioeconomic disparities [6]. This method does not analyze as broad social data, but provides in-depth and real-time analysis of temperature data. A combination of both approaches would identify areas that require policy and/or design interventions in a timely manner based on current weather conditions, rather than in annual reports.

4.2. Study Limitations

Significant limitations for this study include reliance on OpenWeather's model, which is not as reliable as ground-based measurement systems. While validation against the NOAA Central Park station demonstrated validity of OpenWeather's data, their estimates may not capture hyperlocal microclimatic variations caused by building configurations or localized heat sources [2]. Second, the one-week study period (November 15-22, 2025) represents only a small temporal sample during mild autumn conditions. This timeframe does not capture the extreme temperature events, summer heat waves or winter cold snaps, that pose the greatest risks to elderly populations [3, 4]. Extended monitoring through complete seasonal cycles will provide a fuller picture of weather conditions and potential health impacts. Third, comprehensive ground-truth verification was not feasible for this study. While collaboration with existing networks such as New York State Mesonet, NYC-Micronet, or NYC Urban Hydro-Meteorological Testbed could provide additional validation points [24, 25], deployment of weather stations meeting World Meteorological Organization standards across a representative sample of census tracts would strengthen confidence in the temperature estimates [26]. Finally, the demographic data utilized in the vulnerability index originates from the 2020 U.S. Census Bureau Decennial Census, now over five years old. Elderly population distributions may have shifted due to residential mobility, gentrification, new housing developments, or mortality. Updated demographic estimates from the American Community Survey 5-year data (expected in 2026) will enable refinement of the vulnerability model to reflect more current populations [15].

4.4. Ongoing and Future Research

This project continues to collect data beyond the one-week study period, with temperature observations recorded three times daily at terrestrialresearch.com. This ongoing collection enables several planned analyses that will address current limitations and expand the study's scope. A one-year analysis (planned for November 2026) will encompass full seasonal cycles. This extended dataset of approximately 211,000 temperature observations (193 residential tracts × 3 daily measurements × 365 days) will provide sufficient data for identification of the most consistent hot and cold tracts. A two-year analysis (planned for November 2027) will enable year-over-year comparisons to assess microclimate patterns and identify emerging trends potentially linked to climate change or urban development. As updated demographic data becomes available from the U.S. Census Bureau's American Community Survey 5-year estimates (expected December 2026), the vulnerability model will be refined to incorporate more recent elderly population distributions and potentially expanded to include additional socioeconomic indicators such as poverty rates, disability status, and more [15]. As the dataset expands to encompass extreme weather events and multi-year trends, it will provide increasingly robust evidence to inform urban planning decisions, emergency response protocols, and climate adaptation strategies for protecting vulnerable populations [7, 18].

5. Conclusions

This study demonstrates the feasibility and value of continuous temperature monitoring for urban temperatures using open data and open source web tools. By combining OpenWeather API for temperature measurements, U.S. Census data for demographic characteristics, and GIS for visualization, this method creates a replicable framework applicable to cities nationwide.

The one-week pilot analysis successfully identified census tracts with elevated vulnerability scores, primarily driven by elderly population concentration in Manhattan's Upper West Side and Upper East Side neighborhoods. While temperature deviations during the November 15-22 study period were minimal due to stable weather conditions, the methodology demonstrates capacity to detect microclimate variations and integrate them with demographic risk factors [2].

The technical architecture of combining PostgreSQL/PostGIS for spatial data management, automated PHP collection scripts, and interactive JavaScript visualization, provides a maintainable foundation for ongoing research [13, 28]. As the dataset expands to encompass full annual cycles and extreme weather events, the system will generate increasingly robust insights into Manhattan's vulnerable populations [7].

Future enhancements incorporating additional vulnerability variables, such as income, access to air conditioning, and more, and seasonal pattern investigation will strengthen this project’s ability to support climate adaptation planning and public health interventions [31, 7, 18]. Verifying the OpenWeather data with on-the-ground sample temperature collection will ensure integrity of data being used for this project and an examination of OpenWeather’s NWP model.

This replicable, low-cost approach to urban temperature monitoring represents an addition to existing climate vulnerability assessments. It can offer real-time data and continuous coverage that can inform emergency response, long-term planning, and public health initiatives in cities confronting escalating temperature risks [3].

Data Availability: Data collected by this study and the interactive web mapping tool are openly available at https://terrestrialresearch.com. The database is actively collecting data and the code is available at https://github.com/aurashak/manhattantemp/.

Abbreviations

API	Application Programming Interface
CSS	Cascading Style Sheets
DOHMH	Department of Health and Mental Hygiene
EST	Eastern Standard Time
GIS	Geographic Information System
HVI	Heat Vulnerability Index
HTML	HyperText Markup Language
NOAA	National Oceanic and Atmospheric Administration

NWP	Numerical Weather Prediction
NWS	National Weather Service
NYC	New York City
NYS-MET	New York State Mesonet
NY-uHMT	New York City Urban Hydro-Meteorological Testbed
PHP	Hypertext Preprocessor
SQL	Structured Query Language
UHI	Urban Heat Island
WMO	World Meteorological Organization

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