**a document describing the project, the results, and the technical methods used in each step (collection, analysis and visualization)**

1. **Introduction**

Heat islands are urbanized areas that experience higher temperatures than outlying areas1. It usually occurs when natural land cover is replaced with dense concentrations of pavement, buildings, and other surfaces that absorb and retain heat. Urban heat island effect increases energy costs, air pollution levels, and heat-related illness and mortality2. Under the context of climate change and global warming, urban areas will suffer in higher temperature and harsher heat in heat island areas. It is a challenging urban problem not only impact sustainability and human health, but also reflects social, racial, and economic inequalities associated with disproportionate green spaces in cities.

Multiple studies of urban heat island indicate green space can mitigate urban heat island effect by creating cooling buffer zones. tree canopy. For instance, Chow’s study indicates air temperature green space can be 1–3 °C, and sometimes even 5–7 °C, cooler than surrounding [built-up areas](https://www.sciencedirect.com/topics/earth-and-planetary-sciences/built-up-area)3. Park’s research in South Korea found that small green spaces can reduce air temperature of an urban block, especially polygonal type has better cooling effect4. Pearsall analyzed the socio-spatial pattern in land surface temperature and vacant land across Philadelphia, indicating the opportunities of converting vacant land to green space to reduce urban heat island effect5. Recent research from Mitz also explored the relationship between urban landscape and surface temperature in case study of Philadelphia6. However, little research conducted a quantitative analysis of the mitigating effect of converting vacant lands to green spaces.

Against the backdrops of existing literature, this study aimed to predict the conversion effect from vacant lands to green spaces with machine learning technology. Philadelphia was one of industrial centers in the U.S. and contained vacant lands as many as approximate 428 acres in the city according to an assessment of City of Philadelphia administrative datasets created in 20167. Under context of global warming, temperature anomaly appears more and more frequently. Philadelphia experienced the hottest summer on record for the contiguous United States in 2021, with five heat waves8. Though green spaces could cool down surface temperature compared to paved areas, there is limited spaces and resources to develop new parks and recreation open spaces across city. Thus, we examined the potential of converting paved areas and bare earth in vacant lands to green space and predict the mitigation effect with machine learning technology in this study.

First, we extracted surface temperature map of Philadelphia from Landsat Normalized Difference Vegetation Index (NDVI) satellite image downloaded from USGS.GOV. Next, we intersected various datasets, like median surface temperature, census tracts, land covers, and vacant lands, into a data frame. We further did two Random Forest regressions, with the former one to explore the relationship between surface temperature and land covers, and later one to test the correlation between land covers, and socioeconomic conditions, like the mean household income, the percentage of white, the percentage of poverty and the percentage of vacant lands. Finally, we got a predicted relationship between conversion rate from paved areas to green space in vacant land and surface temperature decrease.

The rest of the paper is organized as follows. In section 2, we introduced the proposed methodology. Section 3 presents the result of the regression and analysis the correlations among three datasets. The conclusions and future work are given in Section 4.

1. **Methodology**

**2.1 Data Collection**

We downloaded the satellite image of Philadelphia, which was taken by Landsat 8 satellite to quantify vegetation greennesson August 26, 20219. Then we used API to download data of American Community Survey (ACS2019)10 from U.S. Census Bureau, Vacant Property Indicators - Land11, and City Limits12 from Open Data Philly. The dataset of vacant lands records vacant plots in the city according to an assessment of City of Philadelphia administrative datasets created in 2016. Philadelphia Land Cover13 provides data on the types of surfaces in Philadelphia in 2008, and we downloaded it from Open Data Philly and saved it in local devise for further use.

* 1. **Data Wrangling**

The satellite image was converted to land surface temperature (LST) with calculating from LSE, BT and NDVI (Normalized Difference Vegetation Index). The formula is as below:

NDVI = (NIR - Red) / (NIR + Red) 14

We selected “Total Population”, “White”, “Median Household Income”, “Vacant Property”, “Estimate of Total Housing Units”, and “Number of below 100 percent of the poverty level” as variables and queried them within Philadelphia County from census website. Then we aggregate variables into percent of white, percent of poverty and percent of vacant to represent socioeconomic conditions of each tract.

The dataset of vacant lands records 28451 plots in polygon format and we would use it as boundary to intersect with other data and get land cover, mean temperature status of these vacant lands.

The data of Philadelphia Land Cover identifies seven categories: tree canopy, grass/shrub, bare earth, water, buildings, roads, and other paved surfaces. We converted it from raster to polygon in ArcGIS and imported it for further use. To make all datasets have same coordinate reference system (crs) as the Satellite image, we converted dataset’s coordinate system to EPSG32618.

* 1. **Data Analysis**

First, we calculated the median land surface temperature of each census tract with zonal statistics tool. Then we removed the extreme temperature lower than 11°C or higher than 35°C, and median household income less or equal to zero, as outliers. Census tracts whose LST is higher than 26°C are identified as “urban heat islands”.

Next, we spatial joined vacant lands data to heat islands data, and intersected land cover data with vacant lands in tracts under “urban heat islands” conditions. In that case, we got a data frame with percent of each type of land cover in vacant lands under “urban heat islands” conditions. We also intersected land cover data with heat island data and calculated the proportion of each land cover type in heat islands and plot the comparison of LST and land cover map.

From sklearn. ensemble we imported Random Forest Regression, which is a supervised learning algorithm to combines predictions from multiple machine learning algorithms to make a more accurate prediction than a single model 14. First, we identify the dependent (y) and independent variables (X). Next, Split the dataset into the Training set and Test set with proportion of 7 and 3. Further, we trained the Random Forest Regression model on the whole dataset. Finally, we got the prediction of the test set results, which includes average absolute error, accuracy, best score, and important features. The first regression model was used to evaluate the relationship between median temperature in census tracts with urban heat island effect (y) and proportion of each land cover type in each tract (X). The second regression model was used to evaluate the relationship between socioeconomic conditions of each tract across the city (y) and proportion of each land cover type in each tract (X). It includes five sub models targeting on different socioeconomic conditions of median household income, percent of white, percent of poverty, and percent of vacant, with median temperature as another dependent variable for general context.

* 1. **Data Visualization**

The comparison of LST and land cover map was plotted in Figure 1 with Matplotlib toolkit. The map of LST on the left shows the land surface temperature of Philadelphia, with range between 11°C and 35°C. The map on the right present land cover types across the city, with most tree canopies clustered in Pennypack Park, Wissahickon Valley Park, and Fairmount Park. Most land cover of other paved surfaces are industrial zones in the South Philadelphia West.

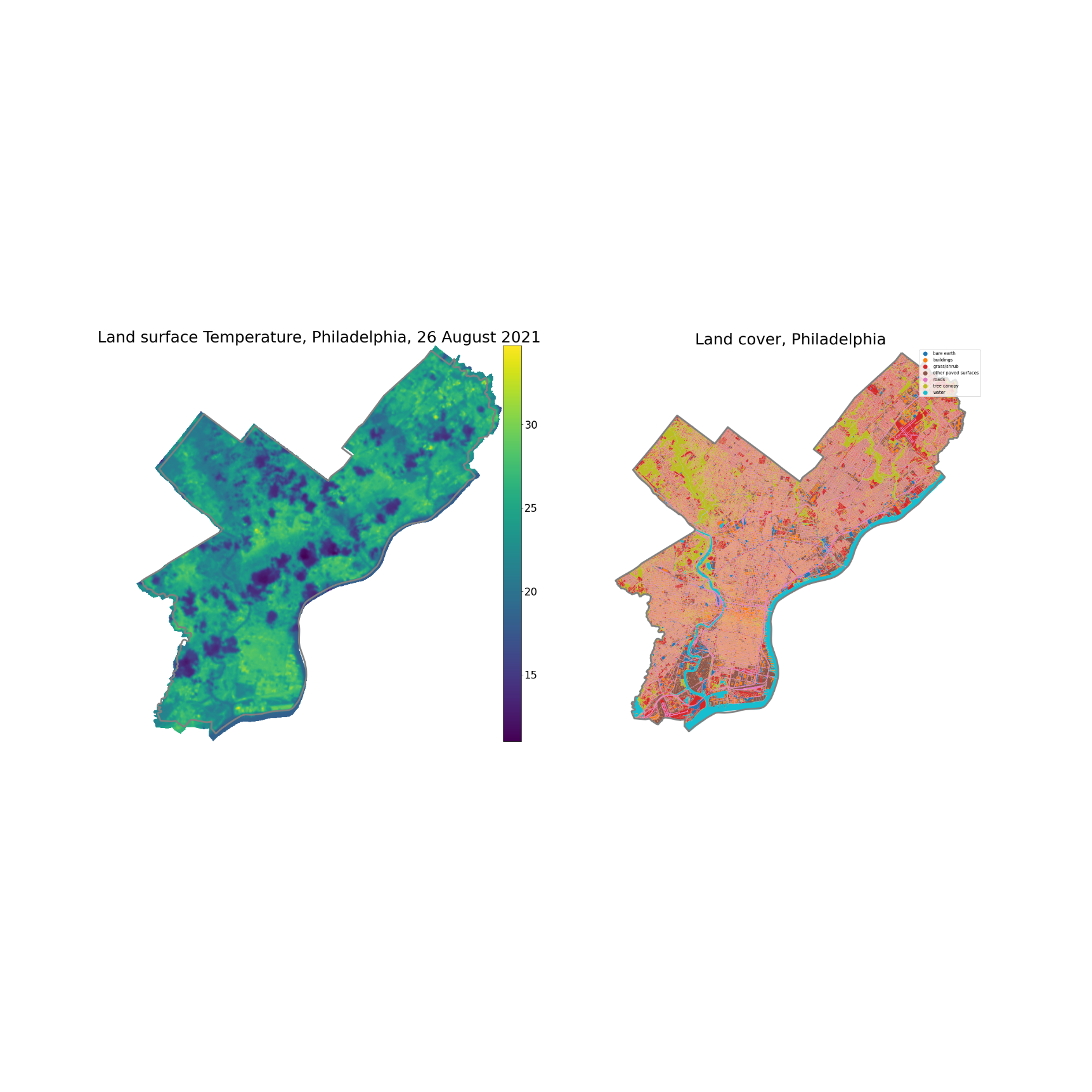


Figure1. Comparison of LST and Land Cover Map

In Figure 2, we plotted the map of LTS in each tract, highlighted “urban heat islands” zones (LST higher than 26°C) with red, and added city limit and base map with contextily function. Under the context of land cover map, we found that urban heat islands always appear in areas with high density of buildings and low coverage of tree canopies.

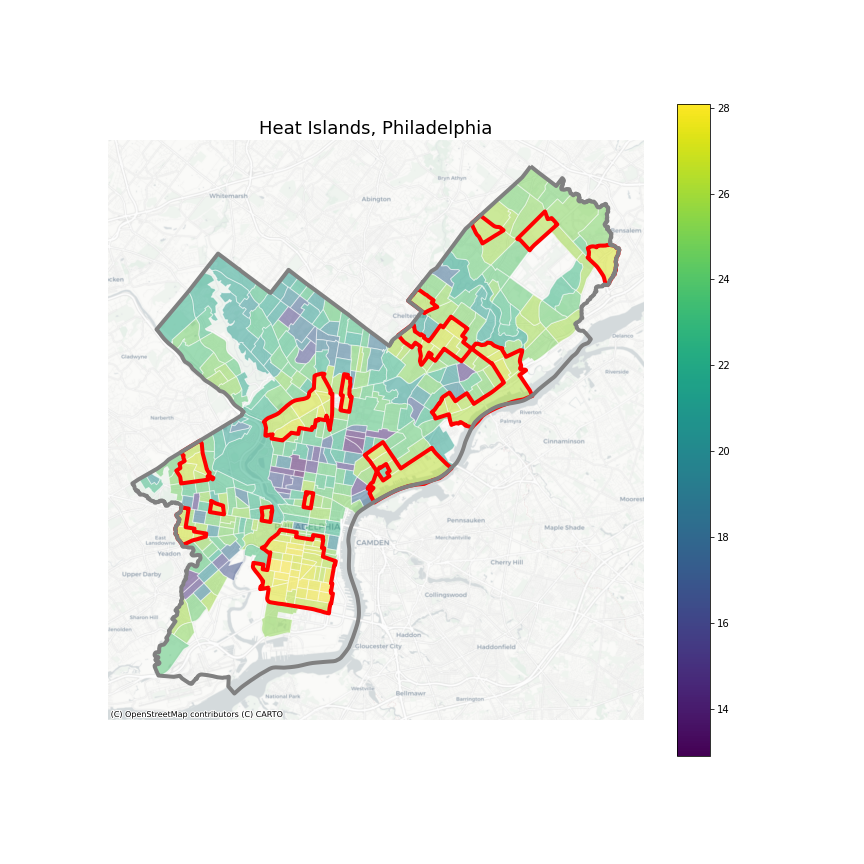


Figure2. Urban Heat Island in Philadelphia

In Figure3, we created an interactive map with panel tool to visualize how the median temperature will change with replacing road, bare earth and other paved areas with tree canopy. By using the coefficients, we got from the regression model, user can select conversion rate, including 10 intervals from 0 to 100%, to find out the mitigation effect. Theoretically, the median temperature should reduce at certain level. But it is hard to identify in a city scope with limited change of temperature.

Looking at Figure 4, we created an interactive map with hvplot tool to show different socioeconomic conditions by census tracts across the city. The variables include median household income, percent of white, percent of poverty, and percent of vacant.

We also created interactive maps in Figure 5 to show qualitative relationship among variables of socioeconomic conditions, land covers and land surface median temperature. By using autompg tool from bokeh.sampledata and panel tool, we explored qualitative relationship in scatter plots. The best thing is that user can switch variable of x and y easily and review their relationships in plot.

A picture containing map

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Figure3. Conversion Map Figure4. Social Conditions Map

Chart, scatter chart

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Figure5. Socioeconomic Variables Visualisation

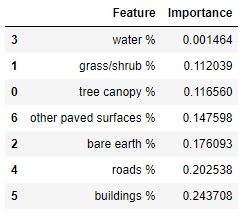
1. **Result & Analysis**

**Landcover & temperature in urban heat islands**

Average Absolute Error: 0.0238

Accuracy = 99.28%.

Test Score of the best model = -0.1475

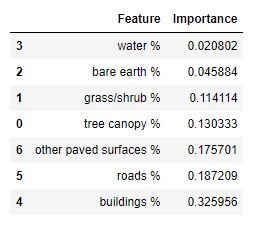


**Median household income**

Average Absolute Error: 0.2745

Accuracy = 97.41%.

Test Score of the best model = 0.3061.

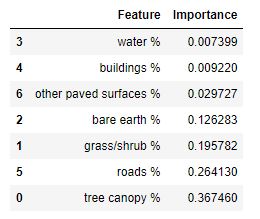


**Percent of white %**

Average Absolute Error: 0.6765

Accuracy = 69.93%.

Test Score of the best model = 0.1902.

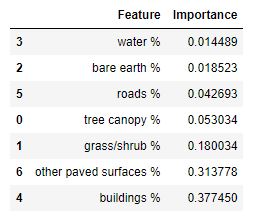


**Percent of poverty %**

Average Absolute Error: 0.4532

Accuracy = 78.21%.

Test Score of the best model = 0.1102.



**Percent of vacant %**

Test Score = -0.0132.

Model Performance

Average Absolute Error: 0.4366

Accuracy = 78.90%.

Test Score of the best model = 0.1883.

![Table

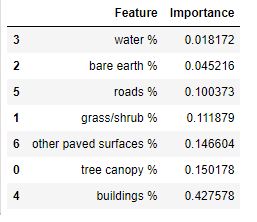
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**Median temperature**

Average Absolute Error: 0.0187

Accuracy = 99.43%.

Test Score of the best model = -0.3899.



1. **Discussion**

This study achieved two key contributions: (1) it tested relationships between each two datasets of land cover, surface temperature, and socioeconomic conditions; (2) it quantified the conversion rate between paved areas and green space in vacant land and mitigation effect in urban heat island areas.

1. [Heat Island Effect | US EPA](https://www.epa.gov/heatislands)
2. [Reduce Urban Heat Island Effect | US EPA](https://www.epa.gov/green-infrastructure/reduce-urban-heat-island-effect)
3. [Observing and modeling the nocturnal park cool island of an arid city: horizontal and vertical impacts | SpringerLink](https://link.springer.com/article/10.1007%2Fs00704-010-0293-8)
4. [The influence of small green space type and structure at the street level on urban heat island mitigation - ScienceDirect](https://www.sciencedirect.com/science/article/pii/S1618866716301194)
5. [Staying cool in the compact city: Vacant land and urban heating in Philadelphia, Pennsylvania | Request PDF (researchgate.net)](https://www.researchgate.net/publication/312318741_Staying_cool_in_the_compact_city_Vacant_land_and_urban_heating_in_Philadelphia_Pennsylvania)
6. [Frontiers | Structure of Urban Landscape and Surface Temperature: A Case Study in Philadelphia, PA | Environmental Science (frontiersin.org)](https://www.frontiersin.org/articles/10.3389/fenvs.2021.592716/full)
7. [Vacancy (arcgis.com)](https://phl.maps.arcgis.com/apps/webappviewer/index.html?id=64ac160773d04952bc17ad895cc00680)
8. [United States endured hottest summer on record in 2021, NOAA says (fox29.com)](https://www.fox29.com/weather/united-states-endured-hottest-summer-on-record-in-2021-noaa-says)
9. <https://www.eos.com/landviewer>
10. [American Community Survey Data via API (census.gov)](https://www.census.gov/programs-surveys/acs/data/data-via-api.html)
11. [Vacant Property Indicators - Datasets - OpenDataPhilly](https://www.opendataphilly.org/dataset/vacant-property-indicators)
12. [City Limits - Datasets - OpenDataPhilly](https://www.opendataphilly.org/dataset/city-limits)
13. [Philadelphia Land Cover Raster - Datasets - OpenDataPhilly](https://www.opendataphilly.org/dataset/philadelphia-land-cover-raster)
14. [Landsat Normalized Difference Vegetation Index | U.S. Geological Survey (usgs.gov)](https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index#:~:text=Landsat%20Normalized%20Difference%20Vegetation%20Index%20(NDVI)%20is%20used%20to%20quantify,assessing%20changes%20in%20plant%20health.&text=Sources%2FUsage%3A%20Public%20Domain.)