The Grass is Bluer on the Other Side: Analyzing Greenspaces and Bluespaces as Substitutes

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Greenspaces (e.g. parks and vegetation) and Bluespaces (e.g. bodies of water) have separately been linked to their positive impacts on the microclimate of urban sprawls like New York City. Here, we focus on quantifying the extent of these impacts simultaneously, examining the *complementarity or substitutability* of these spaces. Using an original Gaussian Distance metric and K-means Clustering, we identify four groups of census tracts in New York city that are very well suited to disentangling the effects of these spaces. Results showed that while greenspaces and bluespaces both had a positive effect, their combined impact was much weaker than the sum of their individual impacts, indicating strong substitutability. Moreover, we link these climate parameters to human mental health through proxies such as human sentiment, where we analyze geotagged Twitter data using time series analysis and rigorous statistical testing. The results showed consistent patterns. To further establish the duality with microclimate, we use a nearest neighbors minima-finding algorithm to predict potential locations for blue/green spaces. Finally, we provide a quantitative application of our findings by modeling the marginal benefit of installing green infrastructure by using a novel differential model to predict which counties would benefit the most from these efforts.

1 Background and Central Question

Urban green and blue spaces play a critical role in shaping local climates and environmental conditions in cities. Greenspaces refer to areas covered by vegetation such as parks, gardens, and other green areas within a city. On the other hand, bluespaces refer to bodies of water such as lakes, rivers, ponds, oceans, and canals. These spaces are crucial for mitigating the effects of urban heat islands, improving air quality, and providing recreational and aesthetic benefits to residents. However, despite their importance, the interplay between greenspaces and bluespaces in affecting local climates and related perceptions of residents is still not fully understood.

In New York City, where the high density of buildings and hard surfaces can exacerbate the urban heat island effect, the provision and management of greenspaces and bluespaces is particularly important. These spaces can provide a much-needed respite from the heat, improve air quality, and enhance the quality of life for residents.

Given the significance of these spaces in shaping the local climate and environment, it is imperative to understand the nature of the relationship between these two types of spaces in New York City. To this end, this research aims to answer this question:

> **How do greenspaces and bluespaces <u>differentially</u> impact microclimate, especially temperature and air quality, in an urban milieu such as New York City? Are they complementary or substitutes in their effects? In turn, how does this affect the local residents' climate sentiment?**

The findings from this study will provide valuable insights into the optimal provision of green infrastructure in cities and will inform the development of sustainable and livable urban environments.

2 Executive Summary

Our research question delves into the intricacies of the relationship between the presence of bluespaces and greenspaces and their impact on the climate. We seek to quantify the extent to which greenspaces and bluespaces impact climate factors and examine the natural complementarity or substitutability of bluespaces and greenspaces. Finally, we evaluate the feasibility of forecasting the optimal site for the establishment of additional greenspaces using a *differential novel model* that uses the current locations of bluespaces and greenspaces. We limit our geographical scope to New York City throughout the study.

We select a census tract as our unit of analysis. To supplement all our analyses, we use an original gaussian distance metric to construct variables that reflect the amount of green and blue infrastructure around a region. Using these distances, we then employ a k-means clustering algorithm to identify four groups of regions to disentangle the effects of green and blue spaces. Semantically, these groups mean the following: `(High Green Cover, High Blue Cover)`, `(Low Green Cover, High Blue Cover)`, `(High Green Cover, Low Blue Cover)` and `(Low Green Cover, Low Blue Cover)`.

Firstly, we ask what is the effect of bluespaces and greenspaces on specific climate metrics and how do they interact with each other. We perform fundamental analyses on two climate parameters: temperature, and air quality (particulate matter). All our analyses unanimously answer that bluespaces and greenspaces associate positively with these parameters. Furthermore, we are able to show that together the bluespaces and greenspaces are much less effective than their sum (in other words, a spaces-version of the *law of diminishing* returns) i.e. they act as substitutes *as far as* the considered parameters are concerned.

To further strengthen our analysis, we find proxies that directly tie these parameters to human mental health. One of them, in general, is human sentiment. Through geo-tagged Twitter data, we analyze the time variation of human sentiment across these four groups. Through rigorous statistical testing, we once again establish the positive effects and substitutability of these spaces.

To demonstrate the duality between green/blue infrastructure and microclimatic variations, we ask the *reverse question*. Can we infer where the greenspaces and bluespaces are likely to be present given the climate of the city? Using a Top-k out-of-n nearest neighbors minima-finding algorithm, we are able to predict potential places where there are bluespaces/greenspaces. By seeing how effective we are in terms of finding the bluespaces/greenspaces, we were able to further show that the climate metrics are strongly correlated with the bluespaces/greenspaces.

Our analysis was motivated by discovering the subtle nuances in the interplay of bluespaces and greenspaces to affect a change at the policy level. We demonstrate a quantitative application to our findings, where we try to model the marginal benefit of installing green infrastructure in terms of the potential local climate change it might bring. By maximizing this gradient, we predict which counties would benefit the most upon the addition of a greenspace i.e. have the potential to give the maximum return on investment in the context of that climatic parameter.

Contents

3 Technical Exposition

3.1 Dataset

In this section, we describe how we came to choose the New York dataset that we used for our analysis as well as how we cleaned the dataset. We also talk about the external datasets we used as well as some pre-processing we do (Blue/Green Gaussians and Clustering) to ease our analysis.

3.1.1 Why New York?

Why a single city? The greenspaces/bluespaces change significantly as we move around but so do a lot of other factors. Any of those changes could be responsible for the results we obtain instead of bluespaces/greenspaces. Consequently, using multiple cities might introduce a lot of other variables such as demographic change, income change, geographical changes, and so on. Finally, we believe that our approach is general and not specific to New York and therefore can be replicated for other cities. Therefore we decided to stick to a single city.

Why New York City? New York is a coastal city with 3 rivers and having more than 2300 parks immediately gives us access to an excellent dataset. Furthermore, in the data provided to us the most data was available for the city of New York ($\sim 10 - 15\%$ of the overall data). Finally, external dataset availability was likely to be extremely high for New York City (among other cities in the US). Furthermore, we postulated that because of New York's diversity and immense size, there would be a minimal correlation between the bluespaces/greenspaces and the other demographic information. We can find the correlations in Figure 1.

3.1.2 Motivation: Bluespaces and Greenspaces

While analyzing census tract-level data, we observed a low correlation among green and blue spaces but strong trends to signify their effect on microclimatic conditions. Naturally, we wanted to see how the interplay among these would play out. We got a sense that it would be easy to isolate their individual and combined effects due to the correlations. It would also be an important finding from a policy standpoint because it can further guide where and how to manage the installations of these infrastructures.

3.1.3 Data Cleaning

All of our datasets were processed to ensure accuracy at the census tract level. Out of the total $2,168$ census tracts in NYC, a comprehensive analysis was conducted on $2,117$ tracts, which constitute approximately 98% of the total. Starting out, we cleaned all the datasets given to us to supplement our explorative data analysis going forward.

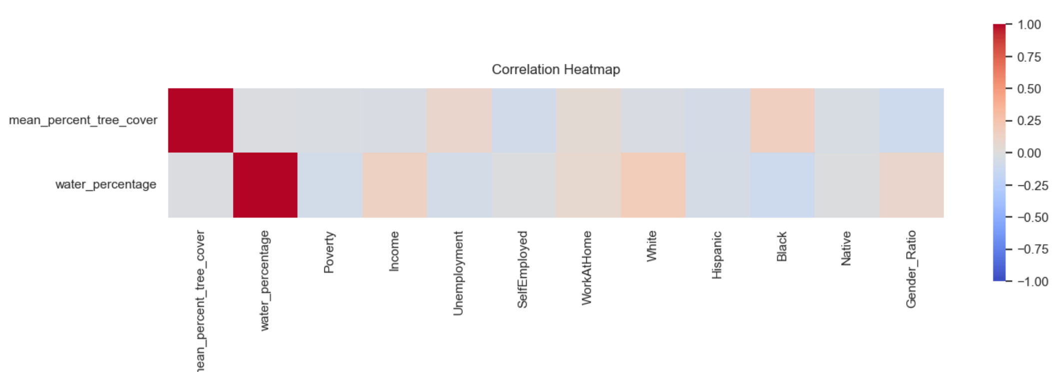


Figure 1: Bluespaces/Greenspaces correlation with demographic data

Greenspaces Dataset: For the `5_million_trees` dataset, we first dropped a lot of columns that were largely uninteresting for our study. The missing values were then either imputed based on semantics or were removed. Some value pairs (for eg. $scientific\_name$ and $common\_name$) could be reasonably inferred from each other. We also dealt manually with some locations like Washington D.C. and St. Louis. The CEHI datasets underwent a similar process. We found them to be much cleaner overall and were later merged to form a larger dataset including both inputs and outputs. A similar procedure was followed for the urban tree canopy dataset and the percent cover datasets.

Health Dataset: The `big_cities_health_cdc` data was cleaned by first the removal of *notes* and *methods* columns, as they were mostly nulls. An additional feature that was introduced was `per`, which indicated the magnitude of the value, as the data were often on different scales. Finally, the FIPS number indicating the geographical area was added through the census mapping dataset and expression parsing of the location column.

3.1.4 External Datasets

Throughout the course of this study, we have also used the following datasets:

1. The $\mathrm{PM}_{2.5}$ 2016 dataset from the Centers for Disease Control and Prevention (CDC) [1]. This census tract-level datasets contain estimates of the mean predicted concentration of $\mathrm{PM}_{2.5}$ particles collected over a 24-hour period along with the standard deviation.
2. The Heat Health Census Tracts dataset [2]. This dataset is enriched with demographic and environmental variables in support of climate resilience planning for urban heat health. In particular, we use the summer high mean temperature and the summer mean temperature in our analysis. The dataset was in Fahrenheit and was converted to Celsius.
3. The New York City Census Data [3]from Kaggle provides demographic information for each census tract in New York City, including information on the population, income, education, and race/ethnicity of residents.
4. The TIGER/Line Shapefiles for New York [4] dataset provides a detailed representation of the geographical and administrative boundaries of New York City, including information on the boundaries of census tracts, which serve as the unit of analysis in this study. They provide information on the location of natural and man-made features, such as roads, rivers, parks, and bodies of water. They contain geographic entity codes (GEOIDs) that we use to link them to the given and other external data. We get the `water_percentage` metric from here as this dataset contains the area of land and water in each census tract.
$$water\_percentage = \frac{area\_water}{area\_water + area\_land} \tag{1}$$
5. Twitter Climate Change Sentiment (TCCS) Dataset (Effrosynidis, 2022; 2021) is the most comprehensive dataset on climate change and human opinions to date, covering over 13 years and over 15 million tweets from across the world, along with geolocation information. Seven dimensions of information are tied to each tweet, including `geolocation`, `user gender`, `sentiment`, `aggressiveness`, `deviation from historic temperature`, and `topic modeling`, with accompanying disaster events information. The dimensions were produced using a variety of state-of-the-art machine-learning algorithms and methods, both supervised and unsupervised. We demonstrate some examples in Table 12 in Appendix A.5.

[1] Air Quality
[2] Heat Health Census Tracts
[3] NYC Census
[4] New York Shapefile Dataset

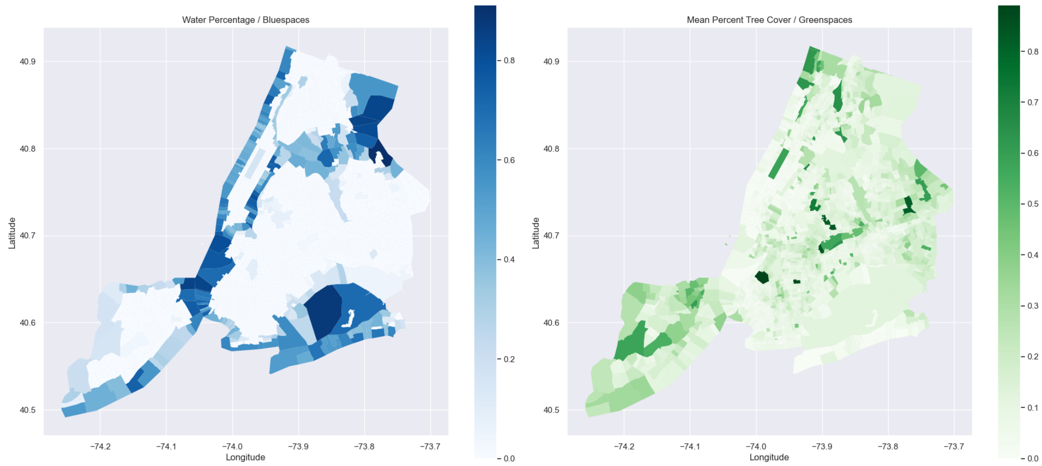


Figure 2: The bluespaces (left) and the greenspaces (right) in New York

3.1.5 The Gaussians

We had a unique problem on our hand. The bluespaces and greenspaces are usually concentrated in some specific locations as opposed to being spread out across the city as can be seen from Figure 2. This makes the census tracts dependent data points due to the confounding effect of nearby green/bluespace-rich regions creeping into a certain tract while being measurably low in these spaces themselves. To counteract this, we were motivated to use a *propagation metric* that removes this dependency and assigns soft proximity scores for each tract. This will more-or-less eliminate the aforementioned confounding effect.

It has been well-studied that both greenspaces and bluespaces have far-reaching effects because of phenomena like evapotranspiration/albedo effect. To model the effect of the greenspaces/bluespaces, we constructed a metric called the blue-gaussian/green-gaussian[5]. A similar model has been used by Carrier et al. (2016) for evaporation. The algorithm for computing the blue/green gaussians is described in Algorithm 1

Algorithm 1 Bluespace/Greenspace Gaussian Generator

Require: For each county: Geometry (G), Bluespace/Greenspace percentage (B)
Ensure: Returns a value Δ that approximates the bluespace/greenspace effect
  Compute the centroids of all counties and store them in C.
  Multiply Latitudes by 0.652 and Longitudes by 0.546 ▷ 1 Lat $\neq$ 1 Long
  for each county $c \in$ NY **do**
    $\Delta_{num}, \Delta_{den} \leftarrow 0, 0$
    for each county $c' \in$ NY **do**
      $\Delta_{num} \leftarrow \Delta_{num} + B(c')e^{-C\cdot\text{dist}(c,c')}$
      $\Delta_{den} \leftarrow \Delta_{den} + e^{-C\cdot\text{dist}(c,c')}$
    end for
    $\Delta(c) \leftarrow \frac{\Delta_{num}}{\Delta_{den}}$
  end for
  Return Δ

Essentially we compute approximate distances from each county to the other and take a negative-exponential-distance weighted sum of the bluespace/greenspace percentages. We plot the blue/green gaussians in Figure 3

[5]Strictly speaking this is not a gaussian (as it is weighted exponentially with the negative distance not the negative squared distance). However, we found that for getting an intuition for how the greenspaces/bluespace have an effect on the surroundings we can approximately think of it as a gaussian.

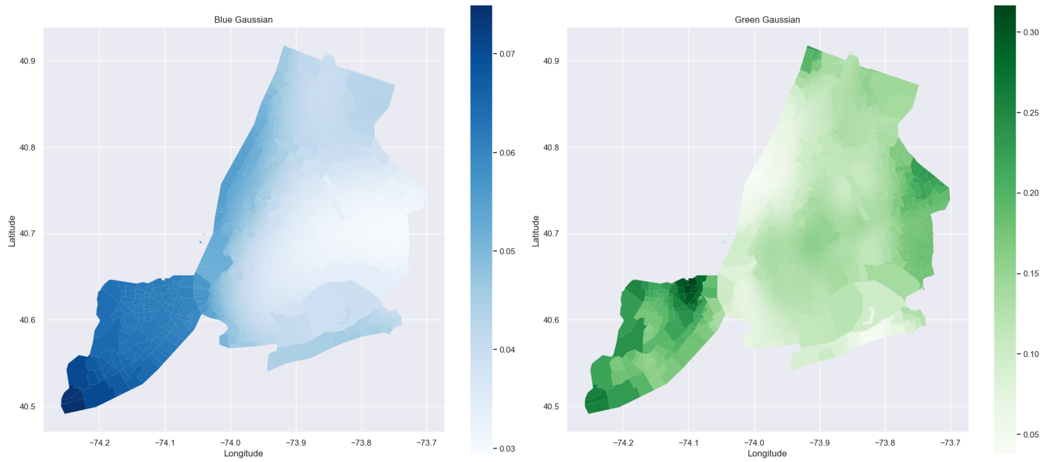


Figure 3: The blue gaussian (left) and the green gaussian (right) of New York City

3.1.6 Census Tract Groups: K-Means Clustering

To reiterate, we aim to selectively analyze the influence of blue and green infrastructure on neighboring census tracts. We thus employ a k-means clustering algorithm on the normalized values of the variables `(water_gaussian, green_gaussian)`. We set $k = 4$. The aim is the have the groups follow the following semantics: `high-tree-high-water`, `high-tree-low-water`, `low-tree-high-water` and `low-tree-low-water`. We realize that the clustering result might be random and thus verify the semantics by visualizing the data.

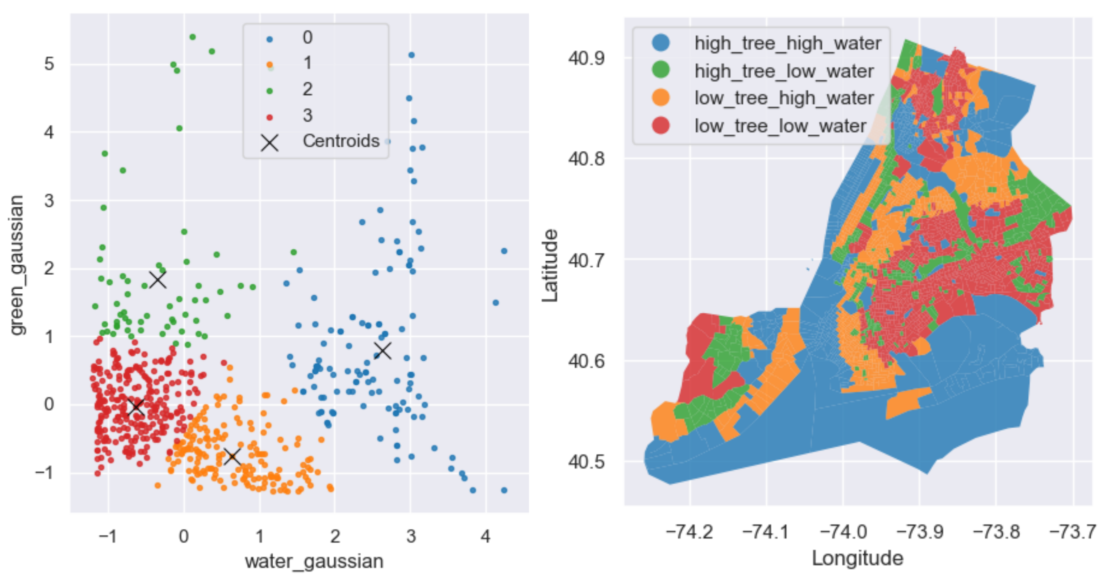


Figure 4: Left: K-Means (with $k = 4$) successfully segments counties using normalized (`green_gaussian, water_gaussian`) values while preserving group semantics. Right: Census Tracts and their classifications displayed. Note: Few unexpected labels (e.g. coastal group labeled as `low-water`) exist due to borough-based county sub-division before doing K-Means, leading to a more locally informed classification.

Moreover, to remain robust to the limitations of the data, we acknowledge that several other confounding demographics can affect the sentiment of tweets coming from the region. To minimize this as much as possible but still respect time constraints, we first divide the city further into the five boroughs i.e. *The Bronx, Brooklyn, Manhattan, Queens, and Staten Island*. Then we run the k-means algorithm on each tract to classify them into four groups. We observe that the k-means classes are able to respect the semantic meaning of the classes very well for all the boroughs.

We considered running k-means in both these scenarios i.e. on all tracts vs separately on the borough-specific tracts. Although the former might give much stronger results, we aggressively chose to go with the latter as it yields the most robustness to our findings. The final classification results are shown in Figure 4. For further verification, we plot some common demographic distributions for the groups in Figure 5. The distributions are very similar and thus we can proceed with more confidence.

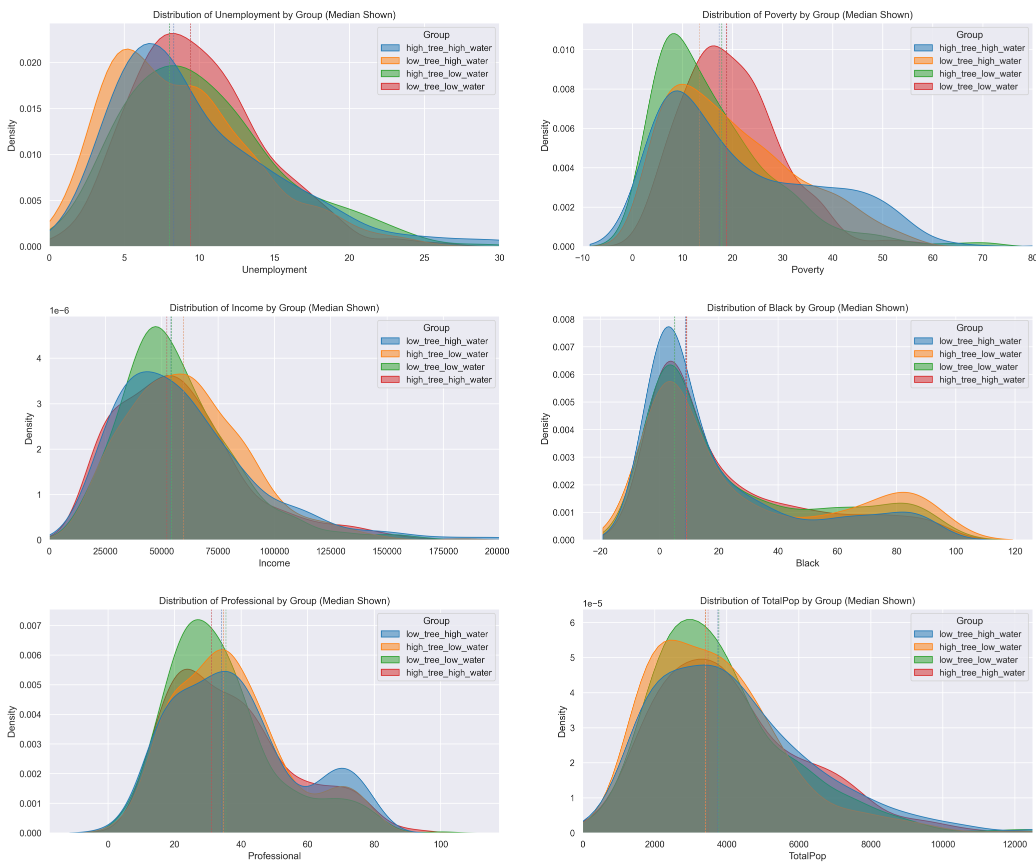


Figure 5: Our analysis entailed a meticulous examination of various socioeconomic metrics across the configurations of census tracts in order to identify and mitigate the possible confounding factors within. The distributions of the following parameters were generated: `Unemployment`, `Poverty`, `Income`, `Black Population`, `Professional Population`, and `Total Population`. The plots indicate a high degree of uniformity in the observed variables across the census tract groups.

3.2 Temperature

Greenspaces have had a significant impact in reducing temperatures around the world (Li et al., 2013; Shih, 2017; Li et al., 2012). Green can reduce the temperature in several ways. Plants release water through evapotranspiration, which cools the surrounding air. Through evaporative cooling, water is released into the air, increasing humidity and reducing the temperature. Green spaces also increase a city's overall albedo, or reflectivity, which can reduce the temperature. This is because green spaces are typically less reflective than urban surfaces like concrete and asphalt. By increasing the overall reflectivity of a city, green spaces can help to reduce the amount of heat absorbed by the urban environment. Similarly Ampatzidis & Kershaw (2020); Völker et al. (2013) have also shown that bluespaces are beneficial in reducing city temperatures. Bluespaces also achieve this by either increasing reflectivity and performing evaporation or by creating cool breezes, which help in reducing the temperature.

3.2.1 Dataset

In the `urban_tree_canopy` dataset, we are already given the mean surface temperature from the column `surface_temp`. Given the importance of temperature prediction, we also consulted the *Heat Health Census Tracts* dataset. This gave us two more metrics: 1. The summer high land surface temperature and 2. The average summer land surface temperatures.

These metrics allowed us to furthermore consider how effective the green and blue spaces were in terms of further reducing the temperature when it was needed the most. Our results show that they are indeed effective in creating a compounded reduction during the summer. We plot the mean temperature and the temperature difference recorded in New York in Figures 6 and 7.

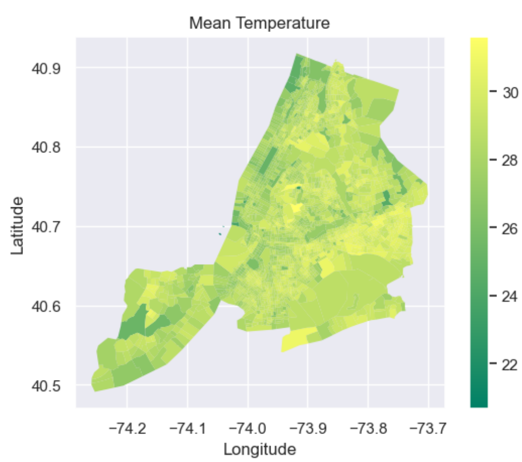


Figure 6: NYC Temperature

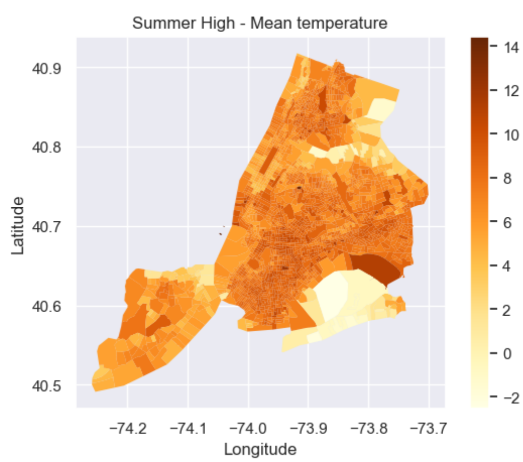


Figure 7: NYC Temperature Difference

3.2.2 Model

We wanted to observe how the temperature and temperature difference varies with both blue space, green space, and the presence of both simultaneously. To achieve the same we consider the regression formula

$$T \sim \Delta(\text{blue}) + \Delta(\text{green}) + \Delta(\text{blue}) : \Delta(\text{green}) \tag{2}$$

where $\Delta(\cdot)$ represents the distance function described in section 3.1.5. We consider a similar formula for the change in temperature. We then try to interpret the T-stats for each of these to consider how well our model holds to the dataset.

Modeling Assumptions Our aim is to investigate the relative and combined effect of having greenspace vs bluespace in a census tract. A linear model is what allows us the most simplicity. We also point out that getting the best possible modeling formula is *not* a very hard criterion for our study. We generally want to get and communicate insights on these effects so a linear model fits this criterion well.

We further investigate the general validity of our regression model.

- The independent assumption between the census tracts may not be true in practice as nearby infrastructure not in the same tract is still expected to influence the

	Temperature	Summer Mean - Mean	Summer High - Mean
Green	-4.599	-7.702	-8.314
Blue	-2.142	-7.161	-7.898
Green:Blue	**4.063**	**6.269**	**7.058**

Table 1: T-stat values when we perform Ordinary Least Squares Regression on Mean Temperature, Summer Mean Temperature - Mean Temperature, and Summer High Mean Temperature - Mean Temperature. We see that green spaces and blue spaces both have a significant correlation with reducing the temperature, meanwhile, the product has a positive T-Stat. This indicates that both green space and blue spaces together are less potent than the sum of their individual effects.

microclimate in the same. We note that our gaussian metric works exactly to counteract this event by propagating the effects to nearby counties and mitigating this confounding.

- We also note that all our regression results obtain very significant results in terms of p-values (and t-stats), thereby reducing any possibility of statistical false positives. Furthermore, we run k-fold-cross-validation to find any other abnormalities as well.
- We additionally do normality testing using QQ plots on residuals from all our models and ensure their consistency. The plots of all residuals can be found in the Appendix in Figure 19.

Note on Causality We also acknowledge the fact that a regression model does not normally test for cause-and-effect relationships. Thus, in very extreme cases, our causal analysis may not fully hold (the correlations will still do). But we comfortably believe that it is highly unlikely for a variety of reasons.

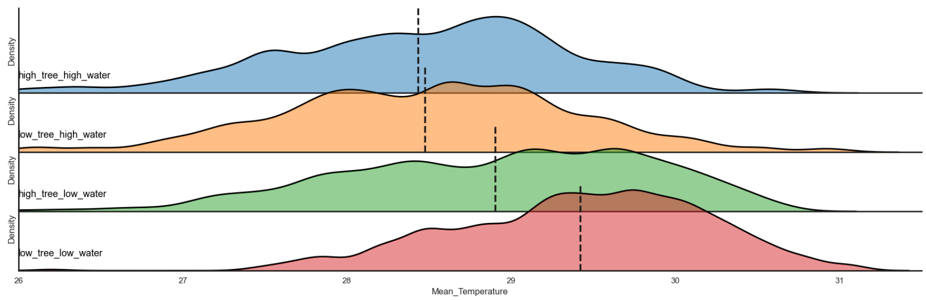
- Firstly, we investigate correlations of green and blue infrastructure with several other tract characteristics (eg. many demographics from census data). We find no evidence of any strong relationships. This reduces the possibility of our analysis being misdirected and focusing on the wrong variable.
- Secondly, the construction of tract sub-groups is exactly suited to reducing any chance of detecting the wrong patterns. We also find *no* a strong relationship between group assignment and tract demographics. They should do a good job of disentangling the effects of green and blue spaces with other variables and between themselves.
- Finally, the vast proportion of blue and green infrastructure is natural, pre-existing, and fairly random. This should reduce the possibility of any reverse causal effect between microclimate and the said infrastructure.

3.2.3 Results

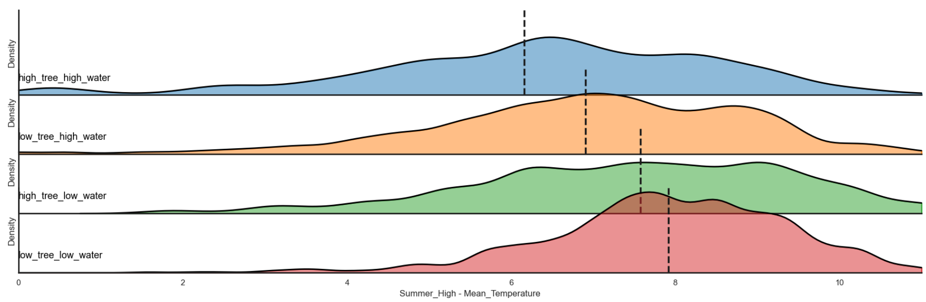
We perform an ordinary least-squares on each of the temperature values using Equation 2.

The results clearly fit our initially mentioned hypothesis. We see that green spaces and blue spaces both have a significant correlation with reducing the temperature, meanwhile, the product actually increases the temperature. It strongly indicates our hypothesis that green spaces and blue spaces act more as substitutes instead of compliments.

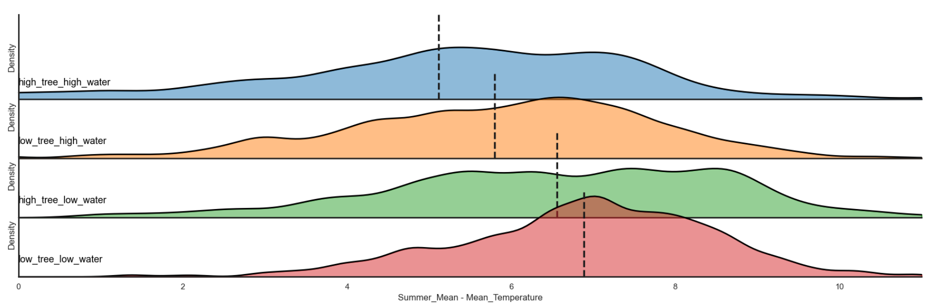
If we consider Figure 18, we see that the blue spaces alone typically have a significantly higher effect on the temperature as compared to the green spaces. We can further support our arguments by considering the clustering used in section 3.3. We create ridge plots for each cluster and for each metric that we want to consider in Figures 8 (a), (b), and (c). We can observe that `high_tree_high_water` outperforms the others for all temperatures, while `low_tree_low_water` is always the worst. It is also worth noting that



(a) The Clusters vs the Mean Temperature



(b) The Clusters vs the Summer High Temperature - Mean Temperature



(c) The Clusters vs the Summer Mean Temperature - Mean Temperature

Figure 8: Ridge plots of the clusters against the Mean Temperature, Summer Mean Temperature - Mean Temperature. We can observe that `high_tree_high_water` outperforms the others for all temperatures, while `low_tree_low_water` is always the worst. It is also worth noting that for the mean temperature setting `low_tree_high_water` performed almost as good as `high_tree_high_water` in the mean temperature setting supporting our claim that the two spaces are substitutes.

for the mean temperature setting `low_tree_high_water` performed almost as well as `high_tree_high_water` in the mean temperature setting. *Most importantly,* we note that `low_tree_high_water` outperformed `high_tree_low_water` on all temperature metrics. Please refer to Table 8 in the Appendix A.1 for more information regarding Figure 8.

We also do 5-fold cross-validation to confirm that we are not overfitting our model. The table of results can be found in Table 10 in the Appendix A.1. As can be seen the train and test R^2-errors are fairly close to each other.

3.3 Climate Sentiment Analysis

3.3.1 Introduction

To further validate our hypothesis, we find additional proxies relating to climatic factors. One important aspect of climate change and human health, in general, is the human sentiment i.e. frustration associated with harsh weather conditions, the dismal state of natural elements, or the calmness one gets by interacting with greenspaces and bluespaces around. To this end, we explore and analyze the Twitter Climate Change Sentiment (TCCS) Dataset. We first filter about $200,000$ in tweets that are posted from New York City and classify them into census tracts according to the longitude and latitude information.

Our goal is now cut out for us: to analyze sentiment levels among the four groups and find out how bluespaces and greenspaces affect human emotion. Past literature (Lim et al., 2018) has found strong positive effects of greenspaces on general human emotion. Our study has a different goal and is more focused on many aspects: (1) We focus especially on the emotion concerning climate change and global warming. (2) We study variations with respect to greenspaces, bluespaces, and their interaction.

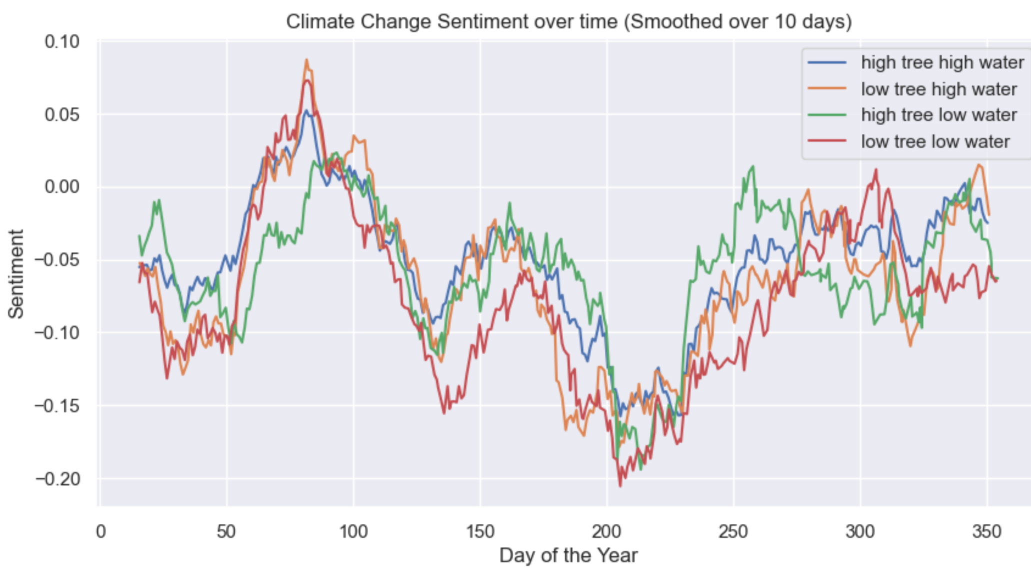


Figure 9: The average sentiment of the Census Tract groups by Day of the Year.

We start by aggregating the tweets on the day of the year and visualize them in Figure 9. We immediately observe the following: (1) Most of the sentiment is negative, which reflects on the fact that people tend to tweet about negative sentiments more than positive ones. (2) Group `low-tree-low-water` is almost consistently worse than the others, which indicates that greenspaces and bluespaces do contribute to human emotion. (3) The plot still does not reveal any other interaction effects.

3.3.2 Quantitative Analysis

We now attempt to study these time-series quantitatively. We notice from Figure 9 that unknown macro factors (eg. seasons, global events, etc.) cause a lot of non-stationarity in the overall trend. We comfortably assume that since the analysis is restricted to a city, these effects are uniform across all the tracts and thus, rather uninteresting for our study. To mitigate this, we subtract the groups `high-tree-high-water`, `low-tree-high-water`, `high-tree-low-water` from the `low-tree-low-water` resulting into Figure 10. For notational purposes, we will call them $\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$, $\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}$, and $\Delta\text{Sent}_{\text{htlw}-\text{ltlw}}$ respectively. We notice that the resulting time series' do not deviate and seem much easier

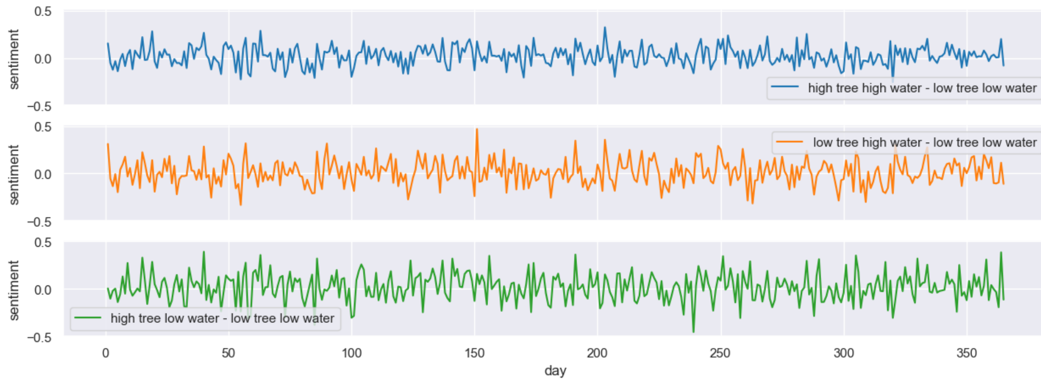


Figure 10: The difference in sentiment w.r.t the group `low-tree-low-water`. We denote them as $\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$, $\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}$, and $\Delta\text{Sent}_{\text{htlw}-\text{ltlw}}$ respectively. This clearly removes the bulk of the seasonality from Figure 9.

	$\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$	$\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}$	$\Delta\text{Sent}_{\text{htlw}-\text{ltlw}}$
Test Statistic	-20.30	-10.33	-20.24
p-value	0.00	0.00	0.01
Num Obs	365	365	365

Table 2: Augmented Dicky Fuller test for verifying the stationarity of the series' in Figure 10. We run with the `autolag=AIC` setting, which selects the lag order that minimizes the AIC value.

to analyze. Most likely, the only effects present now are due to the tract group-specific variations i.e. the proportion of green and blue spaces.

We further verify the stationarity of the time series in Figure 10 using the Augmented Dicky Fuller (ADF) test. We choose this test for a variety of reasons: (1) It has the null hypothesis H_0 : *Series is non-stationary or series has a unit root.* Thus, if we are able to reject it, the series is most likely stationary. (2) It is simple to use and makes virtually no very strong assumptions about the underlying data. The results are shown in Table 2. We notice that we can reject the null hypothesis for all three cases.

3.3.3 Hypothesis Testing

The above test enables us to define a meaningful marginal distribution for a single point i.e. use sample statistics as representatives of population statistics which hold throughout time. Before moving on, we perform *normality testing* on all three series' (after normalization). This influences our choice of hypothesis tests made at a later stage. The results are shown in Table 11 and Figure 21. We comfortably conclude that all the series' *approximately* follow a *normal distribution*.

We now run hypothesis testing on the following alternative hypothesis:

- A1: Regions rich in either greenspaces or bluespaces (or both) enjoy higher sentiment in general than others particularly the group `low-tree-low-water`. This naturally is equivalent to testing if the means of the $\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$, $\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}$ and $\Delta\text{Sent}_{\text{htlw}-\text{ltlw}}$ are bounded away from zero.

- A2: Regions `low-tree-high-water` enjoys less marginal benefit of greenspaces than the Region `low-tree-low-water` i.e. the mean of $\Delta\text{Sent}_{\text{hthw}-\text{lthw}}$ is smaller than $\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$.

	$\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$	$\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}$	$\Delta\text{Sent}_{\text{htlw}-\text{ltlw}}$
Sample Mean	0.026	0.016	0.018
p-value	0.0004	0.0471	0.0482

Table 3: One sample t-test results. All p-values are low enough to establish A1.

	$\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$	$\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}$	$\Delta\text{Sent}_{\text{htlw}-\text{ltlw}}$
$\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$	-	0.21	0.27
$\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}$	-	-	0.44

Table 4: Welch t-test results (p-values). No p-values are low enough to reject the null hypothesis.

To check A1, we perform a one-sample t-test on all three series. (1) We select this test as we have already *established normality*. (2) We choose the alternative hypothesis as the mean > 0 as this is precisely what we want to test. We show the results of the testing in Table 3.

Now we attempt to compare the means of these series' among themselves. We perform Welch's t-test to determine if one mean is greater than the other. (1) We have already established the normality of the series'. (2) This test does not assume equal variance between the compared samples, which is more suited to our case. (3) We choose the alternative hypothesis that one mean is greater than the other. We show the results in Table 4.

In line of A2, we also run one more Welch t-test between $\Delta\text{Sent}_{\text{hthw}-\text{lthw}}$ and $\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$, which returns a p-value of 0.0419, allowing us to comfortably reject the null hypothesis.

Thus, we can conclude:

$$\mu(\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}) >\sim \mu(\Delta\text{Sent}_{\text{htlw}-\text{ltlw}} >\sim \mu(\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}) > 0 \tag{3}$$

$$\mu(\Delta\text{Sent}_{\text{hthw}-\text{lthw}}) > \mu(\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}) \tag{4}$$

where $\sim$ indicates a weak relationship (which needs additional testing) and μ is the mean function.

The conclusions we draw from this testing are as follows:

- Both greenspaces and bluespaces are quite helpful in lifting public sentiment. This is what is established by A1 in Table 3.
- The positive effect of greenspaces is much stronger in areas with a relative scarcity of bluespaces. This is what is established by A2 and equation 4.
- Although we weakly established the trend shown in equation 3, it is somewhat hard to say a lot more than this without additional testing.

3.3.4 Final Thoughts and Limitations

To finish up, we visualize some other properties of the average sentiment across tract groups. For instance, Figure 11 shows the cumulative sentiments of the daily sentiments (added across time). They follow the pattern established and further strengthen our analysis.

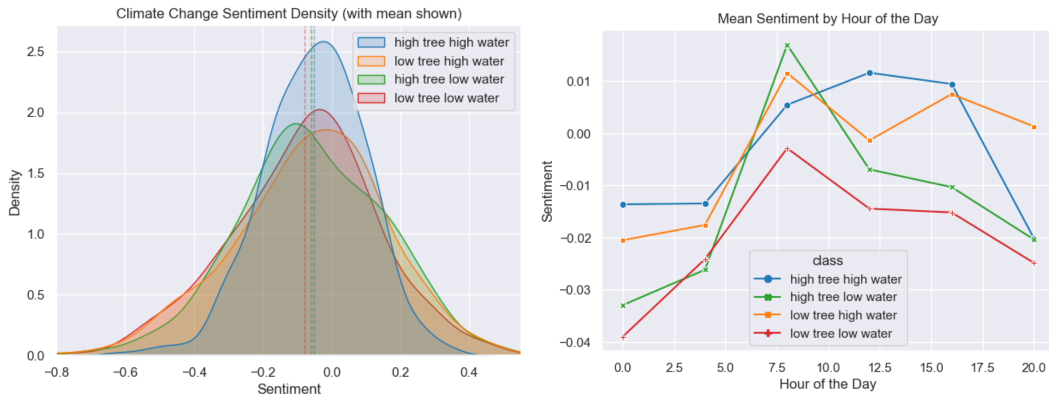


Figure 12: Left: Density distributions of the daily sentiments by classified Census Tracts. Right: Average Sentiment series aggregated by the hour of the day. The sampling is done every four hours.

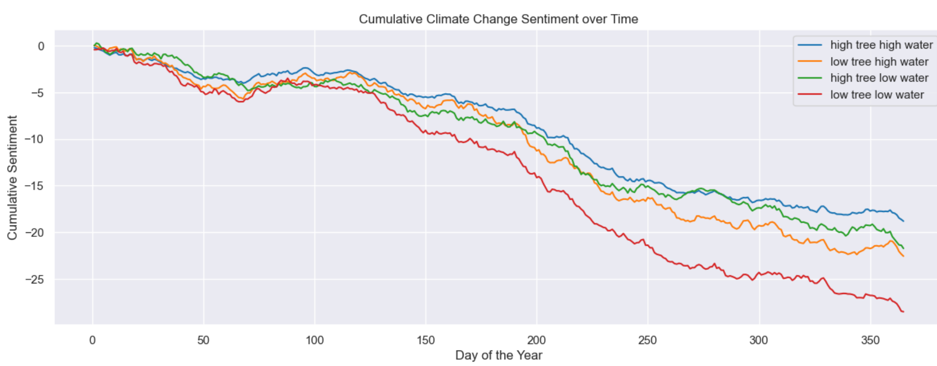


Figure 11: Cumulative Sentiment density across the year by classified Census Tracts.

Another interesting view is provided by Figure 12, where we show the density distribution of daily sentiment. We also show how the average sentiment series looks when aggregated by the hour of the day. It is clear that the region `low-tree-low-water` is significantly worse than the rest and should be the region where municipalities should focus on enhancing natural elements. Other trends, though they somewhat follow the patterns we established, exhibit minor elements which may need more explanation over time.

3.4 Air Quality

Greenspaces have had a significant impact in improving Air Quality around the world (Matos et al., 2019; Ren et al., 2017; Irga et al., 2015). Green spaces improve the greenspace through photosynthesis wherein they remove carbon dioxide from the environment and increase oxygen levels. They are also responsible for Particulate Matter (PM) removal. Trees and plants can act as filters for particulate matter, such as dust, dirt, and pollen, which can contribute to poor air quality and health problems.

Similarly Georgiou et al. (2021); Huang et al. (2015) have also shown that bluespaces are beneficial in improving air quality around different cities. Blue spaces perform atmospheric circulation. They affect the circulation of air masses and help to distribute pollutants, such as smog and particulate matter, more evenly throughout the atmosphere. This can help to reduce their concentration in specific areas and improve air quality. Furthermore, bluespaces also act as sinks for dust and particulate matter, helping to remove these pollutants from the air and improving air quality.

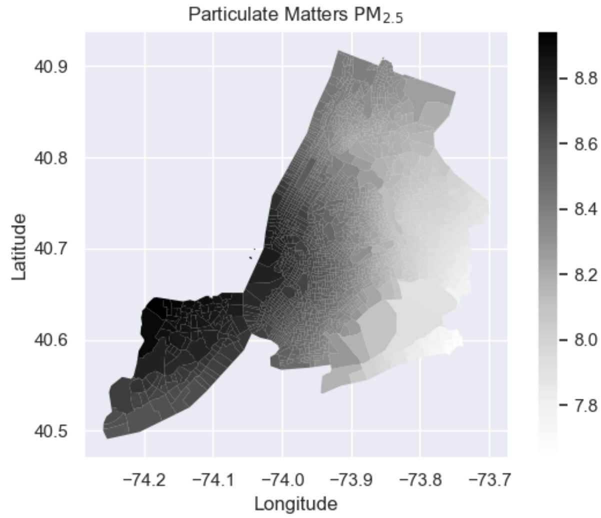


Figure 13: Particulate Matter ($\mathrm{PM}_{2.5}$) in New York

3.4.1 Dataset

Finding an appropriate dataset was significantly harder in the case of air quality. This is primarily because our study was focused more on how the air quality varies on the level of census tract. We were however able to find a dataset for GEOID-level precise dataset for Particulate matters ($\mathrm{PM}_{2.5}$) in the US from the CDC at this link.

A particle matter consists of microscopic solids or liquid droplets that are so small that they can be inhaled and cause serious health complications if they are inhaled in large amounts. There are some particles that are less than 10 micrometers in diameter that can get deep into the lungs and may even enter the bloodstream. Among these particles, those less than 2.5micrometers in diameter, also known as fine particles or $\mathrm{PM}_{2.5}$, pose the greatest threat to health due to their small size.

Particles in the $\mathrm{PM}_{2.5}$ size range are able to travel deeply into the respiratory tract, reaching the lungs. Exposure to fine particles (Mukherjee & Agrawal, 2017; Myong, 2016; Sacks et al., 2011) can cause short-term health effects such as eye, nose, throat, and lung irritation, coughing, sneezing, runny nose, and shortness of breath.

Doing a bit of exploratory-data analysis we plotted the air quality as it varies over the city of New York in Figure 13. The particulate matter is measured in $\mu g/m^3$. The United States Environmental Protection Agency (EPA) established National Ambient Air Quality Standards for $\mathrm{PM}_{2.5}$. The short-term standard is 35 micrograms per cubic meter of air ($\mu g/m^3$) and the long-term standard (annual average) is $12\mu g/m^3$.

3.4.2 Model and Results

Similar to section 3.2, we wanted to observe how the $\mathrm{PM}_{2.5}$ varies with both blue space, green space, and the presence of both simultaneously. To achieve the same we consider the regression formula

$$\mathrm{PM}_{2.5} \sim \Delta(\text{blue}) + \Delta(\text{green}) + \Delta(\text{blue}) : \Delta(\text{green})$$

where $\Delta(\cdot)$ represents the distance function described in section 3.1.5.

Similar to section 3.2, we once again perform an Ordinary Least Square Regression. This time, our results turn out to be even stronger with significantly higher T-stats as compared to section 3.2 as can be seen from Table 5. The modeling and causality assumptions follow from section 3.2 as well.

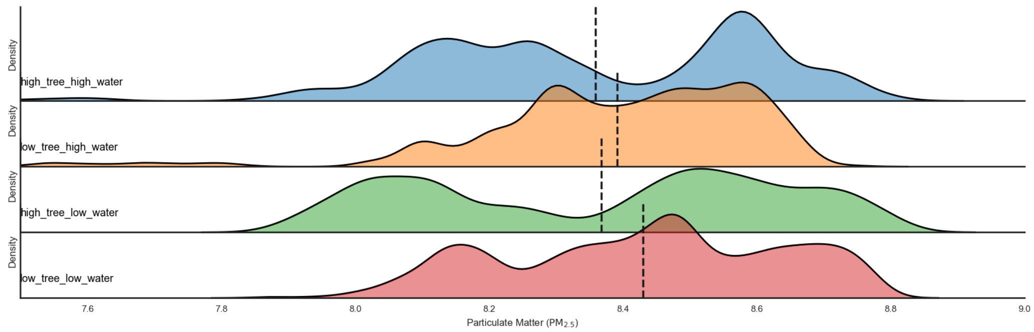


Figure 14: Ridge plots of the clusters against $\mathrm{PM}_{2.5}$ in $\mu g/m^3$.

	T-Stat
Green	-20.526
Blue	-30.623
Green:Blue	22.318

R-squared	0.741
F-Statistic	2059
Observations	2164
Skew	-0.771
Kurtosis	4.396

Table 5: The large negative T-Stats for green and blue spaces denote a significant effect of both in terms of reducing air-impurity. A large positive T-stat for Green:Blue implies that both green and blue spaces together are less effective than their individual effects.

Similar to section 3.2, we can further support our arguments by considering the clustering used in section 3.3. We create ridge plots for each cluster and for each metric that we want to consider in Figure 14. We can observe that `high_tree_high_water` continues to outperform the others for air impurity, while `low_tree_low_water` is the worst.

However, this time we observe that the green spaces prove to be slightly more useful than blue spaces as can be seen from Figure 14. But once again there is not a lot of difference between `high_tree_high_water` and `high_tree_low_water`, further supporting our claim that the construction of a blue space close to a green space is impractical.

3.5 Extremum

Through the course of this report, we used the gaussian estimators for the blue and greenspaces. We consider an alternative to the method of using gaussian estimators. We believe that all the climate metrics are likely to have local extremum at green / bluespaces.

3.5.1 The Method

Finding the minimas when we have the data in the form of some metrics over the counties of New York City is a challenging task primarily because of:

1. As opposed to a discrete grid-like structure, the NYC census tracts are irregular in shape not having clear neighbors. To check if a GEOID is an extremum we cannot simply see the neighbors to the left/right/up/down and immediately proclaim that the GEOID is a minima/maxima.
2. As opposed to a typical continuous surface our function currently looks like a piecewise constant function. It has either an undefined gradient or a zero gradient
3. Based on the metric that we are considering the neighboring GEOIDs can vary a lot just because the metric has a fairly large standard deviation.

To remediate these issues we propose the following algorithm to compute the minimas

Algorithm 2 Minima-Finder

Require: The geometry of the counties (G) and the metric values at the counties (M)
Params k, n
Ensure: Returns a list of counties that are approximately minimas
Compute the centroids of all counties and store them in C.
Multiply Latitudes by 0.652 and Longitudes by 0.546
Minimas $\leftarrow$ [ ]
for each county $c \in \mathsf{NY}$ **do**
  Find the n closest counties to c using the centroids by using C
  if $M[c]$ is among the top k values in n counties **then**
    Append c to Minimas
  end if
end for
Return Minimas

3.5.2 Results

Based on the plots in Figure 15 we hypothesize the following:

1. For Temperature, we see that minimas are found both close to greenspaces and bluespaces (but not on the coast).
2. For the Particulate matter, we observe that the minimas are largely found along the river/coastal line with few being adjacent to greenspaces.

Since the distributions for $mean\_tree\_percent\_cover$ and $water\_percentage$ are unknown, we perform a Kolmogorov-Smirnov Test (Massey, 1951) to confirm that these minimas are not being randomly drawn. Table 6 shows us the KS-Test results for the same. We also consider the mean of the $mean\_tree\_percent\_cover$ and the $water\_percentage$ at the minimas as compared to the entire city to further gauge the effectiveness of our claims in Table 6.

As can be seen from Table 6 we get very strong indicators that our original hypothesis was correct. We see that for temperature we have a negligible p-value as well as a significant boost in the mean of the minimas compared to the overall mean for both greenspaces as well as bluespaces.

Similarly for Particulate matter, we see that the greenspaces neither have a good p-value nor a good mean of the minimas. On the other hand, bluepsaces have an extremely high mean of the minimas (≥ 6 times higher than the overall mean) for particulate matter, showing a very high correlation.

Space	Metric	Mean of Minimas	Overall Mean	Statistic	P-Value
Green	Temperature	**0.2702**	0.1229	0.3962	**3.423 e-21**
Blue	Temperature	0.1127	0.0470	0.1859	6.634 e-05
Green	Particulate Matter	0.1439	0.1229	0.1713	0.6778
Blue	Particulate Matter	**0.2923**	0.0470	0.6451	**5.759 e-07**
Green	Temperature Difference	0.0896	0.1229	0.2054	1.145 e-05
Blue	Temperature Difference	0.0747	0.0470	0.094	0.04022

Table 6: KS Test Statistics and p-values for extremum finding, Indicates that greenspaces might not be good at reducing particulate matter and that bluespaces might not be good at reducing the summer temperature difference.

3.6 Policy

We conclude by using our findings to formulate some recommendations for counties that might benefit the most from adding greenspace *as far as climate change is concerned*. We fully

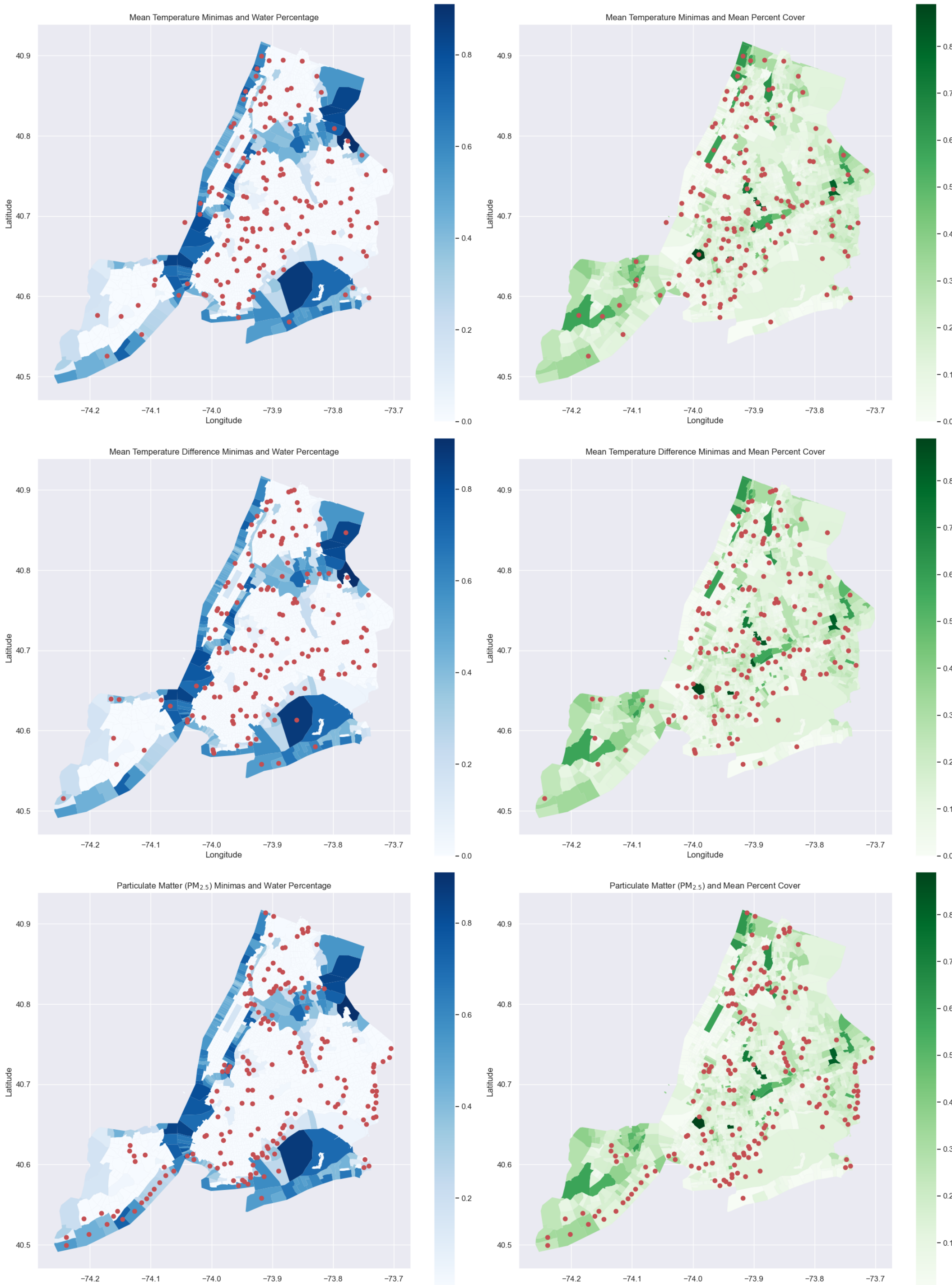


Figure 15: The left column represents the blue spaces while the right column represents the green spaces. The First row represents the Mean Temperature, the second row represents the Temperature difference and finally the last row represents the Particulate Matter levels. The red points represent the minimas

acknowledge that there are *other public health benefits* of greenspaces not considered in this study and that will need a separate analysis.

We choose `surface_temp` for our analysis going forward. Note that a similar analysis can be done with any other variables as well. We start by investigating the percent change in `surface_temp` brought about by green and blue cover. To model the percent change, we model log transformed `surface_temp` with variables for `tree_cover` and `water_gaussian`, across all counties.

$$\log(T) \sim a_0 + a_1 \cdot \text{tree\_cover} + a_2 \cdot \text{water\_cover} + a_3 \cdot \text{tree\_cover} * \text{water\_cover} \tag{5}$$

Note that *neither our claim nor our aim* here is to know that the true relationship is given by Equation 5, even if it is linear. It is simply a formulation we are using for approximate inference. It does not need to be the exact relationship as we will soon see.

Prior to the initiation of our analytical endeavors, it is imperative to scrutinize the presence of undesirable correlations within our dataset that could potentially impede the validity of our future inferences. After examining the correlation matrix depicted in Figure 20 located in Appendix A.3, we see that the interdependence among our endogenous variables is modest and therefore, our statistical models should be capable of producing credible predictions.

We consequently run our regression model. The results are shown in Figure 3.6 and Table 7.

The results largely mirror what we have observed so far i.e. the effects of greenspaces and bluespaces are highly non-additive. The coefficients of `water_gaussian` and `percent_tree_cover` are very significantly negative, indicating the positive effect of greenspaces and bluespaces in bringing down the temperature. But their combined effect has a significantly positive coefficient, indicating that having them both leads to diminishing gains.

We also plot the residuals for the regression on the full dataset in Figure 3.6. They are randomly dispersed around zero in a roughly normal distribution, with no noticeable pattern. The spread of the residuals also is constant and not increasing or decreasing with the fitted values. Durbin-Watson statistic brings in an additional confirmation of homoskedasticity. We observe some outliers but they are fairly rare and should not affect the validity of our model.

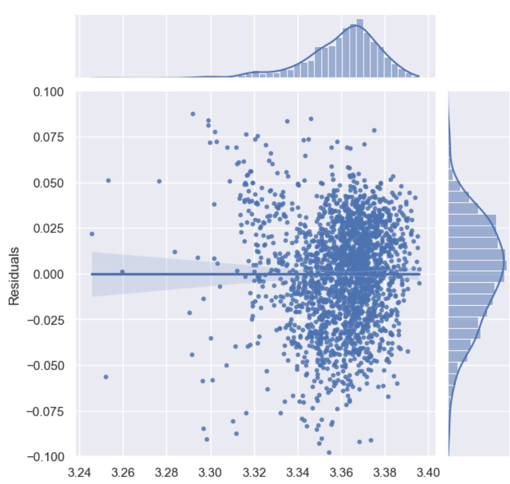


Figure 16: Residual Plot

	OLS
Intercept	3.409***
	(0.002)
water_gaussian	**-0.858*****
	(0.042)
percent_tree_cover	**-0.207*****
	(0.012)
water_gaussian *	**2.040*****
percent_tree_cover	(0.221)
R-squared	0.265
R-squared Adj.	0.264
N	2117
R2	0.265
Skew	-0.419
Kurtosis	4.480
Durbin-Watson	1.438

Table 7: Regression results for equation 5

For additional sanity, we run 5-fold-cross-validation using the model and obtain *train* and *test* R^2. We get a *train* $R^2 = 0.2656$ and *train* $R^2 = 0.2645$. We observe that they are fairly similar and consistent for model validity.

Now we proceed to use our model for some policy predictions. Due to logistical reasons, we acknowledge that constructing bluespaces is much harder than greenspaces. Thus, knowing the amount of tree cover and water cover in each county, it can be interesting to see which counties are likely to respond the most after an increase in green cover i.e. delivers maximum return on our investment. We formalize and arrive the following question:

> **Which counties will show the maximum marginal benefit of installing greenspaces?**

To this end, we differentiate Equation 5 to calculate the change in temperature per unit change in green cover.

$$\frac{\partial T}{\partial \text{green\_cover}} = T \cdot (a_2 + a_3 \cdot \text{blue\_cover}) \tag{6}$$

We thus calculate the above quantity for each tract using the fitted parameters and filter out the counties where it is most negative i.e. to achieve the maximum reduction in temperature. The values are visualized in Figure 17. Using these values, we identify 21 census tracts (Top $\sim 1\%$) that have our recommendation as likely to display maximum benefit out of green infrastructure. We further analyze these tracts and find: (1) $6/21 \sim 30\%$ of these tracts are local temperature maximas. This follows partly from the T term in Equation 6 and partly from the discussion in Section 3.5. (2) $20/21 \sim 95\%$ of these tracts belong to the group `low-tree-low-water`, which bolsters our hypothesis that these tracts have the most to gain from going green.

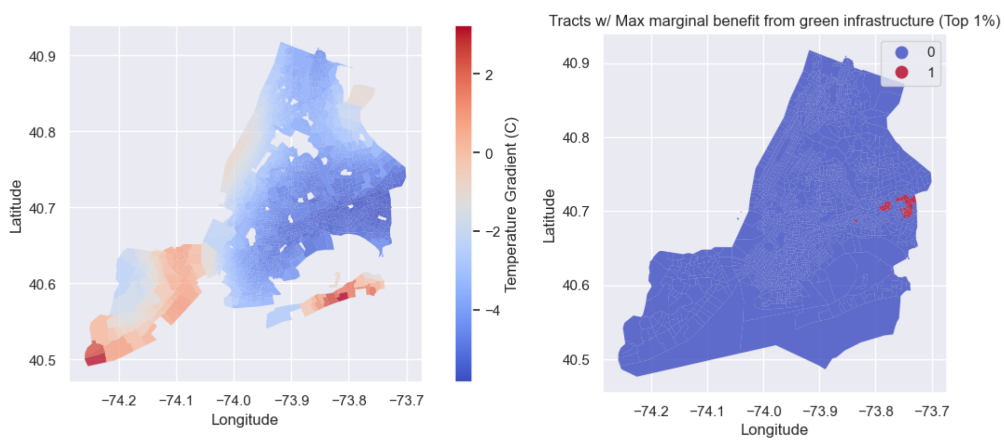


Figure 17: Left: New York counties by the predicted marginal benefit of increasing green cover. A more negative value indicates a high marginal benefit with maximum temperature reduction. Right: Top 1% counties recommended to increase green cover

3.7 Future Work and Limitations

We have tried to ensure maximum robustness throughout this study. But in order to respect time constraints, we could only test for very specific hypotheses. We recognize the following directions to extend this work in the future.

- Analyses to generalize the argument to other cities would help establish the universal substitutability of this infrastructure.
- We would also like to go deeper into our policy model, specifically where it points to having a positive gradient. This may reveal limitations and scope of improvement for our model.

- Other climatic metrics like humidity and direct human health indicators like depression, obesity, etc. still need to be analyzed.

Some additional important hypotheses that can be tested are listed in Appendix A.2.

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A Appendix

A.1 Temperature and Air Quality

Tree	**Water**	**Temperature**	**Summer Mean - Mean**	**Summer High - Mean**
High	High	28.434	5.015	6.162
Low	High	28.476	5.801	6.905
High	Low	28.904	6.561	7.576
Low	Low	29.422	6.886	7.918

Table 8: Mean of the clusters against the different temperature parameters. We can observe that `high_tree_high_water` outperforms the others for all temperatures, while `low_tree_low_water` is always the worst.

Metric	**Mean**	**Std. Dev.**	**Skew**	**Kurtosis**
Mean Temperature	-0.0	0.908	-0.937	3.51
Summer High - Mean Temperature	0.0	1.658	-1.491	5.744
Summer Mean - Mean Temperature	0.0	1.675	-1.539	5.877
Particulate Matter	-0.0	0.178	-0.447	1.253

Table 9: Normality testing of the residuals along with all the moments upto Kurtosis

Climate Parameter	Train Error	Test Error
Mean Temperature	0.21	0.202
Summer High - Mean Temperature	0.158	0.152
Summer Mean - Mean Temperature	0.168	0.162
Particulate Matter	0.524	0.518

Table 10: Train and Test Errors when we perform a 5-fold cross validation on our linear regression models.

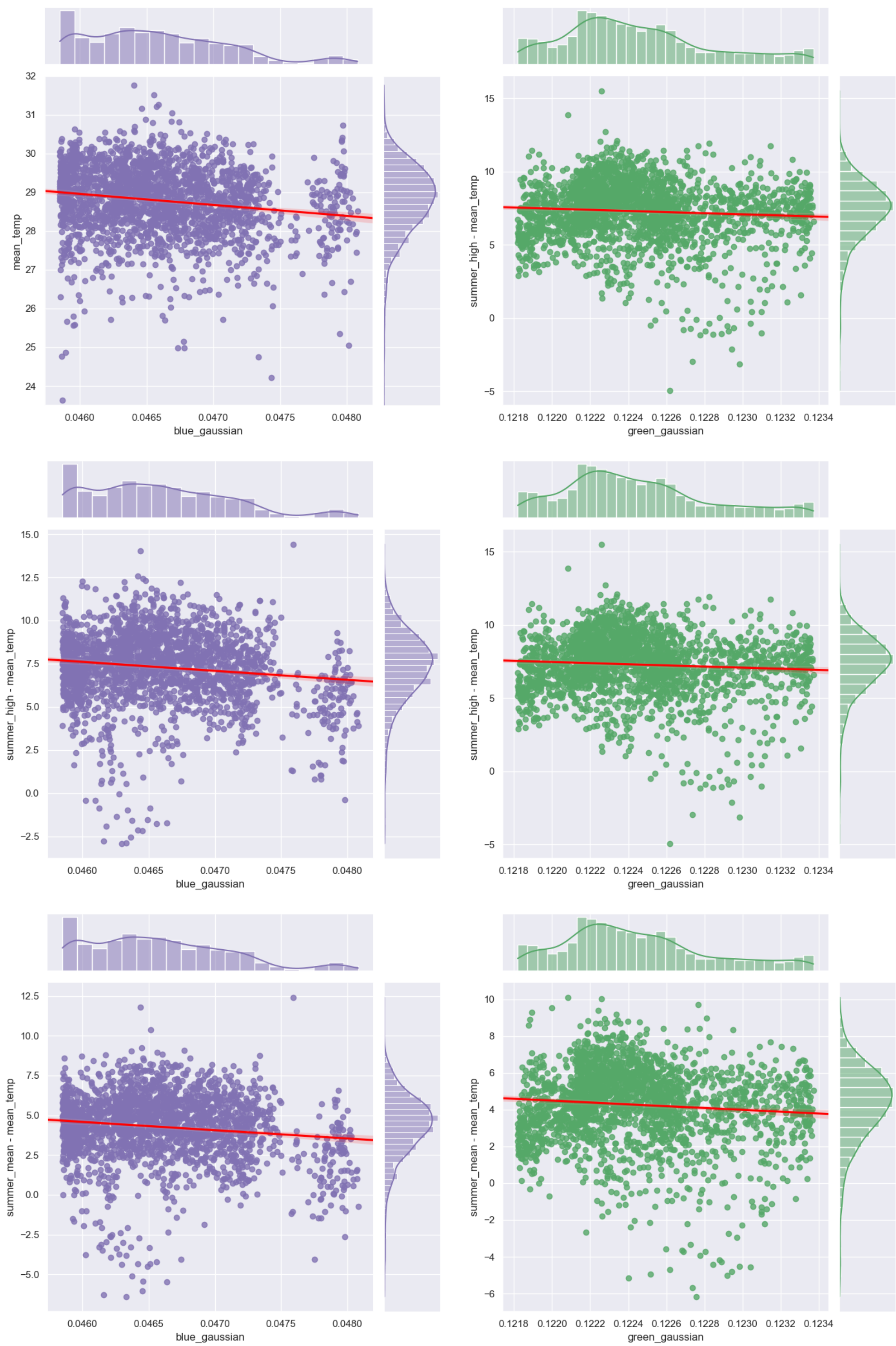

Figure 18: The single variable regression for the Mean Temperature, Summer Mean Temperature - Mean Temperature and Summer High Mean Temperature - Mean Temperature respectively against the bluespace and greenspaces

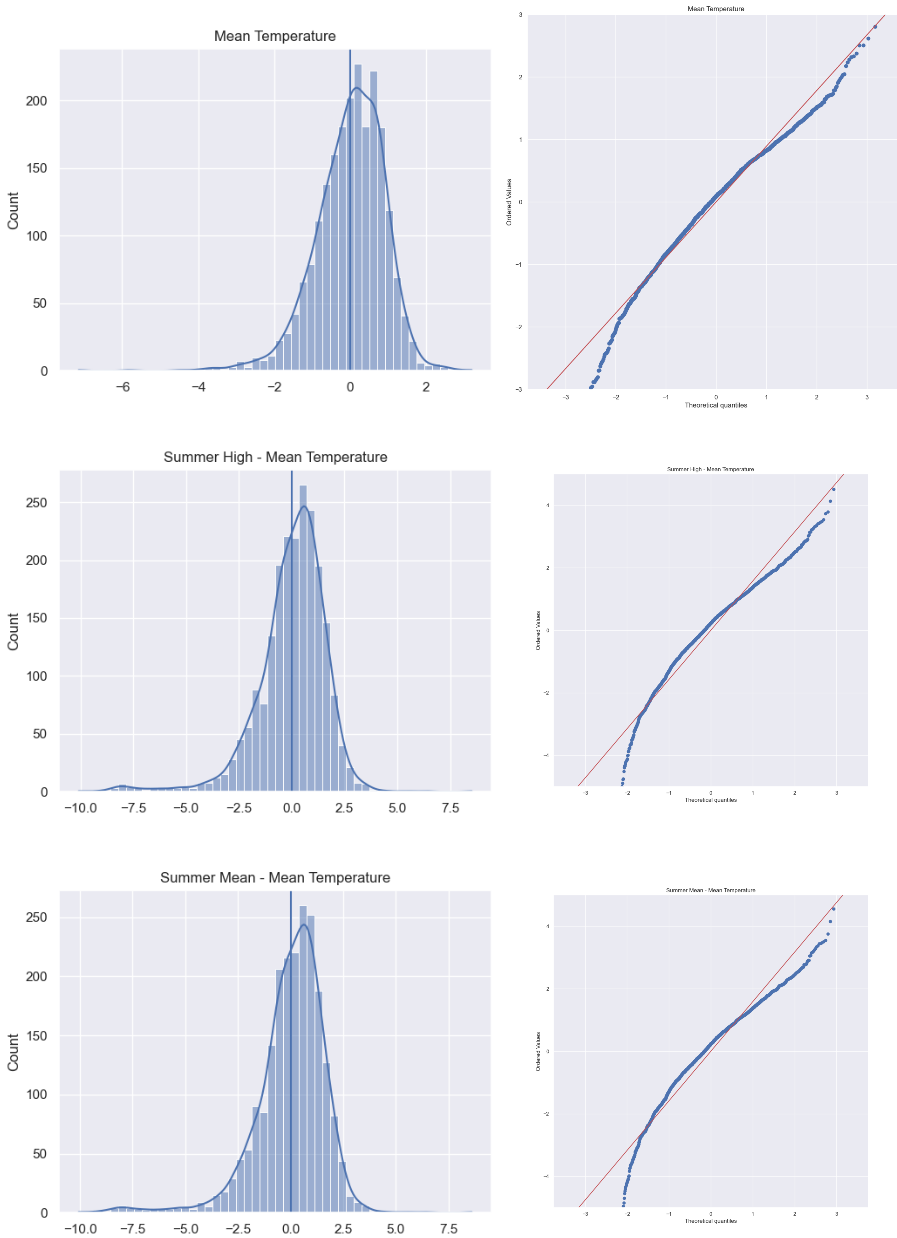

Figure 19: QQ plots of the residuals after performing OLS with blue and green gaussian

A.2 Additional Pathways Considered

We outline some other interesting hypotheses we considered before settling on our current one. The reasoning for hypothesis selection came down to robustness and time constraints. We still believe that these directions hold promise and can be investigated in future work.

1. Crime: Do greenspaces give rise to criminal activity by providing shelters to miscreants? This was an interesting question we considered as well.

2. COVID-19: We investigated how populations living around differing amounts of green infrastructure reacted to the pandemic. Do greenspaces help by improving mental health during the lockdown? Maybe they lead to better lung quality and

provide immunity against the virus. However, it was very hard to ensure robustness in our findings.

3. Road Safety: It would be interesting to compare road safety and related statistics in areas with low/high greenspaces. While trees may act as a nuisance on the road, they bring a calming effect on drivers and pedestrians at the same time.

A.3 Exploratory Data Analysis: Correlation Matrices

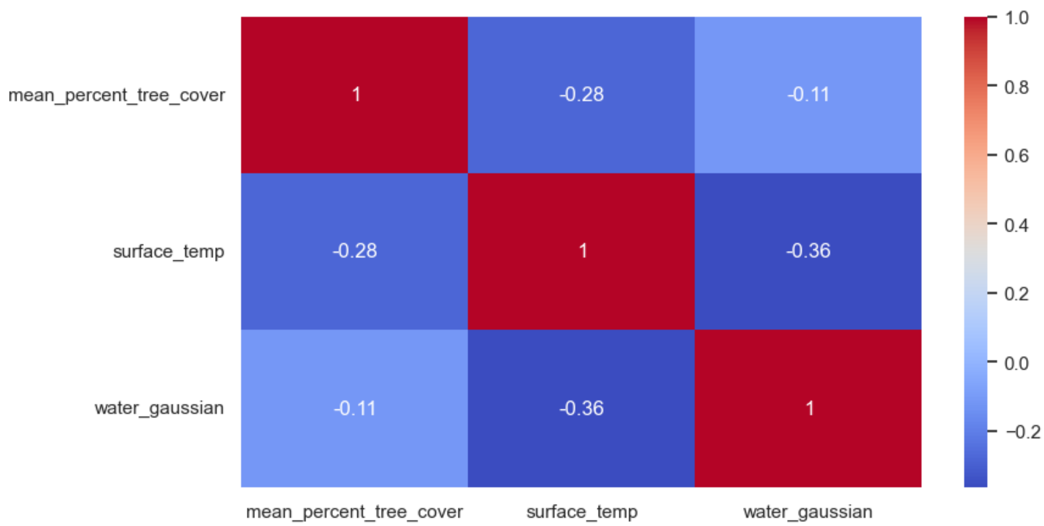

Figure 20: Correlation Matrix for all Census Tracts in New York city.

A.4 Normality Testing

	p-value
$\Delta\mathrm{Sent}_{\mathrm{hthw-ltlw}}$	0.97
$\Delta\mathrm{Sent}_{\mathrm{lthw-ltlw}}$	0.72
$\Delta\mathrm{Sent}_{\mathrm{htlw-ltlw}}$	0.09

Table 11: p-values for the Shapiro-Wilk test. In each case, we fail to reject the null hypothesis H_0 : The sample comes from a normal distribution.

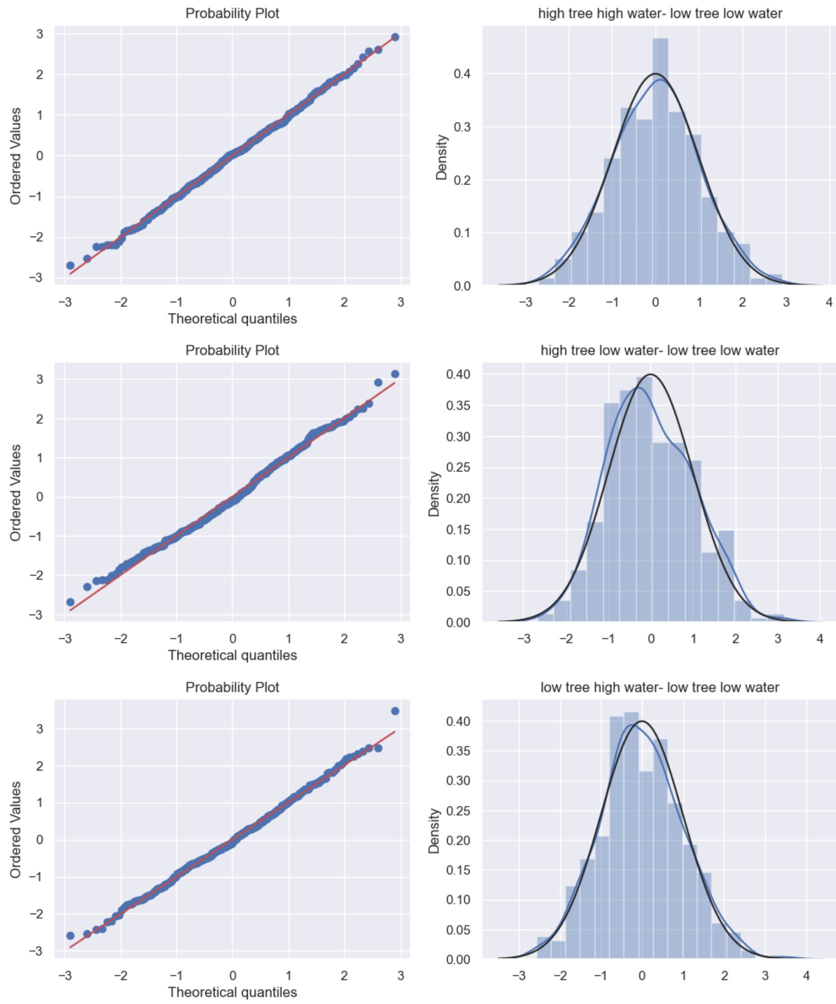

Figure 21: Normality Testing: We make QQ plots and histograms to verify that $\Delta\text{Sent}_{\text{hthw}-\text{ltlw}}$, $\Delta\text{Sent}_{\text{htlw}-\text{ltlw}}$, and $\Delta\text{Sent}_{\text{lthw}-\text{ltlw}}$ are approximately normal.

A.5 Twitter Climate Change Dataset

created_at	lng	lat	topic	sentiment
2006-07-23 21:52:30+00:00	-73.95	40.65	Weather Extremes	0.58
2007-01-06 17:36:51+00:00	-73.95	40.65	Weather Extremes	-0.57
2007-01-17 02:18:13+00:00	-73.95	40.65	Weather Extremes	0.03
2007-02-02 18:15:51+00:00	-73.95	40.65	Weather Extremes	0.16
2007-03-16 19:11:10+00:00	-74.01	40.71	Weather Extremes	-0.38

Table 12: Some examples from Twitter Climate Change Sentiment Dataset