Analysis of the 3D shape of cities with respect to Urban Heat Island effect

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Abstract

The aim of this study was to explore how building shapes interact with urban policies and regulations. We plan to develop urban planning strategies aimed at mitigating Urban Heat Island effect as well as the impacts of climate change to urban areas. In this project, we explored the relationship between large-scale urban morphology based on the distribution of building heights relative to proxies of vegetation, green space distribution, shadow and the UHI effect/ climate change (H M Abdul Fattah, 2024, p2)

Research has shown that urban areas tend to have higher temperatures compared to the surrounding rural areas. This effect is known as the urban heat island (UHI) [1]. The temperature increase within urban areas is known to lead to various problems including human health issues, increase in energy consumption thereby increasing greenhouse gas emissions, as well as further contributions to climate change. To reduce these effects there is need to identify factors related to UHI and take appropriate actions to mitigate its effect in urban areas. One aspect that remains unclear is whether the overall shape of cities affects their responses to urban-heat related descriptors.

Work done by H M Abdul Fattah on this project [8] consisted of downloading city shape file, building height dataset, calculating city wise area vs building height distribution and classifying cities into one of the four categories. Dataset about the heights of buildings globally (GHS-BUILT-H - R2023A) was obtai ned from GHSL - Global Human Settlement Layer dataset[13] . Additionally, shapefiles, defining urban areas , were obtained from World Urban Areas, LandScan, 1:10 million (2012) [14] . Data of heights of buildings was filtered using shape files and analysed to find the distribution of building heights in the city. Based on the shapes of distribution (their skewness and dip statistic values), the shape of city was classified as unimodal right skew (Pyramid) shape, unimodal left skew (Inverse Pyramid) shape, or has no significant skew (Diamond) shape [15] [8]. In case of presence of multimodality, indicated by the dip statistic, shape was classified as "Hourglass." The "Pyramid" class signifies a concentration of shorter buildings, while "Inverse Pyramid" indicates a concentration of taller buildings. "Diamond" suggests a balanced distribution of building heights, while "Hourglass" implies varying patterns in building height distribution.

Work that needs to be done is getting UHI effects data for the year 2018 [9] and other variable data like green vegetation [10], solar radiation [11], surface water [12]. Since the latest dataset available for building height is of year 2018, the rest of the datasets will also be downloaded for the same year 2018 wherever possible. It was possible to download full global UHI data with resolution of 3000m/pixel The resolution of building height dataset is around 30m/pixel whereas most of the datasets in googleearth engine are around 300m/pixel. Attempts can be made to improve resolution as close as 100 m or 3 ss as possible. This downloading can be done either using Javascript scripts in google earth engine or using geemap api in Python

Introduction

Urban Heat Island (UHI) leads to increased vulnerability to human health issues like heat strokes, exhaustion, suicidal tendancies. It is also impacting air quality due to more amount of pollutants released in air and poor scattering of these pollutants. Water quality also gets impacted due to increase in water tempaerature affecting native aquatic life.[3]

Urban areas are densely populated with more people. Closely constructed building and skyscrapers mean a lot of waste energy is emitted and can not escape the area. Increase in temperature also causes increase in energy consumption thereby increasing greenhouse emissions for the city dwellers. [2]. According to David L. Chandler, Urban heat island effects also depend on a city's street and building layout Some cities, such as New York and Chicago, are laid out on a precise grid, like the atoms in a crystal, while others such as Boston or London are arranged more chaotically, like the disordered atoms in a liquid or glass. The researchers found that the "crystalline" cities had a far greater buildup of heat compared to their surroundings than did the "glass-like" ones.[4] It is found that UHI is positively correlated with city area. Building materials which absorb and radiate heat back into the air gets trapped in the nearby vicinity in the area densely crowded with buildings instead of spreading out evenly[5]. Hence effect of heights of skyscrapers also needs to be studied apart from the area of city. This can help in planning for urban area expansions or in new urban area developments

According to Nyuk Hien Wong, Chun Liang Tan, Dionysia Denia Kolokotsa & Hideki Takebayashi [6], Green infrastructure acts to cool the urban environment through shade provision and evapotranspiration. Typically, greenery on the ground reduces peak surface temperature by 2–9 °C, while green roofs and green walls reduce surface temperature by ~17 °C, also providing added thermal insulation for the building envelope. However, the cooling potential varies markedly, depending on the scale of interest (city or building level), greenery extent (park shape and size), plant selection and plant placement . This can be a tool for mitigating UHI

Climate change is impacting cities and their residents in many ways, from poor air quality to flooding, biodiversity loss and extreme heat. Mackres et al. [7] with the help of a dashboard provides insight into connection between climate change and urban life which will be useful for city designing in a more sustainable and nature-positive ways to mitigate climate change

Objective – To determine the impact of building heights, city area expressed as city 3D shape on urban heat island effect observed in cities along with the impact of other variables like vegetation, water surfaces in the proximities of various cities spread across in the world

Scope There are various factors related to urbanization like building material building heights, industrial areas, city areas, NDVI, surface water which are responsible for urban heat island effect. The factors currently considered for this study are City shape which is based on building heights distribution, NDVI, surface water of around 6000 cities across the world

List of cities excluded in this study are Bathurst, Damanhur, Düsseldorf, Jalón, Luderitz, Münster, Cadiz, Newcastle, Ciudad Juárez, Osnabrück, Piraeus, Saint Georges, San Sebastián, St. John's, Ypacaraí

Limitations

Due to cloud cover many of the observations (around 2459) showed up as NA.

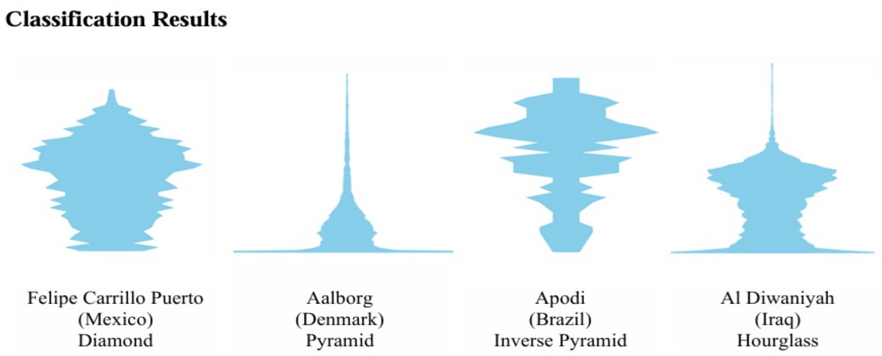
The resolution of UHI (300m), NDVI (30m), surface water (300m) was not as high as that of building data.

The latest data available for buildings was that of 2018.

Material and Method

Raw Dataset Description:

Building Height data – For determining city shape, dataset was downloaded from the website [13]. This data was available for year 2018 so all the rest of the variable data was downloaded for year 2018 whereas Shape file data was downloaded from World Urban Areas website [14]



Hypsographic curve for different cities from various classification level

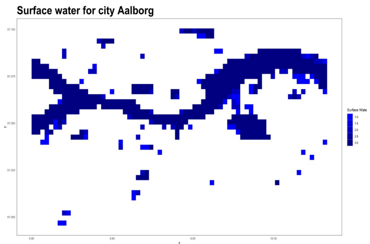
Figure 1 City shapes - no significant skew (Diamond) shape, unimodal right skew (Pyramid) shape, unimodal left skew (Inverse Pyramid) shape, Varying pattern(Hourglass)

Urban Heat Island effect data - Urban Heat Island effect (UHI) dataset is available at the website [9] as geoTiff file. There are several different types of datasets of UHI available like summer, winter, annual, averaged for multiple year on the website. The dataset considered for this study is annual dataset for the year 2018. The resolution of file is 300m. This file has 2 bands ‘Daytime’ and ‘Nighttime’ for annual daytime average UHI value and annual nighttime average UHI value. Using this data, 3 mean values were derived per city viz. UHI daytime mean, UHI nighttime mean, UHI daynight time UHI mean which averages over 24-hour period of daytime and night time. The unit of measurement used for UHI is (Degree C) .

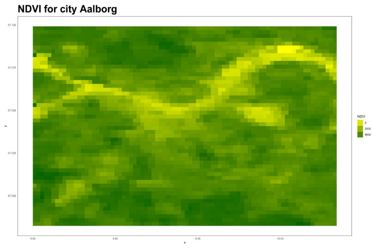
Out of 6000 records of cities, 3837 cities have non zero UHI value. The highest value of both day and night UHI out of these cities was found to be 6.77057165329402 (^{o} C) for city ’ Pontianak’ whereas lowest value for same was observed for city Aden with value -6.4956758212178 (^{o} C). The highest value of day UHI was found to be 5.83911699001886 (^{o} C) for city ’ Pontianak’ whereas lowest value for same was observed for city Aden with value -6.77188387224751 (^{o} C). The highest value of night UHI was found to be 3.75197793743963 (^{o} C) for city ’ Tehran’ whereas lowest value for same was observed for city Nagaoka with value -2.5011636231867 (^{o} C)

Raster map of city Aalborg for City height distribution and corresponding Urban Heat Island effect, NDVI, surface water (SRC caption to be added)

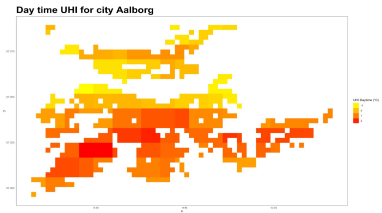
1. 3D visualization of city heights represented as a raster grid for a sample city named 'Aalborg (Denmark, Europe)'



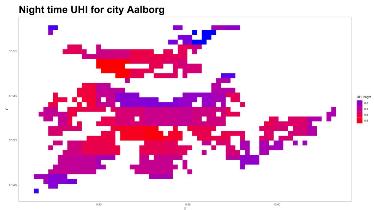
2. Surface water for Aalborg [12]



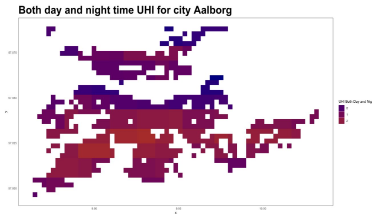
3. NDVI for Aalborg



4. Day time UHI for city Aalborg [9]



5. Nighttime UHI for Aalborg [9]



6. Both day and night time UHI for Aalborg [9]

Figure 2 Raster maps of city of Aalborg displaying building heights(1), surface water(2), NDVI(3), Daytime UHI(4), Nighttime UHI(5), Both Day and Nighttime UHI

For NDVI (Normalized Difference Vegetation Index) and surface water data was downloaded from google earth engine.

NDVI data-

NDVI files are available on the website[10] as 16 day files . So 24 files -two per month were averaged for year 2018 and then downloaded from google earth engine. The download is in the form of 21 .tif tiles. There is only one band 'NDVI' in the file. Resolution is 30 m

Out of 6000 cities, 5731 records have non zero NDVI mean values

The highest value of NDVI was found to be 8383.38 for city Ikela whereas lowest non zero value for same was observed for city Mejillones with value 136.73

Surface water data –

Surface water dataset was found at the google earth engine website [12] and downloaded as geoTiff file for the year 2018. The file is available as annual file containing only one band 'waterClass'. Resolution is 30 m originally but data was downloaded at 300m resolution to enable download without errors . Since the file contains a larger geometry, the file was downloaded as 6 tiles each of with latitudes ranging from -85 degrees to +85 degrees and longitudes of size 60 degrees each with resolution of 300m

For Surface water, values were averaged pixelwise for the city area. 5487 cities out of 6000 have non zero mean value. Surface water measures the seasonality of water with value

1 indicating no water,

2 indicating seasonal water and

3 indicating water permanent water throughout the year

The highest value of surface water of 3 was observed for various cities like Brochet, Port Hope Simpson, Jaque etc indicating permanent water whereas lowest value of 1 for same was observed for cities like Schefferville, Apodi, Lethem etc indicating 'no water'. Value of 2 indicates seasonal water.

Data processing Method- For UHI data processing, using Terra::crop() in R program, the .geoTiff data file is opened ,cropped and saved as individual city raster .tif files in rasters folder. Also the raster is converted to data frame and used to calculate mean values per city viz. daytime, nighttime , both day and night time UHI mean values . The program was run in batches of 600 cities at a time and all the mean values are stored in Citywise Means[0-10].csv files. NDVI and surface water data is also processed along with UHI so NDVI and surface water mean values are also stored in Citywise Means[0-10].csv files This data is then later merged with geographical coordinates and cityshapes csv files in a single ML_input_data_coordinates.csv file using a python program

For NDVI and surface water files, data was processed similarly for creating rasters. Using Terra::crop(), the .geoTiff files are opened ,cropped and saved as individual raster .tif files in rasters folder. Also, the raster is converted to data frame and used to calculate mean values per city in R program. Since the data for both NDVI and surface water is spread in multiple .tif files, for finding the tile/tiles containing city data, CSV files containing list of cities and their corresponding tile is accessed. For NDVI data, the csv file is 'City_NDVI_files.csv' where as for surface water data it is 'City_surface.csv' (These CSVs were created using python program by comparing shape file with individual tiles in case of NDVI data or the the coordinate locations in case of surface water data)

All NDVI and surface water mean values are stored in Citywise Means NDVI[0-10].csv , Citywise Means Surface water [0-10].csv file respectively and simulteneously city means are also updated in Citywise Means[0-10].csv files as mean_ndvi and mean_surface_water columns.

Geographical coordinate information was extracted from shape file containing city data and stored in a csv file in a python program . This data along with cityshapes data and UHI, NDVI, surface water means was merged in ML_input_data_coordinates.csv and ML_input_data.csv file based on the city names using python program

Statistical Data Analysis

Citywise Means[0-10].csv containing mean UHI , mean NDVI and mean surface water values are merged to form a single CSV file which is then merged with coordinates and cityshapes csv file using city name as key and used for further statistical data analysis

Distribution of city shapes across world

World map (Figure 3) is plotted using ggplot, geom_sf (sf package) and distribution of around 6000 cities under study and their shapes is examined. Majority of cities are either pyramid (3354 cities identified by yellow triangle) or hour glass (2453 cities identified by red hourglass). Location of cities under study is represented as blue dots and are spread all over the world. 144 Diamond shaped cities identified by pink diamond shapes. 10 Cities of Inverted pyramid shape are found more closer to equator region identified by skyblue inverted pyramid shape

Boxplots (Figures 4a ,4b, 5a, 5b) are plotted using ggplot and facetwrap with ML_input_data_coordinates.csv to examine value distribution of various variables in an R program. Figure 4a shows distribution of various variable values viz. UHI daytime, UHI nighttime, UHI both day and nighttime, , NDVI, Surface water across 3 different city shape categories (City shape categories 'NA' and 'Unknown' were dropped and 'Inverse pyramid' cities had NA UHI values so those records were deleted for later analysis). UHI values are highest in hourglass city shapes followed by Pyramid shapes. Diamond city shapes have the lowest UHI values but the outliers in pyramid shapes are lowest for daytime and both day and night whereas hourglass has lowest outlier values for nighttime. Drop in nighttime UHI values is significant in Pyramid shape cities. NDVI values are highest in pyramid shapes whereas Diamond shape has lowest median NDVI value among 3 shapes Surface water median values are highest in pyramid shapes whereas Diamond shape has lowest median surface water value among 3 shapes. Figure 4b shows distribution of various variable values viz. UHI daytime, UHI nighttime, UHI both day and nighttime, , NDVI, Surface water across all 6 different city shape categories (including Unknown and NA city shapes) Inverse pyramid and unknown categories seem to have NA values for UHI. Cities with NA shapes have highest 'UHI both day and nighttime' median values. Figure 5a shows boxplots of variable log values viz. UHI daytime, UHI nighttime, UHI both day and nighttime, , NDVI, Surface water across 3 different city shape categories viz. Diamond, hourglass and pyramid (without including Unknown city shapes, NA values). Figure 5b shows boxplots of variable log values viz. UHI daytime, UHI nighttime, UHI both day and nighttime, , NDVI, Surface water across all 6 different city shape categories (including Unknown and NA city shapes) UHI both day and nighttime median values for hourglass city shape look highest . Figure 6a shows violin plots of variable log values viz. UHI daytime, UHI nighttime, UHI both day and nighttime, , NDVI, Surface water across 3 different city shape categories (without including Unknown city shapes, NA values) viz. Diamond, hourglass and pyramid. Figure 6b shows violin plots of various variable log values viz. UHI daytime, UHI nighttime, UHI both day and nighttime, , NDVI, Surface water across all 6 different city shape categories (including Unknown and NA city shapes). Asymmetrical violin shape can be observed in case of hourglass and pyramid shape. Box plot (for Anova test) (Figure 7) plotted using ggpubr::ggline() of UHI both day and night cityshapewise mean values against City shape (along with standard error) provides an insight into distribution of UHI day and night group mean values among three major city shapes. UHI mean value quartile ranges(both day and night)(Q1-Q3) of diamond shape have the lowest values where as that of hour glass shape are highest. UHI values for three different city shapes indicated by boxplots are spread across three completely different UHI mean value ranges suggesting correlation among city shapes and UHI values and discussed later in data analysis using Kruskal wallis test.

PairPlot (figure 8) - City shapes are converted to numerical values and pairplot of all variables using GGally::ggpairs() is plotted which suggest correlation among variables like UHI-NDVI

ML model and correlation discussion

Anova test- ANOVA (Analysis of Variance) [16] is an extension of independent two-samples t-test for comparing means of more than two groups. In one-way ANOVA, the data is organized into several groups base on one single grouping variable (also called factor variable- city shape in this case) and is performed with following assumptions-

- The observations are obtained independently and randomly from the population defined by the factor levels
- The data of each factor level are normally distributed.
- These normal populations have a common variance.

Correlations suggested in cityshape group means boxplot (for anova test) become more clear with one way Anova test shown below in Fig.9. UHI day and night mean value is compared with city shape using aov() and the P-value obtained from Anova test is 1.44e-07.

Kruskal-Wallis test by rank [17] is a non-parametric alternative to one-way ANOVA test, which extends the two-samples Wilcoxon test in the situation where there are more than two groups. It's recommended when the assumptions of one-way ANOVA test are not met.

Kruskal Wallis test further provides comparison among the city shapes as shown in Figure 10. The value of (Pyramid, Hourglass) pair is 5e-07 while that of (Hourglass, Diamond) pair is 0.0047

Machine learning models-

Logistic regression model is fitted on variables Mean day and night UHI against city shape,surface water, NDVI, mean height, dip statistic, skewness in a python program using statsmodels.formula.api library functions. Another similar model is fitted between city shape and Mean day and night UHI. On fitting logistic regression machine learning model, the coefficient summary of two models is listed below. p-value of NDVI is 0.005 where as p-value of mean height is 0.033 which is lesser than significance level 0.05. p-value less than 0.05 indicates the results are statistically significant at the 5% significance level and that NDVI, mean height is unlikely under the null hypothesis and a correlation exists between mean NDVI, mean height and UHI where as in second table column , p-value of 'both day and night UHI mean' is 0,02 which is lesser than 0.05 indicating correlation among two. So 'both day and night UHI mean' is unlikely under the null hypothesis of UHI mean independent of city shape

Target variable - mean_uhi_DayNight
Other variables - mean_ndvi + Class +mean_surface_water +Mean_Height+skewness+dip statistic
(After deleting all NA values)

Logit Regression Results

Dep. Variable:	mean_uhi_DayNight	No. Observations:	3748
Model:	Logit	Df Residuals:	3741
Method:	MLE	Df Model:	6
Date:	Tue, 03 Dec 2024	Pseudo R-squ.:	-1.009
Time:	03:10:53	Log-Likelihood:	-2456.9
converged:	True	LL-Null:	-1222.9
Covariance Type:	nonrobust	LLR p-value:	1.000

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.0566	0.200	-0.282	0.778	-0.449	0.336
mean_ndvi	0.5181	0.183	2.833	0.005	0.160	0.877
Class	-0.0265	0.408	-0.065	0.948	-0.826	0.773
mean_surface_water	-0.1737	0.138	-1.258	0.208	-0.444	0.097
Mean_Height	0.8087	0.378	2.138	0.033	0.067	1.550
Skewness	1.1729	0.844	1.390	0.165	-0.481	2.827
Dip_Statistic	-0.0315	0.121	-0.261	0.794	-0.268	0.205

Target variable - Class
Other variables - mean_uhi_DayNight
Optimization terminated successfully.
Current function value: 0.501699
Iterations 5

Logit Regression Results

Dep. Variable:	Class	No. Observations:	3819
Model:	Logit	Df Residuals:	3817
Method:	MLE	Df Model:	1
Date:	Mon, 09 Dec 2024	Pseudo R-squ.:	-0.3264
Time:	16:19:55	Log-Likelihood:	-1916.0
converged:	True	LL-Null:	-1444.5
Covariance Type:	nonrobust	LLR p-value:	1.000

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-1.6500	0.256	-6.450	0.000	-2.151	-1.149
mean_uhi_DayNight	0.9911	0.424	2.335	0.020	0.159	1.823

Correlation matrix plotted using corrgram::corrgram() [18] can display correlation between variables with a different colors.

Darker colors indicate a stronger correlation whereas lighter colors indicate a weaker correlations. Figure 11 indicates correlation between City shape and variables like UHI, NDVI, Surface water. UHI_daynight and NDVI block is in blue color where as UHI_daynight and shape is pink in color. Figure 12 indicates a weaker correlation between City shape and both day and night mean UHI value with the pink shaded blocks

Results-

Pairplot (figure 8) suggest correlation among variables like UHI and NDVI. P-value obtained from Anova test by comparing mean UHI day and night group mean value with city shape is 1.44e-07 lesser than 0.001. This indicates UHI day and night mean value is correlated to city shape. P-value in Kruskal Wallis test is 2.027e-08 which indicates that there are significant differences between the treatment groups. and the pairwise comparison shows that, only Hourglass and Pyramid are significantly different ($p < 0.05$) (Figure 10).

In logistic regression models, p-value of NDVI is 0.005 where as p-value of mean height is 0.033 which are lesser than significance level 0.05. p-value less than 0.05 indicates the results are statistically significant at the 5% significance level and that NDVI, mean height are unlikely under the null hypothesis and a correlation exists between mean NDVI, mean height and UHI where as in second table column , p-value of 'both day and night UHI mean' is 0.02 which is lesser than 0.05 . So 'both day and night UHI mean' is unlikely under the null hypothesis of UHI mean independent of city shape suggesting correlation among two

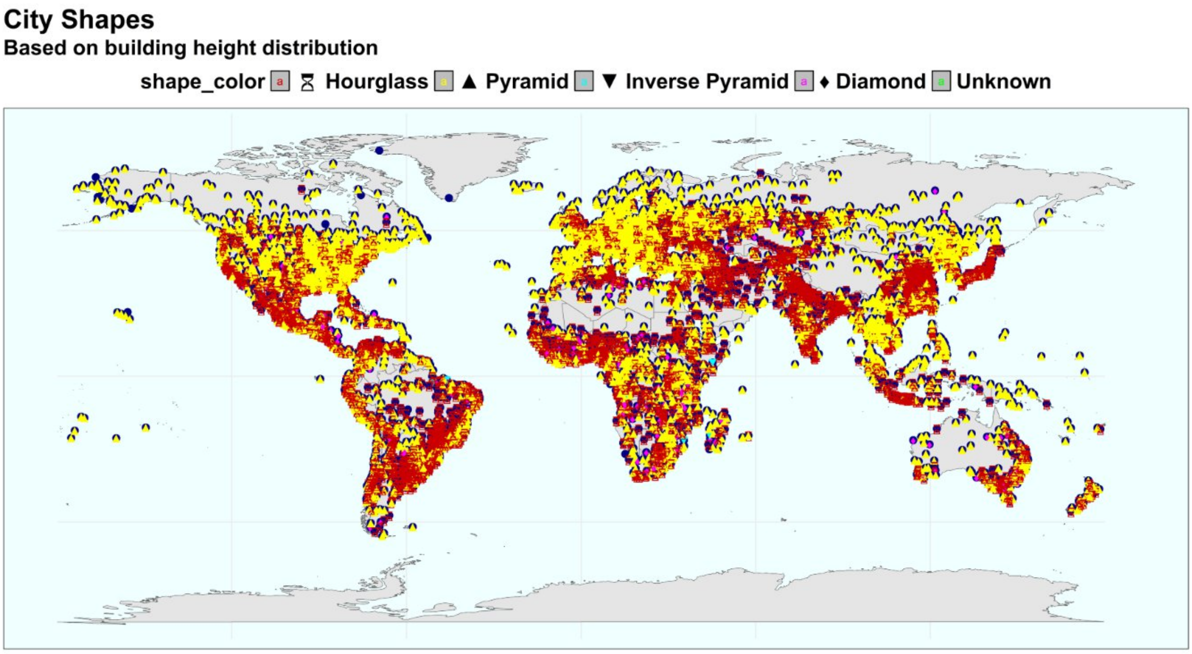


Figure 3 City shape distribution on world map

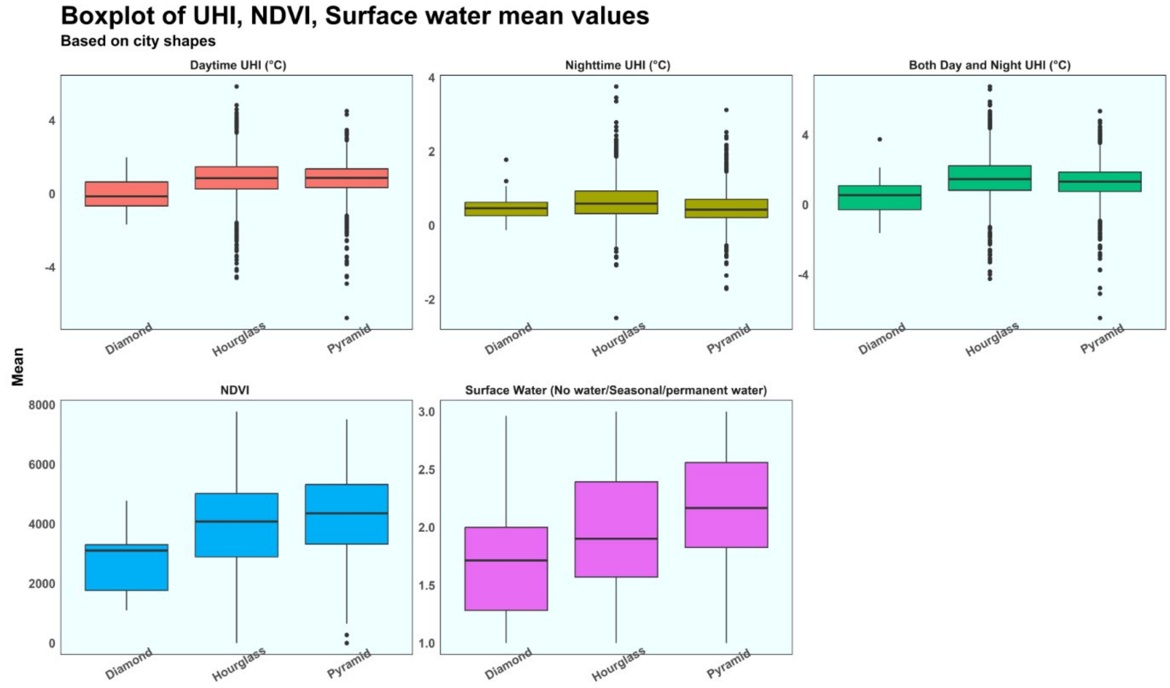


Figure 4(a) Boxplots UHI, NDVI, surface water across city shapes (Without including NA values)

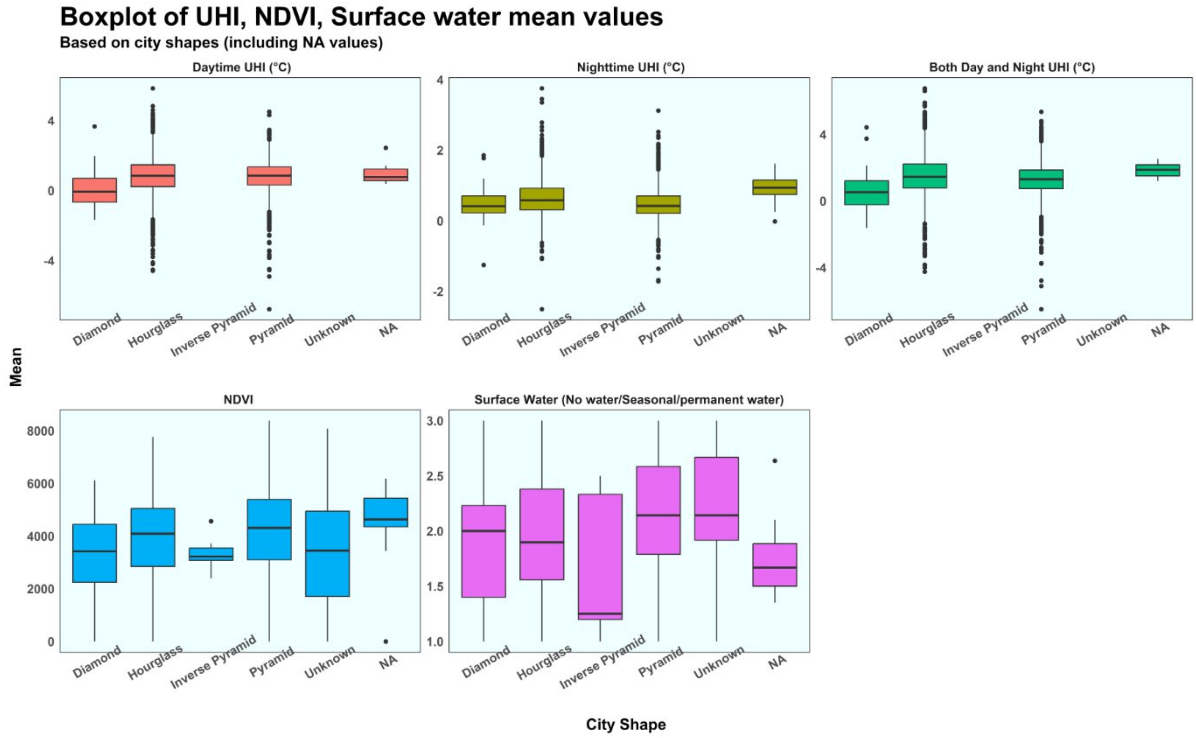


Figure 4(b) Boxplots UHI, NDVI, surface water across city shapes (including NA values)

Log transformed values

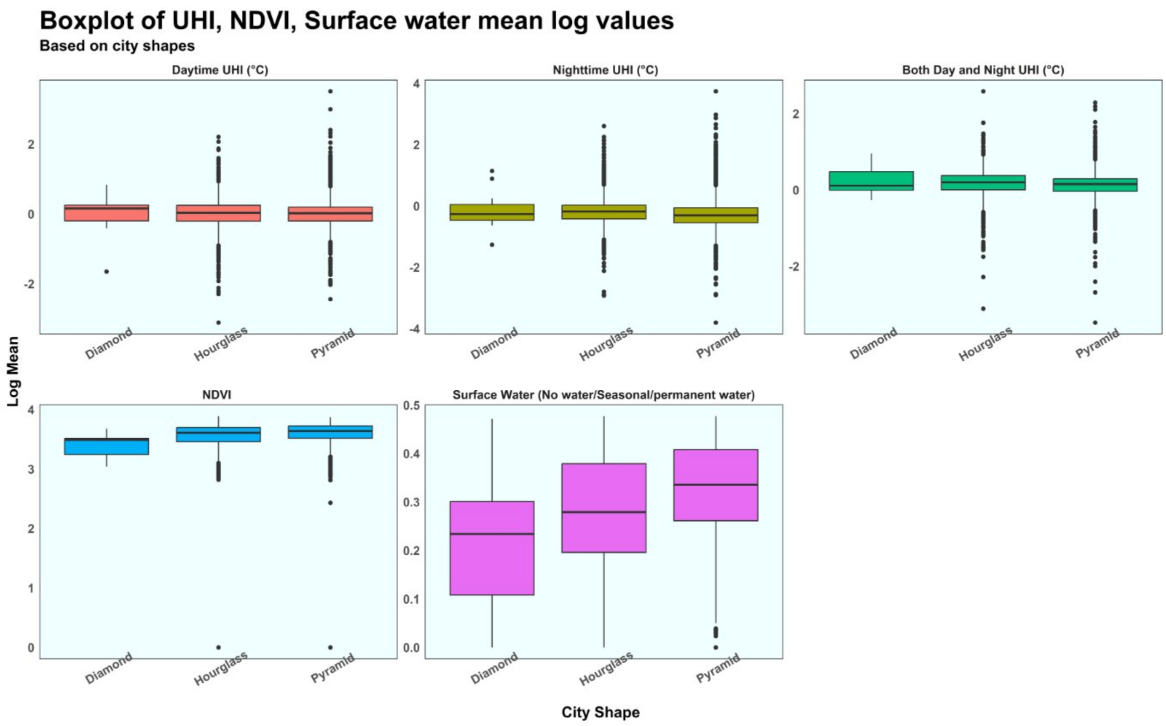


Figure 5(a) Boxplot log values of UHI, NDVI, surface water across city shapes

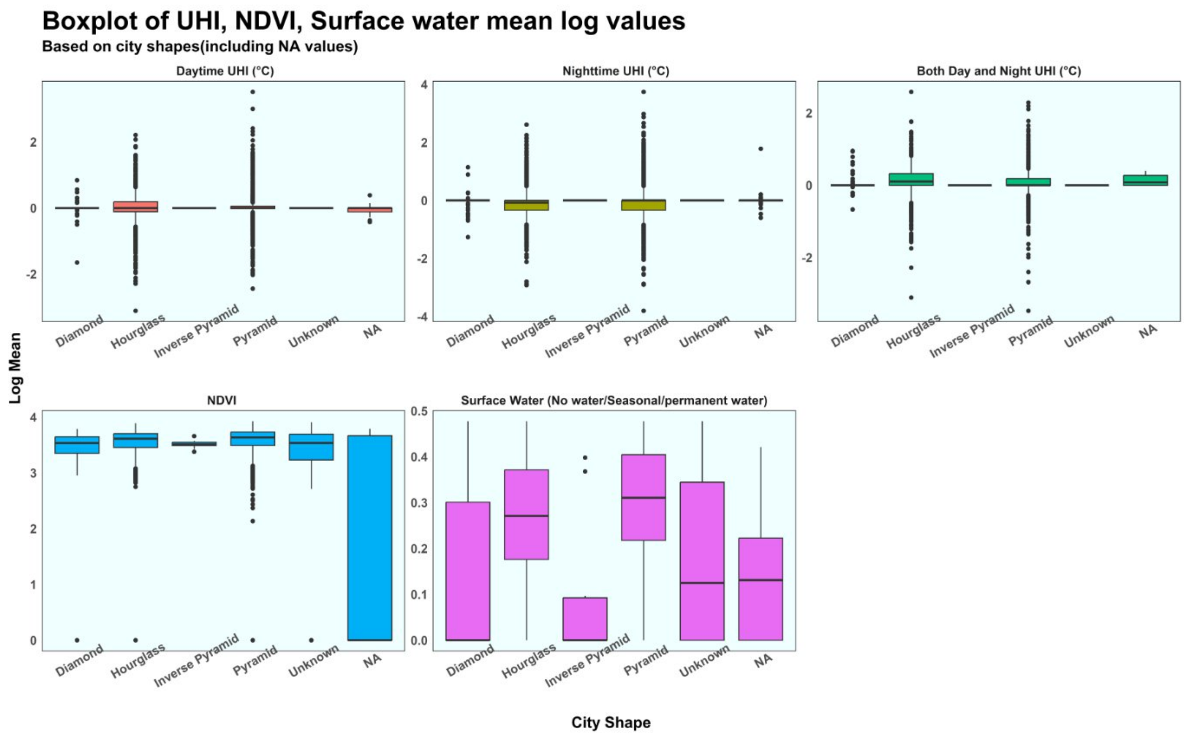


Figure 5(b) Boxplot log values of UHI, NDVI, surface water across city shapes

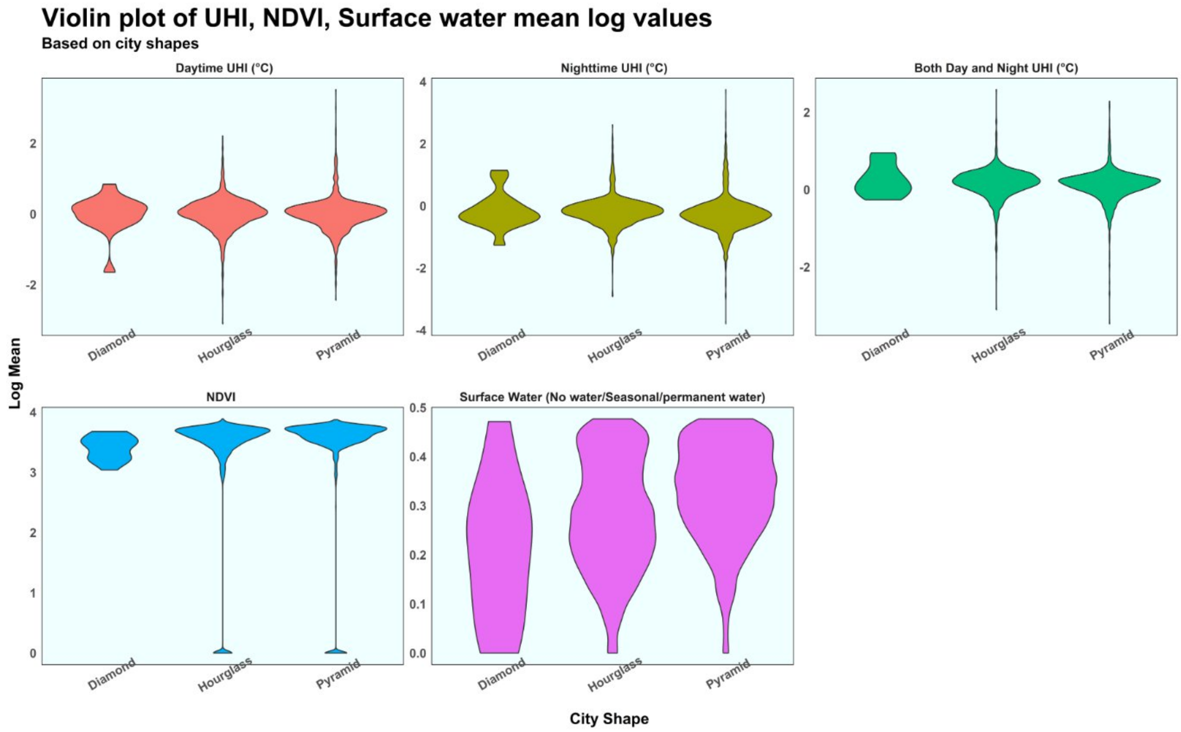


Figure 6(a) Violin plots for Log transformed values of UHI, NDVI, surface water across city shapes

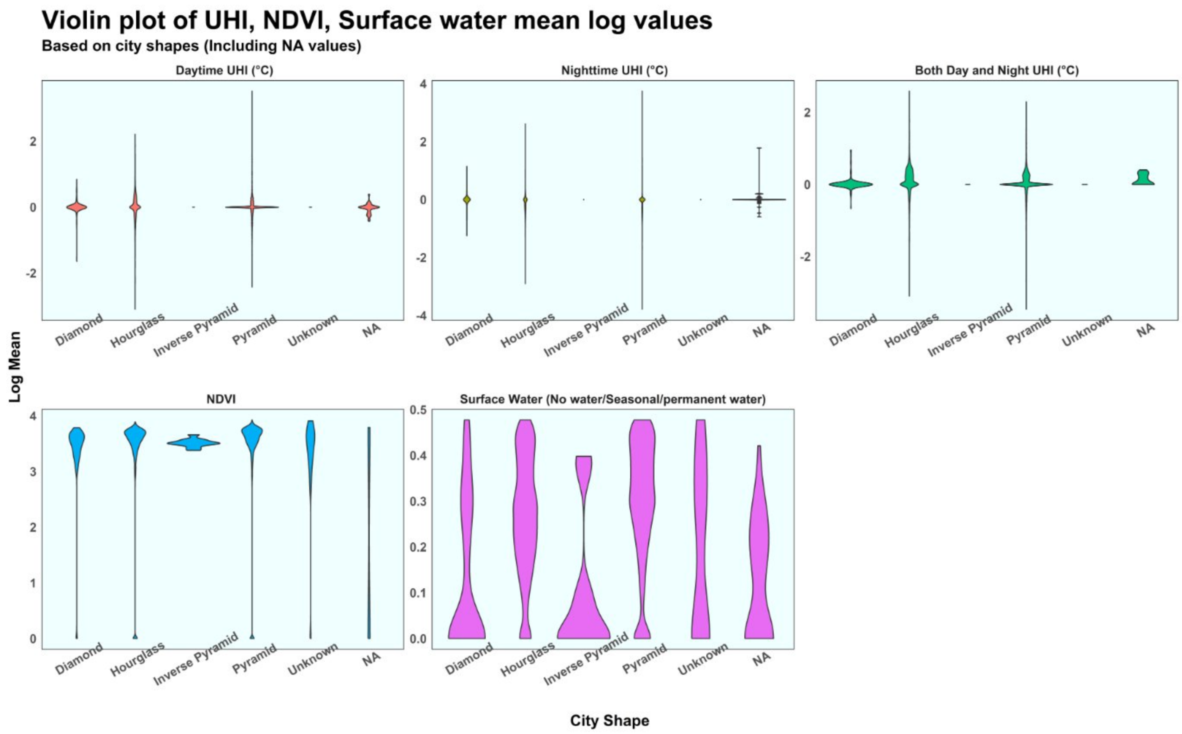


Figure 6(b) Violin plots for Log transformed values of UHI, NDVI, surface water across city shapes

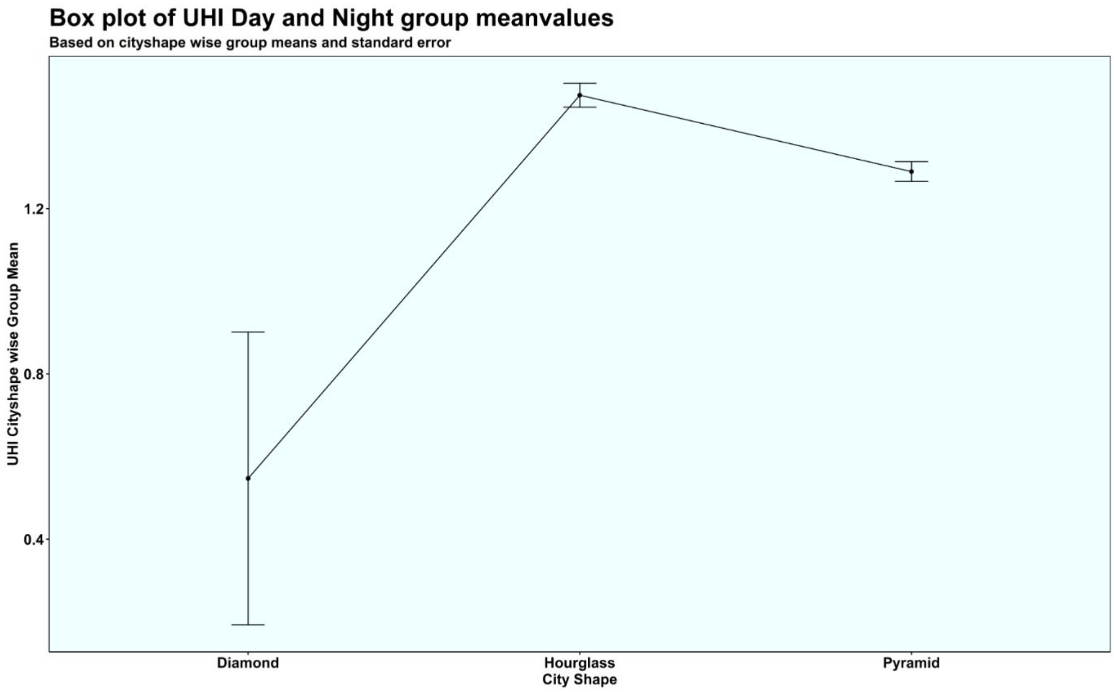


Figure 7 Boxplot (for anova test) using UHI both day and night cityshape wise group means and standard error

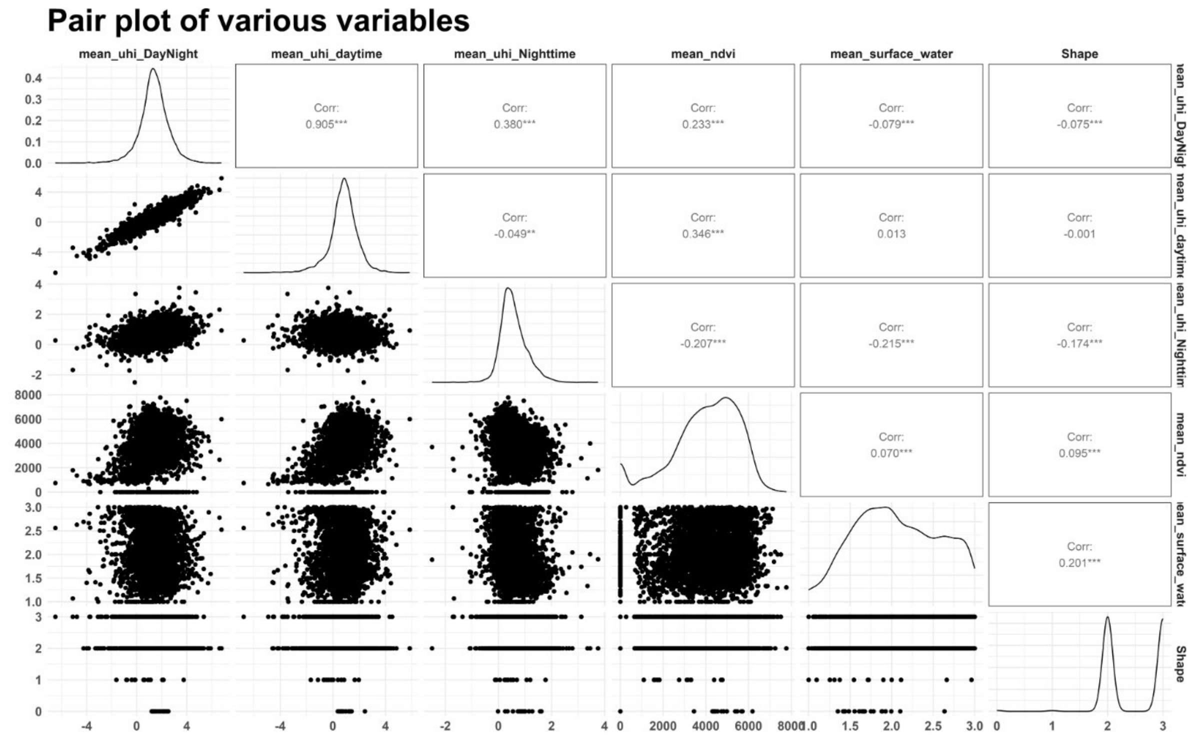


Figure 8 Correlogram displaying relationship among variables

One Way Anova test -

```r
res.aov <- aov(Mean ~ Shape, data = msel)
# Summary of the analysis
summary(res.aov)
```

```
##                 Df Sum Sq Mean Sq F value   Pr(>F)
## Shape            2     42  21.157   15.82 1.44e-07 ***
## Residuals     3745   5008   1.337
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Fig 9 One way Anova test between city shape and UHI both day and night mean values

```r
kruskal.test(Mean ~ Shape, data = msel)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  Mean by Shape
## Kruskal-Wallis chi-squared = 35.428, df = 2, p-value = 2.027e-08
```

```r
pairwise.wilcox.test(msel$Mean, msel$Shape,
                 p.adjust.method = "BH")
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  msel$Mean and msel$Shape
##
##           Diamond Hourglass
## Hourglass 0.0047  -
## Pyramid   0.0060  5e-07
##
## P value adjustment method: BH
```

Fig 10. Kruskal Wallis test and wilcox test showing comparison among city shapes

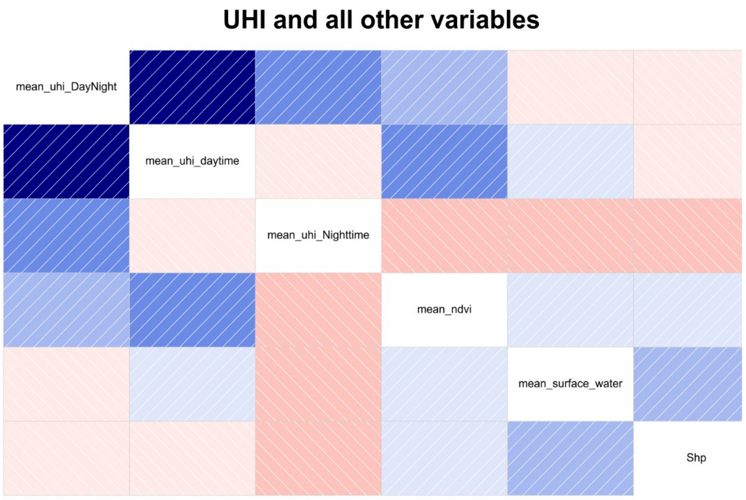


Figure 11 Correlation matrix using corrgram

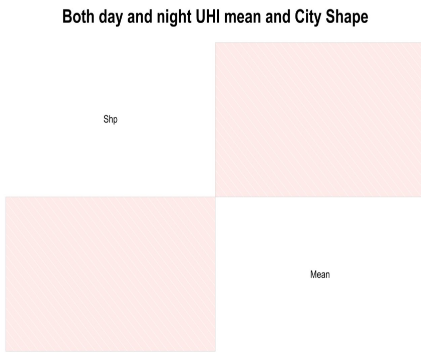


Figure 12 Correlation matrix between Mean UHI and City shape

Inference

Kruskal Wallis test suggests that the results are statistically significant at the 5% significance level so based on Kruskal Wallis test along with one way anova test, we reject the null hypothesis that Urban Heat Island effect is not affected by city shapes. With results of Anova test, Kruskal Wallis test, logistic regression model summary one can conclude that city shapes are weakly correlated to UHI day and night mean values. Diamond city shape contribute least to mean day and night UHI values whereas Hourglass city shape cotribute highest to mean day and night UHI values.

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Programs used and corresponding outputs generated by them -

There is a python program written using ee, geemap API to download surface water data from Google earth engine as 6 tiles.

NDVI and surface data is in the form of multiple tiles. So, a python program is written to determine the list of cities included in each tile. And in R program only the tile containing city is opened at a time in order to reduce memory usage.

Then R program reads all the data files and crops the data based on the shape file, calculates means of cities and merges NDVI, UHI, surface means into a single csv

Python program was written to get the list of cities and their corresponding geographical coordinates for plotting cities in world map.

Python program was written to merge City shape csv created previously with this csv containing various means Also city coordinates information was added to this csv. A single file containing all means along with coordinates is created

R program was used for analysis using Boxplots, Anova and Kruskal-Wallis test Also logistic regression ML model was used in a python program to explore relationship between UHI and city shape, NDVI, surface water

Directory structure of Data and program files-

```
├── data
│   ├── 01_raw
│   ├── 02_intermediate
│   ├── 03_processed
│   ├── 04_models
│   ├── 05_model_output
│   └── 06_reporting
│   └── 07_cities_shapefile        <- Shapefile of cities around the world
│   └── 08_cities_height           <- Building heights (raster data)
│   └── 09_continents_shapefile    <- Shapefile for continents
│   └── 10_raw_Other_variables     <- Downloaded raw data files
│   └── 11_Output_R                <- Output files of R programs
│       └── city_rasters           <- Raster files generated using R programs
│   └── 12_Output_python           <- Output files of R programs
│
├── src_py                <- Python source code for use in this project.
│
├── src_r                 <- R source code for use in this project.
```

Author contributions:

Conceptualization: CRP, PR

Methodology: PR, CRP

Code Writing: UHI, NDVI, surface water- PR, City Heights data-HMAF

Visualization: UHI, NDVI, surface water- CRP, PR, City Heights data-HMAF

Supervision: CRP

Writing—original draft: PR, CRP

Writing—review & editing: CRP, PR

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