



# Remote Sensing Correlations Between Income and Land Cover to

## Analyze Urban Heat Islands - Austin, Texas

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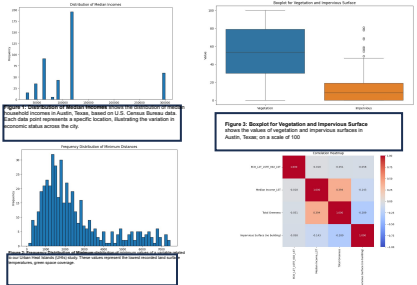


### ABSTRACT

In this study, we investigate the correlation between income and land cover in the context of Urban Heat Islands (UHIs) in Austin, Texas. Utilizing remote sensing data and machine learning, we aim to identify high-risk UHI areas and understand the socioeconomic disparities contributing to these risks. Our initial results indicate a significant correlation between lower income levels and increased impervious surfaces, which exacerbates UHI effects. Clustering analysis further reveals distinct groups of high-risk areas, predominantly in lower-income neighborhoods. These findings highlight the need for targeted urban planning and environmental justice initiatives to mitigate UHI impacts.

### INTRODUCTION

Urban Heat Islands (UHIs) are areas with significantly higher temperatures than their surroundings, primarily affecting urban areas. Our study in Austin, Texas focuses on the correlation between income and land cover in the context of Urban Heat Islands (UHIs). Using remote sensing data, we aim to identify high-risk UHI areas and understand the socioeconomic disparities contributing to these risks. We are examining how factors such as impervious surfaces, median household income, and greenness affect the formation of UHIs.



### METHOD

Land cover data, such as greenness and impervious surfaces, was obtained from remote sensing sources and verified using ground photos from the Globe Observer Database. The data sources include the Globe Observer Database for ground photos, NASA AppEARS for remote sensing data, the U.S. Census Bureau for income data, and SEDAC for socioeconomic and demographic data. Unsupervised learning algorithms, such as K-means, Hierarchical, and DBSCAN, were utilized to cluster land cover and income data. The clustering analysis aimed to uncover patterns and correlations between socioeconomic factors and UHI risk.

### HIERARCHICAL CLUSTERING

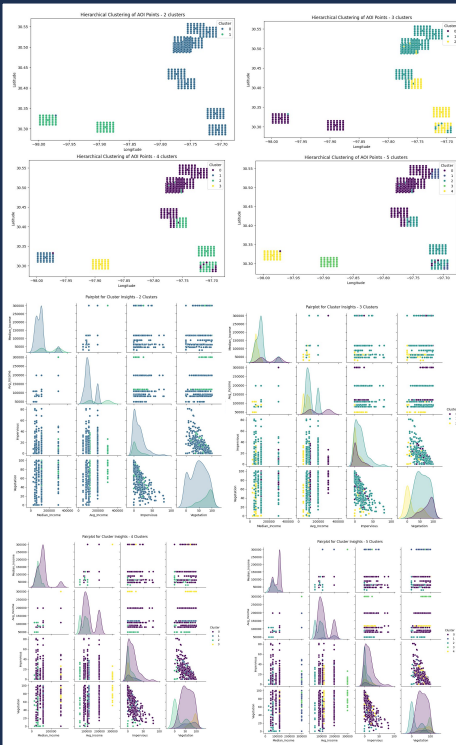
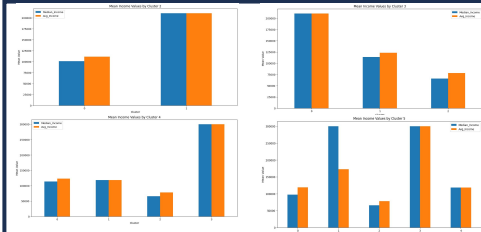
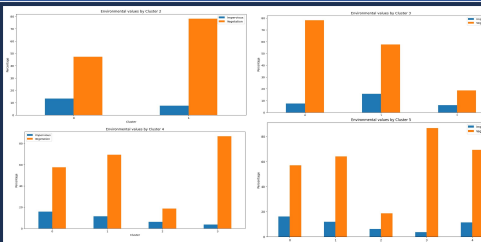


Figure 3: Hierarchical Clustering of AOI Points. These Histograms displaying [DO] concentration of groups 2-5 for the different clustering. Additionally, Pairplots for Hierarchical Clustering are displaying the data in correlation towards the Hierarchical Clustering AOI Points.

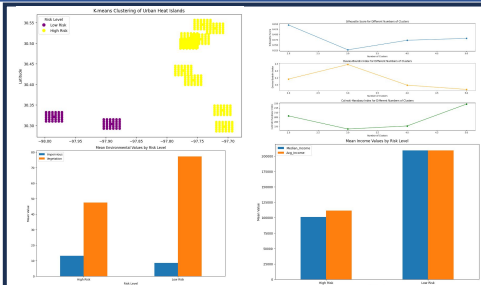
### INCOME DISTRIBUTION



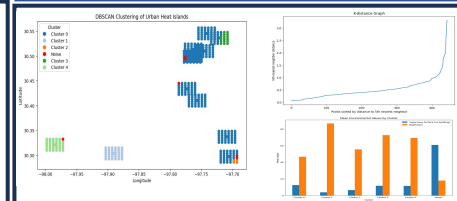
### ENVIRONMENTAL VALUES



### K-MEANS



### DBSCAN



### RESULTS

Our initial findings reveal a strong link between lower income levels and higher impervious surfaces, exacerbating Urban Heat Island (UHI) effects. Lower-income areas are at higher risk for UHIs due to increased impervious surfaces. This highlights the need for targeting urban planning and policies to increase green spaces and reduce impervious surfaces in disadvantaged communities to mitigate UHI impacts.

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