Urban Greenery and Crime: A Comparative Study of Selected US Cities

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***Abstract*—This research delves into the complex relationship between Urban Green Spaces (UGS) and crime rates in four distinct U.S. cities: Orlando, Baltimore, Cincinnati, and Sacramento. Debates surrounding this correlation range from the belief that increased vegetation leads to heightened crime to the contrary perspective. Our study challenges the common assumption that more greenery equates to reduced crime, revealing nuanced and diverse patterns in the examined cities. Employing a comprehensive approach, we integrate crime data from the Federal Bureau of Investigation with satellite imagery classification using a Convolutional Neural Network (CNN). The methodology encompasses pre-processing Landsat imagery, generating spectral indices, and training the CNN for green coverage pixel classification. Acknowledging limitations such as image classification challenges, absence of multivariate analysis, spatial resolution constraints, and crime reporting biases, we underscore the necessity for future research refinements. This study prompts a reassessment of assumptions and underscores the significance of considering multiple variables to attain a thorough understanding of the intricate interplay between urban greenery and crime rates.**

Keywords— Urban Green Space, Remote Sensing, Crime Rate, Spectral Indices, Satellite Imagery

I. Introduction

The argument that regions featuring dense shrubs, bushes, and trees might be more prone to criminal activities finds support in an extensive research study.

According to existing literature [1], there exists a positive correlation between the presence of dense vegetation and an increased fear of crime.This correlation is rooted in the idea that limited visibility and potential hiding spots for attackers contribute to an elevated risk in such environments.

This perspective aligns with historical legislation, such as the "Statute of Winchester of 1285," [2] enacted during the reign of King Edward I.

This statute mandated the enlargement of highways in areas with dense vegetation as a way of increasing safety, thus, recognizing the connection between landscape design and crime prevention.

Recent research suggests that an increase in vegetation may actually correlate with a reduction in crime, especially in inner-city environments, challenging the viewpoint that vegetation increases crime.

A detailed study analyzing 98 buildings [3] within a public housing development in Chicago indicates a lower incidence of crime in areas adorned with more trees, hinting at a potential mitigating effect of vegetation on criminal activities.

The discourse on the impact of vegetation cover on crime remains complex, featuring divergent arguments supporting both its potential to reduce and increase criminal behaviour.

Altering environmental design emerges as a well-established method for crime reduction, with Crime Prevention through Environmental Design (CPTED) [4] standing out as an effective strategy. CPTED emphasizes the manipulation of physical surroundings to enhance safety.

Against this backdrop, this research focuses on a region of interest characterized by distinct geographical and socio-economic profiles. The selection of cities is based on their unique characteristics, contributing to a nuanced exploration of the intricate relationship between vegetation cover and crime dynamics.

II. Study Area

The choice of study areas in this research is deliberate, focusing on four U.S. cities—Orlando, Sacramento, Cincinnati, and Baltimore—There are multiple locations available that have unique geographical and socioeconomic characteristics. These locations have a particular focus on the correlation between criminal activity and the presence of green spaces. Below is a description of these areas and locations with city limits taken from OpenStreetMaps.org [5].

1. Orlando: [6]

• Geographical Features: Positioned in Central Florida, Orlando showcases a subtropical climate, featuring urban parks and water bodies.

• Socioeconomic Dynamics: As a tourist destination, Orlando's urban fabric blends recreational areas with diverse economic activities, creating a unique nexus between crime, tourism, and green spaces.

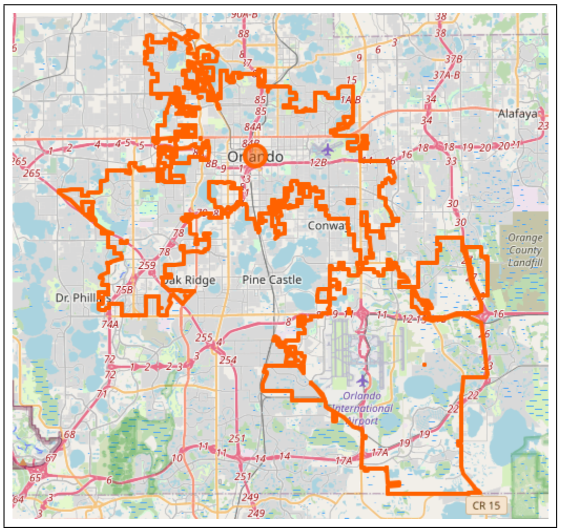

Figure 1: Orlando, FL, city limits

2. Sacramento: [7]
• Geographical Features: Located in California, Sacramento's Mediterranean climate contributes to its diverse green spaces, including parks and the Sacramento River.

• Socioeconomic Dynamics: As the state capital, Sacramento's urban development intertwines with governmental initiatives, offering insights into the intersection of political landscapes and urban greenery.

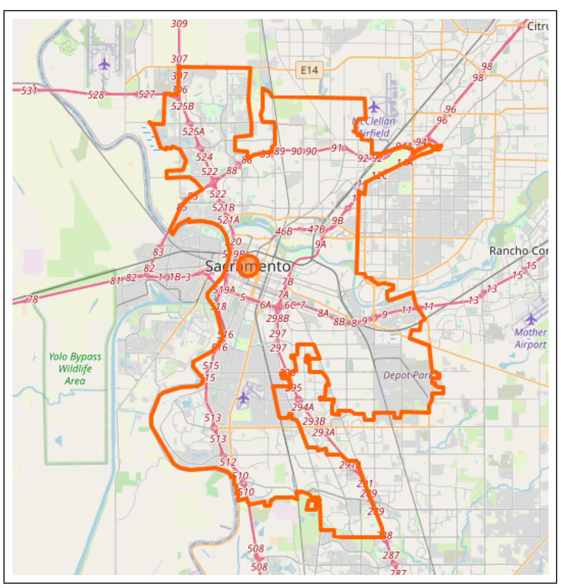

Figure 2: Sacramento, CA, city limits

3. Cincinnati:

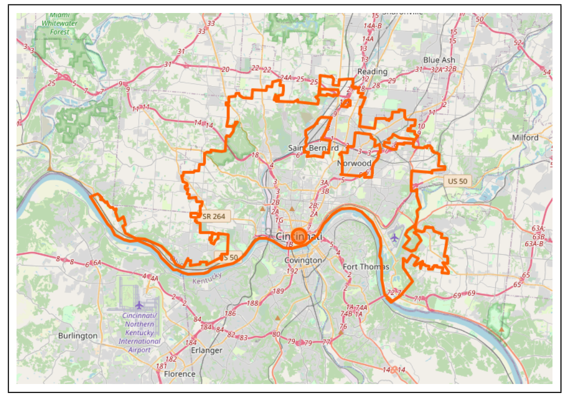

Figure 3: Cincinnati, OH, city limits

• Geographical Features: Situated along the Ohio River, Cincinnati's hills and valleys impact its urban layout and green spaces.

• Socioeconomic Dynamics: From industrial history to a focus on healthcare, Cincinnati's socioeconomic dynamics provide a lens to understand how green spaces evolve alongside economic transitions and crime patterns.

4. Baltimore:

• Geographical Features: Nestled on the Chesapeake Bay, Baltimore's waterfronts and historical neighborhoods contribute to a varied ecological landscape.

• Socioeconomic Dynamics: As a major port city, Baltimore's revitalization efforts and historical context offer insights into the relationship between green spaces, crime, and urban development.

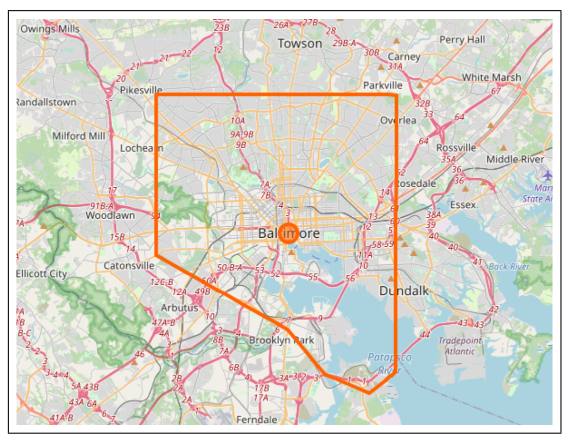

Figure 4: Baltimore, MD, city limits

The inclusion of these cities is guided by the research's overarching objective—to examine the interplay between crime rates and green spaces. By choosing cities with diverse geographies and socioeconomic structures, the study aims to unravel patterns and correlations between urban greenery and crime dynamics. The geographical and socioeconomic variations among these cities provide a robust foundation for understanding how green spaces contribute to crime prevention or potential correlations between the two factors.

III. Methodology

To explore how urban green spaces and crime are related we collected data for four large US cities with metropolitan populations over 2,000,000.

A. Crime Data

Crime data was accessed from the Federal Bureau of Investigation [11], the United States domestic intelligence and security service. However, due to restrictions on bot or scripted access, we utilized a user-agent to retrieve the necessary information. The dataset encompasses various crime types, including violent crime (categorized into murder, rape, robbery, and assault), property crime (burglary, larceny, motor theft), and arson. Notably, we excluded property crime from our analysis of total crimes. Recognizing the influence of city population on crime rates, we calculated per capita crime by dividing the total crime count by the respective city's population.
The FBI statistics website provides a downloadable Excel file containing comprehensive crime data. Post-conversion of the Excel file into a Pandas dataframe, we undertook initial pre-processing steps. This involved removing redundant rows, modifying column headers, and applying forward filling to address empty cells. Subsequently, we created a new structured dataframe, into which we transferred the data from the FBI's original dataframe, enhancing clarity and readability.

B. Google Earth Engine scripting

The acquisition and preprocessing of Landsat 8/9 imagery [9] spanning six years (2013-2019) for the selected cities—Orlando, Sacramento, Cincinnati, and Baltimore—were performed using Google Earth Engine. The process involved cloud masking and spectral index computation to derive meaningful features for subsequent deep learning classification.

1) Image Pre-processing: A cloud masking function was implemented to address the challenges posed by atmospheric interference, including clouds, cirrus, and shadows. The function utilized the Quality Assessment (QA) pixel information within the Landsat imagery. The cloud masking function effectively identified and masked undesirable elements, ensuring the integrity of subsequent analyses.

2) Image Composite Creation: An image composite was generated by merging Landsat 8 and Landsat 9 imagery over the specified time period, applying the cloud masking function, computing the median, and clipping the resulting image to a predefined boundary for each city.

3) Spectral Indices: Spectral indices, including Enhanced Vegetation Index (EVI), Normalized Burn Ratio (NBR), Normalized Difference Moisture Index (NDMI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Built-up and Bareness Index (NDBaI), were computed from the processed Landsat imagery. Additionally, a Digital Elevation Model (DEM) was added to the image bands, contributing to the feature set.
Below, the equations that produce the mentioned spectral indices, taking into account that the images processed have Near Infra Red (NIR), Red and Blue bands.

$$\mathrm{EVI} = \frac{2.5 \cdot (\mathrm{NIR} - \mathrm{RED})}{\mathrm{NIR} + 6 \cdot \mathrm{RED} - 7.5 \cdot \mathrm{BLUE} + 1}$$

$$\mathrm{NBR} = \frac{\mathrm{NIR} - \mathrm{SWIR2}}{\mathrm{NIR} + \mathrm{SWIR2}}$$

$$\mathrm{NDMI} = \frac{\mathrm{NIR} - \mathrm{SWIR1}}{\mathrm{NIR} + \mathrm{SWIR1}}$$

$$\mathrm{NDWI} = \frac{\mathrm{GREEN} - \mathrm{NIR}}{\mathrm{GREEN} + \mathrm{NIR}}$$

$$\mathrm{NDBI} = \frac{\mathrm{SWIR1} - \mathrm{NIR}}{\mathrm{SWIR1} + \mathrm{NIR}}$$

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}$$

$$\mathrm{NDBaI} = \frac{\mathrm{SWIR1} - \mathrm{SWIR2}}{\mathrm{SWIR1} + \mathrm{SWIR2}}$$

C. Training Data Set

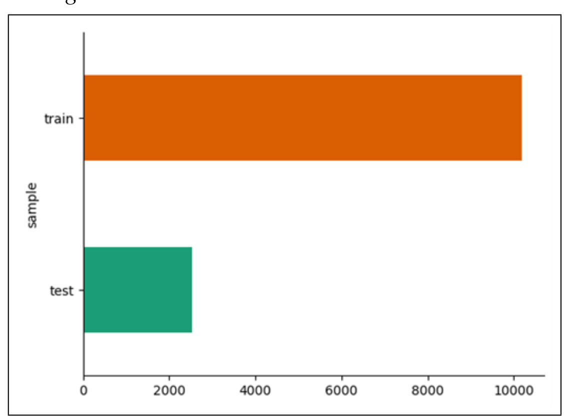

Figure 5: Training and Testing Dataset size.

A comprehensive data set was generated by selecting a region of interest containing several cover types, including infrastructure, water bodies, green areas, and bare land. Pixels in the ROI were labeled to denote these features and organized into distinct feature collections. To ensure a representative dataset, an equal number of pixels were selected for each cover type and subsequently split into training and testing pixels.

The training portion of the dataset was approximately 80% of all labeled pixels and the remaining 20% were used for testing.

D. Convolutional Neural Network

A Convolutional Neural Network (CNN) was constructed using the Keras library. The architecture included convolutional layers, max pooling, dropout layers, and densely connected layers tailored for one-dimensional nature of spectral band data in satellite imagery.

The model is compiled using the Adam optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric. To prevent overfitting, early stopping is implemented as a callback, monitoring the training loss. The model is trained on the specified dataset for a maximum of 100 epochs, with training halted if the loss does not decrease for a predefined patience interval.

The resulting model is a robust framework for satellite image classification, capable of effectively leveraging spectral band information. The CNN architecture, coupled with common deep learning practices such as dropout and early stopping, contributes to model generalization and aims to mitigate overfitting. This methodology presents a valuable approach for the application of deep learning in the analysis of satellite imagery, holding promise for diverse applications in remote sensing and environmental monitoring.

TABLE I
MODEL PARAMETERS

General Parameters	Values
Batch size	1024
Entries for training	10190
Entries for testing	2533
Number of iterations	100
Activation function	ReLU
Loss function	Cross entropy
Optimization method	Adam
Regularization	Dropout = 0.3
Parameters of CNN	
Pooling layer	Max pooling
Convolution type	One-Dimensional Convolution

E. Model Performance

1) Training History Visualization:: Graphical representations of training and validation accuracy, as well as loss, were plotted to provide insights into the model's convergence and generalization performance.

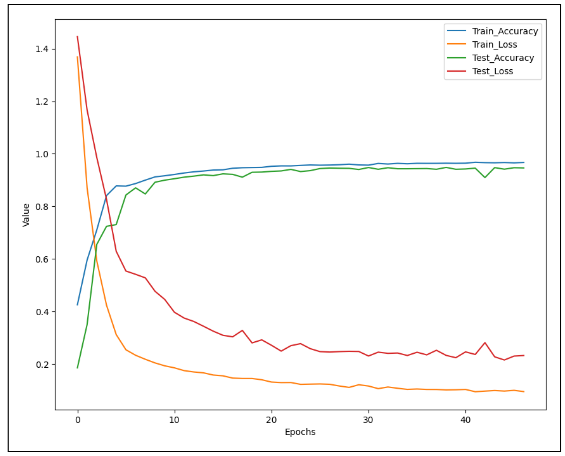

Figure 6:Model Training History.

2) Performance Metrics:: The trained model was evaluated using a confusion matrix and classification report to assess its classification accuracy and effectiveness.

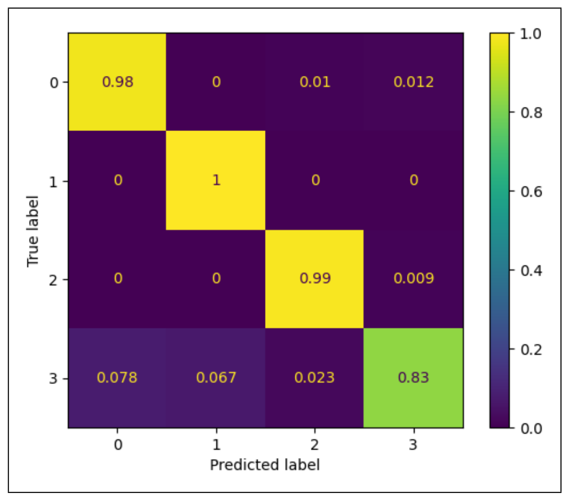

Figure 7: Model Confusion Matrix.

TABLE II
CLASSIFICATION METRICS

Class	Precision	Recall	F1-Score	Support
1	0.95	0.98	0.96	964
2	0.91	1.00	0.96	470
3	0.95	0.99	0.97	442
4	0.97	0.83	0.90	657

F. Image Classification

In this section, we outline the methodology employed for the classification and subsequent vegetation analysis of satellite images using a pre-trained Convolutional Neural Network (CNN). The approach includes the classification of spectral bands, visualization of classified results, and the quantification of vegetation coverage in each of the 4 study areas over a 6-year timeframe.

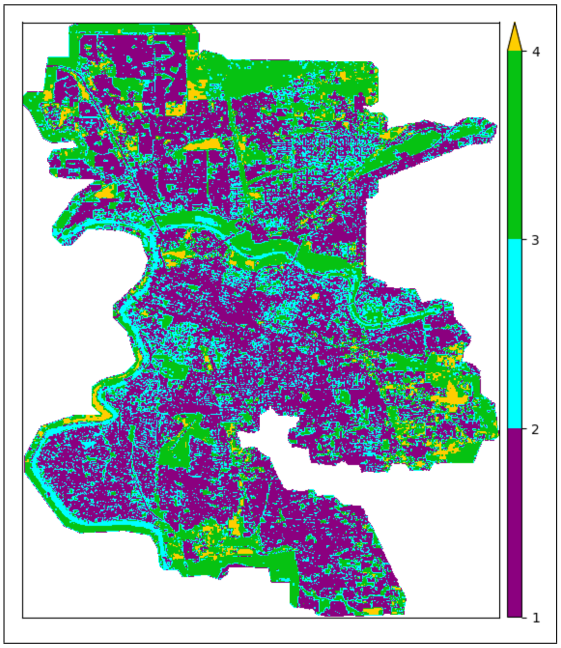

Figure 8: Sacramento image pixel categorization.

Satellite imagery is iteratively passed to the trained CNN model. The predicted values are visualized, providing an immediate insight into the classification results as seen in figure 8. Furthermore, statistical information, such as the count of pixels for each class and the percentage of green area (Class 3), is printed for detailed analysis. The outcomes of the classification process, specifically the percentages of green area pixels, are systematically stored in separate lists. The categorization of results based on the last two digits of the image name facilitates an organized record of vegetation dynamics over consecutive years for each city.

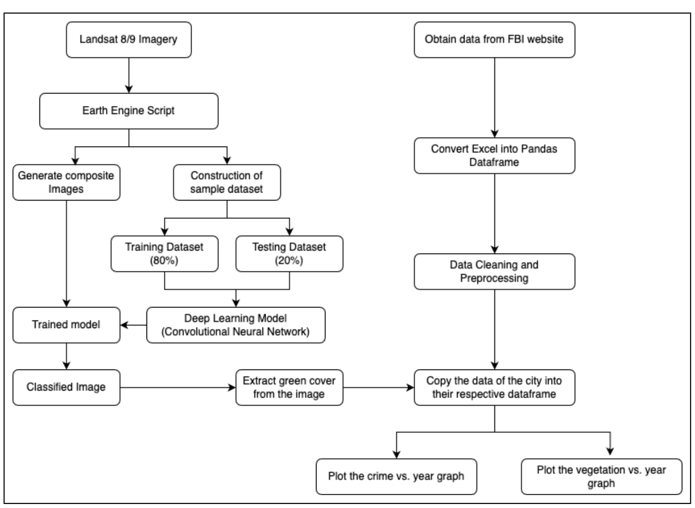

Figure 9: Project workflow.

IV. Results

The exploration into the intricate connection between vegetation cover and crime rates across four distinct US cities—Orlando, Baltimore, Cincinnati, and Sacramento—revealed nuanced trends and temporal patterns.

A. *Regarding Crime Rate:*

1) Baltimore: A Potential Positive Correlation: In Baltimore, a careful examination of crime rates and vegetation cover revealed intriguing patterns. Fluctuations in crime rates were noticeable, and these changes seemed to align with corresponding shifts in vegetation cover. Notably, certain years exhibited a potential positive correlation, suggesting that as vegetation cover changed, crime rates in the city also followed a similar trend. Further investigation is required to identify the specific factors contributing to this correlation and to understand the temporal nuances that might influence the relationship.

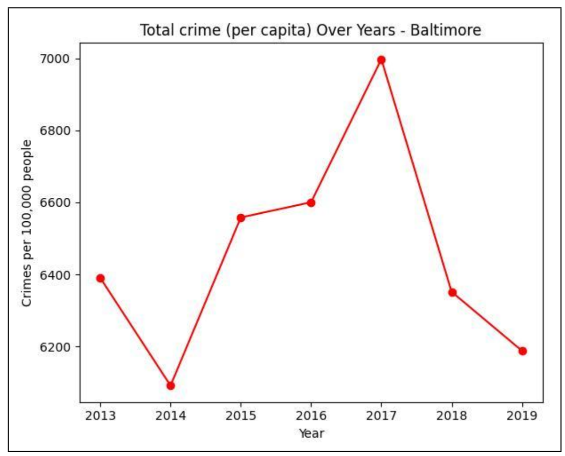

Figure 10A: Baltimore Total Crime Rate Per Capita over Time.

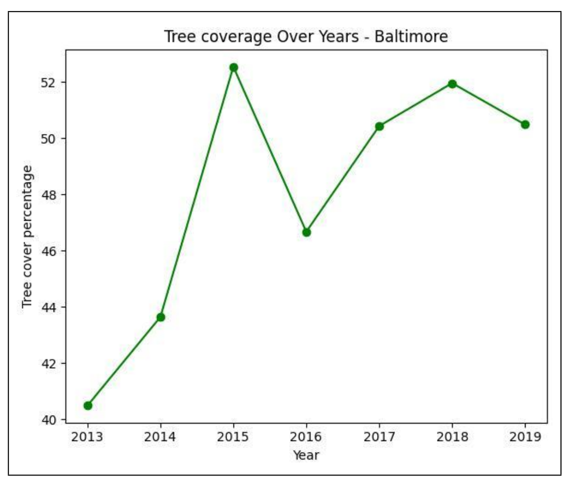

Figure 10B: Baltimore Classified Green Coverage over Time.

2) Cincinnati: Intricate Interplay and Consistent Decreases: Contrastingly, the city of Cincinnati presented a more intricate interplay between crime rates and vegetation cover. Despite variations in greenery levels, Cincinnati consistently displayed decreasing crime rates. This consistent trend amidst varying levels of vegetation cover implies a complex relationship, hinting at factors beyond green spaces that might contribute to the city's crime dynamics. Unravelling these intricate connections will be essential for a comprehensive understanding of the relationship.

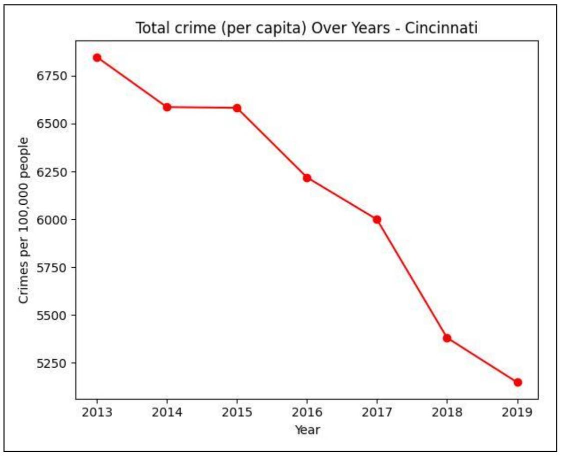

Figure 11A: Cincinnati Total Crime Rate Per Capita over Time.

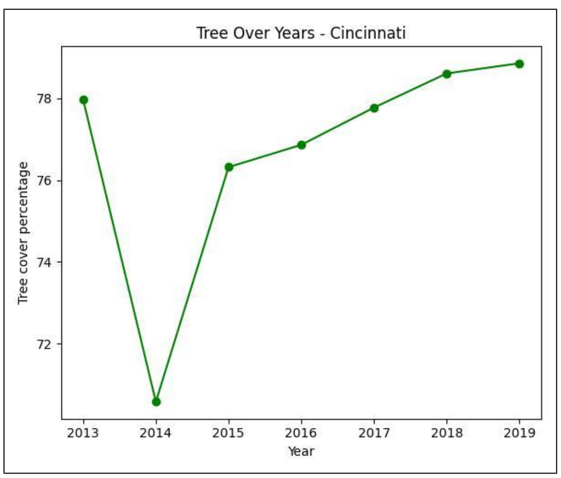

Figure 11B: Cincinnati Classified Green Coverage over Time.

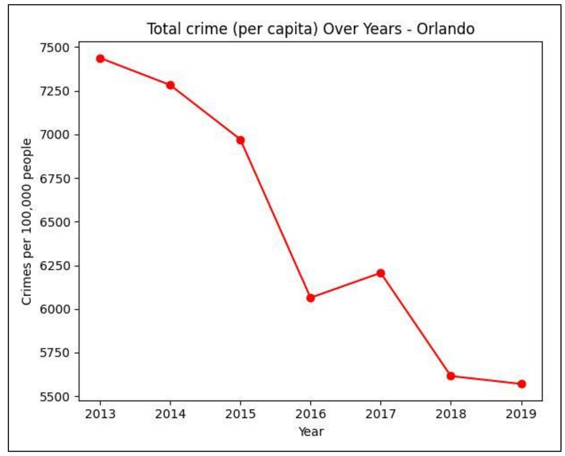

Figure 12A: Orlando Total Crime Rate Per Capita over Time.

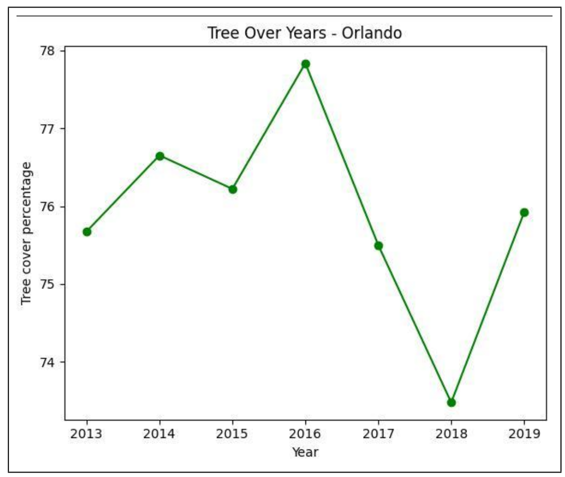

Figure 12B: Orlando Classified Green Coverage over Time.

3) Orlando: Mixed Trends and Multifaceted Dynamics: Orlando's dynamics unfolded with mixed trends in both crime rates and vegetation cover. Observing both declining and escalating crime rates alongside shifts in vegetation cover emphasized the multifaceted nature of the relationship. This complexity suggests that the impact of vegetation on crime rates in Orlando is not unidirectional. Factors such as urban planning, socioeconomic conditions, and community dynamics may play integral roles in influencing the observed patterns. Further analysis will be crucial to disentangle these interwoven dynamics.

4) Sacramento: Diverse Patterns and Contextual Influences: Sacramento exhibited diverse patterns, indicating that the relationship between crime rates and vegetation cover is influenced by contextual factors. The city showcased fluctuations in both crime rates and greenery levels, suggesting that local influences may contribute significantly to these variations. Understanding the specific contextual factors at play in Sacramento will be essential for comprehending the broader picture of how urban environments and vegetation interact to shape crime dynamics.

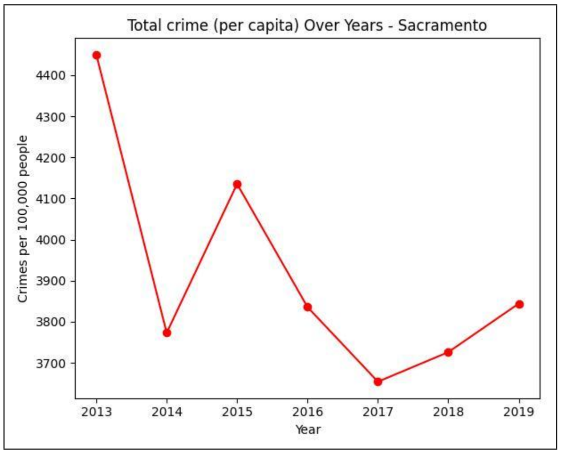

Figure 13A: Sacramento Total Crime Rate Per Capita over Time.

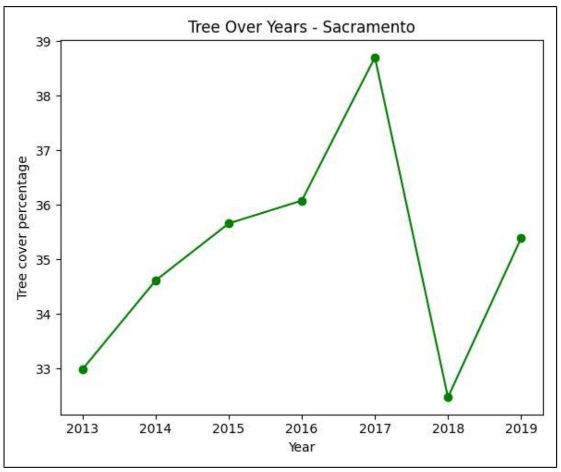

Figure 13B: Sacramento Classified Green Coverage over Time.

B. Regarding Green Coverage:

The classification of green coverage pixels was achieved through the processing and categorization of image pixels. The resulting classification is presented as a percentage of the total image pixels that were classified as green coverage, taking into account the time frame of the image.

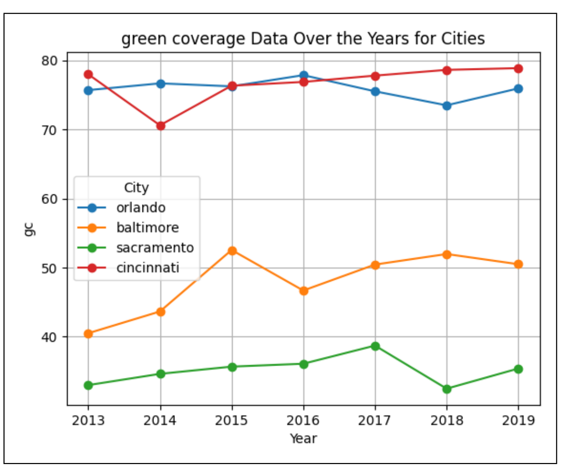

Figure 14: Green Coverage Pixels Percentage per Cities over Time.

TABLE III
GREEN COVERAGE PIXELS PERCENTAGE PER CITIES OVER TIME

City	2013	2014	2015	2016	2017	2018	2019
Orlando	75.67	76.65	76.22	77.83	75.50	73.48	75.92
Baltimore	40.49	43.64	52.54	46.67	50.43	51.96	50.48
Sacramento	32.99	34.61	35.66	36.08	38.71	32.47	35.39
Cincinnati	77.96	70.58	76.32	76.86	77.77	78.60	78.85

The findings present opportunities for further comprehensive exploration, urging researchers to delve into the intricate dynamics shaping the association between urban greenery and crime rates, fostering a more nuanced understanding of this complex relationship.

V. DISCUSSION

The primary objective of this research was to assess the relationship between green coverage in US cities, as determined through satellite image classification, and their respective crime rates.

Contrary to our initial hypothesis, our findings failed to find a direct correlation between green coverage and crime rates.

This unexpected result prompts a revaluation of the assumed correlation and further exploration of potential contributing factors and limitations in the study. The absence of a direct correlation between higher green coverage and lower crime rates challenges traditional assumptions about the crime-reducing benefits of green spaces. This divergence from expectations underscores the intricate nature of urban dynamics, where the impact of greenery on crime rates may be influenced by a multitude of socio-economic and demographic variables.

It is crucial to recognize that urban landscapes are shaped by a complex interplay of factors, and the relationship between green coverage and crime rates may be modulated by variables not explicitly considered in the initial hypothesis.

A. Varied Findings

Some studies have indeed supported the idea that the presence of green spaces is associated with reduced crime rates. For example, research by Kuo and Sullivan [8] suggests that access to nature and green environments may contribute to stress reduction and, consequently, lower crime rates. However, other studies, like those by Taylor et al [10] and Branas et al. [12], have found mixed or inconclusive evidence regarding the crime-reducing effects of green spaces.

B. Limitations

The study has several limitations that must be considered when interpreting the results, and these limitations highlight areas for potential improvement in future research endeavours.

1) Image Classification Challenges: The accuracy of the study heavily relies on the image classification model's ability to accurately identify and delineate green spaces.
The inherent challenges in classifying diverse urban landscapes, particularly the identification of smaller or fragmented green areas, may have introduced classification errors.

One key consideration in interpreting these results is the potential limitation of the image classification model used to delineate green coverage. Overfitting, a phenomenon where a model performs well on training data but fails to generalize to new, unseen data, could have influenced the results.
The complexity of urban landscapes, with varying degrees of greenery and diverse land uses, poses a challenge for classification models.

Future iterations of this study should prioritize the refinement and validation of the image classification model to ensure robust and accurate results.

2) Lack of Multivariate Analysis:: The investigation primarily focuses on the isolated relationship between green coverage and crime rates, neglecting the simultaneous consideration of multiple variables that may influence the observed patterns. To enhance the study's robustness and comprehensiveness, a more sophisticated analytical approach should be employed, incorporating various socio-economic, demographic, and environmental factors in the analysis.

Multivariate analysis allows for the examination of the joint impact of these factors, offering a more nuanced understanding of the complex dynamics within urban environments. For instance, factors such as population density, income distribution, educational levels, and housing conditions, can all play pivotal roles in shaping crime rates.
Employing multivariate techniques, such as regression modeling, would enable the study to disentangle the specific contributions of each factor and assess their interactions, providing a more accurate and context-specific depiction of the relationships between green spaces and crime.
The lack of such a comprehensive analysis might lead to oversimplified conclusions and hinder the identification of specific drivers or mitigating factors in the observed relationships.

Future research efforts should prioritize a multivariate analytical framework to uncover the intricate interdependencies among various urban variables and refine our understanding of the multifaceted relationship between green spaces and crime rates.

3) Spatial Resolution and Heterogeneity of Acquired Satellite Imagery:: The study's use of Landsat imagery introduces certain limitations related to spatial resolution and heterogeneity, aspects that merit a more nuanced exploration. Landsat satellites provide valuable multispectral data but are constrained by a spatial resolution that may not capture fine-grained details in urban landscapes. Urban environments exhibit high heterogeneity, with diverse land uses and varying degrees of green coverage within relatively small spatial scales, which Landsat's coarse resolution may struggle to represent adequately.

This limitation could result in the amalgamation of distinct land cover types within a pixel, potentially leading to the misclassification of complex urban features. Additionally, finer-scale variations in green spaces, such as small parks or vegetation within neighborhoods, might be overlooked.
Such limitations can impact the accuracy of the study's findings, particularly in densely populated urban areas characterized by intricate land-use patterns.

Future research should consider incorporating higher-resolution imagery or employing advanced spatial analysis techniques to address these limitations and enhance the study's ability to discern the heterogeneous nature of green spaces in urban landscapes accurately. Moreover, a deeper examination of how the spatial resolution interacts with the heterogeneity of green spaces across different urban contexts is essential for refining the understanding of the relationships between green coverage and crime rates.

4) Crime Reporting Biases:: The study is susceptible to potential crime reporting biases, a facet that warrants a more comprehensive exploration.
Crime reporting biases arise due to variations in reporting practices across different cities, law enforcement agencies, and communities.
Not all crimes are uniformly reported, and reporting rates can be influenced by factors such as public trust in law enforcement, community engagement, and socioeconomic conditions.
The disparities in reporting practices can distort the accuracy and comparability of crime data used in the study. For instance, cities with robust community policing and proactive engagement may exhibit higher reporting rates for certain crimes compared to areas where there is less trust in law enforcement. Moreover, variations in law enforcement priorities, crime classification criteria, and local policies can further contribute to biases.

The study should delve into the intricacies of crime reporting systems, considering factors that influence reporting behaviour and how these factors might differ across cities.
Addressing crime reporting biases is crucial for ensuring the reliability and validity of the study's findings and requires a nuanced examination of the social, cultural, and institutional factors shaping the reporting landscape in diverse urban settings.

Future research should incorporate strategies to mitigate these biases, such as standardizing reporting criteria or employing statistical techniques to account for potential under-reporting or over-reporting in crime data.

VI. Conclusion

The temporal analysis conducted in this study has unveiled intriguing time lags between changes in urban green spaces (UGS) and subsequent shifts in crime rates, revealing dynamic and nuanced temporal relationships. However, the correlation between UGS and Crime Rate is far more intricate than initially perceived. To draw meaningful conclusions, it is imperative to consider a myriad of additional factors such as population density, poverty levels, employment rates, and state-specific laws.

The findings challenge the simplistic notion that increased greenery universally leads to reduced crime, emphasizing the importance of a holistic approach in understanding the complex interplay between environmental factors and criminal dynamics. The temporal lags suggest that the impact of changes in vegetation cover on crime rates may manifest over time, requiring a more in-depth exploration of the temporal dimension in future studies.

Acknowledging the inherent limitations in data availability and methodological approaches, this study contributes valuable insights to the ongoing discourse on environmental factors influencing crime rates.

Further Improvements

In future research, incorporating cities with similar circumstances, such as comparable population sizes, poverty rates, employment levels, and shared state laws, is crucial. This approach aims to create a more controlled environment for analysis, allowing for a clearer understanding of the specific influence of UGS on crime rates while mitigating the confounding effects of diverse socio-economic and legislative factors. By homogenizing these contextual variables, researchers can enhance the validity of their conclusions and gain more precise insights into the complex relationship between UGS and crime. Additionally, a more refined analysis involving multivariate considerations will contribute to a more comprehensive understanding of the multifaceted dynamics at play.

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APPENDICES

A. *Crime Statistics & Green Cover Data*

TABLE IV
CRIME STATISTICS - BALTIMORE, MARYLAND

Year	Population	Violent	Murder	Rape	Robbery	Assault	Property	Burglary	Larceny	Motor Theft	Arson	Percap_Violent	Percap_Total	Vegetation cover
2019	597239	11101	348	324.0	4856	5573	25748	5414	16395	3939	108.0	0.0185	0.0618	50.4818
2018	605436	11100	309	361.0	5066	5364	27217	6048	16794	4375	138.0	0.0183	0.0635	51.9552
2017	613217	12430	342	382.0	5879	5827	30220	8041	17008	5171	261.0	0.0202	0.0699	50.4303
2016	618385	11010	318	301.0	5236	5157	29547	7375	16855	5317	259.0	0.0178	0.0660	46.6730
2015	621252	9542	344	288.0	4313	4598	30941	7757	17658	5526	260.0	0.0153	0.0655	52.5386
2014	623513	8346	211	247.0	3677	4213	29420	6926	18008	4486	213.0	0.0133	0.0609	43.6433
2013	622671	8725	233	301.0	3734	4460	30789	7391	18946	4452	277.0	0.0140	0.0639	40.4933

TABLE V
CRIME STATISTICS - CINCINNATI, OHIO

Year	Population	Violent	Murder	Rape	Robbery	Assault	Property	Burglary	Larceny	Motor Theft	Arson	Percap_Violent	Percap_Total	Vegetation cover
2019	303335	2562	64	280.0	872	1346	13051	2765	8935	1351	5.0	0.0084	0.0514	78.8535
2018	301952	2535	57	293.0	897	1288	13710	2978	9422	1310	4.0	0.0083	0.0538	78.6049
2017	299116	2833	70	292.0	1196	1275	15105	3448	10172	1485	6.0	0.0094	0.0599	77.7703
2016	298880	2720	57	249.0	1278	1136	15382	3929	10216	1237	485.0	0.0091	0.0621	76.8608
2015	298478	2761	66	236.0	1263	1196	16446	4413	10873	1160	440.0	0.0092	0.0658	76.3159
2014	297671	2695	60	229.0	1356	1051	16557	4820	10639	1098	353.0	0.0090	0.0658	70.5813
2013	296491	2826	70	199.0	1610	947	17231	5467	10488	1276	246.0	0.0095	0.0684	77.9634

TABLE VI
CRIME STATISTICS - ORLANDO, FLORIDA

Year	Population	Violent	Murder	Rape	Robbery	Assault	Property	Burglary	Larceny	Motor Theft	Arson	Percap_Violent	Percap_Total	Vegetation cover
2019	292120	2157	25	204.0	536	1392	14100	1464	11362	1274	15.0	0.0073	0.0557	75.9213
2018	286679	2282	39	200.0	628	1415	13803	1619	10965	1219	13.0	0.0079	0.0561	73.4752
2017	283982	2113	23	183.0	605	1302	15490	2388	11715	1387	22.0	0.0074	0.0620	75.4991
2016	277719	2328	84	NaN	504	1529	14498	3637	9621	1240	15.0	0.0083	0.0606	77.8372
2015	268438	2525	32	NaN	522	1789	16148	3401	11567	1180	39.0	0.0094	0.0697	76.2212
2014	259675	2340	15	188.0	620	1538	16515	3342	12182	991	55.0	0.0090	0.0728	76.6525
2013	253238	2316	17	126.0	573	1600	16489	3485	11984	1020	29.0	0.0091	0.0743	75.6733

TABLE VII
CRIME STATISTICS - SACRAMENTO, CALIFORNIA

Year	Population	Violent	Murder	Rape	Robbery	Assault	Property	Burglary	Larceny	Motor Theft	Arson	Percap_Violent	Percap_Total	Vegetation cover
2019	513934	3223	34	127.0	1039	2023	16354	2993	10644	2717	179.0	0.0062	0.0384	35.3869
2018	507037	3329	36	102.0	1052	2139	15417	2751	9783	2883	146.0	0.0065	0.0372	32.4717
2017	499997	3378	39	99.0	1100	2140	14683	2888	9077	2718	209.0	0.006756	0.0365	38.7058
2016	495471	3549	41	88.0	1136	2284	15283	3070	9389	2824	173.0	0.0071	0.0383	36.0788
2015	489717	3611	43	NaN	1174	2289	16501	3713	9865	2923	140.0	0.0073	0.0413	35.6604
2014	482767	2968	28	95.0	1000	1862	15078	3238	9443	2397	169.0	0.0061	0.0377	34.6146
2013	478182	3137	34	100.0	1158	1850	17980	3886	11233	2861	164.0	0.0065	0.0445	32.9881

B. Satellite imagery & Classified Pixels Image

Figure 15: Baltimore 2018 Satellite Image.

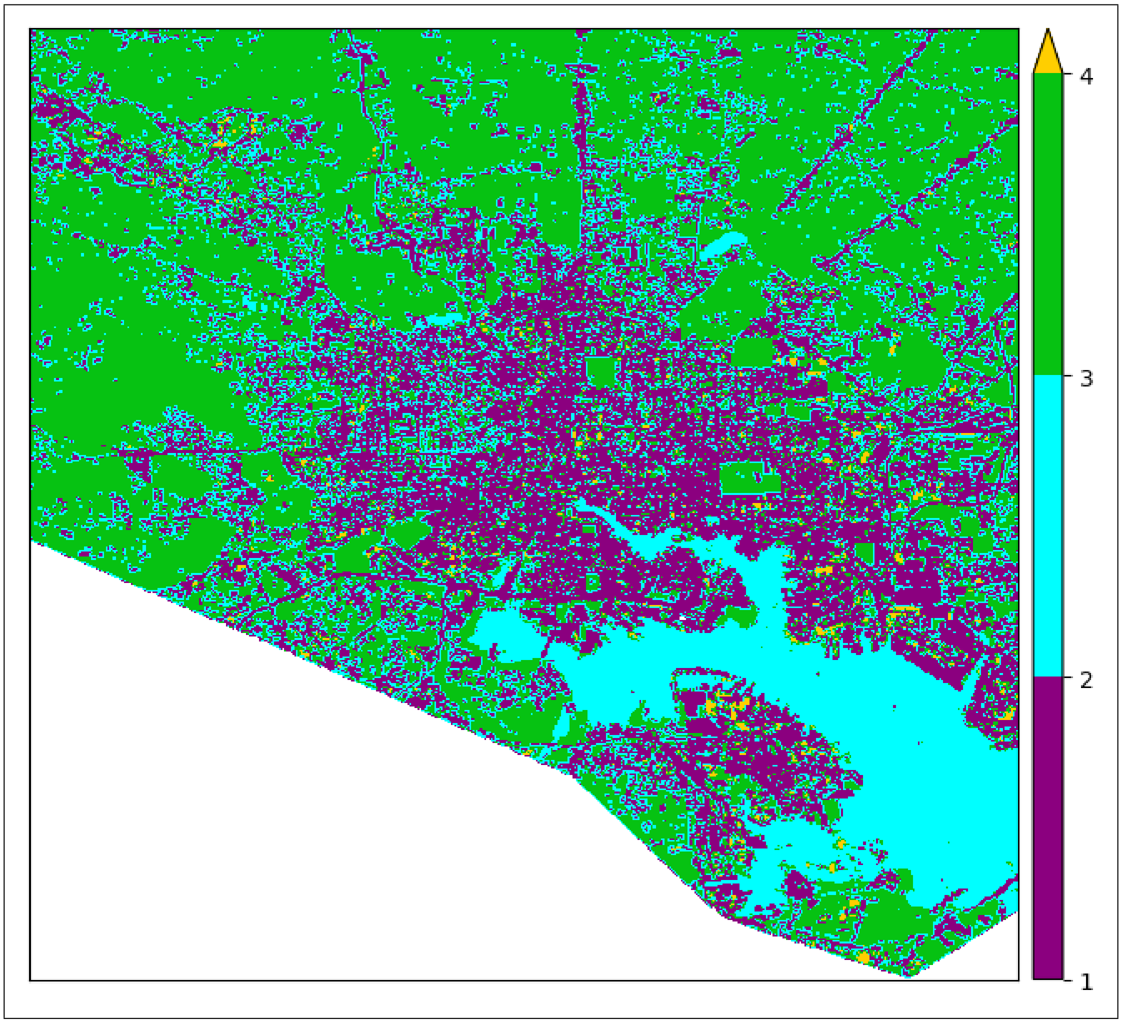

Figure 16: Baltimore 2018 Classified Pixels Image.

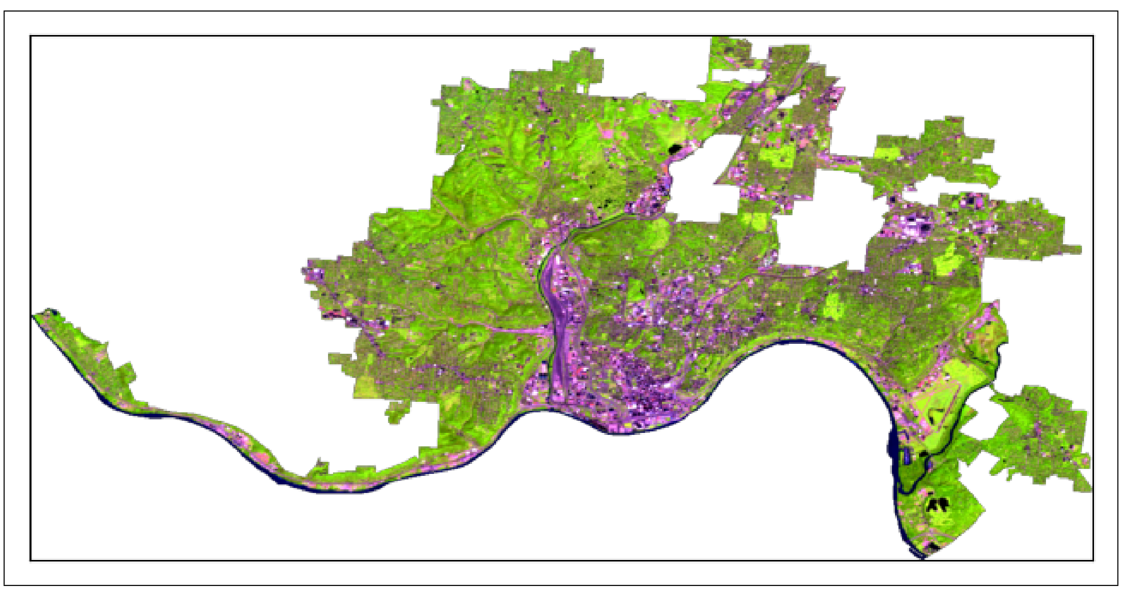

Figure 17: Cincinnati 2018 Satellite Image.

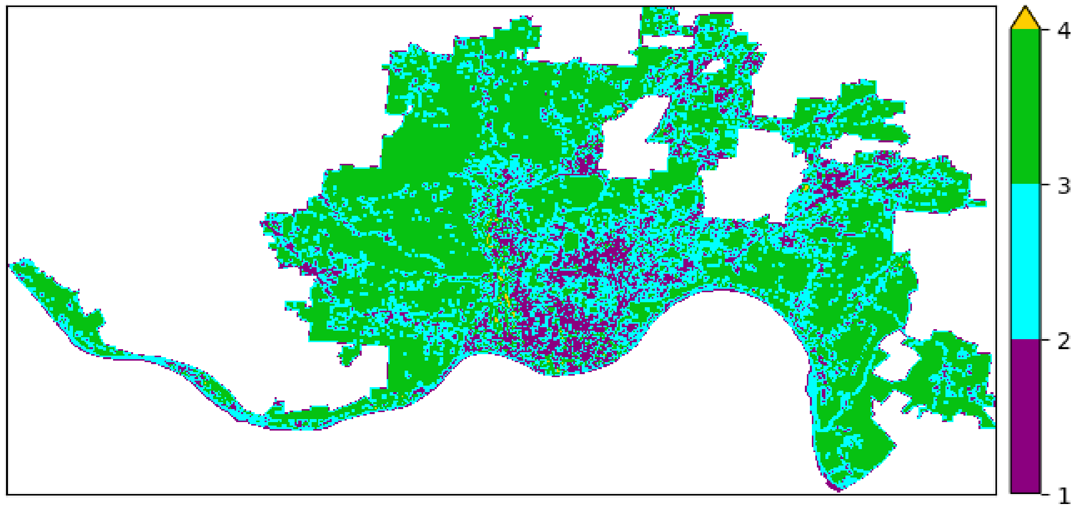

Figure 18: Cincinnati 2018 Classified Pixels Image.

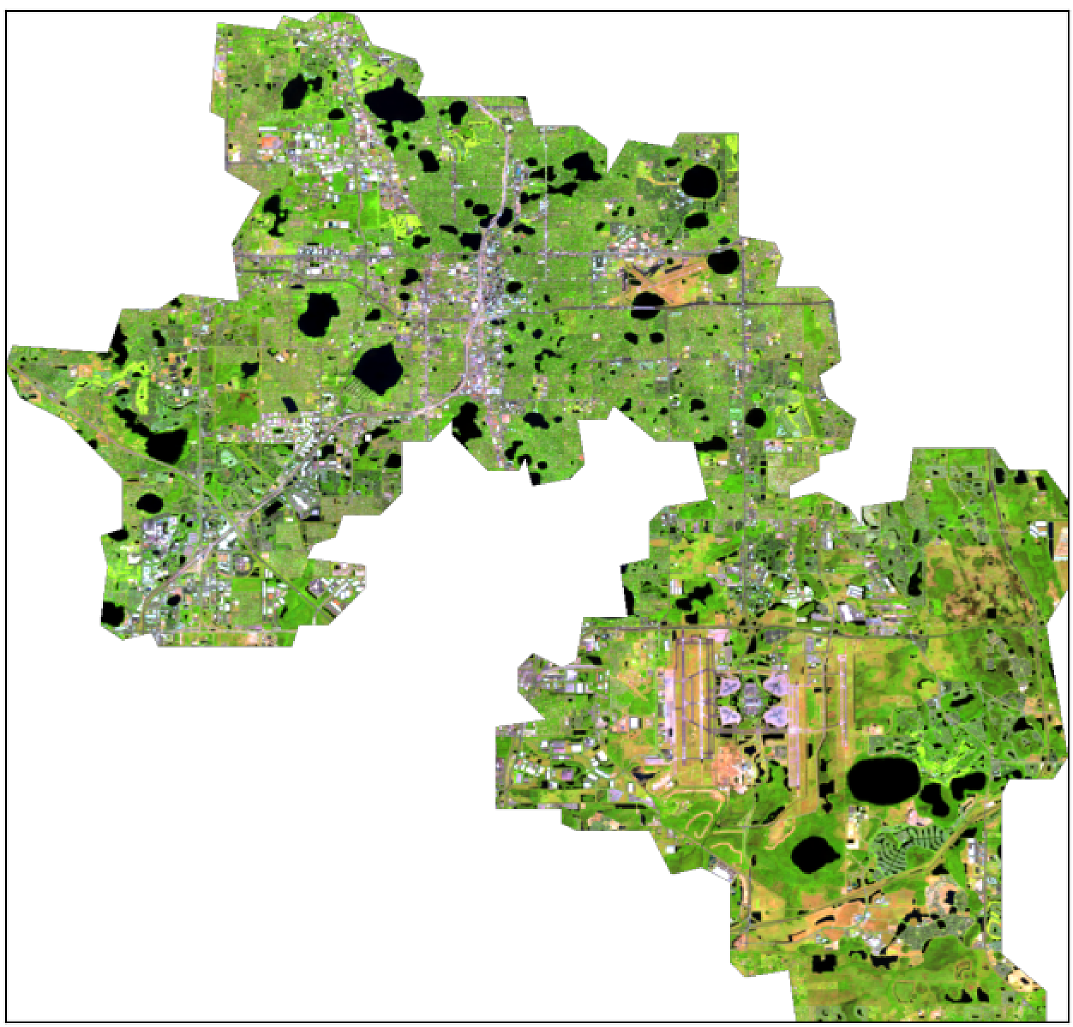
Figure 19: Orlando 2018 Satellite Image.

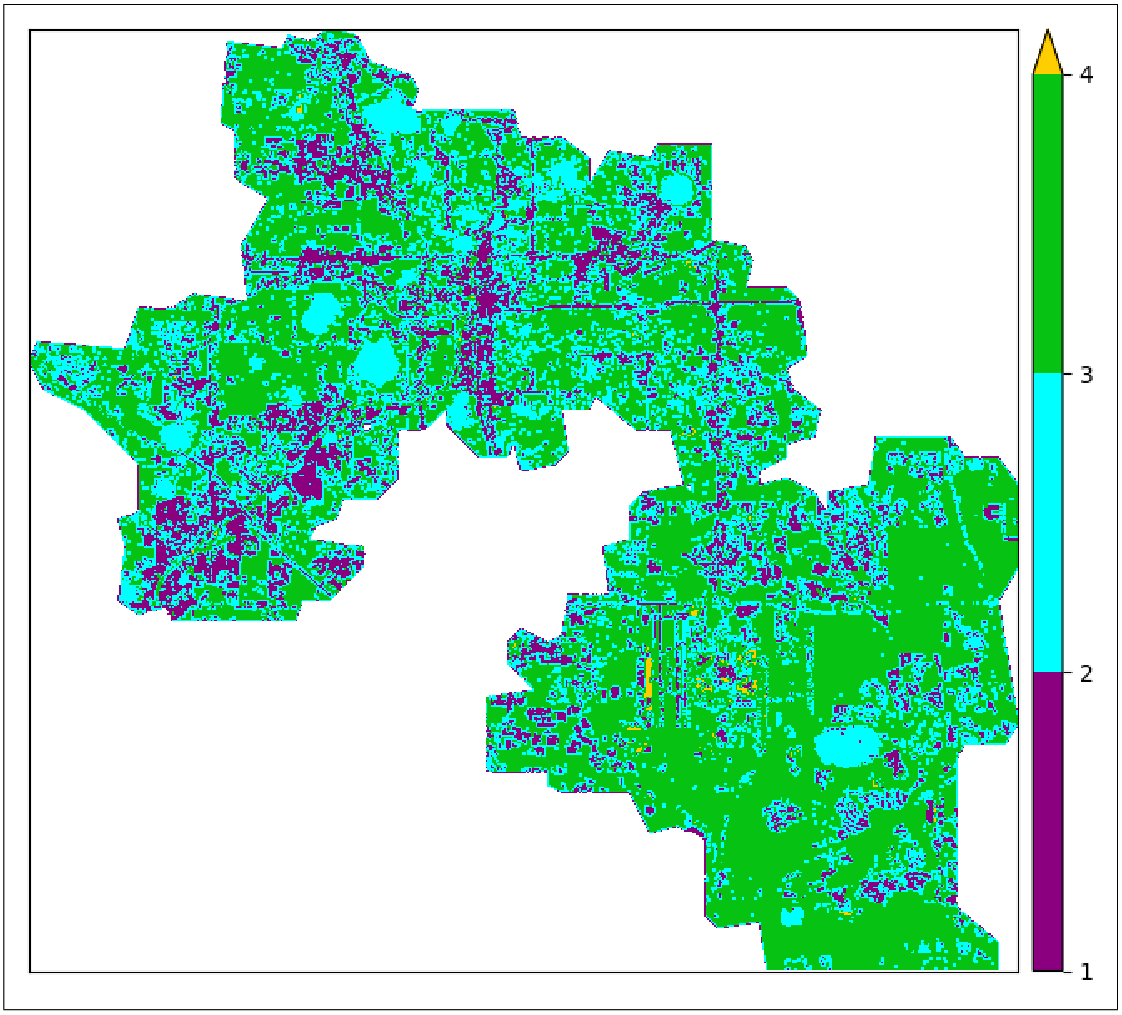

Figure 20: Orlando 2018 Classified Pixels Image.

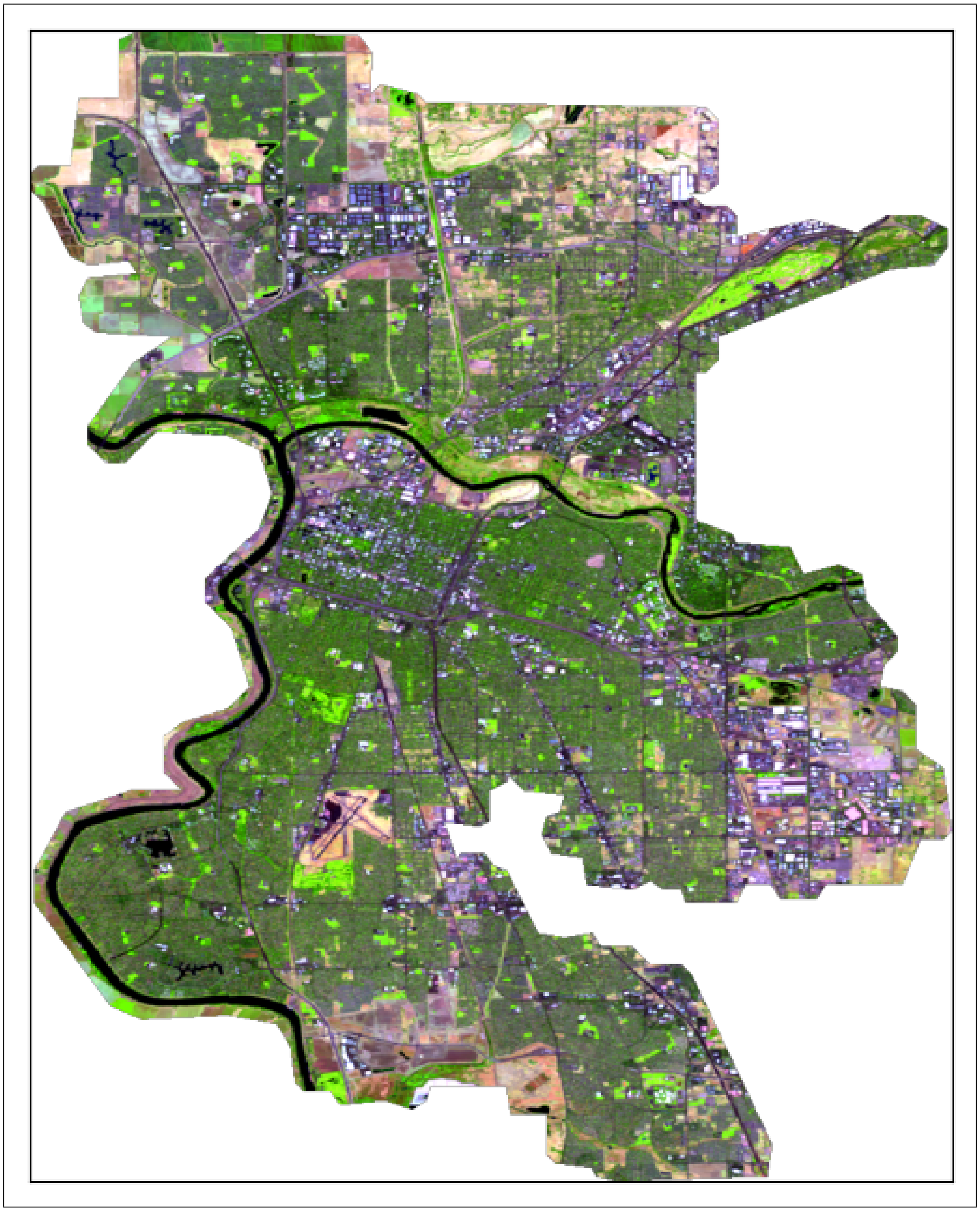

Figure 21: Sacramento 2018 Satellite Image.

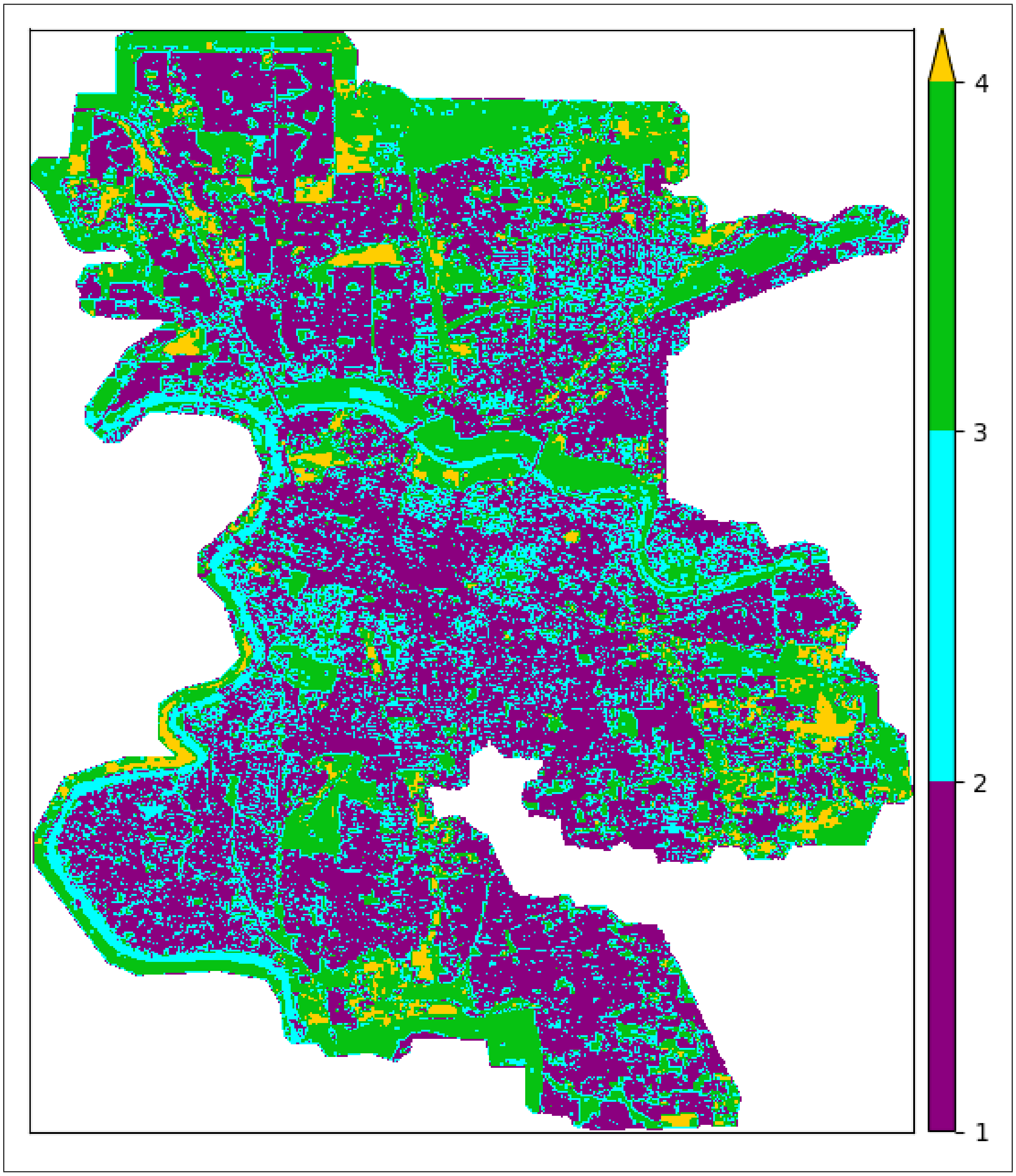

Figure 22: Sacramento 2018 Classified Pixels Image.

C. Google Earth Engine Code

D. Python Code