Caitlin Carlisle

Dr. Petya Campbell

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The Cost of Urban Sprawl in Austin, TX

INTRODUCTION

Background. Urban sprawl refers to the uncontrolled expansion of urban areas into rural or natural land, characterized by low-density residential development, increased reliance on automobiles, and fragmented land use patterns (Egidi et al., 2020). This phenomenon poses significant environmental and social challenges, including the loss of wildlife habitats, increased pollution, and higher infrastructure costs. Austin, Texas, is a prominent example of urban sprawl, especially given its rapid population growth over the past decade. According to the U.S. Census Bureau, Austin's population increased by nearly 22% from 2010 to 2020, making it one of the fastest-growing cities in the US. This explosive growth has resulted in extensive suburban development, transforming areas of natural and agricultural land into residential, commercial, and industrial zones.

Urban sprawl presents challenges for urban planners, environmentalists, and policymakers. Urban planners must understand land cover changes to develop efficient infrastructure and sustainable communities. Environmentalists are concerned with biodiversity loss, increased greenhouse gas emissions, and natural resource degradation due to sprawling development (Genovese et al., 2023). Policymakers must balance economic growth demands with environmental protection to maintain residents' quality of life. The relevance of studying urban sprawl in Austin lies in its implications for sustainable development. Effective urban growth management requires accurate data and comprehensive analysis to mitigate adverse environmental impacts and promote smart growth strategies. According to the Environmental Protection Agency (EPA), smart growth approaches, including higher-density development and mixed-use zoning, can help combat the negative effects of urban sprawl by preserving open spaces and enhancing urban areas' livability (“Smart Growth”, 2021).

Objectives. The primary objective of this study is to analyze the impact of urban expansion on land cover in Austin, Texas, over the period from 2018 to 2024, utilizing Sentinel-2 imagery. This research aims to document how urban sprawl has transformed the natural landscape and influenced natural resources and land use. Through this objective, this project aims to offer a detailed temporal analysis of land cover variations, contributing to the discourse on sustainable urban management and environmental stewardship in Austin. The insights gained will not only enhance our understanding of urban sprawl in Austin but could also serve as a model for other rapidly growing cities facing similar challenges.

METHODS

Study Area. Austin, Texas, is renowned for its vibrant culture, dynamic economy, and rapid population growth. Geographically, Austin is situated on the edge of the Texas Hill Country and is bisected by the Colorado River, contributing to its diverse topography and rich natural resources (“Austin”, 2024). Over the past decade, Austin has experienced significant urban sprawl, driven by a booming tech industry and an influx of new residents. The city's tech boom, often referred to as the rise of "Silicon Hills," has attracted numerous technology and development companies, transforming Austin into a major tech hub (2024). This growth has led to the expansion of urban areas into surrounding rural and natural landscapes, making it an ideal case study for examining the impacts of urban sprawl on land cover and natural resources.

Data. The data used in this study consists of Sentinel-2, Level 2A (L2A) imagery, focusing on timeframes from April 2018 and April 2024. Sentinel-2, a mission under the European Space Agency's Copernicus Programme, provides high-resolution multispectral imagery, ideal for monitoring changes in land cover due to urban expansion (Phiri et al., 2020). The chosen datasets underwent preprocessing steps, including atmospheric correction to mitigate atmospheric effects on the imagery. To ensure data consistency and accuracy, images were filtered to select those with less than 30% cloud cover, identifying clear days in April 2018 and 2024 for analysis.

Classification Scheme. The classification scheme focused on various land cover classes: residential, commercial, forest, grass, roads, water, stream or wet vegetation, bare soil, construction, and shrubs (sparse vegetation and vegetation mixed with soil). A parallelepiped classification method was employed due to its simplicity and effectiveness in handling high-dimensional data and spectral variability within urban environments (Didore et al., 2021).

To enhance classification accuracy, the images were displayed using various false color composites. Natural-like rendering utilized Short Wave Infrared (Band 12, 2190 nm), Visible and Near Infrared (Band 8, 842 nm), and Green (Band 3, 560 nm) to distinctly display healthy vegetation in bright green, grasslands in green, barren soil in pink, and urban areas in magenta. Soil moisture and geological features were highlighted using Short Wave Infrared bands: Band 12 (2190 nm), Band 11 (1610 nm), and Band 8 (842 nm). In the false color composite using Visible and Near Infrared (Band 8, 842 nm), Red (Band 4, 665 nm), and Green (Band 3, 560 nm), urban areas appeared magenta, water bodies were depicted in deep blue, and vegetation varied in shades from green to red depending on health and density.

Analytical Methods. Initially, for each land cover class, 10-15 regions of interest (ROIs) were collected. The histograms of each band were examined to assess distribution normality. Skewed or multimodal distributions led to reviewing and refining the ROIs to ensure accurate class representation.

Subsequently, normally distributed ROIs were merged, and the parallelepiped classification was executed. For the 2018 image, class standard deviations from the mean were thresholded as follows: grass (2.5), construction (2), road (1.3), wet vegetation (1.5), commercial (2.2), and residential (2). For the 2024 image, thresholds were adjusted to: commercial (1.2), roads (1.7), residential (2.5), wet vegetation (1), shrub (2.5), and forest (4). These adjustments were necessary to account for the spectral variability and changes in land cover over time, ensuring more accurate results. Classes not listed were left at the default 3 standard deviations.

Fig. 1: Parallelepiped Classification of Austin, TX in 2018

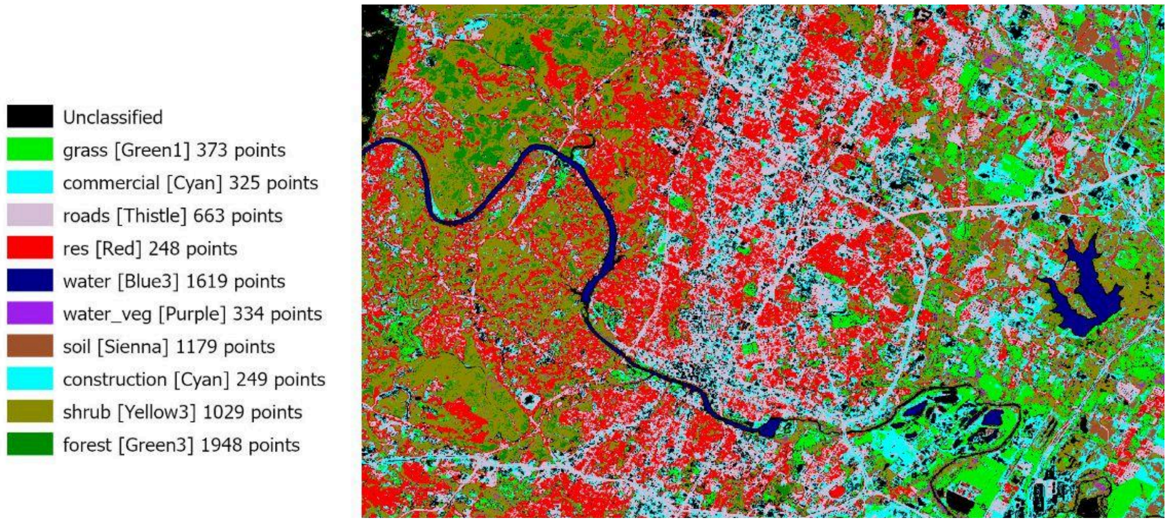

Fig. 2: Parallelepiped Classification of Austin, TX in 2024

Ground Truth. For this study, the accuracy of the classified satellite images was assessed using a post-classification random sampling method. After the completion of the classification process, 50 random points were selected across the entire dataset to ensure they were not included in the training set. This method helps in providing an unbiased assessment of the classifier's performance on new, unseen data. The points were chosen to represent a diverse range of classes and geographical features present in the study area. This approach tries to ensure that the validation data are representative of the different land cover types identified in the classification scheme. The selected points were then used to evaluate the accuracy of the classification, aiding in the determination of the model's ability to generalize across different landscapes and conditions.

RESULTS AND DISCUSSION

Results. Between 2018 and 2024, significant changes in land cover were observed in Austin. This period marked a substantial increase in urban areas, particularly in residential and commercial land use. Residential zones expanded from 19.495% to 23.74%, and commercial areas grew from 5.515% to 7.89%, underscoring Austin's rapid urban sprawl influenced by its booming economy and population growth. Concurrently, the area designated for construction more than doubled, increasing from 5.49% to 12.432%, reflecting ongoing development projects.

This urban expansion came at a considerable environmental cost, notably a reduction in forest areas, which declined sharply from 7.629% to 3.065%. This decrease is indicative of potential deforestation or repurposing of land for development purposes. Additionally, shrub areas significantly increased from 8.272% to 19.933%, likely a result of secondary succession occurring in cleared forest areas, marking a transitional phase in land cover prior to potential urban development. Infrastructure developments, particularly roads, also saw an increase from 12.257% to 17.634%, suggesting enhanced efforts to improve city connectivity in line with residential and commercial growth. In contrast, minor decreases were noted in water bodies and stream vegetation, which dropped from 1.269% to 1.227% and 4.572% to 1.047%, respectively, possibly affected by the encroaching urban landscape.

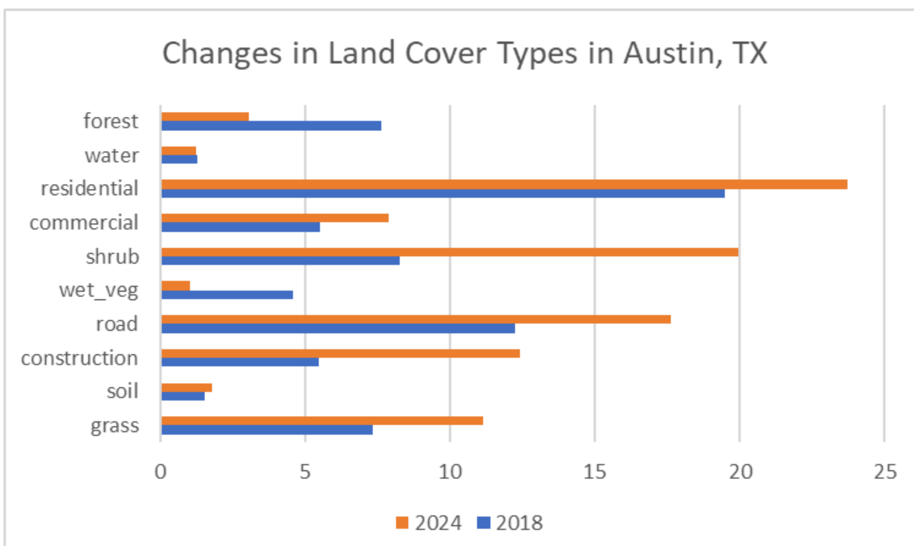

Fig. 3: Change in percent land cover distribution from 2018 to 2024 in Austin, TX.

Accuracy and Challenges. Maintaining consistent classification between images was challenging due to spectral similarities between certain classes. For instance, agricultural and recreational grasses were combined into one category because of their similar spectral reflectance characteristics, primarily their high water needs, which caused confusion during classification. Residential areas often consisted of mixed pixels reflecting rooftops, vegetation, and various road materials. Bare soil, road, construction, and commercial areas also exhibited overlap, especially in road classification due to diverse materials. Construction areas typically appeared brighter than bare soil, as they included both buildings and drier soils. Bare soil was characterized by cleared land or fallow agricultural fields, sometimes wet and dark.

As aforementioned, the classifications were executed using the parallelepiped classification, a supervised classification. The effectiveness of the classifier for both images was evaluated using confusion matrices, which provided a detailed breakdown of performance across all classes. For the 2018 dataset, the classifier achieved an overall accuracy of 76.4% and a Kappa statistic of 0.738 as seen in Table 1, indicating substantial agreement between the classified results and the reference data, well above chance level. This level of accuracy suggests that the classifier performed effectively, with the majority of the area being correctly classified. In comparison, the 2024 dataset, Table 2, showed a decrease in both overall accuracy and Kappa statistic, achieving 70.2% and 0.669 respectively. These values, while still indicating substantial agreement, suggest a slight reduction in classifier performance, possibly due to changes in the landscape, changes in training data, or differences in environmental conditions at the time of satellite image capture. The confusion matrix from each dataset revealed specific areas where misclassification occurred, particularly between classes with similar spectral characteristics.

	Landcover Classifications											Errors of Omission	Producer's Accuracy
Ground Truth	*Grass*	*Soil*	*Construction*	*Road*	*Wet Veg*	*Shrub*	*Commercial*	*Residential*	*Water*	*Forest*	Total		
Grass	**28**	0	2	4	4	10	2	0	0	0	50	0.440	0.560
Soil	0	**46**	2	1	0	0	0	0	0	1	50	0.080	0.920
Construction	0	0	**32**	5	0	1	10	1	0	1	50	0.360	0.640
Road	0	0	10	**30**	0	0	5	5	0	0	50	0.400	0.600
Wet Veg	2	0	0	0	**35**	8	0	2	0	3	50	0.300	0.700
Shrub	6	0	0	0	2	**42**	0	0	0	0	50	0.160	0.840
Commercial	1	0	8	5	0	0	**33**	2	0	1	50	0.340	0.660
Residential	4	0	1	3	0	1	0	**40**	0	1	50	0.200	0.800
Water	0	0	0	0	0	0	0	0	**50**	0	50	0.000	1.000
Forest	0	1	0	0	3	0	0	0	0	**46**	50	0.080	0.920
Total	41	47	55	48	44	62	50	50	50	53	**382**		
Errors of Comission	0.317	0.021	0.418	0.375	0.205	0.323	0.340	0.200	0.000	0.132			
User's Accuracy	0.683	0.979	0.582	0.625	0.795	0.677	0.660	0.800	1.000	0.868			
Overall Accuracy	0.764												
Kappa	0.738												

Table 1: 2018 Confusion Matrix

	Landcover Classifications											Errors of Omission	Producer's Accuracy
Ground Truth	*Grass*	*Soil*	*Construction*	*Road*	*Wet Veg*	*Shrub*	*Commercial*	*Residential*	*Water*	*Forest*	Total		
Grass	**30**	2	0	3	7	5	0	3	0	0	50	0.400	0.600
Soil	2	**44**	2	2	0	0	0	0	0	0	50	0.120	0.880
Construction	0	5	**27**	10	0	0	3	0	0	5	50	0.460	0.540
Road	2	4	9	**24**	0	0	5	6	0	0	50	0.520	0.480
Wet Veg	5	0	0	0	**38**	5	0	0	0	2	50	0.240	0.760
Shrub	3	0	0	0	5	**34**	3	0	0	5	50	0.320	0.680
Commercial	0	0	5	5	0	0	**23**	10	0	7	50	0.540	0.460
Residential	5	0	0	2	2	0	5	**36**	0	0	50	0.280	0.720
Water	0	0	0	0	0	0	0	0	**50**	0	50	0.000	1.000
Forest	0	3	0	0	2	0	0	0	0	**45**	50	0.100	0.900
Total	47	58	43	46	54	44	39	55	50	64	**351**		
Errors of Comission	0.362	0.241	0.372	0.478	0.296	0.227	0.410	0.345	0.000	0.297			
User's Accuracy	0.638	0.759	0.628	0.522	0.704	0.773	0.590	0.655	1.000	0.703			
Overall Accuracy	0.702												
Kappa	0.669												

Table 2: 2024 Confusion Matrix

Relation to Objectives. The findings of this study effectively align with the initial objectives, providing a detailed examination of urban expansion and its impact on land cover in Austin, Texas, from 2018 to 2024. Through the analysis of Sentinel-2 imagery, this research has successfully documented the significant transformation of Austin's natural landscape due to urban sprawl. The increase in residential and commercial areas by approximately 4.245% and

2.375% respectively, alongside a more than doubling of construction sites, illustrates a dynamic shift towards urbanization.

This substantial change in land use has led to a marked reduction in forested areas, from 7.629% to 3.065%, highlighting a pressing concern for environmental stewardship in the region. The results underscore the challenges faced by Austin in managing urban growth without compromising its natural resources. Again, the expansion of shrub areas likely indicates secondary succession which may temporarily fill the gaps left by deforestation but also suggests a potential for future urban development.

CONCLUSION

Key Findings. This study has mapped and analyzed the impact of urban expansion on land cover in Austin, Texas, over a six-year period from 2018 to 2024. The significant findings reveal that urban sprawl has led to a substantial increase in residential, commercial, and construction areas, with residential zones expanding by nearly 4.25% and construction sites more than doubling. These developments have come at the cost of natural landscapes, most notably with a marked decrease in forested areas by over 4.5%, highlighting significant environmental concerns.

Furthermore, the transition in land use is indicated by the increase in shrub areas, suggesting secondary succession in regions previously occupied by forests. This reflects a landscape in flux, potentially setting the stage for future urban development. The study underscores the challenges of managing urban growth while preserving natural resources, emphasizing the need for sustainable urban planning practices.

Future Research. To advance the precision of land cover classification in future studies, I would like to explore the application of various sophisticated machine learning classifiers. Techniques such as Random Forests, Support Vector Machines, and Convolutional Neural Networks have shown impressive results in other geographic contexts for their ability to handle complex datasets and improve classification accuracy. These methods could effectively manage the spectral variability and mixed pixel issues inherent in high-resolution imagery, which were limitations in the current study using more traditional methods.

Additionally, integrating higher resolution imagery would allow for finer detail in capturing land cover changes, particularly in rapidly urbanizing regions. This could provide deeper insights into small-scale environmental impacts of urban sprawl, such as the encroachment on ecologically sensitive areas and changes in microhabitats. Employing these advanced classifiers and higher resolution datasets would not only enhance the accuracy of detecting subtle changes but also improve our understanding of the interactions between urban development and natural landscapes.

Works Cited

"Austin." *Encyclopædia Britannica*, 8 May 2024, www.britannica.com/place/Austin-Texas. Accessed 10 May 2024.

Didore, V., Nalawade, D., & Vaidya, R. "Remote Sensing Data Classification Technique: A Review." *International Journal of Advanced Research in Science, Communication and Technology* (2021). https://doi.org/10.48175/ijarsct-2084.

Egidi, G., Cividino, S., Vinci, S., Sateriano, A., & Salvia, R. "Towards Local Forms of Sprawl: A Brief Reflection on Mediterranean Urbanization." *Sustainability*, 12 (2020): 582. https://doi.org/10.3390/su12020582.

Genovese, D., Candiloro, S., D'Anna, A., Dettori, M., Restivo, V., Amodio, E., & Casuccio, A. "Urban sprawl and health: a review of the scientific literature." *Environmental Research Letters*, 18 (2023). https://doi.org/10.1088/1748-9326/ace986.

Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V., Murayama, Y., & Ranagalage, M. "Sentinel-2 Data for Land Cover/Use Mapping: A Review." *Remote. Sens.*, 12 (2020): 2291. https://doi.org/10.3390/rs12142291.

"Smart Growth." *EPA*, 4 Apr. 2024, www.epa.gov/smartgrowth. Accessed 10 May 2024.