# Assessing Urban Biodiversity trends using Satellite Imagery

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## Abstract

The interconnection between global climate change and biodiversity is widely acknowledged. Human-induced destruction and degradation of ecosystems intensify the adverse and multifaceted impacts of climate change, further exerting pressure on the remaining ecosystems and wildlife. Hence, it is crucial for climate change mitigation efforts to incorporate strategies that safeguard and preserve biodiversity, thereby maximizing ecosystem productivity, resilience, adaptability, and sustainability. To this end, it is imperative to identify and prioritize ecosystem functions that sustain key ecosystem services for targeted conservation actions, especially in cities. Urban areas have doubled since 1992 and, compared to 2020, are projected to expand between 30% and 180% until 2100. Notably, most of the urban growth will happen in the global south in regions of high biodiversity, and it will affect global ecosystems far beyond urban areas through resource demands, pollution, and climate impacts. Urban biodiversity management is an emerging field, and there are significant gaps in our understanding that are critical to improving biodiversity conservation policies and management in urban areas to support global biodiversity outcomes. As the understanding of ecosystem services continues to evolve, researchers increasingly recognize the significance of urban vegetation in fostering the sustainability of urban ecosystems and the environment. In recent years, remote sensing technology has emerged as a valuable tool for acquiring detailed information and mapping urban vegetation, offering numerous advantages. Leveraging satellite imagery enables extensive coverage of urban areas, providing an opportunity to evaluate biodiversity patterns across entire regions without causing disturbance to ecosystems. Remote sensing indicators of photosynthetic activity, notably the Normalized Difference Vegetation Index (NDVI), have found widespread application in predicting plant species' biodiversity across temperate and tropical ecosystems. NDVI derived from satellite data offers a quantitative measure of vegetation abundance and health, serving as a suitable indicator of urban vegetation productivity and biodiversity richness assessment. While remote sensing imagery has significantly improved our capacity to monitor landscape-level biodiversity losses, its application for assessing urban biodiversity has been limited. This research paper addresses this gap by developing a computational pipeline that utilizes satellite imagery and clustering algorithms to evaluate urban biodiversity trends across 65 urban biodiversity hotspots in the U.S., Mexico, and Colombia. Through this study, we showcase the potential of time-series analysis based on satellite imagery to characterize biodiversity trends within urban areas.

Furthermore, we introduce a clustering algorithm to group cities exhibiting similar biodiversity performance trends. Our analysis reveals three distinct emerging trends: increasing, decreasing, and stabilizing biodiversity patterns critical to urban biodiversity management. The findings of this research have significant implications for urban sustainability and biodiversity conservation in rapidly urbanizing regions. By leveraging the potential of satellite imagery and NDVI analysis, urban planners, policymakers, and conservation practitioners can make informed decisions to protect and enhance urban biodiversity management.

## 1. Introduction

Urbanization has emerged as one of the most transformative global phenomena, with over half of the world's population residing in urban areas, and this figure is projected to rise substantially in the coming decades [1]. While cities serve as hubs of economic and social development, the rapid expansion of urban landscapes has exerted unprecedented pressures on surrounding natural ecosystems, leading to a significant loss of biodiversity and disruption of vital ecological processes [2,3]. Recognizing the imminent need for a comprehensive assessment of urban biodiversity, researchers have increasingly turned to innovative tools and methodologies to monitor and understand these changes. Satellite imagery and remote sensing technology have revolutionized our ability to observe Earth's surface at large scales, providing valuable insights into land use, vegetation patterns, and ecological dynamics [4]. Recently, there has been a growing interest in employing satellite imagery to assess biodiversity in urban environments, with studies revealing its potential to capture and quantify urban green spaces and wildlife habitats [5,6]. Integrating satellite-based assessments with traditional ecological methods can unlock critical information about the distribution and trends of urban biodiversity, facilitating targeted conservation strategies to mitigate the impacts of urbanization on native flora and fauna. In this paper, we comprehensively analyze urban biodiversity trends using satellite imagery in 65 cities located within biodiversity hotspots across the U.S., Colombia, and Mexico. These three countries are renowned for their diverse ecosystems, rich biodiversity, and distinct urbanization patterns. By focusing on biodiversity hotspots, regions known for their extraordinary biological diversity and high endemism [7], our study aims to address the pressing concerns surrounding urban development within ecologically sensitive areas. By integrating cutting-edge remote sensing techniques and ecological analysis, we seek to quantify the richness and distribution of biodiversity across these cities, unraveling key drivers of biodiversity change within an urban context. The findings from this research are expected to not only enhance our understanding of urban biodiversity dynamics but also contribute to evidence-based policymaking and urban planning, fostering sustainability and resilience in the face of increasing urbanization. Ultimately, this study aims to serve as a foundational resource for urban planners, conservationists, and policymakers, providing valuable insights to shape the development of greener, more biodiverse cities, and safeguard the integrity of our shared natural heritage.

## 2. Context and Background

As the urban population grows and urbanized lands expand [8], preserving urban biodiversity becomes globally relevant for conservation efforts [8]. Enhancing the urban environment to be more hospitable to nature can offer a significant portion of the population increased opportunities for regular interaction with and appreciation of biodiversity [9]. However, developing a widely applicable methodology for assessing, planning, and conserving urban biodiversity poses challenges [10,11]. The main obstacles lie in the lack of comprehensive wildlife habitat and species occurrence data in urban areas and the insufficient understanding of how spatial variations in human-related factors and climate factors may influence habitat distributions across urban landscapes. Simultaneously, urbanization creates novel habitats suitable for a limited number of species that can adapt to the changing urban environments [12,13]. Recent advancements in remote sensing technology, particularly satellite imagery and the Normalized Difference Vegetation Index (NDVI), have opened new avenues for assessing urban biodiversity and understanding the impact of urbanization on natural ecosystems [4]. NDVI, represented by Equation 1, quantifies the ratio of the difference between the near-infrared band (NIR) and the red band (R) to the sum of these two bands [14].

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad \text{Equation (1)}$$

The normalized difference vegetation index (NDVI) utilizes reflectance values in the near-infrared band (NIR) and the visible red band (RED). It capitalizes on the distinction that green vegetation reflects less visible light and more NIR. In contrast, sparser or less green vegetation reflects a higher proportion of visible light and less NIR. By combining these reflectance characteristics into a ratio, NDVI becomes an index closely related to photosynthetic capacity. The resulting range of NDVI values lies between -1 and +1. Positive values indicate vegetated areas; the higher the index, the greater the chlorophyll content in the target region. NDVI has found extensive applications in identifying and interpreting various phenology metrics, which describe cyclic plant life-cycle events and how seasonal and inter-annual climate and habitat variations impact them. The duration of photosynthetic activity, determined using NDVI, can indicate the length of the growing season; the time of maximum NDVI corresponds to the peak of photosynthesis; seasonally integrated NDVI reflects photosynthetic activity during the growing season; and the rate of change in NDVI may reveal the speed of photosynthetic increase or decrease. These metrics are influenced by several vegetation characteristics, with the leaf area index (LAI) referring to the projected area of leaves per unit of ground area [15], being one of the most crucial parameters in remote sensing.

### 2.1 Satellite Imagery, NDVI, and Biodiversity Assessment

A growing body of knowledge has emerged concerning the tools and techniques used to assess and anticipate ecosystem responses to global environmental changes [16–18]. For instance, in mapping and studying protected lands, Yeqiao [18] highlights the broad geospatial information that satellite remote sensing can provide, encompassing various spatial scales, temporal frequencies, spectral properties, and spatial contexts. Traditional approaches to measuring species richness offer detailed local data but face challenges in upscaling the information. Conversely, methods employed to measure species richness on small spatial scales are limited in their application to large geographical areas [19]. With NDVI playing a crucial role, remote sensing tools present opportunities for systematic, repeatable, and spatially comprehensive descriptions of biodiversity over large areas [19,20]. NDVI plays a crucial role in developing land cover maps, serving as a valuable tool for the direct approach or first-order analysis of species occurrence [20]. Depending on the scale, biome, and ecosystem under consideration, land cover maps offer implicit or explicit data on the composition, abundance, and distribution of individual species or species assemblages [16,19,20]. Using data derived from vegetation productivity and other environmental parameters, such as climate and geophysical factors, we can derive statistical relationships that can be valuable data to establish species abundance or occurrence [19].

Using the Normalized Difference Vegetation Index (NDVI) and satellite imagery in urban biodiversity assessment has become a valuable and practical approach to monitoring and assessing city biodiversity patterns. NDVI, derived from satellite imagery, provides a quantitative measure of vegetation density and health, enabling researchers to assess the extent and quality of green spaces in urban environments. For instance, applying AVHRR-derived NDVI in Kenya provided insights into the spatial variability of bird species richness at a quarter degree spatial resolution, revealing a robust positive correlation between species richness and maximum average NDVI [21]. Another study by Huang et al. [5] employed the Google Earth Engine to assess urban green spaces in 28 cities using NDVI. The authors found that NDVI provided reliable information about the distribution and connectivity of green areas within the urban landscape. This approach allowed for a comprehensive understanding of urban vegetation cover, which serves as critical habitat for various plant and animal species. Also, Benedetti et al. [22] present a comprehensive meta-analysis investigating the significance of urban green spaces in promoting avian biodiversity in urban environments using NDVI as an indicator of urban greenery.

Furthermore, Turner et al. [23] emphasized the significance of using free and open-access satellite data, including NDVI, for biodiversity conservation in urban areas. Such data facilitate monitoring urban green spaces and their contribution to biodiversity. Using satellite imagery and NDVI, researchers can assess the distribution and health of vegetation cover in urban environments, aiding in identifying potential biodiversity hotspots and informing conservation strategies.

NDVI also contributes to the indirect approach in assessing species composition, abundance, and distribution. Various aspects of vegetation condition, derived from vegetation indices like NDVI, can aid in mapping environmental variables that indicate species composition, abundance, and distribution based on biological principles [16,19]. As an illustration, the occurrence and distribution of the locust species in Mauritania were explained using high NDVI values derived from NOAA/AVHRR satellite imagery as indicators of high resource abundance [24]. Overall, NDVI plays a pivotal role in both direct and indirect approaches to studying species occurrence and distribution, making it an indispensable tool in biodiversity assessment and conservation. Finally, satellite imagery has allowed identifying potential biodiversity hotspots and assessing ecosystem health in urban areas [16,23]. Pettorelli et al. [16] emphasized the relevance of satellite-derived essential biodiversity variables, including NDVI, for monitoring and conserving global biodiversity patterns.

Despite the valuable contributions of satellite imagery and NDVI, certain limitations, and research gaps remain in this field. First, while NDVI provides information on vegetation density, it may not capture species-specific biodiversity patterns or account for non-vegetation-dependent biodiversity components [23,25]. As a result, assessments solely based on NDVI may overlook essential aspects of urban biodiversity. Also, the applicability of satellite imagery and NDVI can be limited in densely urbanized areas with high levels of impervious surfaces and limited vegetation cover [4,25]. In such cases, the accuracy and sensitivity of NDVI as a biodiversity indicator may diminish. Finally, the resolution of satellite imagery may influence the accuracy of biodiversity assessments. Low-resolution imagery may not adequately capture fine-scale urban biodiversity patterns, whereas high-resolution imagery may be resource-intensive and limited in availability for all cities [26]. In this paper, we examine the main drivers behind changes in urban vegetation trends using NDVI to indicate potential impacts on biodiversity richness in 65 cities in the U.S., Mexico, and Colombia. The analysis presented in this paper will help examine how environmental factors could play a significant role in biodiversity management in these cities, considering possible future risks from climate change.

## 3. Scope and Context

Globally, anthropogenic activities have significantly altered approximately three-quarters of the terrestrial land surface and subjected around two-thirds of the oceans to severe threats. Moreover, over 85 percent of wetland areas have experienced substantial destruction. These human interventions have resulted in a decline of more than 20 percent in the average abundance of nonhuman species within their native habitats. Additionally, approximately 1 million species are now on the brink of imminent extinction [27]. Urbanization exerts substantial negative impacts on global biodiversity. Notably, approximately 60 percent of urban areas projected to exist in 2050 are yet to be developed [28]. The expansion of urban land cover has been relentless, with an annual increase of nearly 10,000 km$^2$ between 1985 and 2015 [29]. Over the period from 1992 to 2000, urban growth resulted in the loss of 190,000 km$^2$ of natural habitat, and by 2030, an additional 290,000 km$^2$ of natural habitat is anticipated to be at risk [30]. Given the growing impacts of urbanization on biodiversity richness in cities, we focus on examining current trends of urban vegetation through an assessment of NDVI to indicate potential effects on biodiversity management under climate change challenges. We chose 65 cities in biodiversity hotspots in the U.S., Mexico, and Colombia based on Atlas of The End of World [31], as illustrated in Figure 1 below.

Within the U.S. context, there are numerous growing challenges to biodiversity richness in cities. For example, New York City, located within the North American Coastal Plain biodiversity hotspot, faces the challenge of maintaining biodiversity amidst intense urbanization. Central Park serves as a prime example of an urban green space that hosts various bird species, including migratory birds. However, climate change poses a significant threat to avian populations in the city. Rising temperatures and altered migration patterns may disrupt the timing of breeding and food availability for migratory birds [32]. Furthermore, increased heat stress and reduced habitat availability could exacerbate the risk of extirpation for local species. Another example is Los Angeles, which showcases the complex interactions between urbanization, climate change, and biodiversity. Urban expansion has resulted in habitat loss and fragmentation, impacting wildlife such as the California gnatcatcher, which relies on native coastal sage scrub habitats. Moreover, increasing temperatures and drought conditions in Southern California may exacerbate the threat of wildfires, further affecting biodiversity [33].

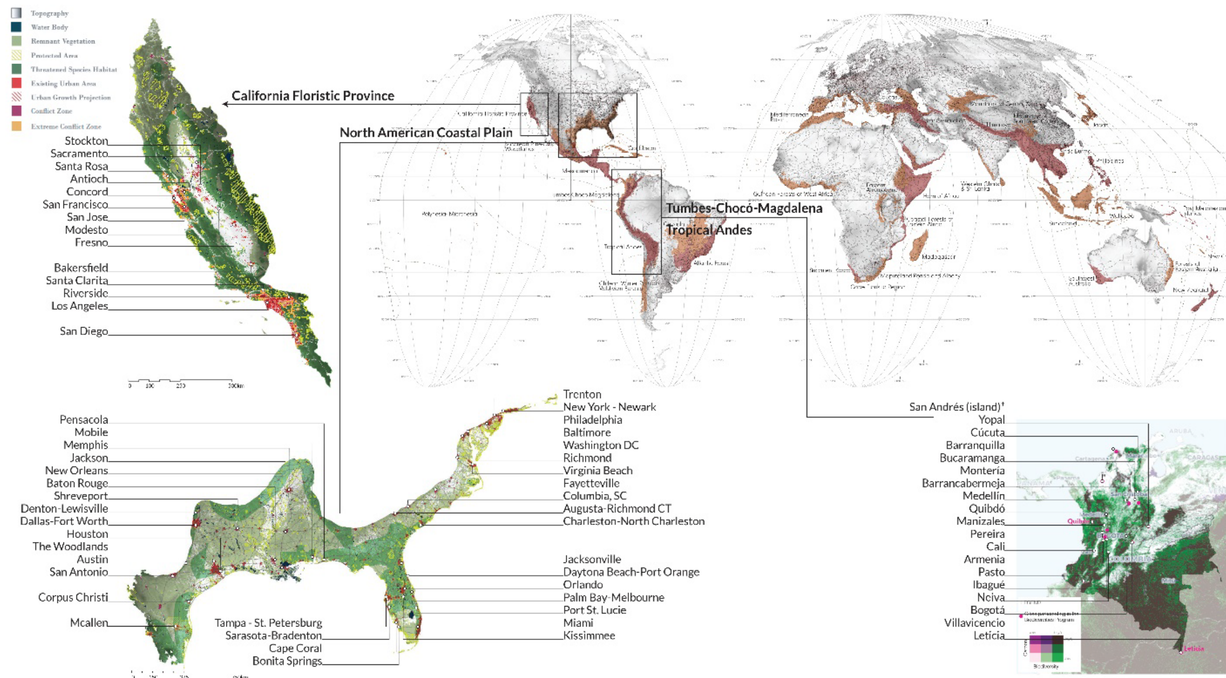


Figure 1: Biodiversity hotspots in the U.S., Mexico, and Colombia and the associated 65 cities examined in the paper [31].

In the context of Mexico, Mexico City lies within the Mesoamerican Biological Corridor biodiversity hotspot. The city's rapid expansion has led to habitat destruction and fragmentation, putting immense pressure on biodiversity. Climate change further exacerbates the situation, with altered precipitation patterns affecting water availability for wildlife and urban residents [34]. For Monterrey City, one of the primary drivers of biodiversity loss is habitat destruction due to urbanization. The expansion of infrastructure, residential areas, and industrial zones has cleared natural habitats such as forests, grasslands, and wetlands. Consequently, many native plant and animal species have lost their homes, leading to population declines and local extinctions (Kong-A-Siou et al., 2017). The fragmentation of remaining natural areas further isolates populations, reducing genetic diversity and hindering species' ability to adapt to changing environmental conditions [35].

Colombia, known for its remarkable biodiversity, is home to several biodiversity hotspots, including the Tropical Andes and the Tumbes-Choco-Magdalena. However, rapid urbanization in cities within these hotspots poses significant threats to the country's unique and diverse flora and fauna. The expansion of urban areas has led to habitat destruction, fragmentation, and increased pollution, resulting in the loss of critical ecosystems and native species. As the capital of Colombia and located within the Tropical Andes biodiversity hotspot, Bogotá faces substantial challenges in preserving biodiversity amid urban growth. The city's expansion has led to the clearance of natural habitats and increased air and water pollution. For instance, the destruction of native páramo ecosystems surrounding Bogotá threatens unique species, such as the endemic frailejones (Espeletia spp.), which are vital for water regulation and carbon storage [36]. Also, Medellín, situated within the Chocó-Darién-Western Ecuador biodiversity hotspot, has undergone significant urbanization in recent years. The city's expansion has resulted in the loss of vital habitats, including cloud forests and riparian areas, affecting diverse plant and animal species. For instance, the critically endangered Antioquia Brush-Finch (Atlapetes blancae) faces severe threats due to habitat destruction and fragmentation in the surrounding regions of Medellín [37]. Furthermore, pollution from urban runoff affects local waterways and the aquatic biodiversity of the city.

## 4. Methodology

To examine trends of urban vegetation coverages and how environmental factors and urbanization can influence biodiversity richness in cities, we assess urban vegetation trends through three key steps; first, we calculate NDVI, Precipitation, and Land surface temperature (LST) for the 65 cities using satellite imagery and Functional Urban Area (FUA) as the boundary definition of each city. Second, we assess the statistical relationship between NDVI, Precipitation, and LST to examine the effect of these two climatic factors on urban vegetation coverage. Finally, we cluster the trends across metrics with KMeans clustering to highlight which cities have the highest opportunities for biodiversity richness, as shown in Figure 2. Opensource data sets from The National Centers for Environmental Information were used to calculate NDVI for 65 cities examined in this paper from 2016 to 2021. We also calculate precipitation and Land Surface Temperature (LST) to examine the effect of climatic factors on increasing or decreasing urban vegetation coverage as an indicator of potential stress on biodiversity richness.

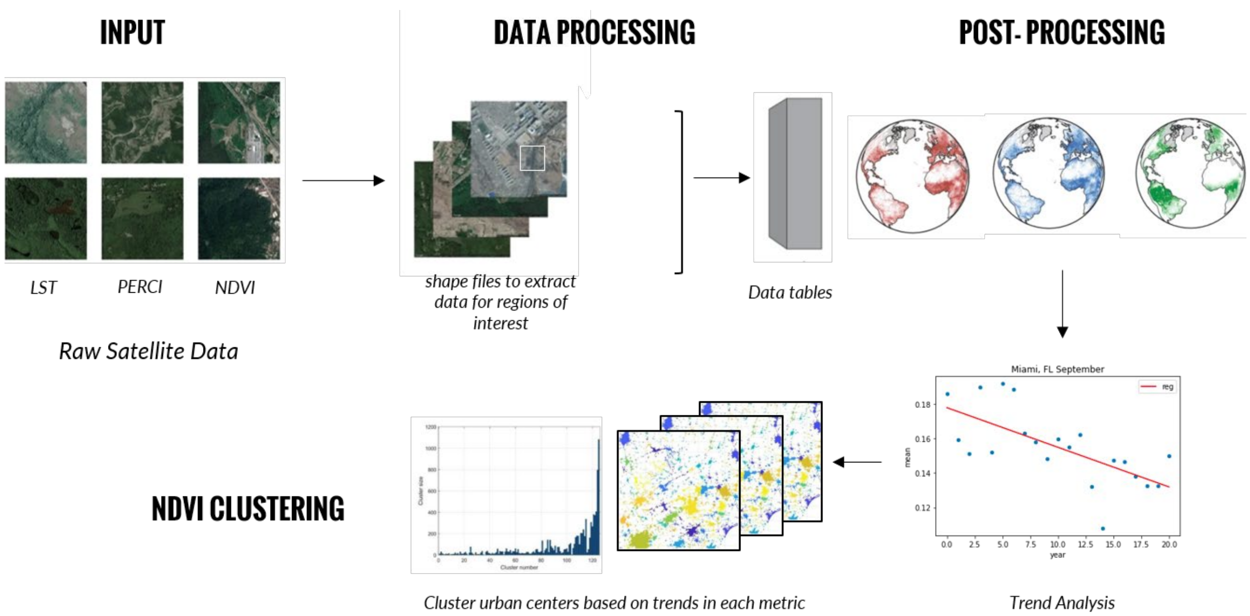



Figure 2: Framework of NDVI calculation and biodiversity trends assessment.

The data was collected using Visible/Infrared Imager/Radiometer Suite (VIIRS) sensors onboard the NPOESS Preparatory Project (NPP) spacecraft launched by NASA and the JPSS launched jointly by NOAA and NASA. These images are available in .nc files which can be loaded into georasters. Two main products are generated from the satellite images. The first is the Bidirectional reflectance distribution function (BRDF)-corrected Surface reflectance and associated Normalized Difference Vegetation Index (NDVI) from the VIIRS sensors. Quality information such as cloud state, cloud-shadow flags, and overall aerosol quality flags are given along with the images. The outputs are mapped daily onto a 0.05°x0.05° grid, corresponding to a 3600x7200 array over the globe, and we used the generated global CMG-grid daily L3 NDVI product. The VIIRS instrument has 22 channels; the one responsible for NDVI is the first and second high-resolution image band or the I1 and I2 bands. The I1 band has a center of .64 microns and a full width at half maximum of 0.075. The I2 band center is 0.865 microns, and the full width at half maximum is 0.039. Table 1 below shows the technical specifications of the VIIRS sensor.

Table 1: Technical specification of the VIIRS sensor [38]

| | |
|---|---|
| Orbit: | 830km, 1:30 pm means local solar time. sun-synchronous, polar |
| Repeat Cycle: | 16 days |
| Swath Dimensions: | 3000km, nearly global coverage every day |
| Weight: | 275kg |
| Spatial Resolution: | 750m |
| Data Rate: | 5.9 Mbps |
| Quantization: | 12 bits |
| Field of View: | Deg |
| Wavebands: | 9 visible/NIR bands plus day/night pan band<br>8 mid-IR<br>4 L.W. I.R. |
| Design Life: | Seven years |
| Duration: | Operational |

We computed the NDVI for each urban center as follows:

$$\mathrm{NDVI} = \frac{\rho\mathrm{NIR}-\rho\mathrm{red}}{\rho\mathrm{NIR}-\rho\mathrm{red}} = \frac{(\mathrm{I2}-\mathrm{I1})}{(\mathrm{I2}+\mathrm{I1})} \qquad \text{Equation (2)}$$

Equation 2 quantifies the ratio of the difference between the near-infrared band (NIR) and the red band (R) to the sum of these two bands. In this case, the first image band, I1, is the red band, and the second image band, I2, is the near-infrared band. The dataset has quality assurance as flag bits on layers in generated NetCDF files. The CDR code is run on an 8-core 2.5GHz 64-bit Xeon server, running CentOS Linux 3.10 x86_64. The code was compiled with C-compiler GCC 4.8.5. The main C-libraries were: HDF5 1.8.12, HDF 4.2r10, NetCDF 4.2, Zlib 1.2, and szip. A whole year of NPP09C1 and NPP13C1 products are processed in 3.5 days corresponding approximately to a 100x speed.

We used google earth engine's SPEIbase, Standardized Precipitation-Evapotranspiration Index database, Version 2.8, to calculate precipitation for each city [39]. The dataset provider is The Spanish National Research Council (CSIC), and it has monthly precipitation values with a 0.5-degree pixel size. The land surface temperature data came from google earth engine's MOD11A1.061 Terra Land Surface Temperature and Emissivity Daily Global 1km [40]. The dataset provider is NASA LP DAAC at the USGS EROS Center; it has daily values in 1 km squares. The temperature value is derived from the MOD11_L2 swath product. Above 30 degrees latitude, some pixels may have multiple observations where the criteria for a clear sky are met. When this occurs, the pixel value is the average of all qualifying observations. Daytime temperature observations were used for the paper to examine effects of changing temperature on urban vegetation coverage.

## 4.2 Urban Boundary Extraction

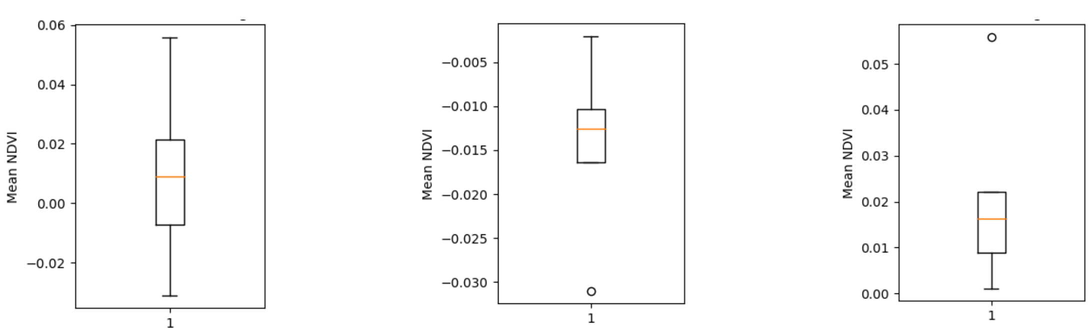
To extract the boundaries of the 65 examined urban centers, we used the Functional Urban Area (FUA) definition according to the United States Census Bureau, National Institute of Statistics and Geography (INEGI), and the Agustín Codazzi Geographic Institute (IGAC) for the U.S., Mexican and Colombian cities respectively. We chose the shape file for each city representing the municipality's FUA. The Functional urban area (FUA) is defined as having a core city and the surrounding commuting zone. FUAs outline a city's functional and economic extent based on people's movements [41,42]. FUA guarantees a link to the government level of a city or metropolitan area while providing a visual for the city's area of influence. The definition of an urban center in FUA is a cluster of contiguous grid cells with a population density of at least 1500 residents per square kilometer and a total population of at least 50000 people in total. A commuting zone includes the local administrative units where at least 15% of the workforce commute to the city. This is determined from commuting data. There are some instances where an area satisfies the conditions of a commuting zone for more than one city; this case is referred to as a polycentric functional urban area (PFUA); in our dataset, Palm Coast, Daytona Beach, Port Orange in Florida is an example of a PFUA.

## 4.3 Data Processing

The data processing was conducted using Python 3 and leveraging the following libraries: pytorch, numpy, pandas, geopandas, sklearn, and xarray. The inputs are the raw satellite images and shape files corresponding to the 65 urban centers. The satellite images are easily mapped to a 2-dimensional array with dimensions based on the resolution. For faster computation, the NDVI values were mapped to a torch tensor. To extract the values for the municipality, a binary mask of NaNs and 1s with the exact dimensions of the satellite image was created with the one value in the pixels the municipality is present in. Torch makes the element-wise multiplication quick, resulting in an array of NaN with the municipality NDVI values. Means, maxes, mins, and medians were extracted, ignoring the NaN values, and entered into a data frame with the date of the satellite photo. After extracting the data for all the years of interest (2016-2021), each city's differences were calculated. With these differences, quartiles were found and used to define three categories of trends; increasing, decreasing, and stabilizing cities were labeled accordingly. After labeling each urban center as increasing, decreasing, or stabilizing, we clustered the trends across metrics with KMeans clustering. Then we compared the similarities between the generated clusters and the manually labeled buckets.

## 5. Results

Figure 3 shows Whisker plots of the net NDVI change for all 65 cities, the urban centers classified as decreasing and the urban centers classified as increasing. The stabilizing cities live between the two latter plots, which is the center of the first plot.




All 65 Cities | Decreasing Cities | Increasing Cities

Figure 3: Net change in NDVI between 2016 – 2021 for all 65 cities, cities with decreasing trend in NDVI, and cities with increasing trend.

When looking at all centers of interest, the minimum, first quartile, median, third quartile, and maximum are as follows (-0.031, -0.0073, 0.009, 0.021, 0.055). The median shows that NDVI generally slightly increases over the 2016-2021 window. Part of this can be likely credited to COVID-19 and the subsequent lockdown stalling construction projects and people staying home, making it harder for people to make decisions to impact greenery negatively. The KMeans clustering was used to find the most similar cities based on monthly NDVI, precipitation, and surface temperature. The elbow method was used to determine the optimal number of clusters. The elbow method determines the cost of the distance function when clustering with different values for k or the number of clusters. The within-cluster sum of square (WCSS) is plotted against the corresponding k value, and the choice is the smallest value of k with a low WCSS. The chosen value of k is 3, and the three final clusters for 65 cities are illustrated below with spider graphs in Figure 4.

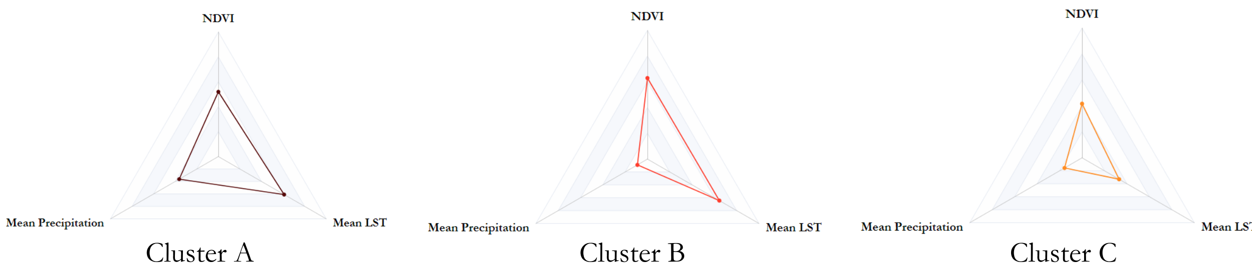



Figure 4: The 3 clusters for 65 cities across the mean of NDVI, Precipitation, and LST between 2016-2021

To prevent LST from dominating the clustering, all three dimensions were normalized within the dataset to values between 0 and 1. The LST could dominate the decision boundaries due to a difference in the magnitude of the values in its range. From Figure 4 above, cluster A contains cities with higher precipitation, surface temperatures, and middle NDVI values than the other clusters. Examples of cities in this cluster are Tampa, St. Petersburg, Orlando, and Baton Rouge in the summer months. Cities like Medellín, Neiva, Quibdó, and Miami have high temperatures and rainfall most of the year. Cluster B contains cities with higher NDVI, surface temperature, and low precipitation values. Examples of cities in this cluster are Los Angeles, Long Beach, and Anaheim for most of the year and Guadalajara and Cali in the dry season. Finally, cluster C includes cities with lower surface temperatures, moderate precipitation, and low NDVI values. Examples of cities in this cluster include Memphis, New York City, Newark, and Washington D.C. in winter and Bogota during the rainy season. We also examined the relationship between cities' FUA and mean NDVI and there does not appear to be a correlation between them.

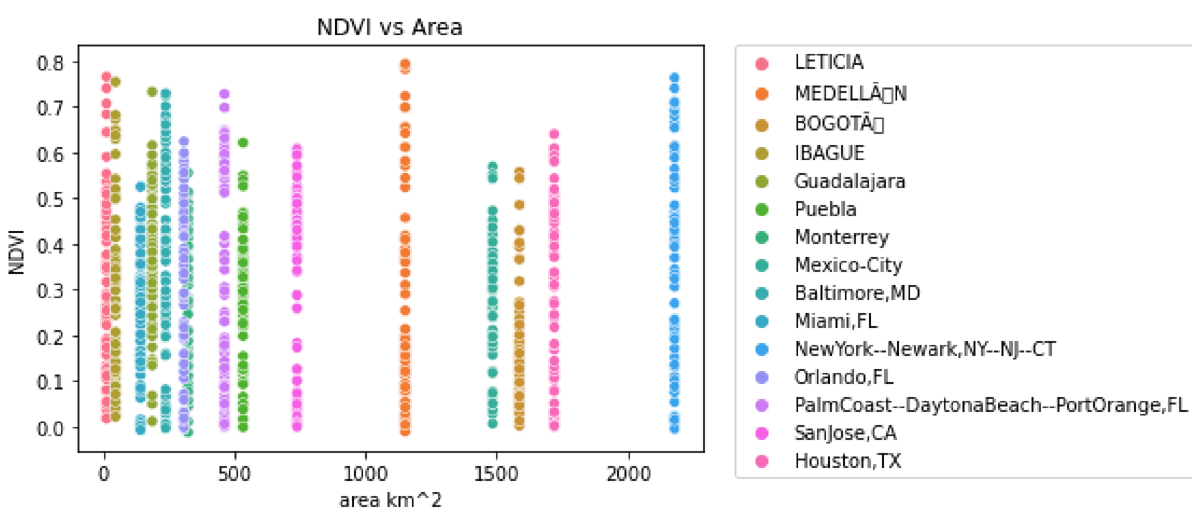



Figure 5: Correlation analysis between NDVI and FUA across the 65 examined cities between 2016 to 2021.

In cluster A, 14.7% of cities showed a decreasing trend in NDVI values, 58.8% had an increasing trend, and 26.5% stabilized over the 2016-2021 time period, as shown in Figure 6 below. For example, Medellin showed a decreasing trend in NDVI, San Jose had no change in NDVI between 2016 and 2021, while Miami showed an increasing trend. In cluster B, 23.1% of cities in this cluster had a decreasing trend in NDVI values, 51.3% had an increase in NDVI, and the remaining 25.6% stabilized. Examples of cities with a decreasing trend in cluster B are Los Angeles, Long Beach, and Anaheim in California. In cluster C, 23% of the cities in that cluster had a decrease in NDVI between 2016 and 2021, like Sacramento, CA; 51.3% showed an increase, such as Virginia Beach, VA and 25.7% had no change in NDVI values; like New York, Newark, and New Jersey in N.Y. This analysis showed two key findings: most examined cities in U.S, Mexico, and Colombia had an increasing trend in NDVI compared to cities with a decreasing trend. Also, most cities with similar trends in the U.S. were located in the same state, which implies the role of state-level policies in preserving the natural ecosystem at the city level.

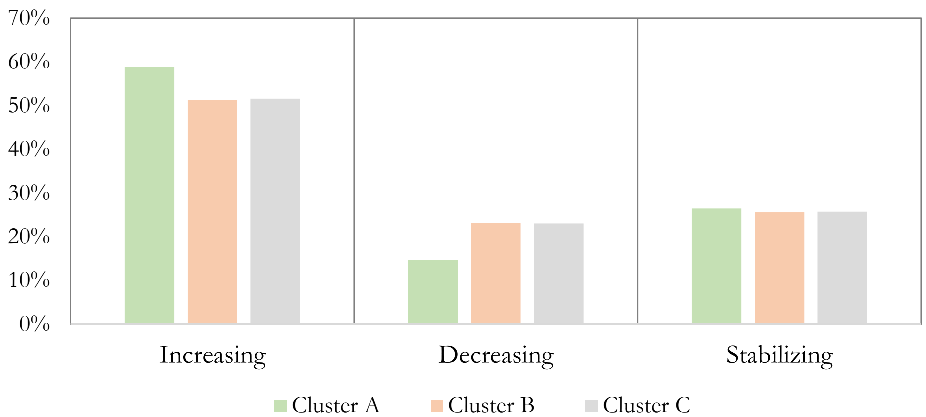



Figure 6: Distribution of cities with increasing, decreasing, and stabilizing NDVI trends across the three main clusters.

Multiple avenues exist to advance the analysis presented in this paper and achieve new insights. The shapes of the clusters may offer a clue about the correlations of these dimensions. To uncover these correlations across metrics using a Pearson's r test or a chi-squared correlation. If the metrics are correlated, it offers a more straightforward space to cluster, reducing computation time and complexity. Unlike clustering through normalized values of each metric, time-based clustering can be performed on the year-to-year trends of each metric to find which cities are changing the most and which are significantly similar. For example, If two cities mitigate urban heat island effects under the precipitation levels and NDVI, they will be grouped in the same cluster.

The clusters presented in this paper can offer significant opportunities between similar cities in the same cluster to advance policies in biodiversity management. For instance, two cities with similar climatic conditions and NDVI trends can establish policies relevant to biodiversity management, improving communication and expertise sharing between cities. Also, establishing clusters based on historical trends can help predict how cities may change from one cluster to the other in the future, which can assist in evaluating which policies can have the highest impacts on biodiversity opportunities. Leveraging both forms of clustering offers a pipeline where a city can find scenarios in other cities that are similar within the same cluster based on its current state of NDVI and climatic conditions. Consequently, cities can establish goals of increasing NDVI and lowering LST through successful policies in the same cluster. The time-based trend clustering can guide other cities' policies and define pathways for policymakers toward the sister city they want to emulate in the same cluster. Future expansion for the work presented in this paper will focus on examining the relationship between increasing trends of NDVI, associate policies in leader cities, and a detailed assessment of species richness that can be correlated to these trends.

## 6. Conclusion

The considerable variation in the quality of life within and among cities worldwide highlights the significance of addressing urban biodiversity and nature in the context of urbanization. Rapid urbanization often leads to the emergence of informal settlements, posing risks to the health and wellbeing of human communities and natural ecosystems, as supported by the interconnectedness advocated in the One Health approach. Integrating nature-based solutions into problem-solving strategies within informal settlements presents a viable pathway for sustainable urban development incorporating considerations for nature and biodiversity. The assessment of urban biodiversity is paramount due to the increasing global trend of urbanization. As cities expand and human populations concentrate in urban areas, the impact on natural ecosystems and wildlife becomes profound. By utilizing NDVI and satellite imagery, we can gain valuable insights into the distribution and health of urban vegetation, which serves as a crucial indicator of urban biodiversity. Understanding vegetation dynamics in cities enables us to identify areas of high biodiversity value and potential opportunities for conservation and restoration.

Cities have the potential to play a pivotal role in preserving the natural ecosystem, even within their dense urban landscapes. By recognizing the importance of biodiversity and integrating it into urban planning and development, cities can create more sustainable and livable environments for both humans and wildlife. Several key strategies can be employed to preserve the natural ecosystem within cities:

a. Urban Green Spaces: Creation and maintenance of urban green spaces, such as parks, gardens, and green corridors, provide essential habitats for native flora and fauna. These green areas act as refuges for biodiversity and contribute to ecological connectivity, facilitating species movement and gene flow.
b. Nature-Based Solutions: Implementing nature-based solutions, such as green roofs, green walls, and rain gardens, can enhance urban biodiversity while mitigating the impacts of urbanization, such as urban heat island effects and stormwater runoff.
c. Ecological Restoration: Engaging in ecological restoration projects within cities can help revitalize degraded areas and bring back native plant and animal species. Restored ecosystems contribute to the overall ecological health of the city and promote a more balanced and resilient urban environment.
d. Wildlife-Friendly Infrastructure: Incorporating wildlife-friendly infrastructure, such as wildlife corridors and wildlife crossings over roads, helps reduce the fragmentation of habitats and supports the movement of urban wildlife.
e. Public Education and Engagement: Raising public awareness about the importance of urban biodiversity and involving citizens in conservation efforts fosters a sense of stewardship and collective responsibility for preserving the natural ecosystem within cities.

Assessing urban biodiversity using NDVI as a metric for urban vegetation is an interesting approach to understanding vegetation dynamics and cities' biodiversity opportunities. This paper has highlighted the importance of examining biodiversity opportunities within cities and the role that cities can play in preserving the natural ecosystem. By adopting proactive strategies and integrating nature into urban planning and development, cities can take significant steps toward creating sustainable and biodiverse urban environments. As urbanization continues to accelerate globally, these efforts become even more critical to safeguarding the natural world and promoting harmonious coexistence between urban residents and the diverse flora and fauna that enrich our cities.

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