Urban Revival: Analyzing urbanization through changing land cover and its effects on surrounding communities

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Abstract

Urban development is altering land cover globally, impacting ecosystems, biodiversity, and climates. Our study investigates how satellite imagery and remote sensing can identify patterns of urban development and analyze related environmental changes. We used initial field observations from the GLOBE Observer App, where citizen scientists collect high-resolution, ground-level, using their smartphone cameras. Each observation included geotagged photographs taken in standardized directions. This data revealed that existing land cover classifications varied in accuracy, prompting our investigation into their value and in future research. This led to our primary research question: How effectively can remote sensing detect urban expansion and its impacts on surrounding communities? Using urban cities like Chicago, Atlanta, Los Angeles, Detroit, and Austin, we studied impacts such as green space gains/losses, heat island formations, and nighttime brightness changes. To do this, we utilized Landsat and Sentinel-2 imagery, NDVI, ECOSTRESS, and VIIRS data. Integrating multiple remote sensing datasets, we trained a machine learning model that classified geographic zones into three categories of development: regenerative, unequal, and stable. This classification differentiated areas that experienced positive environmental and urban recovery, harmful development, and minimal change. Our findings demonstrate that remote sensing can reveal patterns of urban growth and their impact on communities. Moving forward, the zone classifications could be used as a valuable resource for urban planners and local communities. By identifying areas at risk of environmental degradation, intervention could be more targeted and effective. This framework could also be extended to other cities to support global comparisons of urban development.

Keywords: Urbanization, Satellite, Regeneration, LandCover, RemoteSensing

Introduction

Remote sensing is crucial in a variety of scientific and commercial fields, and will only become more relevant in the data-driven world of the present and future. In environmental monitoring, remote sensing enables scientists to monitor and visualize deforestation in tropical forest areas, track the rate of desertification in arid zones, observe coral bleaching as a result of increased seawater temperatures, and monitor the retreat of glaciers and polar ice caps in the face of climate change. These observations rely on two main types of remote sensing technologies: passive and active systems. Both are essential for gathering environmental data on a global scale, with passive sensors depending on sunlight to collect reflected or emitted energy, and active sensors generating their signals to detect and measure the Earth's surface. Together, they offer complementary insights into natural and human-made changes across various landscapes and climate systems.

Remote sensing comes in two main varieties: passive and active (Remote Sensing - NASA, 2023). Passive remote sensing uses natural energy (sunlight) that naturally reflects or naturally emits from Earth's surface. For instance, cameras and satellite sensors optically collect visible, infrared, or thermal radiation. With passive remote sensing, the daylight controls what can be sensed, and passive remote sensing can be affected by factors in the atmosphere that obscure the view, such as clouds. Passive remote sensing can be either "multispectral" or "hyperspectral" (Adam, 2025). Multispectral sensors collect data in several frequency bands with a larger width, such as the Landsat satellites, which consider vegetation, water, and urban surfaces, whereas hyperspectral sensors can separate materials and surfaces by collecting hundreds of very narrow and adjacent wavelengths. In summary, passive remote sensing collects and identifies electromagnetic radiation, whereas active remote sensing sends its energy to collect or measure what comes back from those surfaces (GisGeography, 2018).

Active remote sensing can be used at night or in cloudy conditions as well. Radar systems use microwaves to obtain a reading that can penetrate clouds that are visible on images and to plot the relief of land surfaces, glacier lines, ice sheets, map mountain heights down to the soil surface, and the level of moisture in the soil. Laser Light Detection and Ranging, or LIDAR, sends laser pulses and records the length of time for the pulse from the satellite to the surface and back to the system (Remote Sensing - NASA, 2023). When it can collect very precise elevation, a Lidar system is capable of making very accurate 3D maps of urban and land features and is popular for forest management and urban modelling.

Satellites like the Sentinel-1, Sentinel-2, WorldView-4, and Landsats 5-9 play a vital role in tracking and analyzing land cover changes, especially in the context of urban development, land use planning, and environmental monitoring. Each of these satellites brings unique capabilities that, when combined with ground observations like those collected through NASA's GLOBE Observer app, provide an accurate picture of how landscapes are transforming over time.

Sentinel-1, operated by the European Space Agency, is an active radar satellite that uses Synthetic Aperture Radar (SAR) to collect data regardless of weather or sunlight conditions. This makes it especially useful for monitoring surface changes such as urban expansion, deforestation, or flood impact, even in cloudy or nighttime conditions. It is also greatly useful in detecting surface roughness, built-up areas, and even moisture levels in soils, which are all relevant for tracking how natural land is converted into impervious surfaces during urban revival projects (Shimelis Sishah Dagne et al., 2023).

Sentinel-2, on the other hand, is a passive multispectral satellite that provides high-resolution optical imagery across 13 bands, including visible and near-infrared, allowing detailed observations of vegetation health, surface reflectance, and land cover classification (Xu et al., 2022). Its data is crucial in distinguishing between vegetation, water bodies, bare land, and urban features (Phiri et al., 2020).

The Landsat series, particularly Landsats 5 through 9, is among the most historically valuable Earth observation satellites due to their consistent, long-term imagery, which dates back to the 1980s. Landsat 5 operated for almost 29 years, while Landsats 7, 8, and 9 continue to build on this archive with increasingly advanced sensors like the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) (Landsat Applications | Landsat Science, 2013). These instruments allow for the monitoring of urban sprawl, vegetation cover loss, heat islands, and changes in water usage. Landsat imagery is especially helpful in conducting temporal analysis, where researchers can compare imagery across decades to detect patterns of land degradation or recovery.

WorldView-4, a high-resolution commercial satellite, offers imagery with sub-meter spatial resolution, making it ideal for detailed mapping of urban infrastructure such as roads, buildings, and individual plots. Though its mission ended in 2019, the data it produced remains relevant for high-precision studies and urban planning.

When paired with GLOBE Observer app data, these satellites aid in validating remote sensing models and improving classification algorithms. Ground truthing with GLOBE ensures that what satellites observe aligns accurately with real-world conditions, which is essential for urban planning, conservation, and environmental justice. The integration of satellite data and GLOBE observations strengthens the reliability, trust, and resolution of land cover maps, enabling urban planners and scientists to make informed decisions about sustainable development, green space preservation, and the long-term effects of urban revival efforts on surrounding ecosystems (Observer, n.d.).

Discussion

The aforementioned satellites were utilized to aid in the production of certain datasets that we extensively used to help classify land cover data in our poster. We recorded 36 points of interest during our time at NASA, and we took 216 photos from just the GLOBE Observer app. We also had to use the Tree Canopy, World Cover, Sentinel 2, ESRI, Landsat Time Series, and Collect Earth Online.

The META/WRI Global Canopy Height dataset mainly showcased how much tree cover was in each of our selected points. This dataset helped show the heights of tree canopies all around the world, which helped us understand how forested an area was and how dense the vegetation might be. The data uses AI models like DiNOv2 and satellite images, mostly from 2018 to 2020, to predict tree heights with high accuracy (within 2.8 meters on average) (Tolan et al., 2024). This made it useful for comparing different locations in our AOI, or area of interest, as we were able to classify how much greenery or forest structure was actually present. Overall, the dataset helped us see which areas were more natural versus built-up based on how many tall trees and overall vegetation were still around.

The European Space Agency (ESA) WorldCover 10m dataset helped us compartmentalize what kind of land was at each of our points. The dataset included classifications for areas such as trees, built-up (urban), shrubland, grassland, cropland, barren or sparse vegetations, snow and ice, open water, mangroves, wetlands, and finally, moss and lichen (ESA WorldCover 10m V100 | Earth Engine Data Catalog, n.d.). This amount of detail made it easier for us to see what was actually on the ground in each location and correctly classify the land, as there were a plethora of classifications to accurately choose from. The 11 different land cover classes were mainly used to compare how natural or developed our area was. Utilizing the 2020/2021 version, we were able to keep in mind the disparities between the land classified then and the current situation, which was directly shown through the GLOBE Observer App.

The Dynamic World dataset, aided by the Sentinel-2 satellite, was used to obtain a more real-time look at what was happening on the ground in each of our points. This dataset updates much more frequently than the other ones as well. We utilized the yearly averaged version, which helped build an overall picture of what the land was used for during that year. This included the coverage of land by water, trees, grass, flooded vegetation, crops, shrubs and scrub, built areas, bare ground, and snow and ice (Brown et al., 2022). Dynamic World helped double-check the consistency of other datasets, such as the WorldCover 10m, as they complement each other in a significant context of classifying land. Ultimately, the dataset helped show how the land might have changed over time or in different seasons, specifically. This classifier was especially useful in the context of urban growth and development as well.

The ESRI series, for example, classified land use and land cover globally at 10-meter resolution. It is based on Sentinel-02 imagery and also uses machine learning models to identify forests, water, agriculture, and urban areas (Roy, n.d.). There is also an ESRI Story map series that uses parents' spatial data chronologically or thematically. These data sets can also show surface evaluation and terrain analysis.

The Landsat Time Series Graphs show how vegetation, water, or urbanization has changed over time using data that is collected from Landsat data from 1970 to the present. These often show values including NDVI, surface reflectance, and land cover class. ArcGIS has apps and layers that already have Landsat time series data. As well as using Google Earth Engine, which we used a lot during our time at NASA, and this is the most powerful tool for Landsat time series analysis. Ways to use the Landsat time series include deforestation, urban expansion, glacier retreat, agricultural patterns, fire or drought recovery (Landsat Time Series Explorer, 2025).

Our final thing apart from our poster is we used Collect Earth Online designed for sampling based data that we used during Landsat, Google Earth, or Sentinel- 2. The ways we used Collect Earth Online include viewing satellite imagery from multiple dates for the same location, classifying land cover use from sample plots, we also exported our data to use for machine learning, and we also collaborated within our groups about the data that we collected. We often use Collect Earth Online to determine deforestation, agricultural land use, urban sprawl, use for machine learning, and land degradation. We used it overall to view time series imagery, create samples, and to view deforestation, urban development, and agriculture (Collect Earth Online, 2025).

We used the GLOBE Observer app to collect and submit environmental observations to areas where we lie. There are multiple different tools apart from the app but we primarily focused on which was Land Cover. Land Cover refers to physical materials on the Earth. For example, grass, trees, concrete, water, or soil. Since we classified the things in our areas that were on the ground we were able to see over time the urban development, agriculture, deforestation, and climate change in our desired area (Observer, n.d.).

The process of taking the Land Cover Photos in the GLOBE Observer App was challenging and accurate. It was hard to find 37 points in our area that didn't necessarily look the same. After finding that some things are going to look the same, we found the 37 points and decided to take the points. One North, one south, one east, one west, and one up and down. We also had to make sure that the app had my location on my phone so that we could make sure it had the exact coordinates and so that others could see my images with satellite data. The one thing that was challenging while taking the photos north, south, east, and west was determining what direction we were taking the pictures in. So what we did is we used the Weather app, which has a built-in compass, to determine what direction we were taking the photos. After figuring out the direction of the photos, we sent the photos and then it proceeded to ask to estimate the percent coverage of trees, grass, buildings…etc, it asked if it was a dominant land cover, and then it mentioned if we had any additional comments, which we rarely didn’t have (Observer, n.d.). It was neat to see all the different images that we had over the 37 points on which we did, and the number of images that had built up. We submitted all the images, and we were able to view them all, which was neat and interesting.

Urban Revival is the process of old, unused, or rundown areas of a city to bring them back to life, economically, socially, and physically. This can include renovating buildings and homes, building new infrastructure, attracting new businesses, jobs, and residents, and making areas safer and cleaner. Urban development however is referring to the growth and expansion of cities including building new neighborhoods, shopping centers or highways. Urban development is expanding the cities whereas urban revival is improving older or often neglected urban areas. Features that include urban revival projects are turning abandoned buildings into apartments, creating green space or public parks, rebuilding transit systems, improving sidewalks and overall safety, and encouraging business to startup. This matters because it boosts the local economy because revived areas attract business which creates jobs. It improves the quality of life if residents benefit from safer streets, better housing, and more green space. It supports sustainable growth, revitalizing existing urban areas, reducing the need for urban sprawl by saving natural land and reducing commute times. Urban Revival/development transforms old parts of cities into thriving communities that benefit residents, business, and overall the environment (United Nations, 2023), (Xu et al., 2022).

Machine learning is how we are teaching computers to learn from experience, just like we do. We used machine learning models to help understand how land is changing over time. We use data from Landsat, Earth Map, or GLOBE Observer so that we could automatically classify land into different zones of development. The three main types were urban or developed zone, agricultural or transitional zone , and rural or undeveloped areas. The urban zone for example represents high density built areas which includes towns, cities, roads, and areas where there is large infrastructure. It included visible and infrared bands from concrete and rooftops, stable light from VIIRS, high surface temperature, and low vegetation or low NDVI. The agricultural or transitional zones are areas that are partly developed or are used primarily for farming. These include seasonal changes in vegetation so differences in NDVI, land disturbance, and the presence of soil exposure. The last area is the natural/ undeveloped zone. Those areas include forests, grasslands, wetlands, and protected natural areas with relatively no human alterations. This also includes high and consistent NDVI, low surface temperatures, no artificial light, organic land patterns. This matters because we are able to track how quickly urban areas are expanding, protect natural ecosystems that are shrinking, and be able to identify farmland and convert them into cities (SAS, 2019). Ultimately, machine learning and development help us decide about urban planning and conservation.

To answer our research question, we use a four step workflow that includes a machine learning classifier. The first step in our process was to choose cities to use as case studies. We chose five major cities in the US, including Chicago, Atlanta, Detroit, Austin, and Los Angeles. For each of these five cities, we then choose 20 specific areas that are experiencing urban change across all three of classes: regenerative, unequal, and stable. The regenerative class includes increasing green space and NDVI, decreasing land surface temperature, and other signs that indicate positive land use. The unequal class includes areas that are experiencing rapid urbanization, where land surface temperature is rising, and social effects like gentrification are taking place. Stable, the final class, includes areas that aren't experiencing changes in urbanization and land use. We determined what class each of the 20 areas belonged to through online research in news articles, scholarly papers, and manual exploration of changes in satellite data. The dataset we were able to compile serves as the foundation for the machine learning model.

The next step in the workflow is to extract satellite time series data. As mentioned before, we focus on NDVI from Landsat, Land cover change from MODIS, LST from MODIS Terra, and VIIRS nighttime light. We used the Google Earth Engine API to access all of this satellite data. Using time series data allowed us to provide the machine learning model with data that indicates change over time, which is much more valuable than static measurements like Dynamic World or Meta Tree Canopy Cover. Another source of data is census data, which indicates gentrification and other social changes in the area of interest.

The third step in the workflow is to build the machine learning classifier. We use two types of models, random forest classifier and XGBoost. The features for the model are NDVI trends, LST trends, VIIRS trends, land cover change, and census data. We then use train/test split to create a training set and test set for the different areas of interest. Finally, we are able to train the model on the training data, and evaluate the performance on the test set. To evaluate, we use metrics like a confusion matrix, accuracy, and F1-score.

With a trained machine learning model, the final step of the workflow is to apply the model to other areas of interest. This allows us to find trends in cities where we don't have to manually label the data. Ultimately, this tool can be used as a resource to determine urbanization across cities all across the country.

Conclusion

Our research demonstrates how combining satellite remote sensing, citizen science observations, and machine learning can effectively identify and analyze the environmental impacts of urban development. Beginning with field data collected through the GLOBE Observer App, we noticed inconsistencies in land cover classifications, which led us to further investigate how these changes are reflected from space. By focusing on cities like Chicago, Atlanta, Los Angeles, Detroit, and Austin, we explored key indicators such as vegetation cover, surface temperature, and nighttime brightness. Using datasets from Landsat, Sentinel-2, VIIRS, ECOSTRESS, and canopy height models, we built a comprehensive picture of land cover change and its consequences. Machine learning helped us classify zones into regenerative, unequal, and stable categories, highlighting areas undergoing recovery, areas experiencing harmful development, and those showing minimal change.

The datasets and tools we used, including Dynamic World, WorldCover, Collect Earth Online, and Landsat time series, allowed us to analyze both short-term and long-term urban trends. Ground-truthing with GLOBE data increased the accuracy of our remote sensing models and helped validate our classifications. The framework we created offers a flexible and scalable method that can be used by urban planners, researchers, and communities to track development, assess green space loss or recovery, and target areas for intervention. This project illustrates the potential of integrating multiple data sources to support more sustainable and equitable urban planning. With further refinement, this approach could be expanded globally and contribute to better understanding of how cities grow and how we can guide that growth in a more environmentally responsible way.

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Badge Description

I Work with Satellite Data

In our Urban Revival project, we used NASA satellite data to monitor and analyze urbanization across multiple U.S. cities. We were able to identify changes in land cover over time and categorize these regions into zones of unequal, stability, and regeneration by using records from Earth-observing missions like Landsat and Sentinel. By using remote sensing software such as ArcGIS and Google Earth Engine to show this satellite data, we were able to monitor the development of urban expansion and identify its effects on the environment. Our understanding of how space-based observations might be utilized to investigate land change at both the local and national levels has increased as a result of incorporating satellite imagery into our workflow.

I Am a Data Scientist

Analyzing big collections of citizen science and geographical data was crucial to our research. Across our Areas of Interest (AOIs), we analyzed data patterns, used machine learning models to classify different forms of land cover, and used confusion matrices to validate our findings. We incorporated observations from the GLOBE Observer App to support our classification results, evaluating accuracy by comparing user-submitted land cover images with satellite data. In order to better understand the difficulties of working with real-world data, we also looked at constraints in image resolution and model performance. We improved our ability to make evidence-based decisions and draw conclusions from complex datasets as a result of this process.

I Am an Earth System Scientist

As part of our Urban Revival project, we examined how urbanization influences environmental change by analyzing satellite data from multiple Areas of Interest. We discovered trends like growing development, decreasing greenery, and changed land surfaces by comparing images from various eras. Surface temperatures, stormwater runoff, and the general health of the ecosystem were all impacted by these changes. We found that whereas more stable or recovering regions displayed indications of balanced development, places experiencing fast urban growth frequently experienced environmental stress due to the loss of natural land cover. By examining these connections, we were able to see the close connection between natural systems and human activities. We gained a better grasp of the wider effects of urban land change by using this systems-based approach.

Appendix

Link to raw data:
https://github.com/sushant2082/UrbanRevivalSEES2025-