Best Practice

Qualitative Analysis of Application Remote Sensing towards the Understanding of a Rural Community

Charles Quinn[1,*], Peder V. Nelson[2], and Russanne Low[3]

[1] 11th Grade, Bernards High School, Bernardsville, NJ; https://orcid.org/0009-0003-7110-7024
[2] Oregon State University, OR; peder.nelson@oregonstate.edu; https://orcid.org/0000-0003-3979-9051
[3] Next Generation Global Observatory, NY; low.russanne@gmail.com; https://orcid.org/0000-0002-7912-4350
[*] Corresponding Author: cpquinn2027@gmail.com; +1-908-432-4880

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Abstract: Remote sensing and human observation provide the resources necessary to view changes in land cover and land use (LULC) in an area of interest (AOI). Remote sensing tools have limitations and fail to accurately summarize areas individually. However, tools can be used in collaboration with human observation in order to better analyze an area and overcome their limitations. To accomplish this, numerous datasets such as the 1984–2024 Multi-Resolution Land Characteristics (MRLC), National Land Cover Database (NLCD) Viewer, various layers available in Earth Map digital software from the baseline year 2020, 1984-2025 Landsat satellite imagery, Collect Earth Online (CEO), and ground observations from the Global Learning and Observations to Benefit the Environment (GLOBE) Observer application were synthesized and analyzed. In order to collect data from the same places across all datasets, an AOI measuring 3 km by 3 km was constructed. This AOI contained 37 kernels, each measuring 10,000 m². The kernels were constructed into a 6 × 6 matrix, and the final kernel was placed in the center, totaling 37 kernels. In analyzing these datasets holistically, inconsistencies were found between remote and ground observations. Each provided important information but was sometimes inconsistent. The synthesis of remote and ground datasets, however, was able to shed light on the LULC of the study area and provide an understanding of how it has changed over time. It was found that the study area had a relatively harmonious relationship between urban/built-up elements and vegetation, but that multiple tools were needed to draw this conclusion.

Keywords: land cover, urbanization, vegetation

1. Introduction

The land we live on is instrumental in affecting how we shape our societies, earn a living, and choose where to settle. Land naturally changes over time, but human settlement changes it, too. These changes—both natural and artificial—make up the study of land cover and land use (LULC). There are numerous ways to collect and analyze LULC data. Methods include ground observations and analysis, as well as remote sensing and aerial photography. Each tool has its respective strengths and weaknesses. This study aims to understand how different tools describe Bernardsville, NJ and shed light on Bernardsville's LULC. It is hypothesized that each method of analyzing LULC (i.e., remote sensing, ground observations, aerial images) will provide the same information and conclusions about Bernardsville, NJ. In evaluating the quality and consistency of datasets, the study attempts to recognize whether differences reflect weaknesses in the tools. The paper aims to highlight the inconsistencies in the analysis of LULC in the study area. This sort of understanding could make the region viable for a quantitative analysis described in papers such as "The Sensitivity of Mapping Methods to Reference Data Quality: Training Supervised Image Classifications with Imperfect Reference Data" (Foody et al., 2016).

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2. Study Area and Methods

2.1. Study Area

The chosen area for this study is Bernardsville, NJ. Located in central New Jersey, Bernardsville is a community of 8,020 people (U.S. Census Bureau, 2025). The town is an example of a suburb of New York City, where some residents commute for work, but it is also a rural area with dense forest and farms populated with familial estates. Bernardsville boasts a diverse population with people from a diverse set of backgrounds, including Irish, Italian, and Guatemalan. An outdoor lifestyle makes up a significant portion of community recreation as seen in town amenities such as the town pool, pickleball courts, and turf fields. Recently, Bernardsville has increasingly experienced extreme weather. Heat anomalies are becoming more prevalent, with warmer winters and summers each year. The town was also affected by Hurricanes Irene and Sandy but sustained no extreme damage, although many trees fell. A map of Bernardsville in greater New Jersey context can be seen in Figure 1.

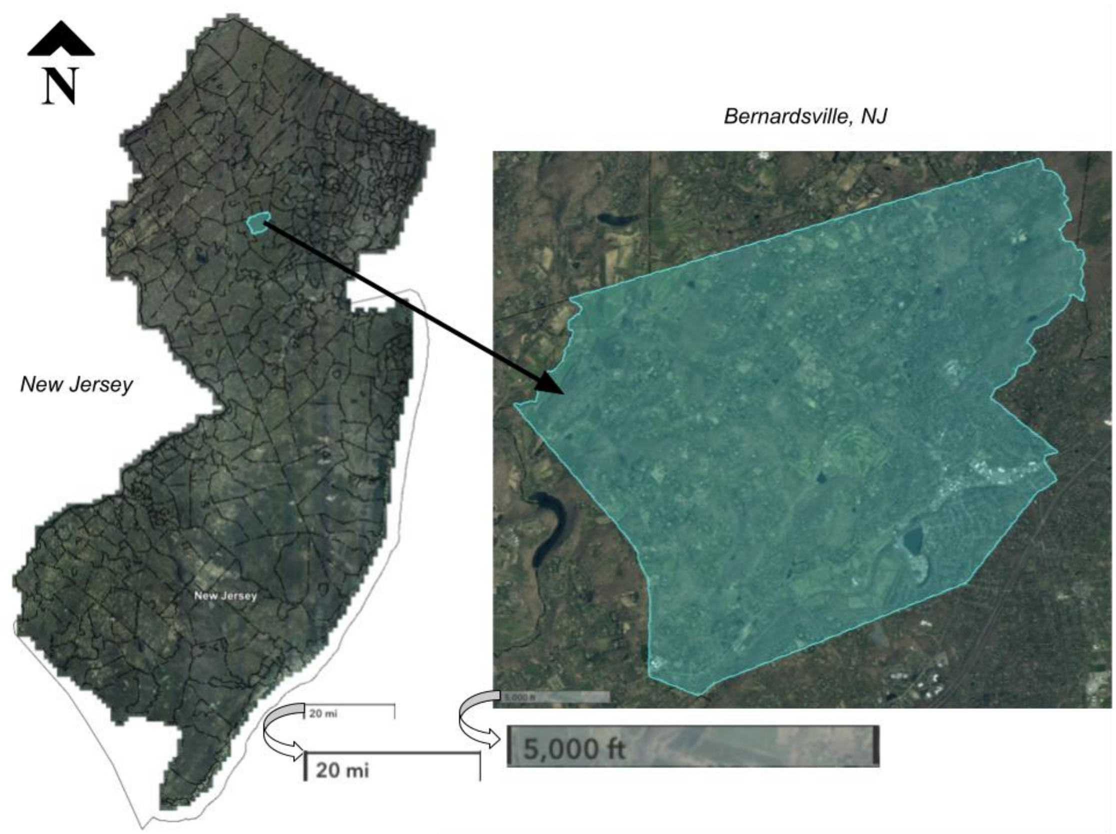

Figure 1. Map of Bernardsville, NJ, created using the NJ Highlands Resource Explorer.

2.2. Methodology and Tools

Changes in Bernardsville's land cover were documented and analyzed using multiple open-source cloud-based software tools in line with the Adopt-a-Pixel-3km (AaP3km) methodology. The AaP3km methodology is a citizen science-based approach in which a researcher selects an area of interest (AOI), divides it into evenly spaced points, and applies a variety of scientific tools to that AOI in order to analyze its LULC (Low et al., 2021). In this study, a 9 km² AOI was constructed. This AOI consisted of 36 evenly spaced points and one center coordinate, totaling 37 distinct locations. Based on the location of the centroid, some points fell outside of Bernardsville but were no more than 2,000 feet from the border. Each point was enclosed within a 10,000 m² bounding box; these 10,000 m² areas will be referred to as kernels. The kernels were numbered 0–36, where 0 was the center. Kernel one is in the bottom-left corner, and the numbering goes upwards in each column, returning to the bottom row once an entire column has been counted. The AOI grid was stored as a GeoJSON and Comma-Separated Values (CSV) file so that it could be used for different software later.

The Global Learning and Observations to Benefit the Environment (GLOBE) Observer application was used to capture ground-truth images within each 10,000 m² kernel. These images were recorded in the four cardinal directions, up, and down in each kernel. If locations were inaccessible due to private property restrictions or natural barriers, the respective ground photos do not appear in the analysis or the dataset for accuracy. These photographs were then uploaded to the GLOBE network through the GLOBE Observer application. The process of how observations are submitted on the application is outlined in Figure 2. Figure 2 demonstrates the ease with which locations can be documented and recorded. The uploading of these images allows the photos to be accessed later and ensure they were properly stored in a database.

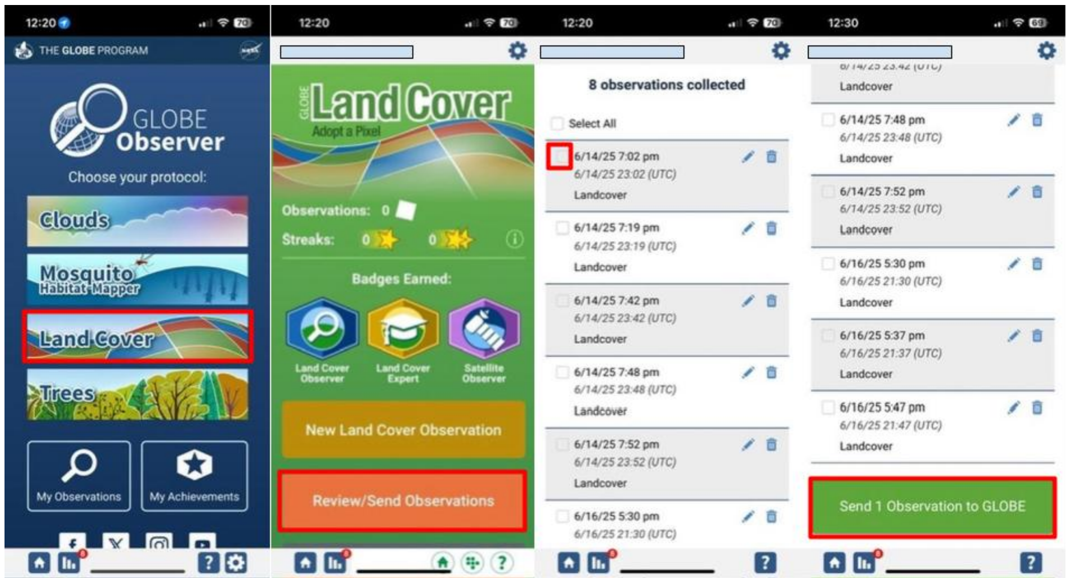

Figure 2. Example submission using the GLOBE Observer application.

The Collect Earth Online (CEO) software was then used to manually classify the land cover profile of each point using aerial photos. CEO is a service designed to bring LULC research to citizen scientists by having them classify imagery for LULC. These classifications are then applied to answer research questions or set baselines for making new satellite datasets (Saah et al., 2019). The software broke each kernel into 100 sub-points. From there, each kernel was magnified to a scale of 20 m for consistency. Then, all 3,700 generated points (37 kernels multiplied by 100 sub-points per point) were classified into one of the following categories: Trees_CanopyCover, Bush/Scrub, Grass, Cultivated Vegetation, Water > Lake/Ponded/Container, Water > Rivers/Stream, Water > Irrigation Ditch, Shadow, Unknown, Bare Ground, Building, Impervious Surface (no building), or Wetlands (Saah et al., 2019). Each filled kernel was assigned a confidence score by the user, and each kernel was assigned percentages of land cover based on the classifications of the 100 sub-points.

Earth Map's mapping software provided four different satellite datasets for the AOI and each kernel within the AOI. This information was recorded by applying the satellite dataset to a map of the AOI and then screenshotting the resulting map and bar graph generated for each kernel. Four satellite datasets were utilized: WorldView-4's Meta 1 m Tree Canopy, Sentinel 1 and 2's 10 m World Cover, Sentinel 1 and 2's 10 m Dynamic World, and Sentinel 1 and 2's 10 m ESRI. The Meta 1 m Tree Canopy package is designed to track forest ecosystems by tracking canopy height at a 1 m resolution using a mixture of temporal readings from 2009–2020 and artificial intelligence; its readings are within a mean absolute error of 2.8 m (Tolan et al., 2023). World Cover is a product designed to take readings from Sentinel 1 and 2 and classify them into one of 11 land classes at a 10 m resolution from 2020 and 2021 (Zanaga et al., 2021). Dynamic World is a satellite package that takes data from Sentinel 2 and uses deep learning to classify it; it updates with speeds as little as 2–5 days and presents the average reading of a point from the past year (Brown et al., 2022). The ESRI satellite package operates using the same satellites as World Cover and Dynamic World but runs it through an AI model trained with human classified observations into one of 9 classes of land; it has an accuracy of 75% (Karra et al., 2021). These filters were used to assess the land cover composition of an area. 2020 was used as a baseline for all four datasets in order to ensure consistency from a measuring standpoint. Figure 3 displays the resulting maps from processing the AOI with each satellite package.

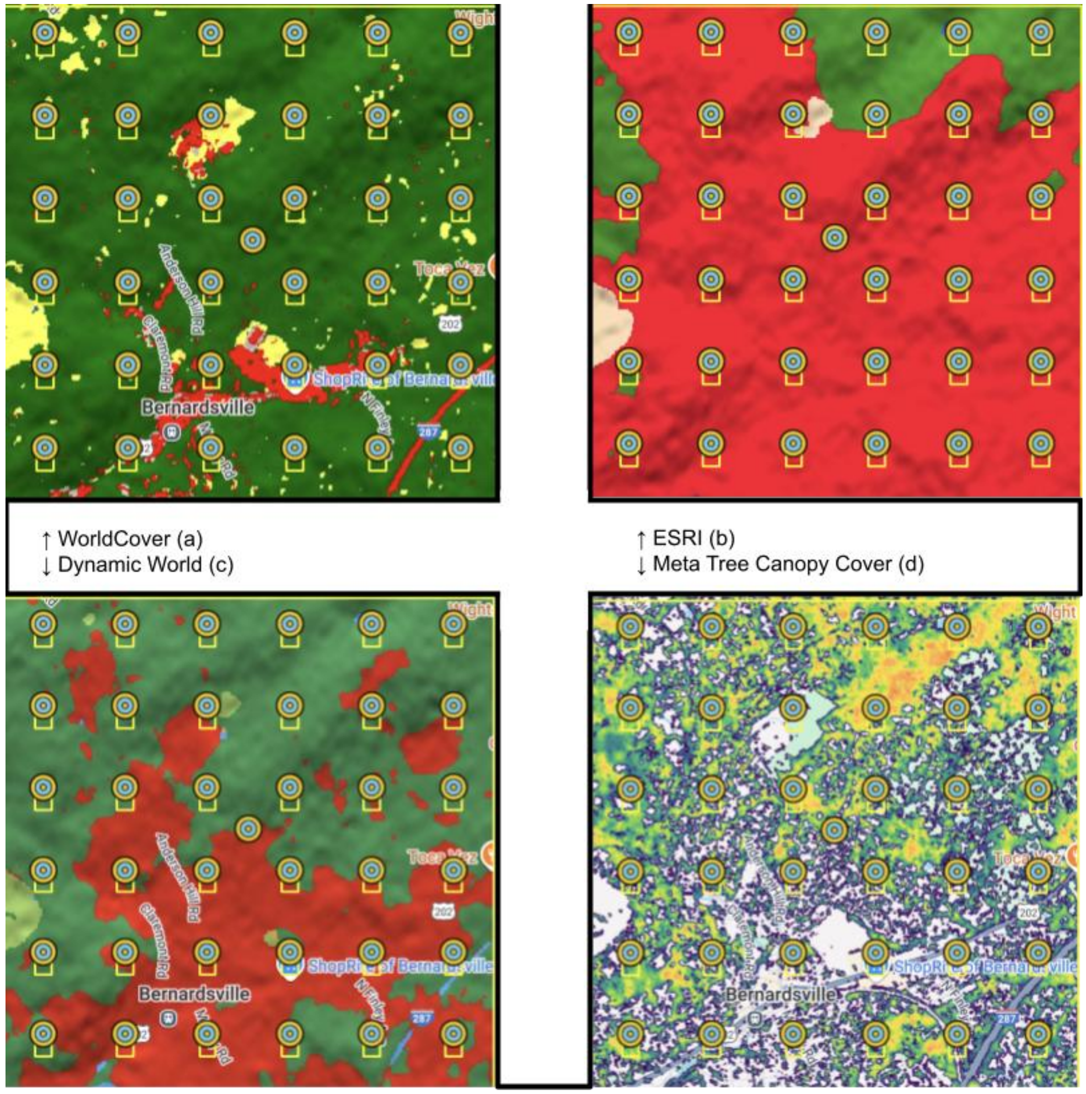

Figure 3. The AOI viewed through various satellite datasets. (a) The AOI viewed through the World Cover satellite package. Yellow refers to grassland, green to trees, red to built-up, pink to cropland, and blue to open water (Zanaga et al., 2021). (b) The AOI viewed through the ESRI satellite package. Red refers to built-up, green refers to trees, and khaki refers to rangeland (Karra et al., 2021). (c) The AOI viewed through the Dynamic World satellite package. Red refers to built-up, dark green refers to trees, light green refers to grass, and blue refers to water (Brown et al., 2022). (d) The AOI viewed through the Meta Tree Canopy Cover satellite package. Cool colors refer to trees and warmer colors refer to taller trees. All heights are on the interval 2 m to 30 m (Tolan et al., 2023).

The next remote sensing platform used was the Landsat time-series (LTS) through Google Earth Engine software. Data from the LTS were used to measure and analyze land cover change in the AOIs during the period of 1984 to 2025. To gather the LTS data for each kernel, the longitude and latitude were uploaded to Google Earth Engine, which generated an LTS map and Normalized Burn Index (NBR) graph of the region in each year from 1984 to 2025 (Gorelick et al., 2017). NBR measures vegetation health and can be used to determine whether vegetation is natural or controlled. High, scattered values indicate healthy, natural vegetation; low values indicate a lack of vegetation; and consistent values indicate maintained vegetation. A kernel's graph with high values and scattering is exhibited in Figure 4. Points on the graph reflect annual NBR readings. The higher values are green while lower values are purple/brown. These graphs were generated for all 37 kernels. In addition to generation of NBR vs. time graphs for each kernel, Earth Engine generated an overlaid NBR map of the AOI for each year. These maps can be seen in Figure 7. Note the yearly consistency.

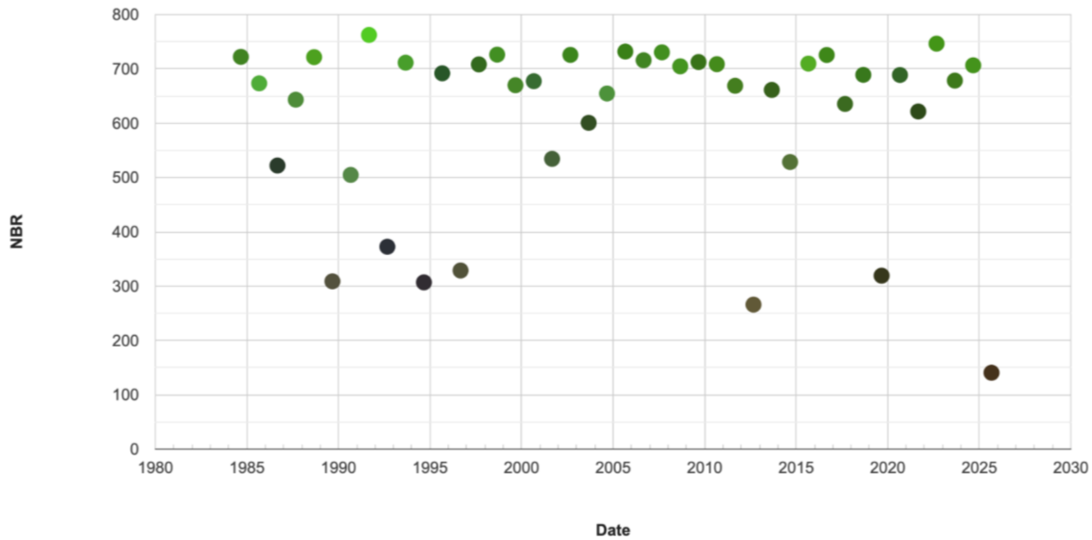

Figure 4. An example of a NBR graph generated from Google Earth Engine.

Changes in land cover were also measured using the Multi-Resolution Land Characteristics (MRLC) National Land Cover Database (NLCD) package (USGS, 2024). MRLC provides NLCD data from 1984–2024. The bounding box for the AOI was input to MRLC using the centroid's latitude and longitude coordinates. However, it is possible that the entire AOI was not covered by MRLC since it rounded to five decimal places for longitude and latitude, whereas the rest of the services offered more accuracy, location-wise, allowing for complete coverage of the AOI. The Annual NLCD package was downloaded, offering sub-packages that presented comprehensive overviews of each AOI through different lenses, such as land cover use trends, impervious surface expansion, tree canopy development, spectral changes, and more. The sub-packages of Fractional Impervious Surfaces (FIS) and Tree Canopy Cover (TCC) were selected to analyze the change in urbanization and the change in vegetation size (USGS, 2024). These sub-packages were selected since the four satellite packages displayed high concentrations of vegetation and impervious surfaces as seen in Figure 4. Each sub-package presented data in the form of a heatmap GIF that displayed its changing concentrations in the region, where one frame represented one year. The download also provided the statistical data in XML files for their respective GIFs. Lastly, each individual frame was provided as a TIFF image. All data was then assembled into a grid in order to organize data and optimize ease of viewing and analysis.

2.3. Data

Bernardsville was classified differently by each satellite package dataset. These differences can be visualized in Figure 3, but also through the statistical data Earth Map provides along with each map. World Cover classified Bernardsville as nearly all forest/greenery (includes both trees and grass), 89.2% forest/greenery by ha, while ESRI classified it as nearly all impervious surfaces and buildings: 3.0% forest/greenery by ha (Karra et al., 2021; Zanaga et al., 2021). Dynamic World provided a reading of 57.4% by ha for Trees and 41.2% by ha for Built-Up land cover. Meta 1 m Tree Canopy demonstrated an abundance of trees with a mean height of 9.53 m, but the AOI map demonstrates there are regions with a much higher tree density than others (Tolan et al., 2023). Collect Earth Online demonstrated a mix of both but indicates that tree canopy primarily describes the majority of the kernels (Saah et al., 2019). MRLC's NLCD packages demonstrate another trend that shows the land cover has had an increase in impervious surface and decrease in canopy cover over time, but both changes were relatively minute. These changes can be visualized in Figure 5. These small changes were marked by rises and drops in the mid-2010s, but they have relatively leveled out within the past 5 years. Bernardsville's land cover currently rests at around 61.5% tree cover. The drop in canopy cover (~5%) was likely the result of expansion projects and hurricanes in 2011 and 2012, as similar large drops are not present in more recent years.

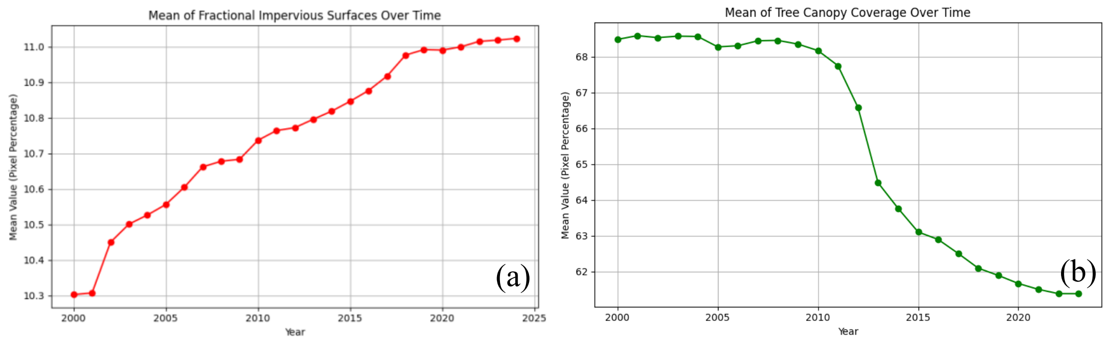

Figure 5. (a) Impervious surfaces vs. Time. (b) Tree canopy cover vs. Time. Graphs from the MRLC NLCD data, courtesy of Vineeth Erram.

3. Results

With the data collected, it became possible to compare and contrast them. To do so, the pictures were arranged for visual analysis. This allowed simultaneous viewing and comparison of the datasets. Selected rows from this grid display results for their respective kernels. Each row of the grid features a kernel's LTS graph, map and bar graph for all four satellite packages, its GLOBE Observer ground-based imaging, and its CEO classifications. These selected rows can be seen in Figure 6.

Comparisons were first made between the four satellite packages. As seen in Figures 4 and 6, the Meta 1 m Tree Canopy dataset demonstrates that there is an abundance of trees in the area. This is indicated by the near complete coverage of the map in Figure 3 and tree presence in every selected kernel's map. Bernardsville thus has an abundance of tree cover. This is further confirmed by the GLOBE Observer imagery, in which trees are present in each selected kernel. These trees could cause classification issues for the other datasets, however. Dynamic World and World Cover's maps show near-total "Tree" classification in the areas where tree canopy is highest; this can be visualized using Figure 3. This could be the result of the trees' height and density, blocking features such as roads and houses underneath the canopy from being captured. Hence, these homes and roads have the potential to go unnoticed by satellites and aerial services such as CEO. Thus, there is a demonstrated need for ground observations underneath the canopy to comprehensively analyze the land cover. This explains the differences in the land cover exhibited in the GLOBE Observer photographs of each kernel and its respective imagery. There is also similar disagreement between CEO observations and GLOBE Observer photographs. This disagreement between CEO and GLOBE Observer is marked by a camera flashing emoji as seen in Figure 6. The tree canopy in Bernardsville thus creates limitations when trying to analyze land cover using remote sensing or aerial analysis. It demonstrates the need to have ground truth imagery to compare the disagreements to. Without having a baseline truth to compare to, the analysis of LULC becomes more difficult.

Figure 6. Selected points from the grid containing data from various tools.

In analyzing where the four sets differed from one another and comparing them to CEO and GLOBE Observer, the data revealed other patterns. One of these patterns was that ESRI tended to make major generalizations by over-classifying built-up areas. There are instances where ESRI marked land as built up when CEO and GLOBE Observer observations showed opposite results. Figure 6 demonstrates this pattern in kernel 34, where it was documented by CEO and GLOBE Observer to be forested and grassland, but ESRI classified it as "Built-Up." Hence, it may be that ESRI serves better as an indicator for land use; this is because kernel 34 is a residential property. The majority of Bernardsville's vegetation and canopy are used for urban activities such as athletics or other outdoor events. This could demonstrate that ESRI tried to account for the fact that it was not reaching the ground due to canopy cover and compensated through its AI model to classify it as "Built-Up."

World Cover seems to overgeneralize opposite to ESRI, classifying a large portion of the AOI as "Tree." As seen with kernel 25 in Figure 6, there is a parking lot that is not captured by World Cover. Rather it classifies the area as forested, but GLOBE Observer images disprove this providing the knowledge there is development underneath. This is likely the result of the abundance of canopy within the region.

Dynamic World does not have the same degree of inconsistency as ESRI or World Cover. Dynamic World overgeneralizes both "Tree" in certain areas and "Built-Up" in others. Dynamic World's overgeneralization of "Built-Up" can be seen through kernel 0 in figure 26, where the lawns, bushes, and trees go undetected. Dynamic World overgeneralizes to "Tree" as seen through kernel 25 of figure 6, where the parking lot on the ground is not read by the satellite.

Analyzed holistically, the satellites' errors in land cover distinction could mean that a spatial resolution of 10m (as used in all 3 satellite packages) may not be small enough to classify Bernardsville, especially given its high tree density. It demonstrates the need for ground observations when possible because that provides comparable truth reading. None of the three LULC satellite packages picked up Bernardsville extremely well, rather, they all made generalizations that tended to be inaccurate when compared to the ground truth observations.

The LTS data demonstrates that Bernardsville's LULC has remained relatively the same over the past 40 years. There is an abundance of green (reflected by the canopy) in every frame as seen in Figure 7. The green does not deteriorate over time. It does fluctuate over some years, such as 1992, 1996, or 2003, but it returns to the same vibrant green reflectance every time after dipping. These anomaly years have been hypothesized to be years in which trees did not gain their leaves until later in the season, thus giving them less time to reflect green back to the satellites, accounting for the changes. There are no repeated years in which there is a notable lack of green. There is also little deviation in the green and brown colors reflected in the LTS except for 1986, where there is lots of purple/blue as seen in Figure 7. Given that these colors indicate pavement and buildings in addition to an understanding of Bernardsville's history, it can be inferred that the change was either the construction or expansion of Bernardsville's local shopping plaza. This plaza is still standing today and happened to be one of the kernels. This kernel can be seen in Figure 6 as kernel 20. It was one of the few kernels where the satellite packages showed more agreement than not, as the satellite packages classified it as built up. CEO and GLOBE Observer corroborate this conclusion about kernel 20, too, making it one of the few kernels where every dataset showed significant agreement. The satellite datasets, however, did miss some shrubbery in the kernel, but this is likely due to their spectral resolution rather than generalization.

The MRLC NLCD, TTC, and FIS data tell the same story: there is very little change. The NLCD image chip looks essentially the same across all 40 years with some ebb and flow. The overall shape and composition of land cover remains generally the same. As seen in Figure 5, Bernardsville has only gained ~1% impervious surface and lost ~6% of tree canopy across 20 years. Part of the loss in canopy could be attributed to damage from hurricanes as well, especially given that the largest drops occur in 2011 and 2012—the same years as Hurricanes Irene and Sandy respectively. Even though the magnitude of the canopy's change was larger than that of the impervious surfaces, it still makes up >60% of all land cover within the area, and impervious surfaces make up ~11%, showing little land cover change in context of the entire area. Figure 7's display of the NLCD data shows the same story, with expansion of the red (built up regions) and little change in the other green (trees) regions.

Our analysis leads us to reject the hypothesis that every dataset would show the same trends and thus the same conclusions about the LULC in an AOI.

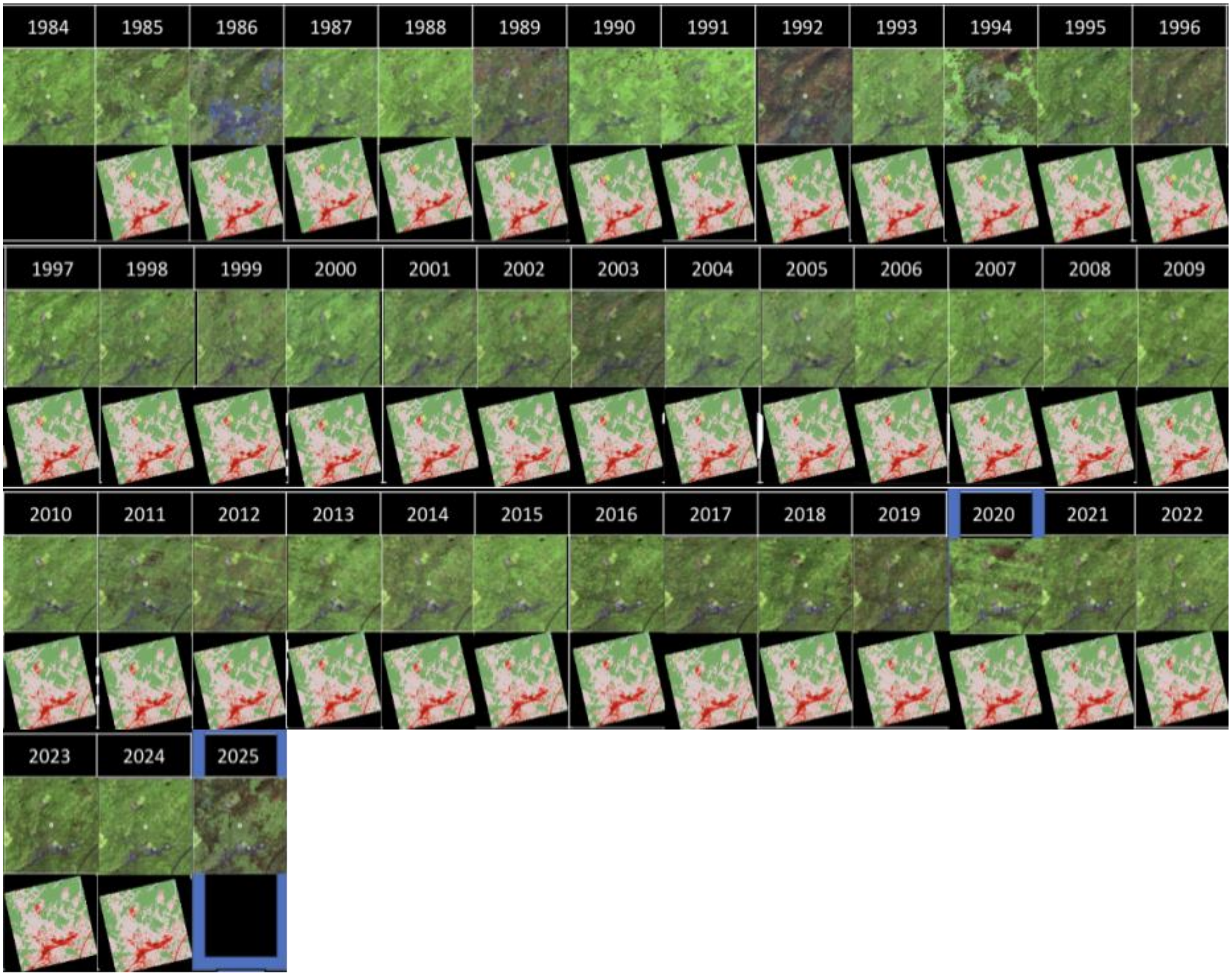

Figure 7. LTS and NLCD data. Landsat is on top, NLCD is on the bottom. LTS data shows NBR maps where green tones represent higher NBR values and brown/blue colors represent lower NBR values (Gorelick et al., 2017). In the NLCD data, green represents deciduous forest, khaki represents grassland, and red represents developed land, the darker the red, the more concentrated the development (USGS, 2024).

4. Discussion

Analysis of Bernardsville requires multiple tools to be synthesized in order to provide a strong understanding of LULC in the area. This study confirms the ability to apply the AaP3km method as outlined in the paper "Adopt a Pixel 3 km: A Multiscale Data Set Linking Remotely Sensed Land Cover Imagery with Field Based Citizen Science Observation" due to its effectiveness at gathering substantial data capable of being analyzed for LULC through citizen science (Low et al., 2021). Through the synthesis of different tools, the data revealed the abundant presence and relative balance between urban and plant elements. The findings in Bernardsville, NJ are significant because they can provide insight on potential impacts of upcoming projects, like the future construction of affordable housing. This study may also be used to help further research of the patterns of LULC across the U.S. Finally, the study demonstrates the imperfection of datasets and provides avenues for further research of these discrepancies.

The AaP3km Framework enabled LULC study to be brought to a suburb without any tools except a smartphone and laptop. It further demonstrates the power of citizen science as this research was not performed by a professional. The AaP3km method thus brings possibility both in furthering the study of LULC and fostering the growth of citizen science to bring research and data to the public (Low et al., 2021). Its techniques enable both the sharing and analysis of LULC data by citizen scientists. This study also confirms that the AaP3km's need for satellite imagery to be compared with ground-truth images and observations; Bernardsville, NJ would not have had meaningful results without these comparisons (Low et al., 2021). The satellite data packages each told different stories and provided conclusions that would have lacked strength without comparison to ground-truth images had they only been compared to one another. While the potential of this methodology is demonstrated, its practicality is not as easy to apply to every AOI.

There was difficulty in gathering data for the AaP3km framework. For example, we encountered challenges collecting GLOBE Observer photos and data for kernels; but the cloud-based resources did not pose similar difficulty. Some kernels were placed in inaccessible areas such as private property or areas that would have been unsafe to access (e.g., railroad tracks, creeks). Data were collected as close as possible when observations were inaccessible, but these were not included in analysis of land cover for purposes of accuracy since they were not the 10,000 m^2 bounding box. Hence, GLOBE Observer imagery only reflects about half of the 37 kernels. The lack of accuracy in these points has the potential to make comparison to satellite imagery extremely difficult, something that is critical to ensuring significant results through the AaP3km methodology. This inaccessibility speaks to the composition of land ownership of Bernardsville. Most of it is composed of neighborhoods with large lots. Many homes have large, fenced-in backyards that are inaccessible to the public. Kernels that fell inside these properties were inaccessible from anywhere except the street, if at all. This meant that these areas could have provided more insight into the AOI but were unable to. It also meant that almost every photo in the downward direction is on pavement, which may not fully speak to the land cover of the point–especially if the majority of the point would have had dirt on the ground. Therefore, areas with a lack of public land may struggle to have enough ground-truth points to compare with satellite imagery for the AaP3km methodology.

As shown in the results, changes in LULC in Bernardsville, NJ can most likely be attributed to large construction projects that are relatively infrequent. Looking at Figure 7, the last time there was a major change in LULC was in 1986. This change was most likely the result of construction on the local shopping plaza, where the LULC change occurred. The town is currently planning to build affordable housing in a major construction project. The affordable housing serves to make Bernardsville a more cost-effective place to live, drawing in more workers, and improving downtown commerce. While this may seem like a threat to the harmony between impervious surfaces and vegetation, the project is taking place in areas that have already been built up. To do this, the town is taking down current buildings and replacing them with new ones. This, therefore, will not have a major impact on the percentages of current tree canopy and impervious surface presence in the area. This may lead to some short-term ecosystem damage, but as seen in Figure 7, these changes often resolve themselves within one or two years. The goal of this expansion project may not have been to preserve ecosystems, but it inadvertently does. This demonstrates that Bernardsville's balance between forest and urban elements is stable and has the potential to last well into the future. Bernardsville thus demonstrates how remote sensing packages can be applied in fields beyond science such as urban planning. Remote sensing tools like the MRLC NLCD Viewer and LTS can allow urban planners to observe the effects of past construction on the LULC of a region in order to predict the impact their construction will have.

The results and data discussed could be applied to Earth Science and further research. As a suburb, Bernardsville, NJ is able to sustain harmony between vegetation and urban elements. This could differ greatly from cities such as New York or Detroit, rural areas in the West, or suburbs that have only been incorporated within the last 25 years. Scientists could utilize the remote sensing patterns seen in Bernardsville and compare them to the aforementioned areas to determine how different types of communities influence LULC. Could Bernardsville's balance be unique to the mid-Atlantic U.S? Could cities in the U.S. have similar patterns despite being more urban? These are potential research questions that could continue research into areas like Bernardsville, NJ. Further research could also aim to quantify the imperfections of data. This could be done through the processes outlined in "The Sensitivity of Mapping Methods to Reference Data Quality: Training Supervised Image Classifications with Imperfect Reference Data" (Foody et al., 2016). This is possible given that this study has proved imperfections and inconsistencies within datasets when analyzing Bernardsville.

5. Conclusions

The study aimed to discover whether tools for analyzing LULC in a rural area agreed, and what conclusions could be drawn using those results. We found that satellite land cover datasets are insufficient by themselves and that they need other ground-truth or aerial observations to corroborate data to provide meaningful results. Furthermore, certain datasets tended to overanalyze and make extreme generalizations such as ESRI, World Cover, and Dynamic World. This outlined the need for truth comparison through Collect Earth Online and GLOBE Observer. In order to observe change in land cover across time, more data was collected through LTS and NLCD MRLC datasets. Once all these different datasets had been collected, they were viewed holistically and used to come to the conclusion that Bernardsville represents a harmony between urban and forest elements, having significant relatively unchanging concentrations of both. Bernardsville was also found to have a large canopy cover. The canopy could be the underlying cause for the differing results across satellite packages. Bernardsville has also undergone very little change in the past half century, gaining little impervious surfaces and losing little canopy cover. Bernardsville demonstrates the strength of the AaP3km methodology in citizen science and LULC research but also shows the difficulty of applying that framework to areas that do not have lots of public land (Low et al., 2021). The study can also be applied towards furthering LULC research to find greater national trends or to demonstrate the power of remote sensing to inform urban planning projects. The AOI is also a good candidate for potential further research into analyzing the LULC quantitatively through processes outlined in papers like "The Sensitivity of Mapping Methods to Reference Data Quality: Training Supervised Image Classifications with Imperfect Reference Data" (Foody et al., 2016).

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