Best Practice

Pixels and Pupils: A Comparative Analysis of Remote Sensing and Citizen Science Land Cover Data in Los Osos, CA

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Abstract: Human impact is constantly reshaping land cover dynamics. Remote sensing technology is revolutionary in its ability to provide imagery and land cover data of local and global regions. However, the accuracy of localized remote sensing data remains uncertain. This validation study uses citizen science data to assess the accuracy of remote sensing datasets at a local scale. This evaluation was performed in Los Osos, California, an environmentally sensitive region currently assessing human impact and the health of habitats and endangered species. The null hypothesis was that there would be no differences between remote sensing and citizen science data sets. Research was conducted through the two citizen science platforms: the GLOBE Observer App and Collect Earth Online. These were compared to open-source remote sensing data sets obtained through the Earth Map platform. Visual analysis of data collected at each of the 37 sample units rejected the null hypothesis because of conflicting classification patterns. Citizen science data revealed that remote sensing disagreements were often associated with the incorrect consolidation of land cover elements or confusion between similar features. While remote sensing is generally more efficient, citizen science field observations were critical to the improved understanding of the land cover of local regions. These findings demonstrate citizen science data's ability to validate remote sensing data sets and identify misclassifications. This emphasizes the need for the inclusion of field observations to improve local land cover maps.

Keywords: land cover, remote sensing, citizen science

1. Introduction

As human and environmental impacts drive changes in land cover dynamics, the demand for observational methods has become more prominent. Land cover data is significant in making informed land use decisions and understanding the root causes of impacts (Xu *et al*., 2024). A data collection method recognized for its efficiency on a global scale is remote sensing data. This is a collection method performed from a distance with instruments such as satellites (NASA, 2025a).

An example of remote sensing technology used to collect land cover data is the European Space Agency (ESA)'s Sentinel missions. The Copernicus Sentinel-2 Mission consists of partner satellites that, within a 5-day period, provide global coverage at 10 m resolution (NASA, 2025b). Google's Dynamic World (DW), ESA's World Cover (WC), and ESRI are all Sentinel-derived data sets used in this study. Despite their shared resolution, their potentially conflicting classifications stem from contrasting classification models and training. ESRI and DW were produced with deep learning models. These models were trained with a reference dataset consisting of 5 billion manually classified Sentinel-2 pixels from 24,000 individual 510 x 510 m grids. Alternatively, WC was produced with random forest classification tree algorithms. This algorithm was trained through 141,000 100 x 100 m manually classified grids (Venter *et al*., 2022; Xu *et al*., 2024). Additionally, the WC and ESRI update every year, while the DW data set is near real time and updates every 5 days. These three data sets were obtained through Earth Map Software. Earth Map is a tool that uses Google Earth Engine to provide multi-temporal environmental and climate-based analysis (Morales *et al*., 2023).

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Along with these three data sets, the fourth was used in the study, also from Earth Map, Meta/WRI Global Canopy Height (MTC). The data for MTC focuses solely on tree cover collected at a 1 m resolution. This data set relies on a model-based training method developed by AI at Meta Research termed DiNOv2 (Meta, 2024).

Limitations to remote sensing data sets come from tradeoffs between satellite resolutions and training models. Spatial, temporal, spectral, and radiometric resolution are the four major resolutions that must be balanced. Spatial describes the smallest area a satellite can observe, otherwise known as the pixel size. The smaller the resolution, the smaller the objects a satellite can observe. Likewise, a smaller temporal resolution is optimal for increasing the frequency a satellite revisits the same place. Conversely, higher spectral and radiometric resolutions increase image detail. Spectral refers to the number of spectral bands a satellite can differentiate between, and radiometric refers to the amount of information measured in bits, in each pixel. If a satellite is multispectral, it can capture multiple wavelengths of light to produce more detailed images. A drawback to remote sensing instruments is the unattainable perfect combination of the most desirable features (NASA, 2025a).

This study aims to evaluate limitations of remote sensing data at a local scale by validating it with citizen science data. Unlike its counterpart, citizen science data is collected through field observations. Ground cover truth alleviates resolution and training model factors. This study tests the null hypothesis that there are no differences between the explored data sets. It is hypothesized that this hypothesis will be rejected and that citizen science data will identify misclassifications and increase the accuracy of localized land cover maps.

2. Study Area and Methods

2.1. Study Area

The study is conducted within the community of Los Osos, CA. The small town of the central coast of California was compelling for the study because of its unique situation and diverse land cover labels. To this day it remains a mixture of developed and undeveloped land. The area rests on a network of ancient dunes. The Mediterranean climate and resulting Baywood Fine Sands Ecosystem host an abundance of unique species. A few of the dominant natural communities include Coastal Sage Scrub, Maritime Chaparral, and Coast Live Oak Woodlands. Coastal Sage Scrub remains highly threatened and rare in California (McGraw, 2024).

Over time, measures have been taken to preserve and protect this precious community. In 1988, a building moratorium was initiated to inhibit new construction permits. This response to a residential boom in the 1970s and septic tank-related concerns lasted until October of 2024 when the moratorium was lifted (Rajagopal, 2024). Despite this, a large portion of Los Osos remains classified as an Environmentally Sensitive Area. This means federal involvement and permit approval for further development (Lynch & Shrager, 2025). The area's sensitivity stems from the recognition of four endangered species, including Morro Manzanita, Indian Knob Mountainbalm, Morro Bay Kangaroo Rat, and Morro Shoulderband Snail (McGraw, 2024). This influenced the county into taking measures to ease the permit process. In February of 2024, the Los Osos Habitat Conservation Plan (LOHCP) and Federal Incidental Take Permit (ITP) were officially approved by the U.S. Fish and Wildlife Service. Essentially, the ITP allows for legal activity that could invoke accidental harm to endangered species. The necessary inclusion of the LOHCP protects the habitats of important species by mitigating damage (U.S. Fish and Wildlife Service, n.d.). Any disturbance is met with a fine used to conserve another parcel of land of similar size. Expansion has been capped at 1 percent (approximately 50 houses). A 0.4% expansion rate was approved for the year 2026 (McGraw, 2024). Current events in the study area are relevant because the demand for land cover monitoring methods promotes further research. Research on how citizen science data validates remote sensing maps is applicable to communities seeking accurate land cover feedback.

The Area of Interest (AOI) for this case study consisted of a 3 km by 3 km grid, as shown in Figure 1 (Low, *et al*., 2021; Nelson, 2024). The grid was centered on the centroid located at (35.316155° N, 120.827508° W). The AOI was divided into 36 sample unit locations, excluding the centroid. Each unit was spaced evenly at 500 m intervals and covered an area of 100 m × 100 m. These sample units were designed to support standardized data collection and comparison. The AOI for this study was placed with consideration to the accessibility of the sample unit locations. Private property and rough terrain would inhibit the collection of field observations. After defining the AOI, it was saved as a GeoJSON file. This file ensured standardized sampling locations by storing the boundaries of the AOI and the location of each sample unit. The file was imported into both Google Maps for directions for collecting field observations and into remote sensing data platforms.

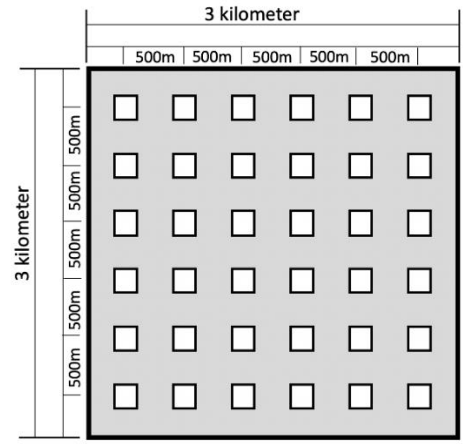

Figure 1: Adopt a Pixel, 3 km by 3 km AOI grid (Low, *et al*., 2021; Nelson, 2024). Each of the 36 squares represents an evenly spaced sample unit. Note that the centroid (sample unit 37) is not pictured.

2.2. Citizen Science Data Collection

Two major platforms were employed to collect field observations: the GLOBE Observer Land Cover App (NASA, 2025b) and Collect Earth Online (CEO) software (Saah *et al*., 2019; FAO, 2023). The GLOBE Observer App is designed for individuals interested in participating as citizen scientists. Its user capabilities include recording ground cover observations and uploading photos at desired locations.

The first step of data collection for this study was uploading the GeoJSON file to Google Maps to generate the 37 coordinate points. This added efficiency and organization to the data collection process because completed locations could be starred on Google Maps. At each location, six directional photographs were taken using the GLOBE Observer App (North, South, East, West, Up, and Down). Additionally, the software recorded the location (i.e., latitude and longitude) of the user. This information was later overlaid with the GeoJSON file using ArcGIS Online to ensure that the observations were collected in the right location. After the photos were taken, the user could choose to describe the perceived ground cover in each image. The following categories–trees, shrubs, herbaceous/grassland, barren, wetlands, open water, cultivated, and urban–are further divided into subcategories for the user to select. Each land cover type must then be followed by the percentage of the area it encompassed in the image. The point of the GLOBE Observer App observations was to capture the surrounding 100 m × 100 m area. This is the same area as the defined sample units. Once the completed photos and observations were uploaded to the GLOBE Observer Citizen Science database, photos and classifications could be accessed.

Field observations were not inherently used as a comparable data set because the photos and observations had incompatible formatting to the aerial image chips of remote sensing data sets. To standardize comparison methods, field observations were integrated into the CEO classification software. These manually classified, 100 m by 100 m image chips could then be directly compared to those derived from remote sensing data sets. Upon uploading the AOI, the CEO software provided overlap between the AOI and satellite imagery. Each of the 37 sample units became 100-point (10 × 10) plots. Each of the points was left blank until manually assigned a color to represent the land cover element beneath it. The colors represented land cover elements including Trees_CanopyCover, bush/scrub, grass, cultivated vegetation, Water>lake/ponded/container, Water>rivers/stream, Water>irrigation ditch, shadow, unknown, bare ground building, impervious surface, and wetlands. The GLOBE Observer photos and observations were continuously cross-referenced when classifying each point to improve their accuracy. Each plot was given a confidence rating on a scale of 0-100. The confidence rating conveyed the estimated accuracy of the land cover classifications. This rating increased when land cover elements were easily identified and confirmed by GLOBE Observer App images. The rating was prone to decrease when image quality or other factors left doubt on the true land cover makeup of a plot. In total, 11 of the 37 points were without GLOBE Observer images. This was due to a location's accessibility, the photo’s failure to upload, and the distance data was collected from a sample unit.

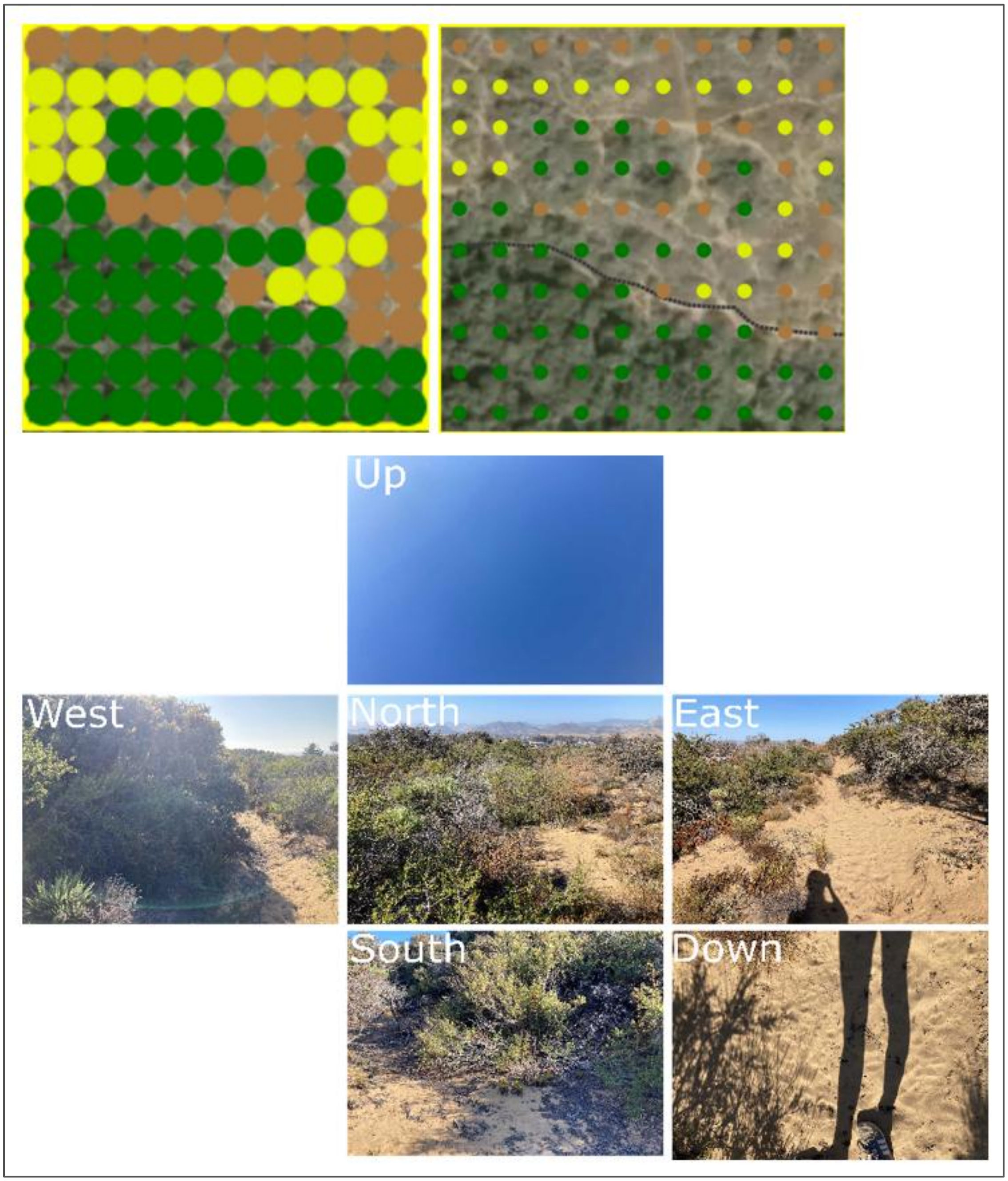

Figure 2. Top – Sample Unit 25, classified using Collect Earth Online software. Bottom – 6 directional photos from Sample Unit 25 uploaded to the GLOBE Observer App.

2.3. Remote Sensing Data Sets

The Earth Map layers provide remote sensing and land cover data. After uploading the AOI to Earth Map, a selection of data filters was overlaid with the region. To analyze Los Osos, three land cover layers were compared. They included World Cover 10 m, Dynamic World 10 m, and ESRI 10 m. They were all derived from the Sentinel-1/-2 satellites. WorldView-4's Earth Map forestry filter, 1 m Tree Canopy Meta (TCM), provided additional and detailed feedback on tree cover distribution. Visually, each filter revealed the land cover makeup of the region by color coding land elements. The land cover element options differed by data set. Within the AOI, the data sets identified differing numbers of land cover elements. In ascending order, WC had 11 land cover categories, DW 6, and ESRI 4. The difference is attributed to ESRI grouping grass and shrubland into a singular "rangeland" category. Furthermore, WC separated water into open water and herbaceous wetland while simultaneously including barren/sparse vegetation. The TCM data set focused solely on the distribution of trees by classifying tree height on a color spectrum ranging from blue to red. Blue being 2 m canopy and red being 30 m canopy.

At each of the sample units, screenshots were taken of each data filter, as shown in Figure 3. These screenshots were then formatted into a grid. Each row represented a sample unit, and each column represented a different data set. GLOBE Observer photos and Collect Earth Online snapshots were incorporated into the grid to permit comparison of observational methods.

Figure 3. A comparison of Earth Map dataset layers. (a) World Cover. (b) ESRI. (c) Dynamic World. (d) Tree Canopy Meta.

2.4. Comparison Methods

The remote sensing and Citizen Science data sets were compared visually. The standard for visual comparison was a classified image chip with the same boundaries and location as the 100 m by 100 m sample units. Each image chip was color-coded to represent a land cover element specified by each data set. In total, each sample unit had 5 corresponding image chips derived from each observational method (TCM, WC, DW, ESRI, CEO). Both the image chips and GLOBE Observer photos were organized into a grid. Each row represented a sample unit and each column a different data set. Preliminary analysis followed, and each image chip was assigned a symbol depending on its agreement with the GLOBE Observer images or CEO image chip. The three symbols included a green box with a check mark (agreement), an orange box (mixed), and a red box with an "X" (disagreement). Agreement meant that citizen science data confirmed that a sample unit map correctly identified land cover makeup. Disagreement meant that citizen science data contradicted a sample unit's classification.

Remote sensing data sets were further compared quantitatively. Quantitative data were compared within the entire 3 km by 3 km AOI. CEO data was exempt from this comparison because no numerical or statistical data for the corresponding color classified image chips was created. Additionally, citizen science data was only collected within the sample units and not for the entire AOI. Remote sensing data sets from Earth Map, however, permitted further analysis by generating land cover charts and tables. These charts and tables provided the quantity, in hectares (ha), of each land cover element observed. These were generated by using the "PROCESS" button in Earth Map with the desired data set and the selected boundaries. The initial bar chart provided information on the changing land cover make-up of a region over time. By selecting the "SHOW CHANGE MATRIX" button, a table was generated. What was confusing was that the chart and table generated for each plot provided conflicting numbers for the same location. For example, when ESRI processed the entire AOI, the initial bar chart only showed four land cover elements while the table had five. Water was excluded, as it accounted for the smallest area. For reasons not investigated, the area of the observed land cover elements also appeared to differ slightly. Extensive research was not undertaken to understand this contradiction. Despite these subtle differences, the chart data for the year 2021 was analyzed. While its accuracy is imperfect, the data it provided did reflect visual observations and were considered cautiously. This quantitative comparison was relevant because differences in the area of land cover elements observed by remote sensing data sets highlight the necessity of citizen science data validation.

3. Results

3.1. Visual Comparison

Overall, the data revealed that approximately half of the AOI was built-up areas, and the remainder consisted of similar portions of rangeland and tree cover, as well as some water and cropland. However, disagreements were common between remote-sensing data sets. This promoted the use of citizen science data to clarify what was present in the sample units. Citizen science data was able to identify misclassifications in the remotely classified sample units. Furthermore, it linked disagreement to several challenges, including similar land cover elements and varying details of the classifications.

Remote sensing's challenge with similar land cover elements was apparent between grassland, shrubs/scrub, and tree cover. This was observed in sample unit 33 (Figure 4). With the assistance of the GLOBE Observer photos, sample unit 33 could be described as a sandy trail through a dry, grassy clearing with several small groupings of trees and shrubs. This characterization was not supported by all data sets. Part of the challenge is the similarity in height and color of certain land cover elements. In some areas, short trees or tall scrub also created doubt about what was truly present and contributed to disagreement in the data sets. This was also true for grass and shrubs/scrubs. The ESRI platform categorized grass and shrubs/scrubs as rangeland. This was in part agreeable with the field observations. ESRI also however identified "built-up" land cover not supported by field observations. DW, on the other hand, classified the sample unit as part tree cover and part shrubland. While both these elements are backed by citizen science data, the grass observed in the field observations was excluded. Finally, WC classified the sample unit as tree cover and grassland. Out of the remote sensing data sets, TCM appeared more consistent with citizen science tree cover classifications. However, its focus on only the tree canopy prevents it from contributing to the understanding of grass and shrub distribution. These observations demonstrate the role citizen science data played in validating the true land cover makeup of sample units. Field observations provided the necessary knowledge to conclude land cover elements being observed, especially when land cover elements were difficult to differentiate.

Another instance where citizen science data was needed for validation was when remote sensing data sets disagreed on the number of land cover elements present. This challenge was identified as a common cause of misclassifications. It was apparent that there was disagreement between remote sensing and citizen science sample unit classifications when remotely classified maps consolidated land cover elements into significantly less categories. For example, this mostly occurred in urban areas when remote sensing data sets classified image chips as solely built-up areas, while citizen science data supported the presence of different land cover elements. Especially for a small scale AOI, the exclusion of major land cover elements (ex. tree cover) decreased the accuracy of land cover maps.

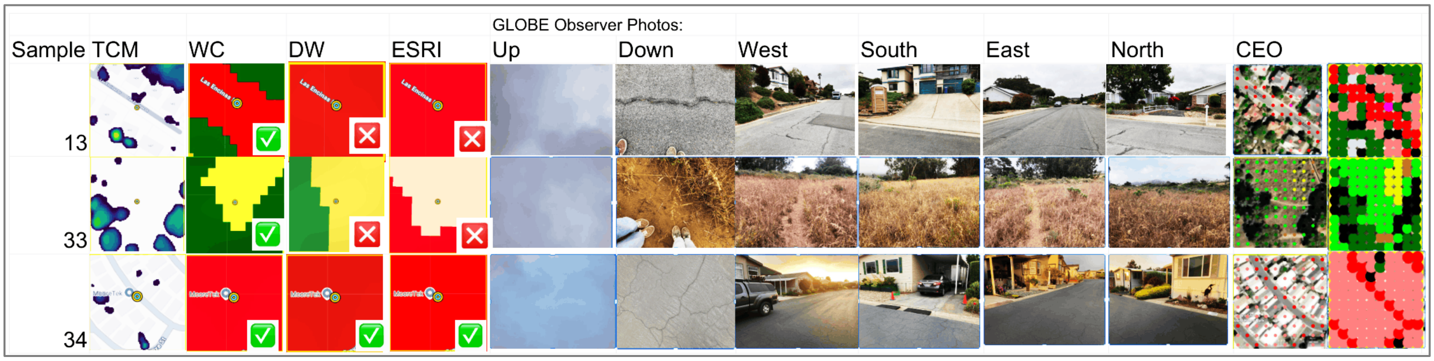

Figure 4. Portion of the grid organized by sample units and data sets. The rows represent sample units 13, 33, and 34.

The habit of consolidating land cover elements into the category "built-up area" was common in the DW and ESRI data sets. Many of these observed sample units were labeled as having "mixed" agreement because of the data sets failure to observe other land types in urbanized areas. On the contrary, the WC layer tended to differentiate each plot, when applicable, into two or more land cover elements. Among the three Sentinel-derived data sets, WC was the most agreeable with citizen science data and CEO. Additionally, WC had the most agreement with both TCM and CEO's tree cover distribution. TCM and CEO land covers were nearly identical in many instances. An example of this is sample unit 13 shown in Figure 4. Unit 13's plot is in an urban area with tree cover. DW and ESRI did not identify any trees. However, both TCM and WC did and were similar to CEO. For this location, DW and ESRI were labeled disagreeable, and WC agreeable.

Furthermore, citizen science data was used to confirm remote sensing observations. Visual inspection of the image chips revealed a common trend between the relationship between fewer observed land cover elements in the CEO classifications and increased agreement. This phenomenon was observed at sample unit 34. Consensus among the data sets concluded sample unit 34 to be an entirely built-up area, as shown in Figure 4. Along this same trend, many of the agreeable image chips had two or fewer land cover elements. While there was agreement between data sets, substantial disagreement was observed. This reveals how field observations not only identify misclassification but can be used in conjunction with remote sensing data sets to validate their accuracy.

3.2. Quantitative Comparison of Remote Sensing Data

The initial form of measuring quantitative agreement was by counting the number of agreement, mixed, and disagreement symbols for each data set. Starting with the number of agreeable image chips, ESRI had the least agreement with 4 image chips, followed by a close DW with 5 image chips. The most agreeable was WC with 12 agreeable image chips. For mixed image chips, DW had 13, and ESRI was barely ahead with 14. WC had the most with 22 mixed image chips. In terms of disagreeable image chips, DW and ESRI were tied for the most with 19. WC had only 3 disagreed on image chips.

Additional quantitative data were derived from the tables supporting visual observations. The data backed the observation that between the Sentinel datasets, WC classified the least amount of the AOI as built-up area and instead classified more as trees and rangeland. This suggests that the data set is less prone to urban consolidation. Figure 5 shows that WC classified 44.6% of the area as built-up, while DW classified 65.16% and ESRI 67.9%. Trees and rangeland areas were also disagreed on, as visualized in the table. For rangeland, DW classified the smallest area of 11.05%, ESRI 14.59%, and WC 23.04%. For tree cover, ESRI had the smallest area of 11.45%, DW had 17.58%, and WC had 28.49%. WC also identified the most cropland out of the three. These values indicate that ESRI and DW were more similar than WC. They, however, were less similar to CEO data than WC.

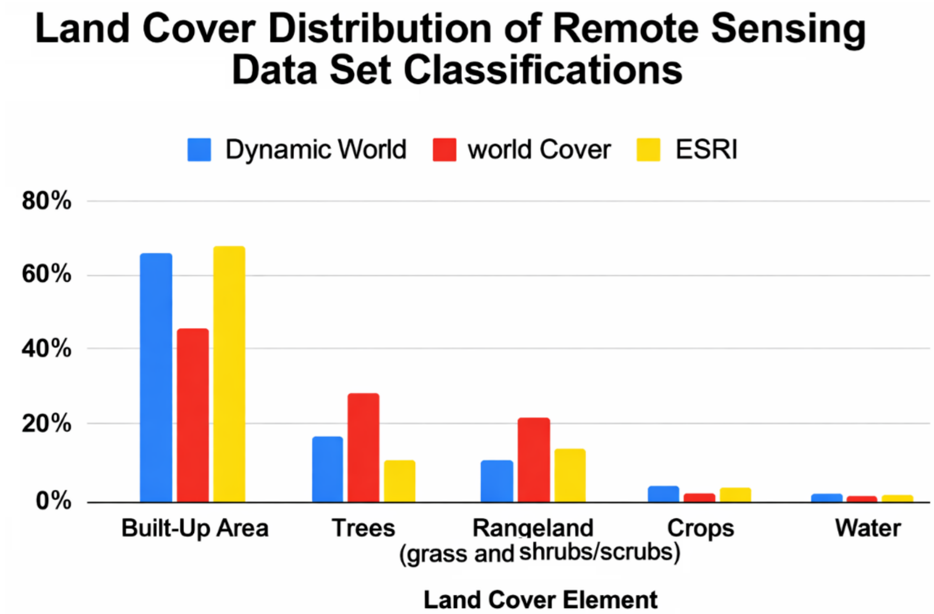

Figure 5. Quantitative comparison of the percentage each land cover element observed in the AOI by different remote sensing data sets. Data was obtained through generated tables in Earth Map.

4. Discussion

The results reveal that there were discrepancies between remote sensing and citizen science data sets. These findings demonstrate how citizen science data can be used to validate land cover maps by confirming classifications or identifying misclassifications. Furthermore, citizen science data proved more effective at separating sample units into a wider range of land-cover categories and at distinguishing between features with similar characteristics. This allowed it to pinpoint weaknesses in remotely classified maps and improve their accuracy.

Qualitative comparison permitted the observation that DW and ESRI classified more of the AOI as built-up area than WC. Additionally, WC classified more rangeland and tree canopy cover. Comparative analysis further revealed DW and ESRI to differentiate between fewer land cover types than WC, especially in urban areas. Overall, WC was most agreeable to the CEO classifications. DW and ESRI, while most similar to each other, had the most disagreement with CEO. Meanwhile, TCM focused solely on tree canopy distribution and proved to be nearly identical to the tree canopy classifications of CEO. The similarities between TCM (1 m resolution) and CEO suggest that higher resolution can improve specific feature classifications. TCM had a spatial resolution of 1 m versus Sentinel's 10 m resolution. This observation promotes the idea that different remote sensing data sets are applicable to different scenarios. Additionally, it illustrates the role of citizen science in recognizing which data sets are applicable to different scenarios because it can confirm which is most accurate. Without field observations, it could have been hypothesized that DW and ESRI more accurately classified the AOI than WC because WC was the outlier. However, citizen science data supported WC classifications more closely in this study. Nonetheless, it also identified cases where WC had incorrectly classified sample units.

In addition, citizen science data suggested there are unique applications of each remote sensing data set. For instance, DW may be advantageous for near-real-time monitoring of regions because it is updated every 5 days as opposed to once a year. However, WC was shown to be more agreeable to the citizen science data and is favorable for studies that require more detail. WC is still limited in its ability to always correctly identify important land cover features, especially those pertaining to rangeland or tree canopy. Citizen science data is assumed to be more applicable to accurate and detailed studies of small-scale regions.

Findings from this study can be applied in the context of Los Osos. The LOHCP states the necessity of continued monitoring studies to track distribution, abundance, status, and response of protected species (McGraw, 2024). This study suggests the future inclusion of field observations to accurately monitor specific land cover types. It would be useful to monitor the two endangered shrubs that the LOHCP outlines.

Meanwhile, remote sensing data could be applied to observe changes in Los Osos's urban land cover. Citizen science data would be less efficient at monitoring the area of the entire community but could check the accuracy of such classifications at sample units.

There were limitations of this study that in future studies would be interesting to pursue. The first is the lack of quantitative data provided by the citizen science data sets. Although qualitative observations were strong enough to provide a comparison with remote sensing data sets, it would be of interest to perform a quantitative comparison of the exact differences of features observed. The biggest limitation of the study was the absence of current remote sensing data. A future study using remote sensing data collected for the year 2025 would be useful for reaching greater conclusions than this study could. This study was effective at analyzing data set patterns and exploring how citizen science data could be used to add to the understanding of an AOI. Land cover is prone to constant change, and a gap as large as 5 years is less than ideal. The gap could influence the agreeability between specific image chips. While this does affect the quality of the comparison, it does not take away from the fact that there was disagreement between remote sensing and citizen science data sets because of varying levels of detail. For example, the tendency of ESRI and DW to exclude trees that have been established for well over 5 years shows that this pattern of disagreement would not be affected. Furthermore, in this study citizen science data were shown to differentiate between more land cover elements.

5. Conclusions

It was hypothesized that there would be disagreement between remote sensing and citizen science data sets. Results supported the hypothesis and promoted the use of citizen science data to validate land cover maps. When compared to remote sensing data sets, citizen science data pinpointed misclassifications present in remotely classified sample units. It also led to the observation that discrepancies were often linked to difficulties distinguishing between land cover elements. Comparison to citizen science data also supported the idea that the applications of each remote sensing data set are unique. WC exhibited the highest classification detail and was similar to citizen science classifications. This makes it suitable for in-depth analysis of a region, even those of a smaller scale. In scenarios where large areas of land are being assessed, citizen science data might seem less ideal. Nevertheless, findings illustrate citizen science data's ability to identify the accuracy of other observational methods by comparing sample unit classifications. This study encourages the future incorporation of citizen science data into localized land cover studies. As land cover continues to evolve with changing human activity and climate patterns, so does the incentive to monitor land cover in many communities. Connecting to Los Osos, the inclusion of citizen science data is highly advised to accurately track the populations of endangered shrub species. Ultimately, the study of Los Osos determined citizen science data to fill in the gaps of land cover maps with verifiable ground-cover confirmation.

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