Land Cover Verification and Error Analysis for Citizen Science Applications

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Abstract

Even though the accuracy of global land cover data products has greatly increased in recent years, our visual understanding of the Earth obtained from orbit often diverges from ground observations obtained during scientist field investigations. Today, many high resolution land cover maps such as the 2020 ESA WorldCover (WC) map stand at an accuracy below 75%. Faced with these accuracy limitations, scientists have turned to in-situ citizen science observations such as those from GLOBE Observer to supplement existing land cover data and to increase its accuracy. Our research focused on increasing the impact of citizen science by identifying the key environmental and geographical factors associated with discrepancies between existing land cover maps and citizen scientist land cover classification of satellite imagery through Collect Earth Online (CEO). Data analyzed suggests that the agreement between citizen scientist and WorldCover land cover classification was highest in areas with mostly homogenous land cover. There is a relatively strong negative association between land cover diversity and classification agreement. Additionally, we observed that classification agreement is positively correlated with the highest amount of shrubland classified between the citizen scientists and the WorldCover map. Using the associations, we can identify the types of areas in which citizen science observations will be most useful in providing new insights into land cover.

Introduction

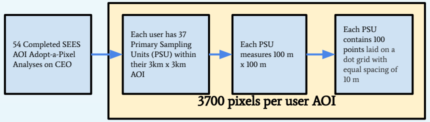
Since the launch of Landsat 1 in 1972, researchers have been using satellite imagery to obtain important data about the Earth's land cover and its change over time. Thanks to major technological advances over the past 50 years, land cover maps produced from satellite data have become significantly more detailed and precise. The best horizontal resolutions once spanned hundreds of meters per pixel, but recent maps span only 10-30 meters per pixel. With this increased precision, many land cover features that were once too small to appear on land cover maps have now been accounted for. Even so, the accuracy of most land cover maps today remains below 80%. Part of the error stems from the fact that there are features easily visible on the ground that are too small to be featured on modern land cover maps, even with their enhanced resolution. Further error results from algorithms behind the interpretation of satellite imagery producing inaccurate land cover classifications.

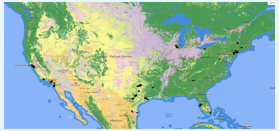
Research Questions

How do various geospatial characteristics affect the accuracy of land cover mapping? What location-related factors make citizen science data more impactful to verify the land cover of a given area (to optimize observer resources)?

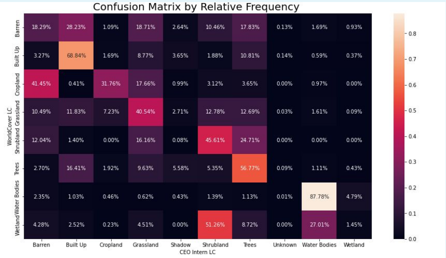
Methodology

Data was collected through systematic random sampling from the Areas of Interest (AOIs) of 54 SEES Earth Explorer interns (Fig 2). Each 9 km^2 AOI consists of 37 100m x 100m plots, yielding 3700 points total (Fig 1). Interns were tasked with taking in-situ land cover (LC) observations using GLOBE Observer at the center of each plot, and identifying each of the 3700 points as LC pixels when overlaid with Sentinel-2 imagery within CEO. The 199,800 pixel points of results of the intern classifications were then compared to their corresponding WorldCover classifications using 11 consolidated LC classes: Trees, Grassland, Shrubland, Cropland, Wetland, Water Bodies, Barren, Built Up, and Snow





Above: Fig. 1 (AOI to pixel flowchart)
Left: Fig. 2 (map of sampled intern AOIs)
Below: Fig. 3 (Confusion Matrix by Relative Frequency)



Results

Looking at agreement data, the top 3 most agreed classes were Water Bodies, Built Up, and Trees. The overall accuracy across all data points was roughly 56.5% match to WorldCover data. The Cohen's Kappa Coefficient value was 0.42, suggesting there was moderate agreement between CEO and WC data. Fig. 3 describes the agreement confusion matrix by relative frequency.

Additionally, there were a number of statistically significant correlations that were established through mathematical investigations between agreement data and other variables. The first is between diversity and agreement. As diversity increases in an area, agreement decreases between the two classifications. Diversity was measured as the lower percentage classified between CEO and WC of the primary land cover classification (PLCC). The correlation coefficient between the PLCC and agreement is +.77. Another association is between population density and agreement. This is a positive correlation of +.484 using a logarithmic regression model. Another correlation between agreement and the amount of grassland classified by WC - that correlation coefficient is -.56. Grassland tends to be associated with decreases in agreement because WC often miscategorizes other LC types, such as shrubland, as grassland. This hints at another correlation between Δshrub and Δgrassland. Let Δshrub = |WC shrub percentage - CEO shrub percentage|. Similarly, let Δgrassland = |WC grassland percentage - CEO grassland percentage|. The correlation between these is a moderate +.47, supporting the observation that grassland and shrubland tend to be confused with one another. An additional correlation discovered is a negative one between LC change and agreement. LC change was quantified by overlaying a map of recent (since 1985) vegetation gains and counting the number of PSUs affected by these changes. The correlation coefficient for this relation is -.45. Several other variables were tested for correlations with agreement, such as Koppen-Geiger climate zones, number of GLOBE Observer observations taken by the citizen scientist before classifying CEO plots, and the presence of several other land cover types besides grass.

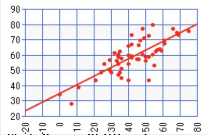


Fig 4- Percent PLCC vs. Agreement

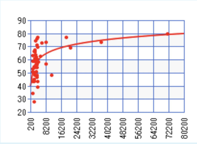


Fig 5- Population Density vs. Agreement

Case Study

This case study examined how GLOBE Observer Photos enhance land cover classification accuracy by analyzing two AOI's. Both AOI's that were analyzed were different; the first one was mostly classified with mostly trees and grass while the second AOI was mostly classified with built-up and impervious surface. However, in both AOI's, GLOBE images increased land cover understanding and accuracy by allowing users to view multiple types of LC at once and understand the nuances of that location. Both AOI's had most of the same classification in one grid though it was difficult to sometimes identify the images help identify the type of trees and buildings the cover the land.

Fig 6 - trees and road at the same location shown through CEO vs. GLOBE. Ground observations show things not visible from the air, like trees built over a built-up/impervious surface

Fig 7 - trees in a densely urban area may be hard to identify on aerial images due to skyscraper height, shadows, and resolution. GLOBE data can further supplement existing LC maps by giving insight into what is visible on the ground level

Conclusion

This information can potentially help provide a more effective and streamlined method for scientists to document and collect impactful crowd-sourced data. By helping to improve global land cover maps through citizen science, our research may assist professionals in diverse fields fight some of the world's most pressing issues, including those involving natural resource management and mosquito source reduction.

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