Land Cover Verification and Error Analysis for Citizen Science Applications

Rebecca Lawton, Rhea Rai, Anahid Vicente

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I. Abstract

Although the accuracy of global land cover data products has greatly increased in recent years due to technological advancements, the visual understanding of Earth's surface that scientists obtain from existing land cover maps often diverges from ground observations obtained during field investigations. Today, many high resolution land cover maps such as the European Space Agency's (ESA) 2020 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 an official land cover map, WorldCover, and citizen scientist land cover classification of satellite imagery through Collect Earth Online (CEO). According to our statistical analysis conducted using computer-generated confusion matrices, the agreement between citizen scientist and WorldCover land cover classifications 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 negatively correlated with the highest amount of shrubland classified between the citizen scientists and the WC map. This is because shrubland is often confused for other types of vegetation and vice versa. Using the numerous associations we found, we were able to identify the types of areas in which citizen science observations will be most useful in providing new insights into land cover. 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.

Key words: land cover, data accuracy, citizen science, remote sensing

II. Introduction and Literature Review

Land cover refers to the material that lies on the surface of the Earth such as buildings, vegetation, snow, etc. Since the launch of the National Aeronautics and Space Administration's (NASA) and United States Geological Survey's (USGS) 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 several decades, land cover maps produced from satellite data have become significantly more detailed and precise. The best horizontal resolutions once spanned more than a kilometer 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 image processing algorithms behind the interpretation of satellite imagery producing inaccurate land cover classifications.

Due to the known presence of these inaccuracies in official land cover mapping, evaluations of the accuracy levels and methods to improve them have been the subjects of much research over the past several years. Previous studies examining the accuracy of multiple existing land cover maps have determined that classifications of mostly homogeneous regions are more accurate than those of regions that serve as transition areas between multiple types of land cover. Additional studies have indicated that discrepancies between existing land cover maps are greater in areas predominantly covered in grassland, shrubland, and barren land, while land cover is more consistently agreed upon in areas mostly covered in trees and water bodies.

Although several studies have determined which land cover categories are most often confused for one another and which categories are associated with higher accuracy on land cover maps, few have examined how demographic factors such as population density and average household income are associated with land cover mapping accuracy. Identifying these correlations has the potential to help pinpoint areas where existing land cover data products are in need of improvement. Additionally, the majority of previous studies in the field of land cover accuracy analysis have evaluated map accuracy by selecting a certain existing land cover dataset and using it as a reference from which to evaluate accuracy and consistency. Few studies, however, have attempted to evaluate the accuracy of land cover maps by means of taking advantage of the local expertise of citizen scientists in their respective areas. This method of land cover accuracy analysis may provide new insights into correlations with data accuracy that may have previously been overlooked.

In this study, we crowdsourced highly accurate land cover data that relied on the local knowledge of citizen scientists and was oftentimes verifiable by means of images obtained through *in-situ* citizen science field investigations. We used this data as our reference to evaluate the accuracy of the European Space Agency's WorldCover map and to identify location-related demographic, geographic, and environmental variables correlated with the accuracy data.

III. Research Methods

To develop the reference data used to evaluate the accuracy of the WorldCover map, a novel method called Adopt a Pixel was used by 52 citizen scientists across the United States and two citizen scientists internationally. This method was recently piloted by Dr. Russanne Low and Mr. Peder Nelson when they mentored a group of STEM Enhancement in Earth Science[1] (SEES) high school interns in the summer of 2020. The Adopt a Pixel method involves each citizen scientist selecting a 9 km^2 Area of Interest (AOI) in which to focus their investigations. The AOIs are split up into 37 100m x 100m plots called Primary Sampling Units (PSUs). The 37 plots consist of 36 equally spaced plots 500 meters apart, and one center plot. Each PSU is then broken down into 100 smaller 10m x 10m plots called Secondary Sampling Units (SSUs). Thus, there are 3700 SSUs in total. After selecting an AOI, each citizen scientist must complete two distinct activities. First, they must collect an observation in each of their 37 PSUs through the GLOBE Observer mobile application. GLOBE Observer is a tool that allows citizen scientists to collect ground-based observations of land cover and other environmental data types and store them in a common database with observations from thousands of other citizen scientists utilizing the app. Upon completion of this step, they must classify the land cover type of each of the 3700 SSUs on Collect Earth Online (CEO). CEO is a platform that allows users to view, interpret, and classify high-resolution satellite imagery of the Earth. Overall, the Adopt a Pixel method enables citizen scientists to systematically sample the land cover within their AOIs and takes advantage of their familiarity with their local areas to increase their land cover classification accuracy. The systematic sample of the land cover within the AOIs, obtained through a combination of field investigations and CEO analysis, mimics a simple random sample and thus serves as a representative sample of the land cover in the entire AOI.

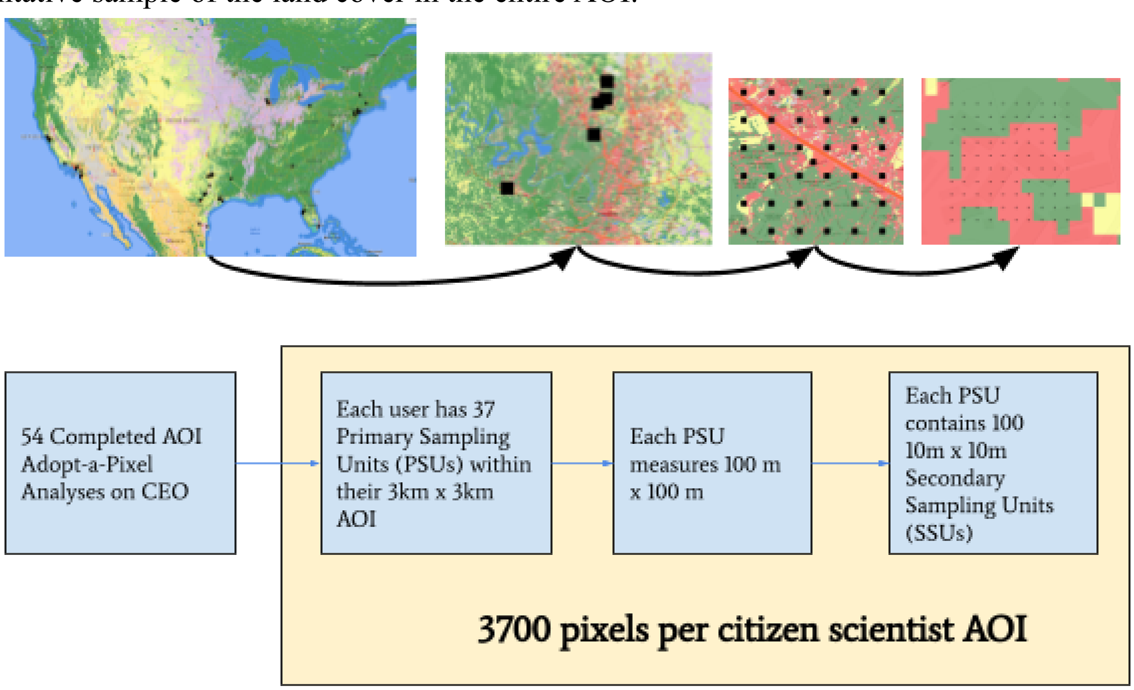

Figure 1. Overview of the Adopt a Pixel Area of Interest land cover data collection method.

[1]STEM Enhancement in Earth Science is a high school research internship sponsored by the Texas Space Grant Consortium, The University of Texas at Austin, and NASA

This reference data was then compared to the ESA's WorldCover map to evaluate its accuracy. This was done through computer algorithms written by former SEES intern, Matteo Kimura. Due to variations in available land cover categories and terminology between the CEO and WC data, the data had to be harmonized. Ultimately, the data was harmonized into 11 total categories. These include trees, grassland, shrubland, cropland, wetland, water bodies, barren, built up, and snow. If the CEO land cover classification matches the WorldCover classification at a particular point, this increases the credibility of the WorldCover map, and it is highly likely that the classification is correct. However, if the CEO and WorldCover classifications disagree, it is likely that the WorldCover map has erred. The CEO classifications are likely correct when such disagreements occur, as the CEO classifications were completed by human beings who are greatly familiar with the areas which they classified. In contrast, the WorldCover map was generated by a machine through algorithms making use of training data. Additionally, the WorldCover map is known to contain plentiful errors. The accuracy of the map is reported by the ESA to be 74.4 percent. Therefore, comparing discrepancies between CEO and WC data helps identify where there are likely errors in the WC map. Identifying patterns present in the discrepancies can help identify the types of areas where *in-situ* citizen science observations will be most useful in improving existing land cover maps.

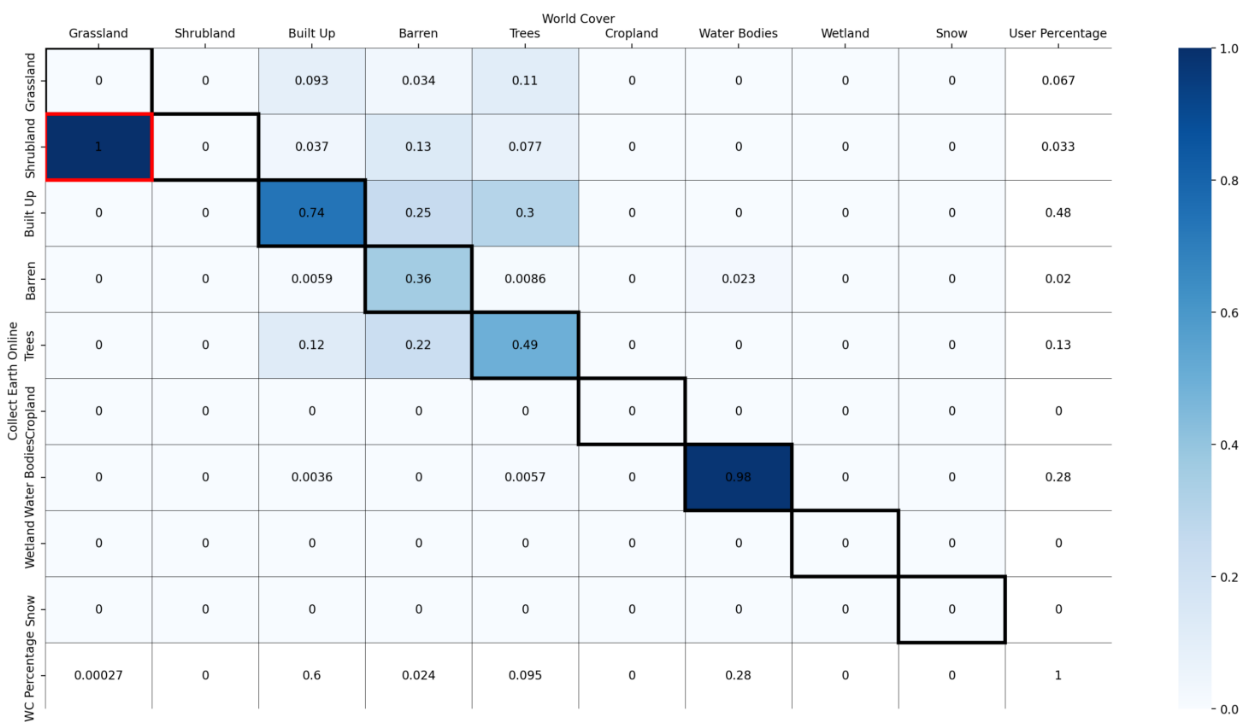

Figure 2. An example of a confusion matrix from one of the 54 AOIs examined in this study.

IV. Results

In order to understand the results of this study, it is necessary to achieve an understanding of what is a relatively "high" or "low" agreement statistic between the two land cover datasets. At the extreme ends of the 54 AOIs examined in this study are the AOIs with the highest and lowest agreement statistics, which are 80.03% and 28.16%, respectively. The average agreement stands at approximately 58.7%, and the median is almost identical at 58.8%. The mode of all the agreement metrics after they were rounded to the nearest whole number is 59%. Since the mean, median, and mode are all approximately equal, the data is approximately symmetric in its distribution. Figures summarizing the measures of central tendency, the distribution, and the measures of spread for the agreement data are pictured below.

Mean	58.7
Median	58.8
Mode	59

Figure 3. Table containing the measures of central tendency of the agreement data.

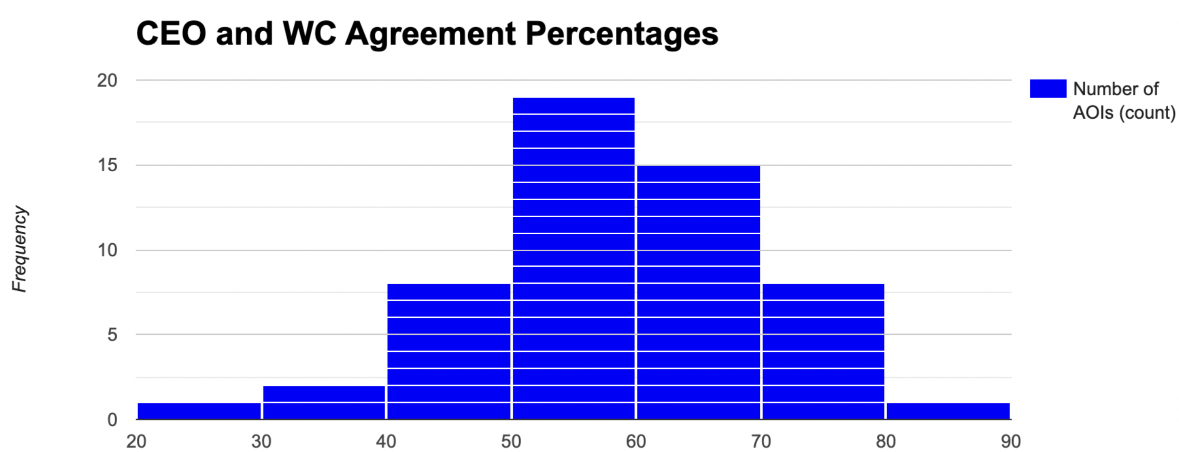

Figure 4. Histogram demonstrating the distribution of the agreement data.

Range	51.87
Interquartile Range	15.59
Variance	122.32
Standard Deviation	11.06
Mean Absolute Deviation	8.52

Figure 5. Table containing the measures of spread of the agreement data.

Several computer algorithms were written to determine the overall agreement of the WC map and the CEO plots, as well as the agreement by specific land cover classification. Figures 6 and 7 below provide an overview of this data. From the full sample of 199,800 SSUs (54 AOIs, each with 3700 SSUs), the overall accuracy across all harmonized classes was 56.5%. Additionally, the Cohen's Kappa Coefficient, which represents the level of agreement between predicted and actual data on a [-1, 1] scale, was calculated as approximately 0.422. This indicates a moderate agreement between the WC and CEO data.

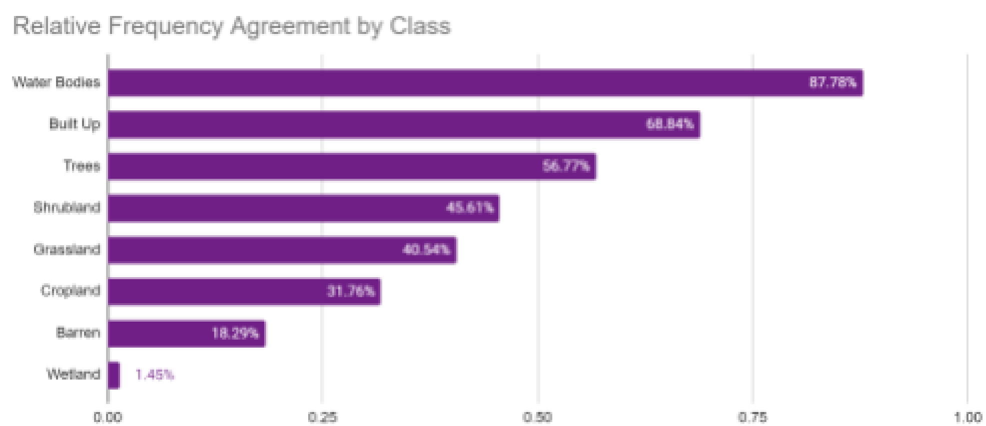

Figure 6. Agreement data by land cover category.

Agreement Statistics	
Sample Size	199,800 points (54 AOIs)
Overall Accuracy	56.5 %
Cohen's Kappa Coefficient	0.422

Figure 7. Overall agreement statistics between CEO and WC datasets.

From the agreement data, there were several statistically significant correlations that were established with a number of different variables. The strongest correlation determined was between percent primary land cover classification (PLCC) and agreement data. The PLCC is the land cover category that is represented the most within an AOI. Generally, the PLCC of a given AOI was the same in both the CEO and WC datasets. However, in the rare case of a discrepancy between the datasets, the WC PLCC was used in this statistical study. The lowest percentage of the PLCC classified between CEO and WC datasets was used to determine what percentage of an AOI was occupied by its PLCC. As the percent of the AOI covered in the PLCC increases, the classification agreement between CEO and WC tends to increase as well. The correlation coefficient for this relationship is +0.77, indicating a strong positive correlation. The p-value for this relationship is incredibly small at <.0001, indicating it is highly unlikely these results occurred by chance and thus establishing statistical significance of the correlation. The statistics related to this correlation are summarized in Figure 6, and a linear regression model is visible in Figure 7.

Correlation Coefficient	+0.77
Coefficient of Determination	0.59
P-Value	<.00001
Linear Regression Model (line of best fit)	$\hat{y} = 0.56671x + 34.6987$

Figure 8. A summary of the correlation between agreement and percent PLCC.

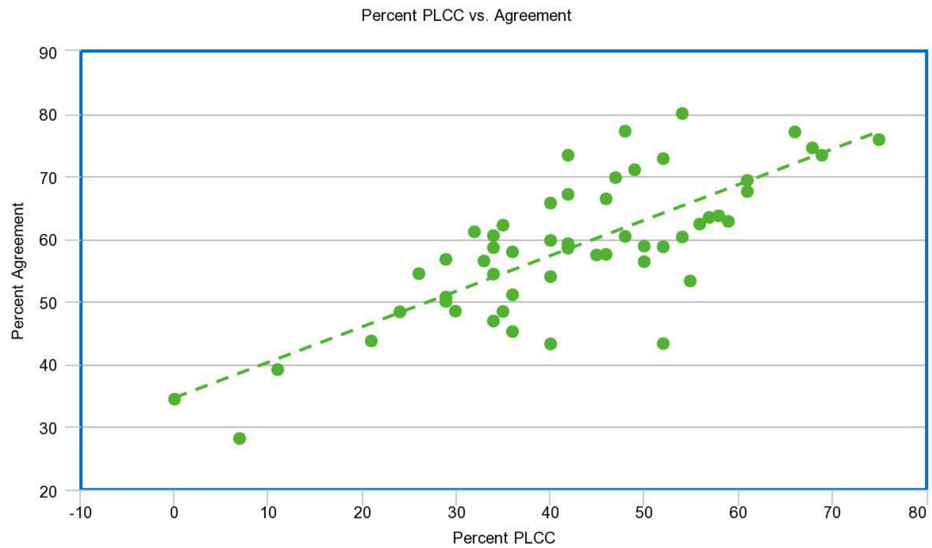

Figure 9. Scatterplot and linear regression model of the correlation between percent PLCC and agreement.

Another correlation we determined was between the percentage of the AOI classified by WC as grassland and agreement. As the amount of grassland increased on the WC map, the agreement between CEO and WC tended to decrease. The correlation coefficient for this relationship is -0.56, indicating a moderate negative correlation. The p-value for this relationship is once again very small at .000011, indicating the statistical significance of the correlation and nearly eliminating the possibility of obtaining such a correlation under the null hypothesis. Additionally, a correlation coefficient of -0.56 was also found for the association between agreement and the highest amount of grassland classified between the CEO and WC datasets. The fact that these correlation coefficients are identical suggests that perhaps the highest amount of grassland classified between the two datasets is often equal to the amount of grassland classified by the WC map rather than the CEO analysis. Indeed, for 50% of the AOIs in this study, the WC map provided a higher estimate for the amount of grassland than did the CEO analysis. The statistics related to this correlation are summarized in Figure 8, and a linear regression model is visible in Figure 9.

Correlation Coefficient	-0.56
Coefficient of Determination	0.31
P-Value	.000011
Linear Regression Model (line of best fit)	$\hat{y} = -53.80921x + 67.39373$

Figure 10. A summary of the correlation between the percentage of grassland in an AOI and the agreement data.

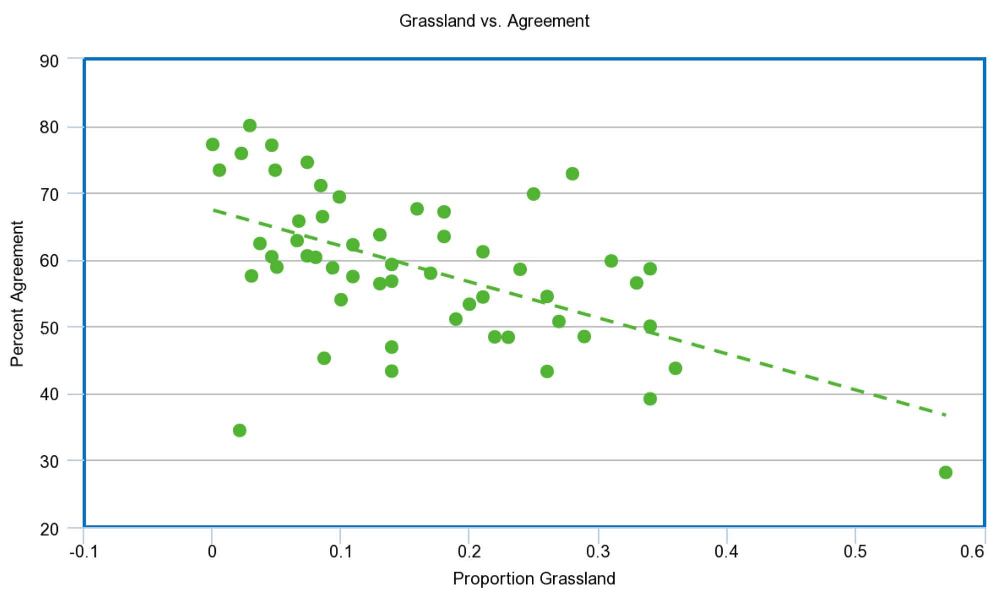

Figure 11. Scatterplot and linear regression model of the correlation between proportion of grassland as classified by WC and agreement.

Investigations of the relationship between land cover changes and agreement data have revealed the correlation of agreement with vegetation gains. Vegetation gains were quantified by a simple count of the number of SSUs within an AOI that had experienced gains in vegetation from the year 1985 through 2021, regardless of the extent of the gain. This number was determined by overlaying an authoritative data layer over the AOI sampling grids on ArcGIS Online. The data layer was provided by the U.S. Forest Service and contained information about vegetation gains across the United States between the years 1985 and 2021. To verify the number of SSUs originally counted and to reduce error, a recount was performed several days later and yielded identical results. The correlation coefficient determined for this relationship was -0.50, indicating a moderate negative correlation. The p-value for the correlation is incredibly small at .000139, indicating the statistical significance of the relationship. It is worth noting that two of the AOIs were removed when determining this correlation. This is due to the fact that those AOIs were located outside of the U.S. and thus accurate vegetation data was not easily accessible for them. Further statistics related to this correlation are summarized in Figure 10, and a linear regression model is visible in Figure 11.

Correlation Coefficient	-0.504
Coefficient of Determination	0.254
P-Value	.000139
Linear Regression Model (line of best fit)	$\hat{y} = -0.61069x + 72.47922$

Figure 12. A summary of the correlation between vegetation gains and agreement data.

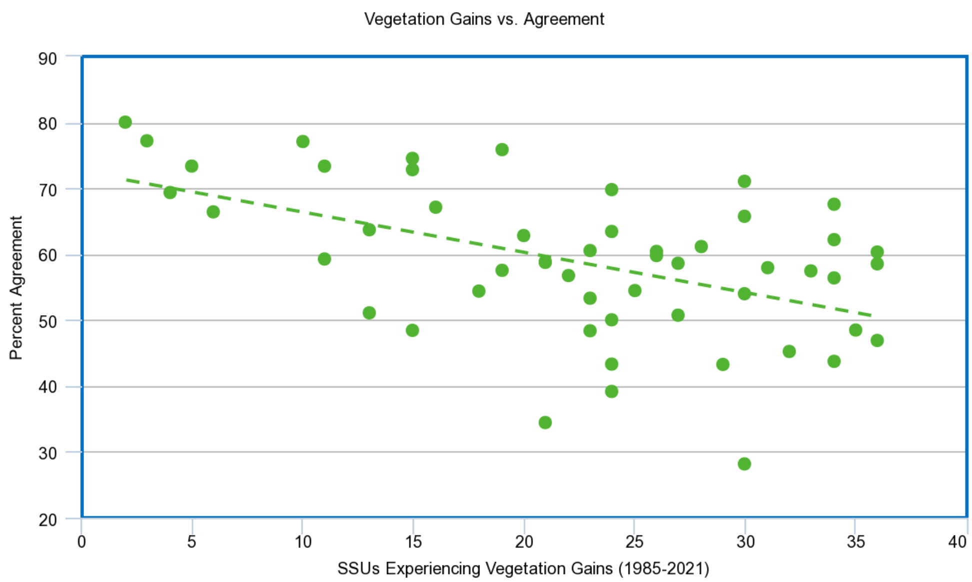

Figure 13. Scatterplot and linear regression model of the correlation between vegetation gains in an AOI and agreement.

Another correlation was established between agreement and the amount of shrubland present in a given location, as determined by the citizen scientist in their CEO land cover analysis. The agreement with the WC map tended to be highest for AOIs in which the citizen scientist classified lower amounts of shrubland, while the agreement was higher when larger amounts of shrubland were classified on CEO. The correlation coefficient for this relationship was a moderate -0.43. Additionally, there is a correlation present between the highest amount of shrubland classified in an AOI between the CEO and WC datasets. The correlation coefficient is slightly higher for this relationship at -0.48. The correlation coefficients for the two associations described above are quite similar, which suggests that the highest amount of shrubland classified between the two land cover datasets may often be the amount classified in the CEO analysis rather than in the WC analysis. Indeed, for 96% of the AOIs (52 out of the 54) in this study, WC provided a lower estimate of the amount of shrubland compared to CEO. Figure 12 summarizes the two correlations described above, while Figure 13 pictures the scatterplots with linear regression models overlaid.

Highest Shrubland Classified Between the Two Data Sets vs. Agreement	**Shrubland Classified by Citizen Scientists vs. Agreement**
Correlation Coefficient: -0.48	Correlation Coefficient: -0.43
Coefficient of Determination: 0.23	Coefficient of Determination: 0.18
P-Value: .00024	P-Value: .001174
Linear Regression Model: $\hat{y} = -52.45323x + 62.20463$	Linear Regression Model: $\hat{y} = -46.67592x + 61.67683$

Figure 14. Table summarizing the correlations between agreement data and shrubland.

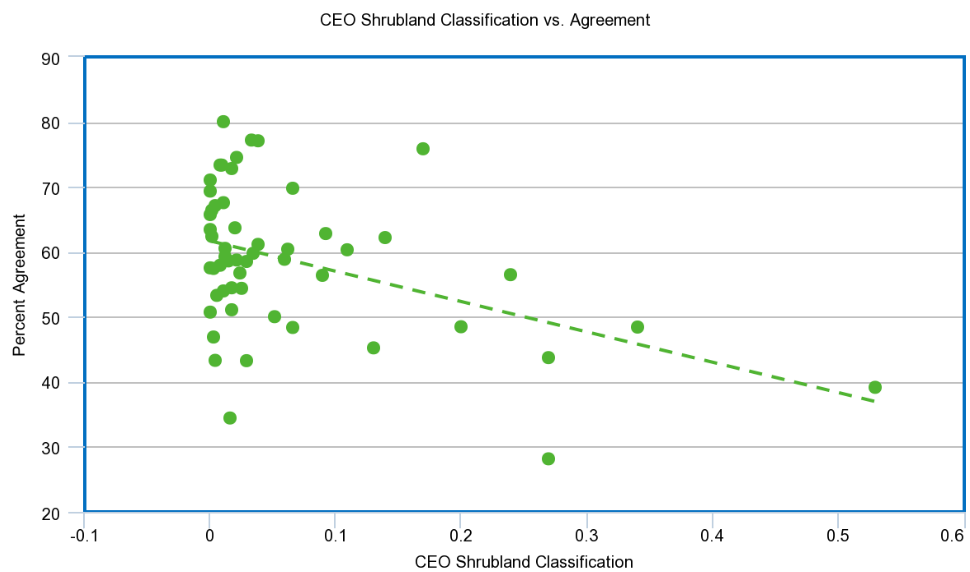

Figure 15a. Scatterplot and linear regression model of correlation between CEO shrubland classification and agreement.

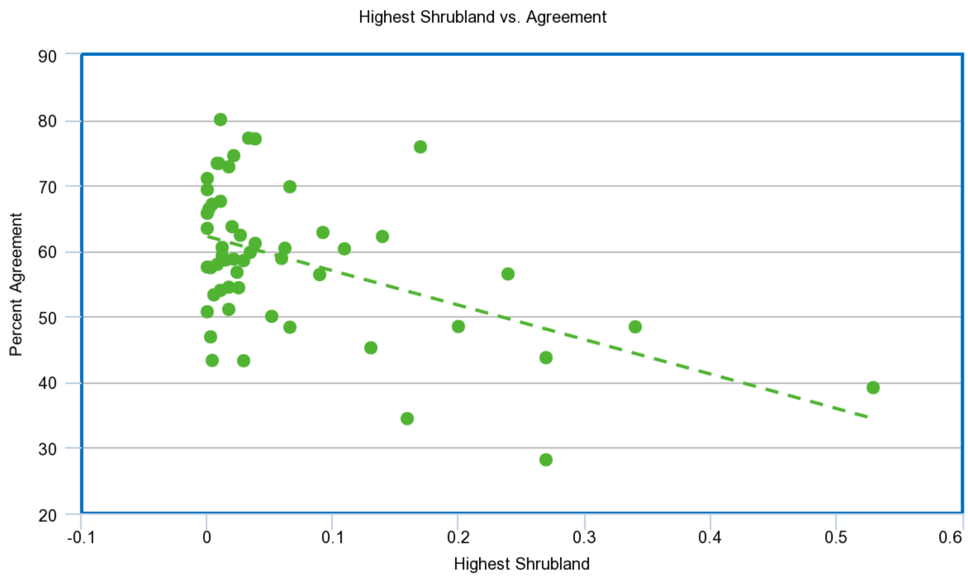

Figure 15b. Scatterplot and linear regression model of correlation between highest shrubland classification and agreement. Note the incredible similarity to figure 13a.

Further correlations were established between demographic variables and agreement data. Such variables included population density as well as mean and median household income values. Population density was measured in people per square mile. When examining the relation between agreement and population density, it was evident that a relationship existed between the variables. However, after examining a scatterplot it became clear that linear regression was not the best choice to model this relationship. Rather, the plot appeared to resemble a logarithmic graph, and thus logarithmic regression was used as the best-fit model for this variable. Comparatively, the logarithmic model was a better fit for the data than the linear one, having a correlation coefficient of .48 rather than the latter's .41. It is important to note that one international AOI was left out of the statistical analysis of this relationship due to the fact that consistent and reliable demographic information was unavailable for that location. Further statistics related to this correlation are summarized in Figure 14, and the logistic regression model is visible in Figure 15.

Correlation Coefficient	+0.48
Coefficient of Determination	0.23
P-value	.000246
Logarithmic Regression Model	y = 4.04+6.71ln(x)

Figure 16. Table summarizing the correlation between population density and agreement.

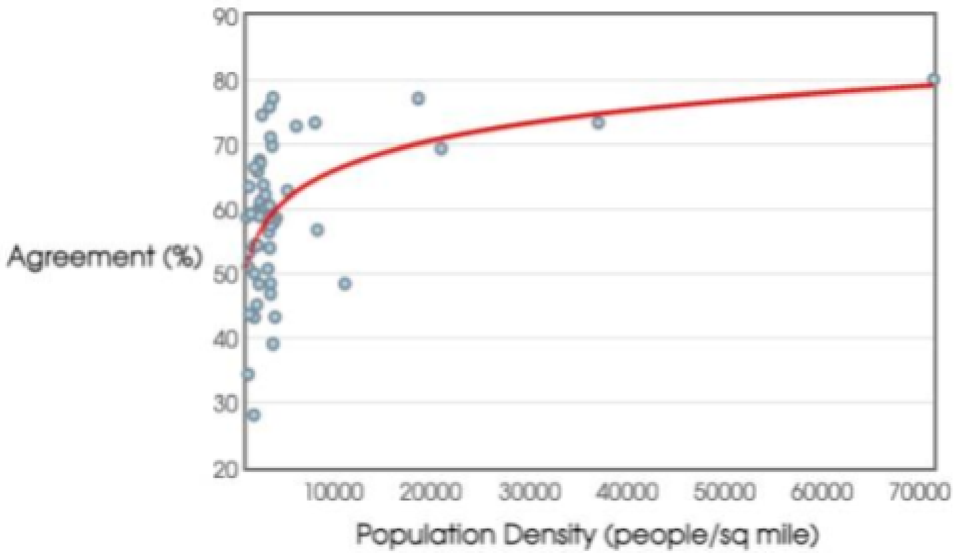

Figure 17. Scatterplot and logarithmic regression model of the correlation between population density and agreement.

Mean and median household incomes were tested to see if either variable shared a statistically significant correlation with the agreement data. However, upon testing it became clear that there were no correlations between income and agreement. Several other variables were tested as well throughout the study which did not yield any strong correlations. These variables are summarized in figure 16 below.

Variable	**Correlation Coefficient**
Latitude	+0.13
Longitude	+0.10
Number of GLOBE Observations within an AOI	+0.18
Number of Plots Classified as "Shadow" on CEO	+0.10
Number of AOIs experiencing losses in vegetation between 1985 and 2021	-0.27
Percent Trees (from WC data)	+0.08
Percent Water Bodies (from WC data)	+0.20
Percent Built Up (from WC data)	+0.36

Percent Cropland (from WC data)	-0.33
Percent Barren (from WC data)	-0.28
Median Household Income	+0.03
Mean Household Income	+0.10

Figure 18. An overview of the variables which share a weak and/or non-statistically significant correlation with agreement data.

A qualitative variable that was examined closely was Köppen-Geiger climate classification. The Köppen-Geiger climate classification is a widely used climate classification system that categorizes areas into five main climate groups and then further into further subgroups based on temperature and precipitation patterns. There are upwards of 25 Köppen-Geiger climate zones throughout the Earth, but only a few are represented by the AOIs examined in this study. Figure 17 summarizes the representation of the Köppen-Geiger climate zones among the 54 AOIs studied.

Climate Zone	**Number of AOIs**
Dfa- Cold without dry season, hot summer	11
Cfa- Temperate without dry season, hot summer	26
Bsh- Arid steppe, hot	2
Csb- temperate dry, warm summer	7
Dfb- Cold without dry season, warm summer	2
Am- Tropical monsoon	1
Bsk- Arid steppe, cold	3
Csa- temperate dry, hot summer	2

Figure 19. Summary of Köppen-Geiger climate zone representation among the 54 AOIs studied.

After examining the statistics of the AOIs within each of these categories, it became apparent that there are no strong relationships between any of the climate zones and agreement. All of the climate zones which contain five AOIs or more have a range upwards of 30, which is incredibly large considering the average AOI agreement is only around 59. Those same climate zones also share mean and median agreement statistics that are almost identical. There doesn’t appear to be a specific climate zone that dominates or falls behind the rest in terms of agreement values.

Dfa- Cold without dry season, warm summer	**Cfa- Temperate without dry season, hot summer**	**Csb- Temperate dry, warm summer**
Mean: 59.71	Mean: 59.40	Mean: 58.95
Median: 58.75	Median: 58.75	Median: 59.78
Range: 36.77	Range: 32.55	Range: 31.86
IQR: 19.06	IQR: 13.32	IQR: 14.39

Figure 20. Basic statistics of the agreement data in each of the most represented climate zones among our 54 AOIs. Note the incredible similarity between the measures of center.

The remaining climate zones represented in the 54 AOIs used in this study did not have enough data points that fell within them to draw meaningful conclusions about their relationship with agreement data. More data will be needed in future studies to determine the presence or absence of these relationships. It is worth noting, however, that two out of the three AOIs with the lowest agreement statistics were located within the climate zone known as Csa. This suggests that perhaps the Csa climate zone is associated with lower agreement data. However, further studies with access to larger datasets would be necessary to determine if this is true.

Finally, the last variable tested for associations with agreement data was primary land cover type, once again a qualitative variable. The primary land cover types that were most represented within the 54 AOIs used in this study were trees and built-up. Grassland, water bodies, and cropland were also represented, but for a very small number of AOIs.

Primary Land Cover Category	**Number of AOIs**
Trees	25
Built Up	23
Water Bodies	2
Grassland	3
Cropland	1

Figure 21. Table providing an overview of the primary land cover categories represented among our 54 AOIs.

After examining the AOIs within each of the primary land cover classifications (PLCC), it appears that there are relationships between PLCCs and agreement data. There are certain categories in which the agreement statistics are generally higher and others where the agreement statistics tend to be lower. These associations are summarized in Figure 22.

Trees	Built Up	Grassland
Mean: 58.03	Mean: 62.88	Mean: 41.98
Median: 58.53	Median: 62.2	Median: 39.16
Range: 32.6	Range: 36.72	Range: 30.45
IQR: 14.34	IQR: 16.07	IQR: NA
MAD: 7.40	MAD: 7.64	MAD: NA

Figure 22. Summary of the AOI statistics within each PLCC represented in our dataset.

From the above statistics, it is evident that AOIs with built up as their PLCC tend to have higher agreement statistics than those that have trees as their PLCC. The difference between the mean of the two categories is just under five percentage points. The above table also suggests that AOIs with grassland as their PLCC may tend to have lower agreement statistics. However, because grassland is only the PLCC of 3 AOIs, more data is needed to determine for sure whether this is true.

V. Discussion

As mentioned earlier, studies conducted by other researchers have concluded that existing land cover maps are most accurate where land cover is homogenous as opposed to diverse. This is consistent with our findings. We stated above that as the percentage of the primary land cover classification increases within an area of interest, so does the agreement between CEO and WC. The percentage of the AOI covered by the PLCC can serve as a metric of diversity. If an area of interest has a large proportion of its land area covered in the PLCC, it means that that particular AOI has mostly homogenous land cover. Thus, the strong positive correlation between percent PLCC and agreement indicates that land cover mapping is most accurate where land cover is homogenous and least accurate where land cover is diverse. Previous studies also indicated that land cover mapping is most accurate in the presence of trees and water bodies. Although our results did not yield any correlation between trees and land cover mapping accuracy, there was a very weak positive correlation between water bodies and agreement data. The correlation coefficient for this relationship was +0.20. Additionally, existing research concluded that land cover mapping is least accurate where there is lots of grass, shrubs, and barren land. This strongly agreed with our findings. We determined that there is a moderate negative correlation between shrubland and agreement, as well as between grassland and agreement. Even though the correlation between agreement and barren land was relatively weak with a correlation coefficient of -0.28, the p-value for the relationship was still small at .04. Thus, at a significance level of 0.05, this correlation is still statistically significant and is unlikely to occur under the null hypothesis.

New correlations that were not mentioned in most articles discussing land cover data accuracy were also detailed above, such as those involving population density and changes in vegetation. The positive correlation between agreement and population density may be because in more urban areas the land cover is homogeneously built up. This correlation thus could potentially be related to the first correlation mentioned between diversity and agreement. Furthermore, the negative correlation between vegetation changes and agreement is logical due to the fact that the images *themselves* that are being classified in the creation of different land cover maps may contain discrepancies. These discrepancies can be minimized by ensuring the satellite images being classified are from similar dates.

Most of the citizen scientists participating in this study did not complete all 37 of their *in-situ* GLOBE Observer observations. The mean number of GLOBE observations taken within an AOI was approximately 20. However, the agreement data was no higher for the citizen scientists who completed the task than for the ones who did not. This may be because most of the citizen scientists participating in this study were already highly familiar with their AOIs to begin with, and thus the extra few hours spent completing observations did not impact the degree to which their local expertise could be leveraged to produce more accurate land cover classifications.

The fact that AOIs with a PLCC of built up tend to have the highest agreement statistics, AOIs with a PLCC of trees tend to have average agreement statistics, and AOIs with a PLCC of grassland tend to have the lowest agreement statistics can be deduced in multiple ways from the above section discussion statistical results. It can first be deduced by means of examining the measures of center presented in Figure 22. It can additionally be reasoned from the correlation coefficients between each of the land cover categories and the agreement data. The correlation coefficient with agreement is positive for built up, is near zero for trees, and is negative for grassland.

VI. Conclusion

The results obtained in this study ultimately point to land cover homogeneity, lack of grass and shrubs, high population density, and vegetation stability as factors that constitute the areas of highest accuracy on the European Space Agency's WorldCover map. Knowing this can help scientists improve existing land cover maps by helping them identify where the most errors may lie in land cover data products, and thus where citizen scientist observations may be most useful.

The reason countless land cover data products exist is because land cover mapping can be utilized by professionals in a multitude of fields for diverse purposes. For example, land cover data can help professionals make decisions about natural resources management at local, national, and international scales (Wulder et al. 2018). Additionally, land cover data can help entomologists and eco-epidemiologists battle one of the world's most pressing public health issues, that of mosquito borne diseases. Water is the primary habitat for mosquitoes throughout the majority of their lifecycle. Some mosquito larvae can survive in minute amounts of water as small as a bottlecap. Therefore, mosquito habitat elimination on local scales requires detailed, high-resolution land cover data. Enhanced land cover maps can help professionals improve their models of mosquito habitats and thus contribute to mosquito source reduction.

Looking forward, further studies utilizing similar methods of land cover error analysis may benefit from incorporating more citizen science data into their analysis to see if the correlations discussed here are upheld at larger data scales. Including more data may also help identify new correlations and patterns that may not have been evident in this study due to lack of data availability. Additionally, an evaluation of the accuracy of the reference land cover data created by citizen scientists will prove invaluable to ensure the results of this study are applicable to land cover map development. Such evaluations may be conducted through a direct comparison between GLOBE Observer land cover observations and citizen science land cover classifications completed through Collect Earth Online.

References

Liang, L., Liu, Q., Liu, G., Li, H., & Huang, C. (2019, June 12). *Accuracy Evaluation and Consistency Analysis of Four Global Land Cover Products in the Arctic Region*. MDPI. https://doi.org/10.3390/rs11121396

Russell, R. (2010, November 29). *Resolution of climate models*. University Corporation for Atmospheric Research. Retrieved August 15, 2022, from https://eo.ucar.edu/staff/rrussell/climate/modeling/climate_model_resolution.html

Rwanga, S., & Ndambuki, J. (2017, April). *Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS*. International Journal of Geosciences. https://doi.org/10.4236/ijg.2017.84033

Sari, L., Weston, C. J., Newnham, G. J., & Volkova, L. (n.d.). *Estimating land cover map accuracy and area uncertainty using a confusion matrix: A case study in Kalimantan, Indonesia*. IOP Publishing Ltd. https://doi.org/10.1088/1755-1315/914/1/012025

Sohl, T., Wimberly, M., Radeloff, V., Theobald, D., & Sleeter, B. (2016). *Divergent projections of future land use in the United States arising from different models and scenarios* (Ecological Modelling). https://doi.org/10.1016/j.ecolmodel.2016.07.016

Wang, J., Yang, X., Wang, Z., Cheng, H., Kang, J., Tang, H., Li, Y., Bian, Z., & Bai, Z. (2022, March 16). *Consistency Analysis and Accuracy Assessment of Three Global Ten-Meter Land Cover Products in Rocky Desertification Region—A Case Study of Southwest China*. MDPI. https://doi.org/10.3390/ijgi11030202

Wulder, M. A., Coops, N. C., Roy, D. P., White, J. C., & Hermosilla, T. (2018, March 27). *Land Cover 2.0*. https://www.tandfonline.com/doi/full/10.1080/01431161.2018.1452075?cookieSet=1

IVSS Badges

Badge 1: I Am a Data Scientist

Our entire research project was based on statistically analyzing large data sets to develop correlations and associations between different variables and land cover map accuracy. In order to do this, we used computer generated confusion matrices to generate data about the agreement between citizen science land cover data analysis and the European Space Agency's WorldCover map. Using this data, we were able to see which types of land cover were often confused for each other as well as the overall agreement between citizen scientist analysis and WorldCover analysis. We thoroughly analyzed this data and used that data analysis as the basis for this paper.

Badge 2: I Am a STEM Professional

Throughout this project, our team was mentored by Mr. Peder Nelson, who is faculty at Oregon State University, as well as with Dr. Rusty Low, a senior scientist at the Institute for Global Environmental Strategies. These STEM professionals helped us improve our research methods by teaching us about different sampling methods and ensuring we chose data with a high data fitness for use. This project makes use of their Adopt a Pixel Area of Interest method, a method which takes a systematic sampling approach to land cover classification and observation collection. This ensures that the data collected serves as a representative sample of the land cover throughout the entire Area of Interest. Mr. Nelson and Dr. Low inspired us to take their Adopt a Pixel idea and analyze it statistically.

Badge 3: I Make an Impact

The research our team conducted throughout the development of this paper has the potential to help scientists improve existing land cover maps. This can indirectly help scientists and public health professionals improve their models of mosquito habitats, as mosquito habitats depend heavily on what the land cover looks like in a particular area. If a particular area is mostly desert, there is not likely to be very many mosquitoes in that area. However, if an area has lots of water and vegetation, there are likely to be many mosquitoes. Thus, by helping improve land cover data, our research team is supporting public health professionals in their fight against mosquito-borne diseases. Additionally, since mosquitoes can survive on tiny amounts of water, such as the amount of water in a plastic bottle cap, improvements of land cover data products from the research we have conducted can help identify and eliminate mosquito microhabitats. Our team members are from northern Texas as well as from northern Ohio. There are several mosquito-borne diseases that are present in both of these areas (such as West Nile Virus), and thus the research we conducted can help our local communities better protect themselves from vectors carrying these pathogens.

Case Studies

Throughout the NASA SEES Internship interns used Collect Earth AOI to label our area of interest and also used GLOBE Observer to photograph our area. We decided to analyze how GLOBE photos enhance land cover classification accuracy. The GLOBE photos were taken in the directions of North, East, South, West, Up and Down. With the AOI's labeling we were able to see the primary and some classification of the land, while the AOI shows the 100m grid, the globe observer shows one location in the grid which helps look at one area closer with more detail and a look at the perspective of the whole plot from one area of the grid. The images also show how close the different types of land cover are. For instance, in the grid some of the sample units might show two types of land cover but with the images from GLOBE you're able to see the land cover side by side. In addition Globe Observer helps better understand how the land cover looks since in the grid it is often hard to identify the type of land cover by only seeing a view from above and the Globe Observer the area is seen in many directions with a clearer view which helps know how the type of land cover looks. We analyzed two AOI's the first one was classified with mostly Trees_Canopy cover and Grass cover land. In some of the plots the grids were identified with mostly one type of land cover and the Globe Observer images are taken from one area which gives a perspective to see what is around the plot. Since most of the grid

Fig. 5.1: Case Study 1

was covered in classification of Trees or Grass the images gave a better visualization of the types of trees they are and how much of the land they cover. In some cases, there were two types of land cover in one sample unit, for instance there was trees and road but you could only label with one classification; however, the Globe images increased the accuracy because you're able to see both the land cover closer and side by side. Similarly, in the second AOI which was analyzed was covered in mostly Building and Impervious Surface in many of the plots. For example, in one of the grids most of them were labeled built up however, it's difficult to tell what type of build up covers the land but the GLOBE Observer gives better features of the area and helps identify if they are suburban, urban, or rural because it can be difficult to tell with only the AOI. The images of Observer give the ability to tell where exactly the land classification is. For instance, in one 100m grid there was a small portion of trees surrounded by build-up. It can cause difficulty knowing how close the land cover is yet, images show the area in many

Fig. 5.2: Case Study 2

directions which makes it easier to determine what surrounds.

Overall, GLOBE Observer increases land cover classification accuracy as sometimes when labeling the 100m grid there might be confusion in knowing what type of land cover the area is because the visual can be hard but with the images it makes the data stronger.