GGR335 Final Paper: Monitoring Deforestation Dynamics in the Amazon: Insights from Remote Sensing Analysis in Rondonia

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1. INTRODUCTION

The Amazon rainforest in the northwestern part of Brazil, which is the largest rainforest in the world, has

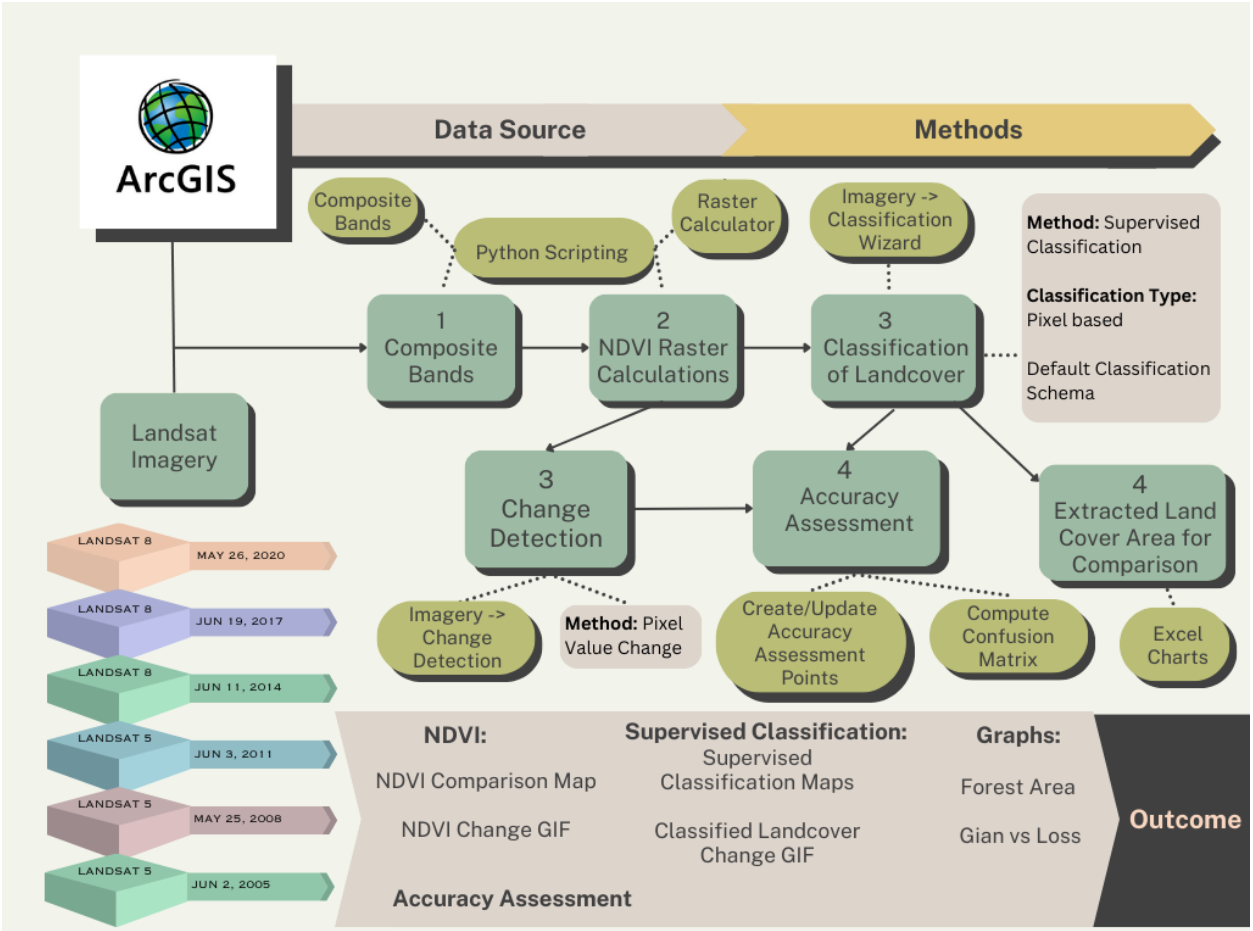
been a significant contributor to the overall biodiversity of the Earth. However, over the years the forest has experienced a steady decline in the number of trees in the area due to various anthropogenic disturbances which include edge effects, selective logging, fire, and extreme drought that have been intensified due to human activities (Lapola, D et al. 2023). One of the major reasons for this man-made disruption of the forest could be possibly due to farming and agricultural use. Furthermore, the Earth's climate tends to undergo degradation due to these spots resulting in becoming hotspots for CO2 emissions leading the air quality in those areas to be impacted negatively (Lapola, D et al. 2023). Carrying out an analysis and understanding the core reasons can help the concerned authorities and the policymakers to take necessary actions to prevent these areas from experiencing deforestation.

2. RESEARCH OBJECTIVES

How can remote sensing techniques monitor the rate of deforestation in the Amazon rainforest and provide insights into its impacts over time? The goal of this project is to collect information about the spatial and temporal changes in order to facilitate informed conservation activities and land management strategies, scientific informed perspective on government policy, environment management. It is imperative to concern ourselves with these questions to find transferable solutions to countries' investments in counteracting issues such as climate change in advance.

3. METHODOLOGY

In order to acquire the results for the research question, different steps were taken into consideration to carry out the analysis. The primary source of data was from EarthExplorer. Using remote sensing data from EarthExplorer was ideal because it is accessible and accurate for the timeframe we require. The study site that has been considered for this research project is Rondonia which is one of the 26 states in Brazil where the latitude and longitude are 11.5057° S and 63.5806° W respectively. The rainforest in Rondonia tends to be the habitat of about 30% of the world's animals and about 40,000 plant species. Furthermore, the area tends to experience an average of 90 days of rain every year (Nobre et. al 2016). Moreover, the area has a mean average temperature of 26 degrees Celsius (Malhi et al, 2009). All comparisons made to analyze change will correspond to the WRS paths 230 and rows 068 to ensure the spatial extent remains consistent. The temporal extent will cover every three years from 2005 to 2020. The Landsat 4 satellite is the oldest satellite to be used in this research. This project used Tier 1 category data because it is the highest data quality available. The temporal extent is focused on May/June because there was no suitable data available consistently for other months across all years. Below is a general flowchart of the methodology.



To classify land cover, pixel-based supervised classification was used. The ArcGIS Pro tool used was the Image Classification Wizard to streamline the process. Pixel classification was used to determine the classes each area was assigned because the types of land cover that needed to be classes had distinct spectral characteristics that were relatively homogenous. There was also no need to consider characteristics of neighbouring pixels to classify effectively. Five classes in total were created for the training samples: forest, agriculture, developed, water, and cloud. The classification chosen was the Support Vector Machine due to its flexibility. It needs fewer samples and does not require the samples to be normally distributed or of equal size, which is a valuable property when classifying many images.

```python
import arcpy
from arcpy.sa import *

def composite_bands(bands_list, out_rast):
    """Script code goes below"""
    comp_band = arcpy.management.CompositeBands(bands_list, out_rast)
    return comp_band

def calc_NDVI(comp_band, out_rast):
    band_NIR = arcpy.Raster(comp_band + "\\" + "Band_4")
    band_Red = arcpy.Raster(comp_band + "\\" + "Band_3")
    rast_NDVI = RasterCalculator([band_NIR,band_Red], ["NIR","Red"], "(NIR - Red
    rast_NDVI.save(out_rast+"_NDVI")
    return rast_NDVI

if __name__ == "__main__":
    bands_list = arcpy.GetParameterAsText(0)

    composite_out = arcpy.GetParameterAsText(1)
    composite_band = composite_bands(bands_list, composite_out)

    raster_NDVI = calc_NDVI(composite_out,composite_out)
    arcpy.SetParameterAsText(1, composite_out)
```

Figure 1: Python script to calculate composite bands and NDVI for each year

To calculate the NDVI, a Python script was written to automate the process for all years. However, an issue encountered was when calculating NDVI, the result would account for change in the cyclical planting and clearing of crops in the agricultural land cover. This could have potentially become a source of error for calculating the NDVI of forest areas, since the calculate NDVI tool takes the whole image as an input, including the agriculture land cover type we do not want. To avoid this, the images were later clipped to our supervised classification layers' forest pixels after converting them to polygons using the Raster to Polygon tool. Below is the Python script performing this function.

```python
def MaskDeforestation(param0, param1, param2):


    polygon = arcpy.conversion.RasterToPolygon(param0, param1 + "_poly")
    dissolve = arcpy.management.Dissolve(polygon, param1 + "_dissolve", ["gridcode"])
    arcpy.management.Delete(polygon)

    arcpy.management.AddField(dissolve, "Area_sqkm", "FLOAT")
    arcpy.management.CalculateGeometryAttributes(dissolve, [["Area_sqkm", "AREA"]], area_unit="SQUARE_KILOMETERS")

    arcpy.management.AddField(dissolve, "Class_Names", "TEXT")
    arcpy.management.CalculateField(dissolve, "Class_Names", "!gridcode!", "PYTHON3")

    arcpy.analysis.Split(dissolve, dissolve, "Class_Names", arcpy.env.workspace)

    renamed = param1 + "T1"
    arcpy.management.Rename("T1", param1 + "T1")


    arcpy.sa.ExtractByMask(param2, renamed)

    return
```

Figure 2: Python script masking the the deforested areas only to the images

To estimate the total change in land cover types, the raster layers from the supervised classification step

were converted to polygons. The area of the polygons were calculated and aggregated by land type for every year, resulting in the chart in Figure 3. These metrics were then compared to each other to graph the rate of change between every three years in the bar graph in Figure 4. All processed images of interest were then mapped formally for ease of interpretation.

4. RESULTS

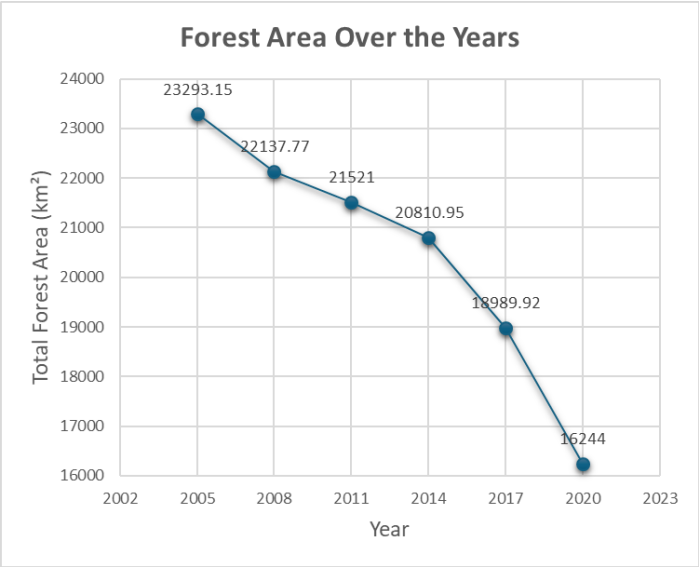


Figure 3: Graph of the total forest area from 2005 to 2020, derived from supervised classification classes

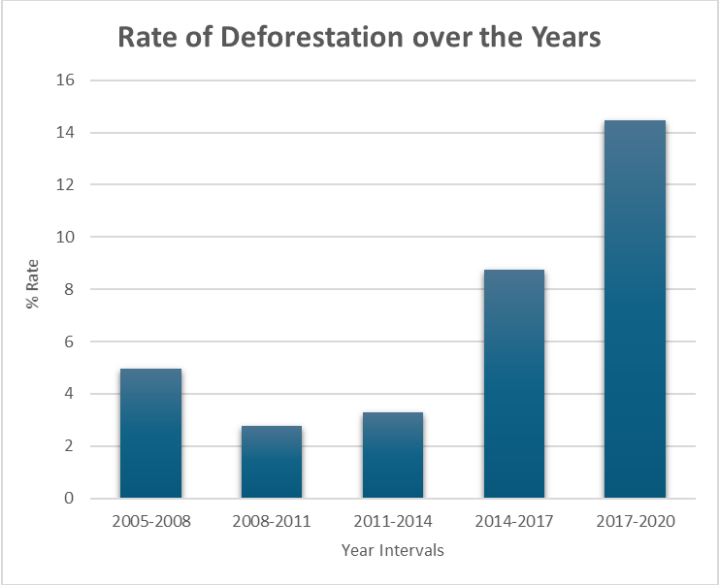


Figure 4: Rate of deforestation every three years

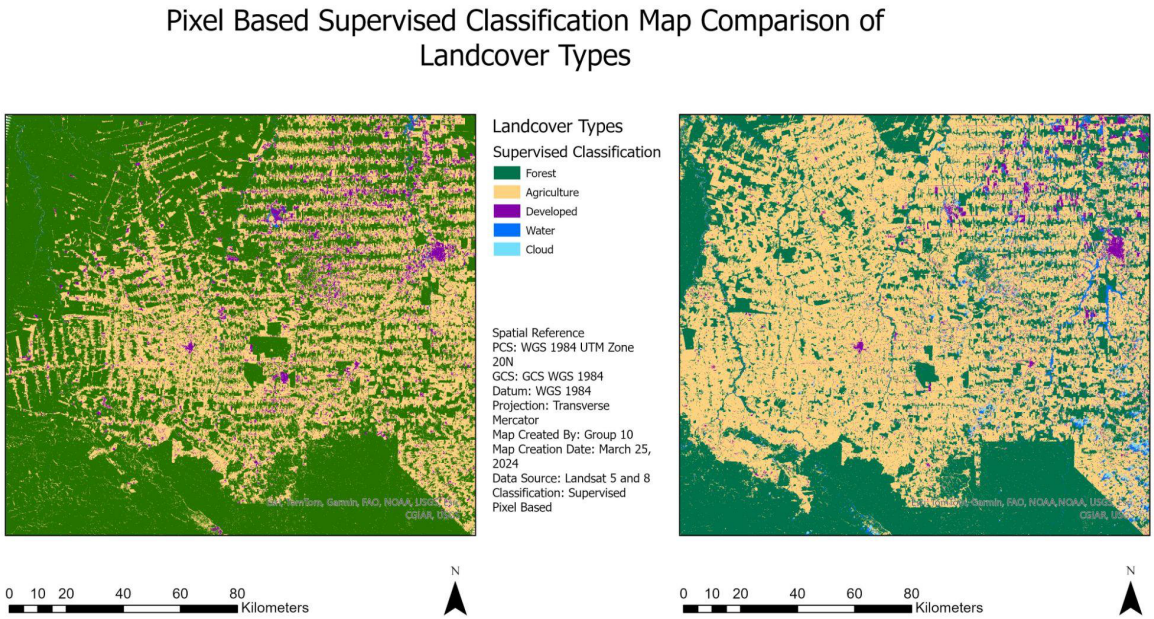


Figure 5: Supervised classification of the entire spatial extent, 2005 & 2020

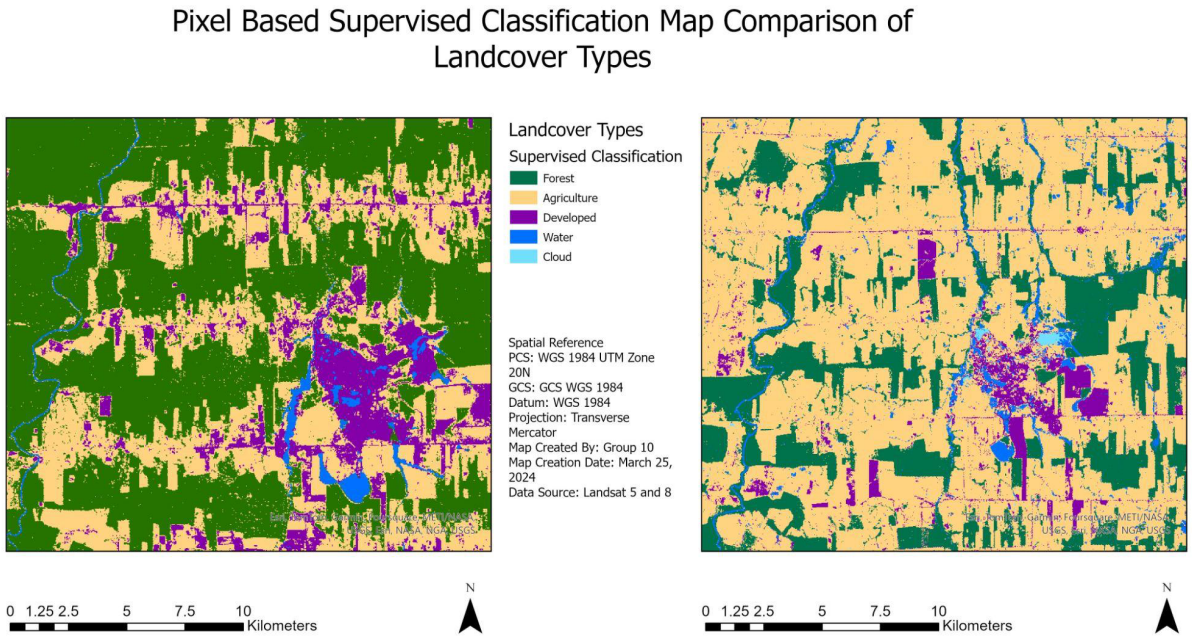


Figure 6: Closer look at supervised classification rasters from Figure 5

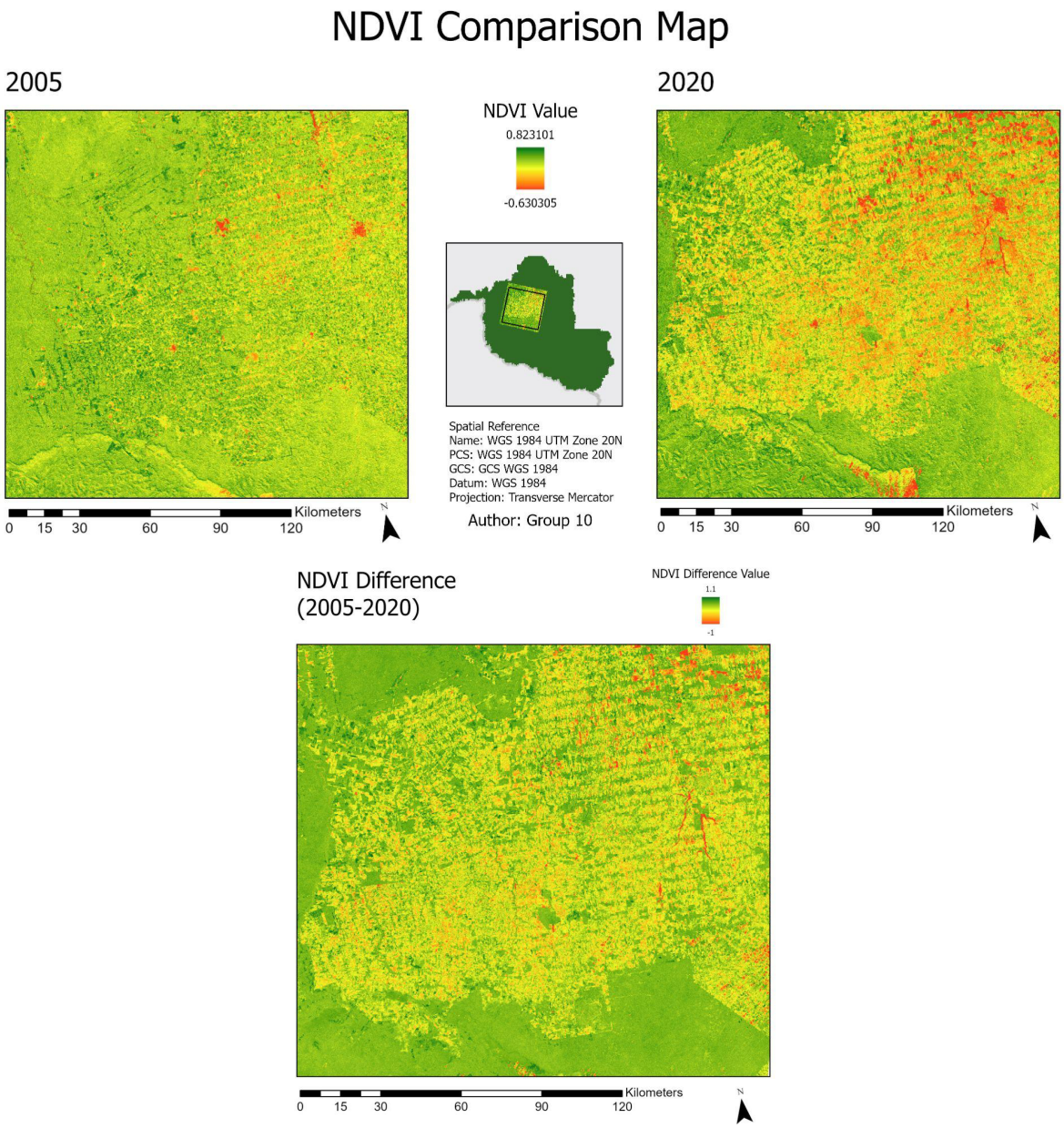


Figure 7: Final NDVI map (2005 and 2020) & NDVI Difference map between 2005 and 2020

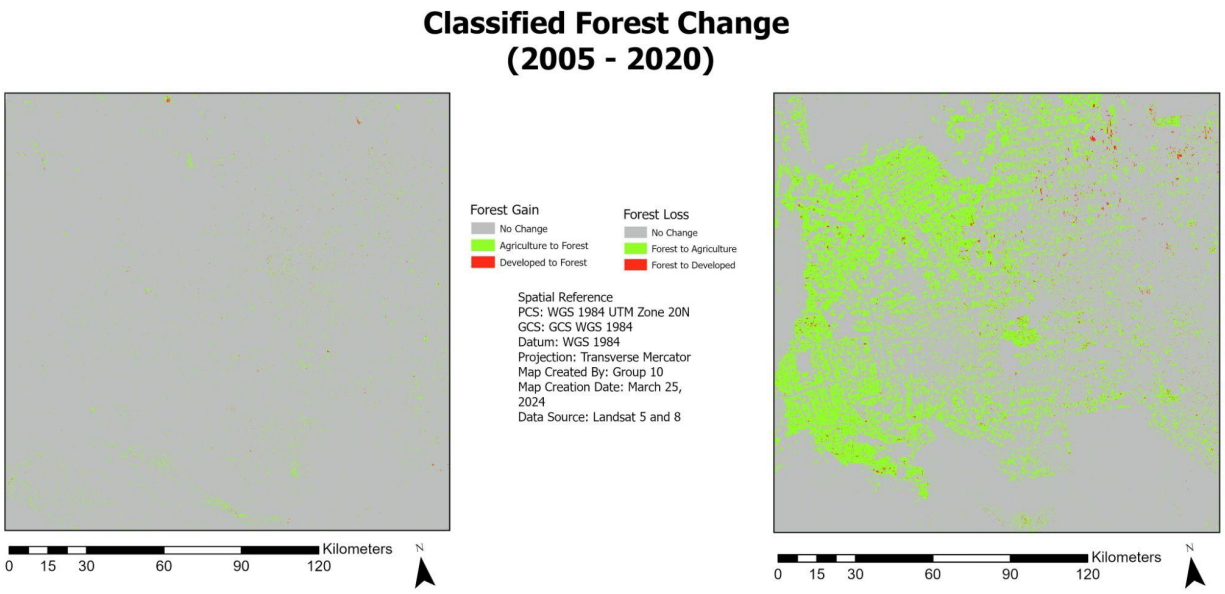


Figure 8: Classified Forest Change map showing where there had been an increase in forest area and where there had been a decrease in forest area over the years

5. DISCUSSION

This project is crucial for understanding global concerns like climate change, species endangerment, and habitat loss. Investigating these trends will offer insights into potential conservation solutions, aligning with informed conservation activities, land management strategies, and scientific-informed policy-making to address pressing environmental challenges proactively.

In Figure 3, we can see the overall land cover has decreased drastically from 2005 to 2020, from a total of about 23000 square kilometers to 16000 square kilometers. This preliminary measurement confirms there is deforestation occurring. The primary reason for this could be an increase in the contribution of small landholders during this time which could include cutting down and removal of trees for farming and agricultural uses. (Kalamandeen et al, 2018)

In Figure 4, we can see the rate of deforestation in percentages. There was an initial rate of 5% in 2005, followed by a dip midway and a dramatic spike from 2017 to 2020. This may indicate the later years may be a temporal extent of great interest and to look at the legislation and companies developing the area during this time. Later on, a significant spike occurred between 2014 to 2017 with rates of over 8% that later increased to nearly 15%. Thanks to data obtained from extracting the classified land cover area, these trends in deforestation become clear, allowing effective monitoring of deforestation rates to make informed decisions and take the necessary action.

As mentioned previously, supervised pixel-based classification was used to expedite the classification of all six images. Figures 5 and 6 depict the results of our classification process. It is apparent there is a large visual difference between 2005 and 2020, which aligns with the results from our previous figures. There is a smaller area of green forest cover which is being replaced mostly by the beige agriculture cover. Upon closer inspection of the image in Figure 6, we can see this is also true.

Figure 7 features a finished NDVI map with an inset map (highlighting the area analyzed), the NDVI of 2005 and 2020, and the change in NDVI between those two years. NDVI surface reflectance analysis allows us to quantify vegetation health and distinguish between forest, agriculture, and developed land cover (Meera Gandhi et al., 2015). High NDVI values (green) indicate healthy vegetation, while lower values (red) signify sparse or unhealthy vegetation. The 2020 map shows lower NDVI values compared to 2005, likely due to changes such as altered land types and environmental conditions over the 15-year span. The 2005 map exhibits higher NDVI values, indicating denser vegetation that reflects more infrared light. In 2020, the presence of green (high NDVI) is reduced, replaced by more yellow and red (low NDVI), possibly due to construction of impermeable surfaces and climate change impacting vegetation health.

Finally, through the NDVI difference map from 2005 to 2020, the change in the health of the forested area can be very easily inferred. Although green patches are present, indicating healthy vegetation with high NDVI values, the map predominantly features yellow and some red areas. This very clearly shows that while there are green areas, the dominant yellow regions highlight a decline in NDVI. These yellow areas signify less healthy or sparse vegetation, as they do not reflect enough of the infrared light, indicating degradation of vegetation in the area.

The last figure was derived from clipping the original images to the supervised classification images to obtain the forest loss and forest gain from 2005 to 2020. Figure 8 includes information about the type of land cover the forested areas were replaced by. Visually, it is apparent there has been much more forest loss than forest gain, as signified by the large difference in green area. Below are ancillary figures quantifying the exact amount of forest gain and loss.

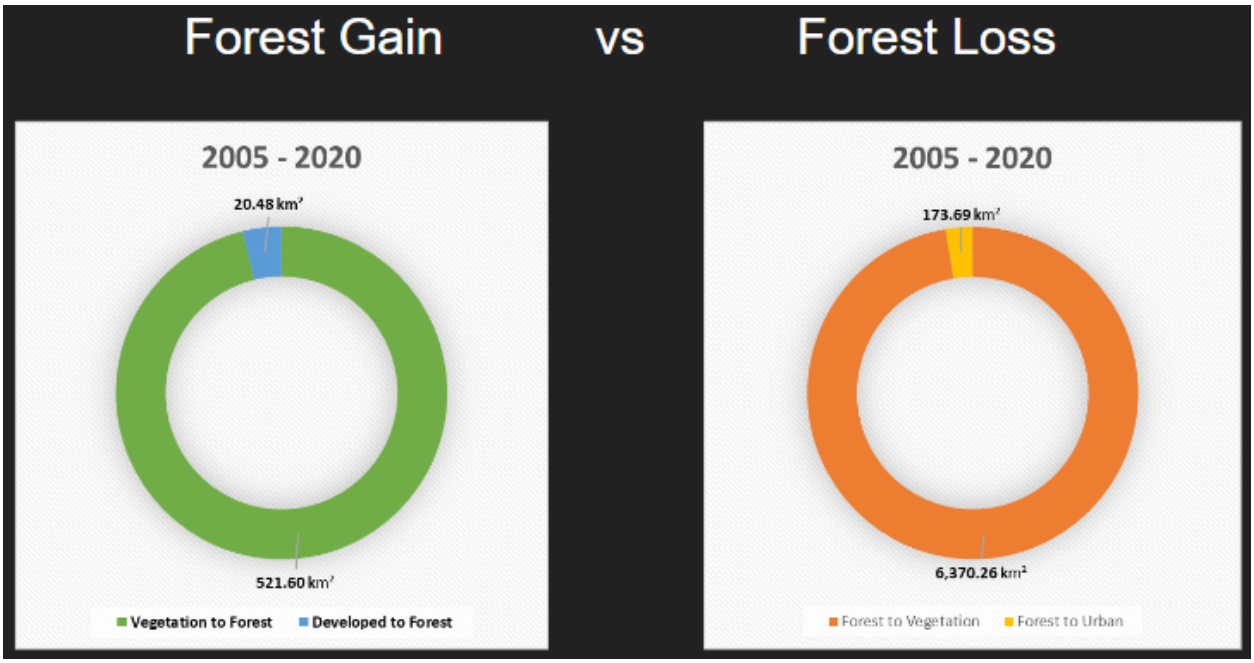


Figure 9: Quantified areas of interest from Figure 8

Due to resource and time constraints, the team was unable to continue with some goals and properly evaluate the accuracy of our methodology. There were some challenges faced by the team during the supervised classification step of the images. It was difficult to accurately classify water cover because the water shared the same spectral characteristics as the forest cover. The water appeared green to the eye and was only distinguishable from forest cover because it was slightly more homogenous and followed an irregular, winding line pattern. Additionally, there was no previous documentation or map of the water cover the team found in any general reference maps, making it difficult to pinpoint the exact number of streams, rivers, etc.. The classification machine was largely unable to distinguish water cover from forest cover. However, since the total area of the water cover was not as great as the other types of land cover, it was assumed to be a seasonal appearance and not a permanent one. The month selected was June, which is in the dry season (Wright et al., 2017). Therefore, it was assumed the water cover was not significant enough to interfere with the analysis. There was also not enough time to include the accuracy assessment of our selected representative training samples, which could have bolstered our results. The next potential step of our study was to graph a regression line to act as a predictive model. The predictive model would be evaluated for accuracy and validity to predict the estimated forest area in the next two decades. As mentioned before, time constraints did not allow for this.

To conclude, the results derived from our analysis aligned with our expectations based on prior research. The rate of deforestation has increased significantly and the overall forest area of the Rondonia region of the Amazon has decreased. It is imperative to be aware of these rapid changes to aid in identifying potential

causes and lead to potential solutions to minimize the damage we have on our environment. The analysis underscores the urgent need for action to address the escalating deforestation in Rondonia, Amazon. Beyond environmental concerns, this loss impacts biodiversity, local communities, and global climate stability. To combat this, we must understand and address the drivers such as agriculture, logging, and infrastructure. By developing targeted strategies and policies, we can promote sustainable land use practices. It's through collective action and conservation commitment that we can safeguard the Amazon for future generations.

6. CITATIONS

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