

## Coordinates

### Polygon Coordinates

Lat: -2.318169152494475

Lon: -60.1446533203125

Radius: 50,000

### Fishbone Coordinates

Path: 231

Row: 059

Lat: 0.9859742824625409

Lon: -60.02655029296875

Radius: 50,000

OLI

Bands= 2,3,4,5,6,7

ETM+=1,2,3,4,5,7

## **Poster details**

### **Slide 1:Introduction to Study Area:**

- Project description,
- Objective
- Map (insert location)

### **Slide 2: Data Description**

- Scene (picture of our data set)
- Include true composite
- Radiometric, spatial, and spectral, and geometric characteristics
- Number of bands and which ones.

### **Slide 3: Image Enhancement**

- Define image enhancement and why it is important to your project

### **Slide 4:” Image Transformation**

- NDVI, NDSI, water content
- Classification: transition, separability
  - a. Transformation
    - Map time1
    - Map time 2
    - Difference
  - b. Classification
    - Training; sig file, AOI, spectral prole

### **Slide 5: Classification Algorithms**

- Map 1
- Map 2
- Change ( in the form of a table/pie chart)

### **Slide 6: Accuracy Assessment ( optional/EC)**

### **Slide 7: Conclusion**

- Dew results
- What it shows
- How the spectral analysis helps

Location- sao luis, sao luiz and sa joa da baliza

### **Classes for signature editor:**

1. Dirt Roads X
2. Clouds X
3. Cloud Shadow X
4. Water/ River in the top left of the image X
5. Forest X
6. Urban Area X
7. Cut DownX

### **Project Description**

We are looking at deforestation in the Brazilian Amazon, a place covered by thick forest. In particular, we would like to see how much of the forest has been cut down to so make room for industrial development. In the Amazon, many areas that were once covered by forest have been converted to mainly agriculture land. Our study area covers an area of (INSERT SQUARE AREA) and contains mainly agricultural land surrounded by forest. We are looking at Landsat 7 ETM+ and Landsat 8 OLI images from May 2013, May 2017, May 2022. Our data utilized 6 bands (2-7): Blue, Green, Red, NIR, SWIR1, and SWIR2. With the region being very big, we cropped our images specifically to North of Manaus, along Hwy 174. The area is located in the centroid of the towns Sao Luis, Sao Luiz, and Sao Joao Da Baliza.

### **Radiometric Correction**

The initial dataset we utilized lacked standardization and error correction. During the collection of reflectance data by sensors, the raw information is influenced by atmospheric absorption and scattering, causing electromagnetic radiation distortion as it travels from ground objects to the sensor. To address this, we perform radiometric corrections to adjust for these effects and convert the reflectance values to top of atmosphere (TOA) reflectance. These corrections involve applying a formula to each pixel, represented as  $p(\lambda) = (M_p Q_{cal} + A_p) / \sin(\theta_{SE})$ , where  $p(\lambda)$  represents TOA reflectance.  $M_p$  and  $A_p$  are band-specific multiplicative and additive rescaling factors obtained from metadata, respectively, and  $\theta_{SE}$  denotes the solar zenith angle retrieved from metadata. Applying this formula to each pixel yields a standardized image with TOA reflectance values ranging from 0 to 1. For Landsat 7 EMT+ images, a different formula is required to convert digital number (DN) values to reflectance. To calculate radiance, the formula  $L = [(L_{max} - L_{min})/255]DN + L_{min}$  is employed, where  $L$  represents radiance for each pixel. To convert radiance to reflectance, the formula  $p_p = (\pi * \lambda * d^2) * ESUN_\lambda * \cos(\theta_s) * p_p$  is used, where  $p_p$  signifies unitless planetary reflectance,  $L$  is radiance obtained from the previous equation,  $d$  denotes the Earth-Sun distance in astronomical units,  $ESUN$  represents the mean solar irradiance varying by wavelength, and  $\theta$  indicates the solar

zenith angle in degrees. Implementing these radiometric corrections ensures standardized reflectance values in the images, enhancing accuracy and facilitating data comparison across sensors.

$$p_p = (\pi * \lambda * d^2) * ESUN_\lambda * \cos(\theta)_s * p_p$$

$$p(\lambda) = (M_p Q_{cal} + A_p) / \sin(\theta_{SE})$$

$$[(L_{max} - L_{min})/255]DN + L_{min}$$

### Image Enhancement (VEGETATION INDEX)

The goal for image enhancement is to improve the appearance of the images so that it is easier to work with, understand, and even visualize. For the image enhancement we used a combination of the SWIR1, NIR, and green bands (Bands 5,4,2). Healthy vegetation has higher values of reflectance in the infrared wavelengths, so it was important we used infrared bands so that the vegetation would stand out. The SWIR1, NIR, and Green band composite allows us to see the vegetation and crops as green and soil and other agriculture as bright purple/ pink. Lastly, we used a histogram equalization to distribute the reflectance values of our images across the full spectrum of available values, resulting in a sharper and more defined image that is easier to work with. The goal was to clearly see any changes between the 15 year tenure, as well as being able to see the landscape clearly, more specifically being able to clearly see how vegetation is being impacted with deforestation effects.

2013

2017

2022

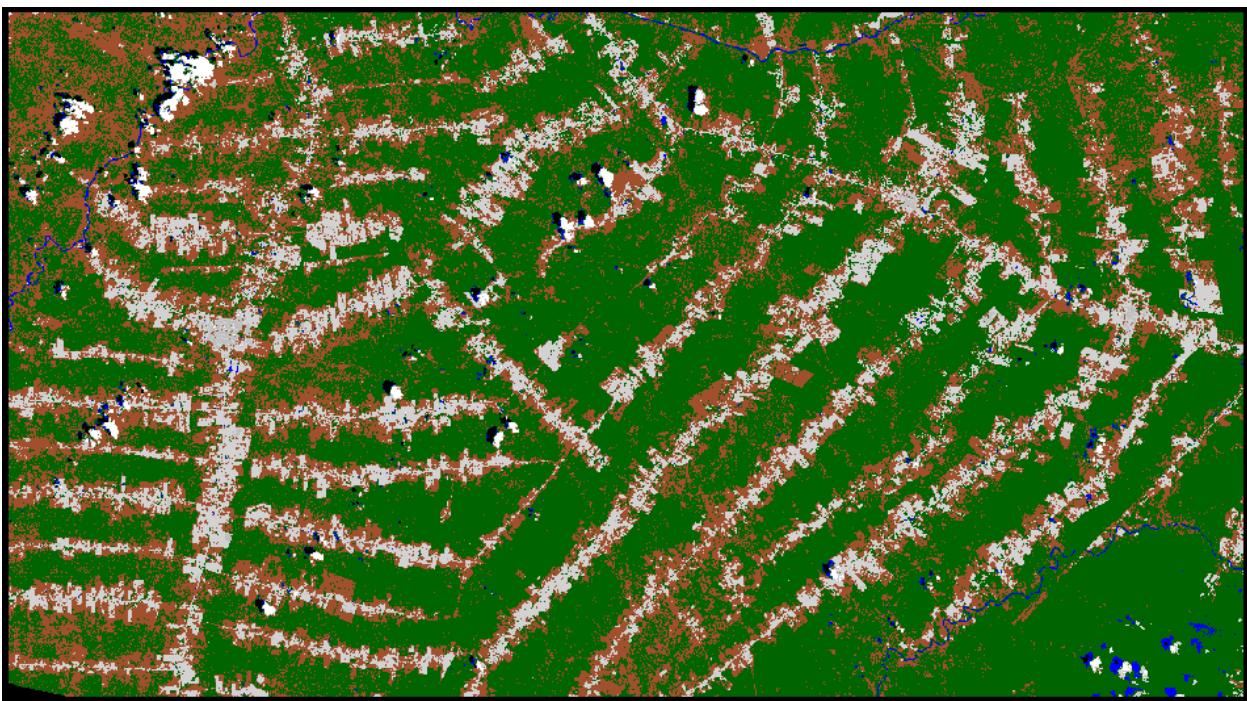
### Image Classification (ASSIGNMENT 4 THINGY)

To be able to more effectively understand and visualize the area of study we performed a supervised classification using the minimum distance algorithm.

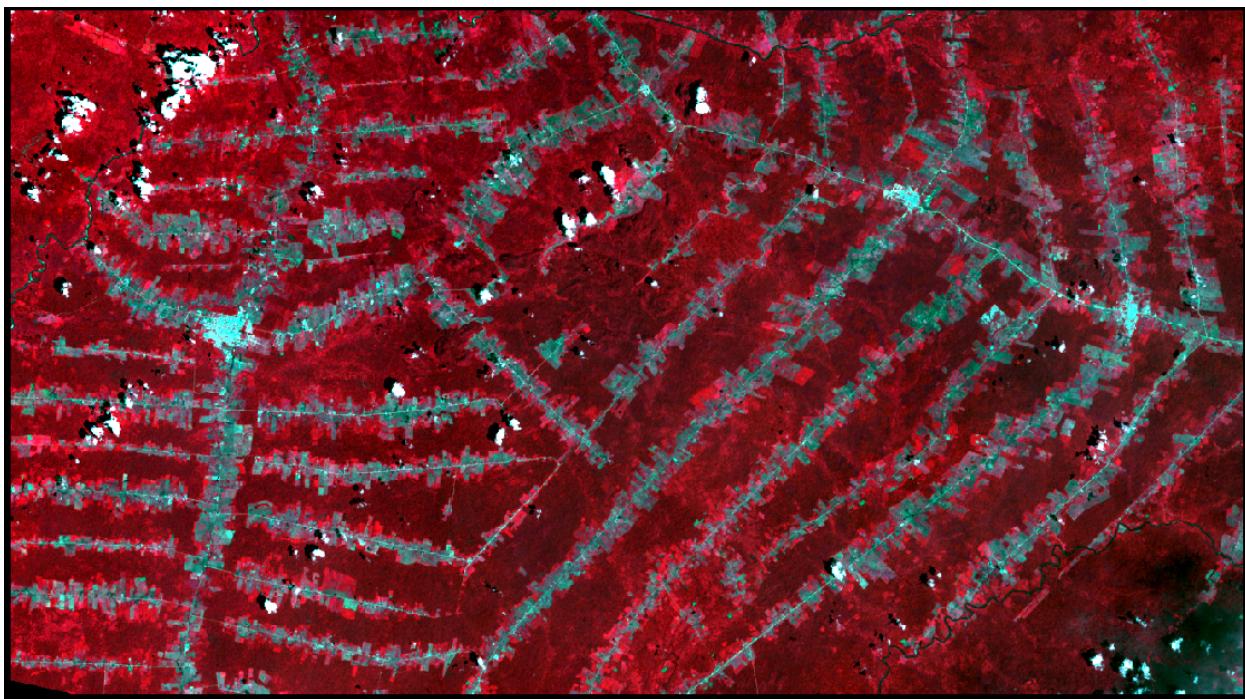
We chose the minimum distance instead of the maximum likelihood because of precise minimum distance came out to be. When we tried maximum likelihood the output was not what we expected because most areas turned out to be water or urban when it was the opposite. We chose to have seven different classes: Water, Clouds, Cloud Shadows, Urban, Roads, Cutdown, Forest. For our training sites we chose 2 forests, 4 clouds, 4 Shadows, 4 waters, 4 Urban, and 4 roads. In total, we had approximately 28 training sites for 2013, 26 for 2017, and 35 for 2022 data. Using these training sites we were able to group pixels from our image into our 7 classes to create a supervised classification. Our Classification allowed us to more easily visualize the landscape, and

**identify the effects of deforestation and urban sprawl in the Amazon from May 2013 to May 2017 to May 2022.**

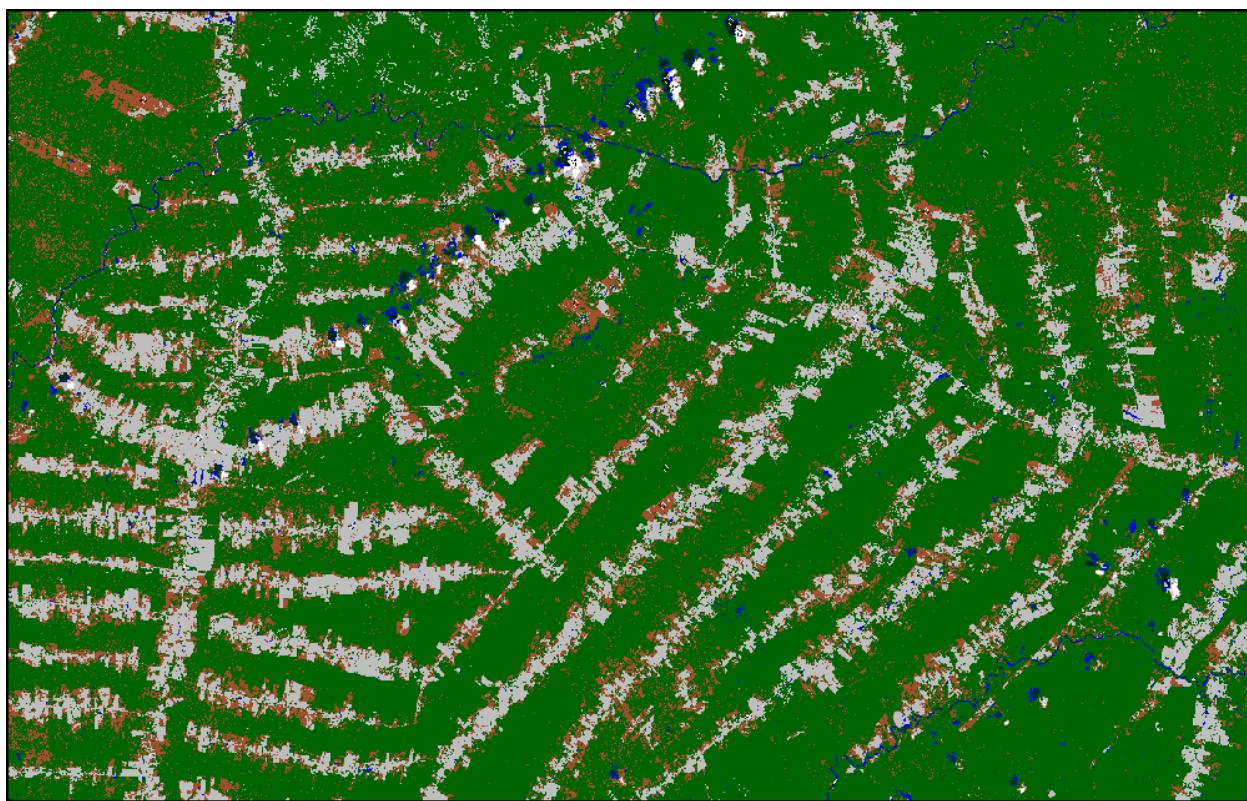
**1. 2013 - alex**



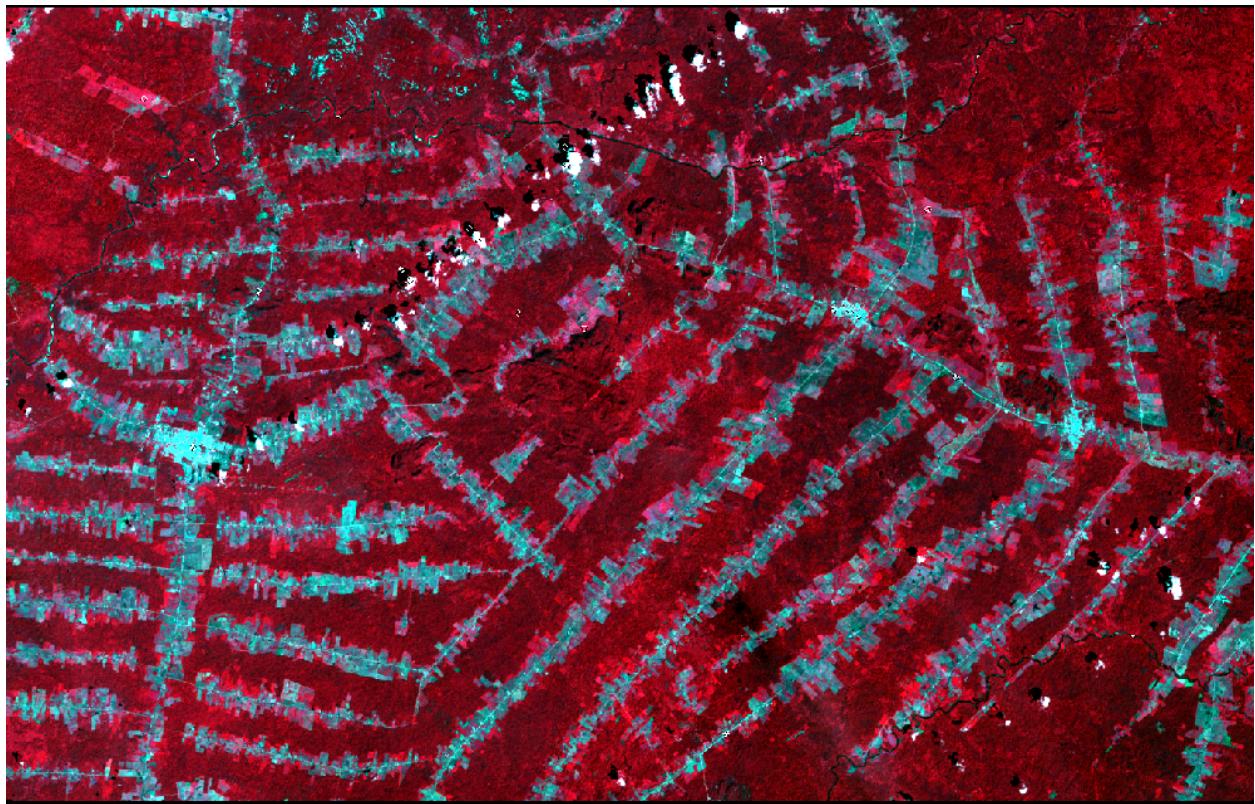
Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1	►	Urban		0.753	0.753	0.753	1	1	100	1.000	✓	✓	✓	✓	
2		U2		0.753	0.753	0.753	2	2	100	1.000	✓	✓	✓	✓	
3		U3		0.753	0.753	0.753	3	3	100	1.000	✓	✓	✓	✓	
4		U4 C2		0.753	0.753	0.753	4	4	100	1.000	✓	✓	✓	✓	
5		U5 C3		0.753	0.753	0.753	5	5	100	1.000	✓	✓	✓	✓	
6		Cloud		1.000	1.000	1.000	6	6	100	1.000	✓	✓	✓	✓	
7		C12		1.000	1.000	1.000	7	7	100	1.000	✓	✓	✓	✓	
8		C13		1.000	1.000	1.000	8	8	100	1.000	✓	✓	✓	✓	
9		C14		1.000	1.000	1.000	9	9	100	1.000	✓	✓	✓	✓	
10		Cloud Shadow	█	0.000	0.000	0.000	10	10	100	1.000	✓	✓	✓	✓	
11		CS2	█	0.000	0.000	0.000	11	11	100	1.000	✓	✓	✓	✓	
12		CS3	█	0.000	0.000	0.000	12	12	100	1.000	✓	✓	✓	✓	
13		Water	█	0.000	0.000	1.000	13	13	100	1.000	✓	✓	✓	✓	
14		Water2	█	0.000	0.000	1.000	14	14	100	1.000	✓	✓	✓	✓	
15		Water3	█	0.000	0.000	1.000	15	15	100	1.000	✓	✓	✓	✓	
16		Water4	█	0.000	0.000	1.000	16	16	73	1.000	✓	✓	✓	✓	
17		Forest	█	0.000	0.392	0.000	17	17	100	1.000	✓	✓	✓	✓	
18		Forest2	█	0.000	0.392	0.000	18	18	100	1.000	✓	✓	✓	✓	
19		Forest3	█	0.000	0.392	0.000	19	19	100	1.000	✓	✓	✓	✓	
20		Forest4	█	0.000	0.392	0.000	20	20	100	1.000	✓	✓	✓	✓	
21		Forest5	█	0.000	0.392	0.000	21	21	100	1.000	✓	✓	✓	✓	
22		Road		0.827	0.827	0.827	22	22	51	1.000	✓	✓	✓	✓	
23		Road 2		0.827	0.827	0.827	23	23	13	1.000	✓	✓	✓	✓	
24		Cutdwon	█	0.627	0.322	0.176	24	24	100	1.000	✓	✓	✓	✓	
25		CD2	█	0.627	0.322	0.176	25	25	100	1.000	✓	✓	✓	✓	
26		CD3	█	0.627	0.322	0.176	26	26	100	1.000	✓	✓	✓	✓	
27		CD4	█	0.627	0.322	0.176	27	27	100	1.000	✓	✓	✓	✓	



## 2. 2017 - vick



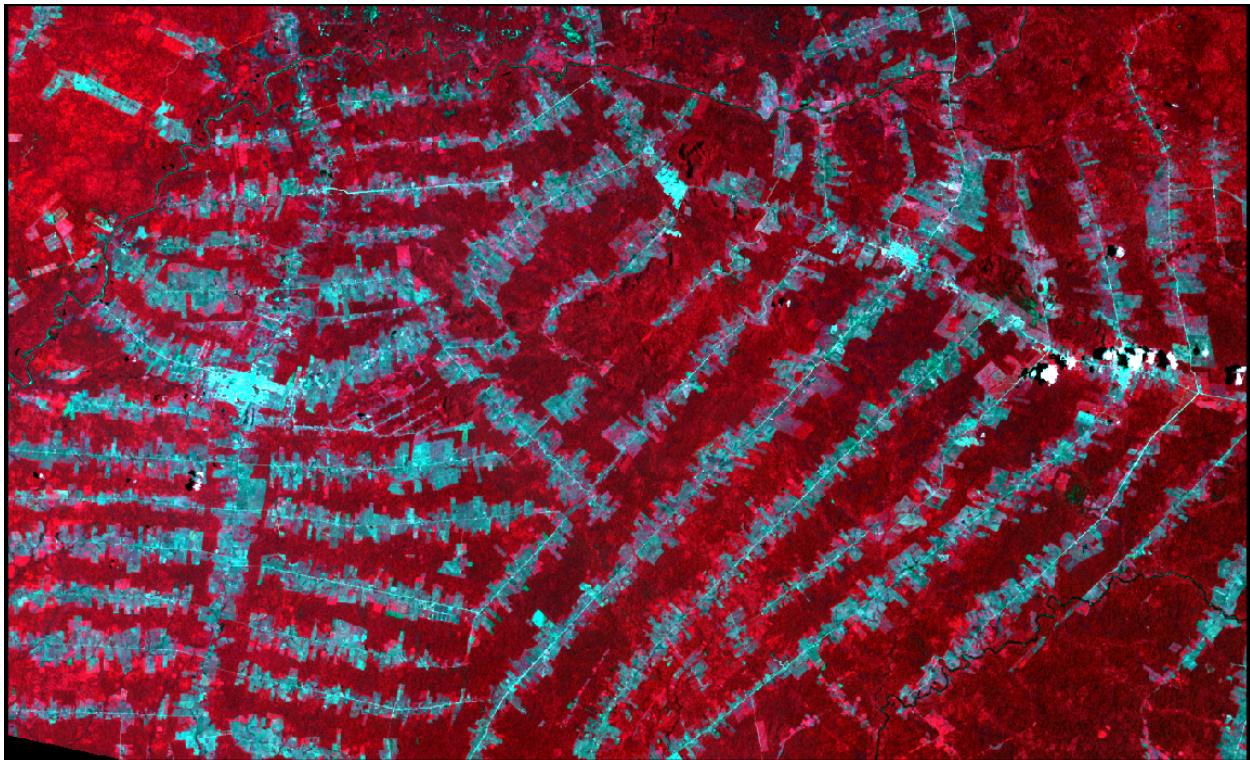
Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1	►	CloudShadow1	[Solid Dark Green]	0.000	0.145	0.000	1	1	108	1.000	✓	✓	✓	✓	
2		CloudShadow2	[Solid Dark Green]	0.000	0.214	0.045	2	2	100	1.000	✓	✓	✓	✓	
3		Cloud Shadow 3	[Solid Dark Green]	0.000	0.056	0.000	3	3	100	1.000	✓	✓	✓	✓	
4		CloudShadow4	[Solid Dark Green]	0.000	0.206	0.009	4	4	100	1.000	✓	✓	✓	✓	
5		Cloud4		1.000	1.000	1.000	5	5	95	1.000	✓	✓	✓	✓	
6		Cloud3		1.000	1.000	1.000	6	6	100	1.000	✓	✓	✓	✓	
7		Cloud2		1.000	1.000	1.000	7	7	100	1.000	✓	✓	✓	✓	
8		Cloud1		1.000	1.000	1.000	8	8	100	1.000	✓	✓	✓	✓	
9		Cutdown1	[Solid Brown]	0.627	0.322	0.176	9	9	100	1.000	✓	✓	✓	✓	
10		Cutodwn2	[Solid Brown]	0.627	0.322	0.176	10	10	100	1.000	✓	✓	✓	✓	
11		Cutodwn3	[Solid Brown ▾]	0.627	0.322	0.176	11	11	100	1.000	✓	✓	✓	✓	
12		Cutdown4	[Solid Brown]	0.627	0.322	0.176	12	12	100	1.000	✓	✓	✓	✓	
13		Forest1	[Solid Green]	0.000	0.392	0.000	13	13	100	1.000	✓	✓	✓	✓	
14		Forest2	[Solid Green]	0.000	0.392	0.000	14	14	100	1.000	✓	✓	✓	✓	
15		Urban1		0.753	0.753	0.753	15	15	100	1.000	✓	✓	✓	✓	
16		Urabn2		0.753	0.753	0.753	16	16	100	1.000	✓	✓	✓	✓	
17		Urban3		0.753	0.753	0.753	17	17	100	1.000	✓	✓	✓	✓	
18		Urban4		0.753	0.753	0.753	18	18	100	1.000	✓	✓	✓	✓	
19		road1		0.753	0.753	0.753	19	19	53	1.000	✓	✓	✓	✓	
20		road2		0.753	0.753	0.753	20	20	50	1.000	✓	✓	✓	✓	
21		road3		0.753	0.753	0.753	21	21	38	1.000	✓	✓	✓	✓	
22		road4		0.753	0.753	0.753	22	22	61	1.000	✓	✓	✓	✓	
23		Water1	[Solid Blue]	0.000	0.000	1.000	23	23	30	1.000	✓	✓	✓	✓	
24		Water2	[Solid Blue]	0.000	0.000	1.000	24	24	16	1.000	✓	✓	✓	✓	
25		Water3	[Solid Blue]	0.000	0.000	1.000	25	25	31	1.000	✓	✓	✓	✓	
26		Water4	[Solid Blue]	0.000	0.000	1.000	26	26	30	1.000	✓	✓	✓	✓	



3. 2022 - Anish



Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1		Urban Area		0.753	0.753	0.753	1	1	100	1.000	✓	✓	✓	✓	
2		Urban 1		0.753	0.753	0.753	2	2	100	1.000	✓	✓	✓	✓	
3		Urban 2		0.753	0.753	0.753	3	3	100	1.000	✓	✓	✓	✓	
4		Urban 3		0.753	0.753	0.753	4	4	100	1.000	✓	✓	✓	✓	
5		CS1	█	0.000	0.000	0.000	7	7	100	1.000	✓	✓	✓	✓	
6		CS2	█	0.000	0.000	0.000	8	8	100	1.000	✓	✓	✓	✓	
7		CS3	█	0.000	0.000	0.000	9	9	100	1.000	✓	✓	✓	✓	
8		CS4	█	0.000	0.000	0.000	10	10	100	1.000	✓	✓	✓	✓	
9		Clouds		1.000	1.000	1.000	11	11	100	1.000	✓	✓	✓	✓	
10		C1		1.000	1.000	1.000	12	12	54	1.000	✓	✓	✓	✓	
11		C2		1.000	1.000	1.000	13	13	100	1.000	✓	✓	✓	✓	
12		C3		1.000	1.000	1.000	14	14	41	1.000	✓	✓	✓	✓	
13		C4		1.000	1.000	1.000	15	15	72	1.000	✓	✓	✓	✓	
14		Water/River	█	0.000	0.000	1.000	16	16	23	1.000	✓	✓	✓	✓	
15		Water/River 1	█	0.000	0.000	1.000	17	17	34	1.000	✓	✓	✓	✓	
16		Water/River 2	█	0.000	0.000	1.000	18	18	100	1.000	✓	✓	✓	✓	
17		Water/River 3	█	0.000	0.000	1.000	19	19	22	1.000	✓	✓	✓	✓	
18		Water/River 4	█	0.000	0.000	1.000	20	20	21	1.000	✓	✓	✓	✓	
19		Road		0.753	0.753	0.753	21	21	26	1.000	✓	✓	✓	✓	
20		Road 1		0.753	0.753	0.753	23	23	41	1.000	✓	✓	✓	✓	
21		Road 2		0.753	0.753	0.753	22	24	100	1.000	✓	✓	✓	✓	
22		Road 3		0.753	0.753	0.753	24	25	36	1.000	✓	✓	✓	✓	
23		Cutdown	█	0.627	0.322	0.176	25	26	100	1.000	✓	✓	✓	✓	
24		Cutdown 1	█	0.627	0.322	0.176	26	27	63	1.000	✓	✓	✓	✓	
25		Cutdown 2	█	0.627	0.322	0.176	27	28	100	1.000	✓	✓	✓	✓	
26		Cutdown 3	█	0.627	0.322	0.176	28	29	26	1.000	✓	✓	✓	✓	
27		Cutdown 4	█	0.627	0.322	0.176	29	30	100	1.000	✓	✓	✓	✓	
28		Forest	█	0.000	0.392	0.000	30	31	100	1.000	✓	✓	✓	✓	
29		Forest 1	█	0.000	0.392	0.000	31	32	100	1.000	✓	✓	✓	✓	
30		Forest 3	█	0.000	0.392	0.000	32	33	100	1.000	✓	✓	✓	✓	
31		Forest 4	█	0.000	0.392	0.000	33	34	100	1.000	✓	✓	✓	✓	
32	►	Forest 5	█	0.000	0.392	0.000	34	35	100	1.000	✓	✓	✓	✓	



## Separability

The tables below show how separate our training sites are, or in other words how different the pixels from our training sets are, which affects how well-made and accurate our classes will be. The only discrepancies we notice are the occasional values going below 1600 (which are usually 2000). Some values go as low as 560, but that is fine as it just means those training sites should be a single class, which they ended up being.

1. 2013

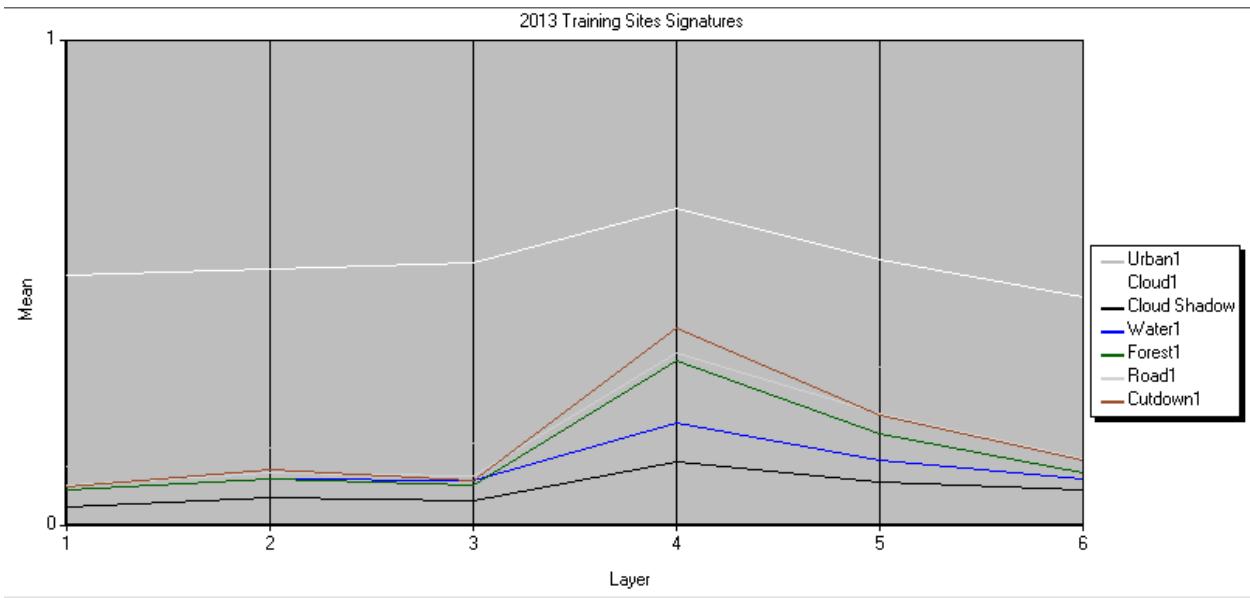
2. 2017

3. 2022

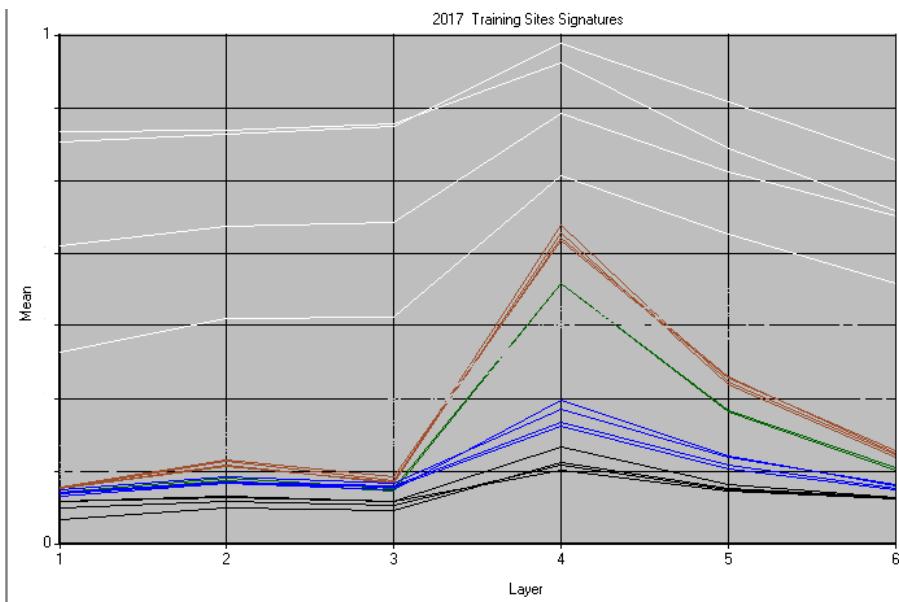
## Signature Mean Statistics

These are the signatures for our training sites. They are graphs showing the relationship between the bands(layers) and the average reflectance values of the layer (mean).

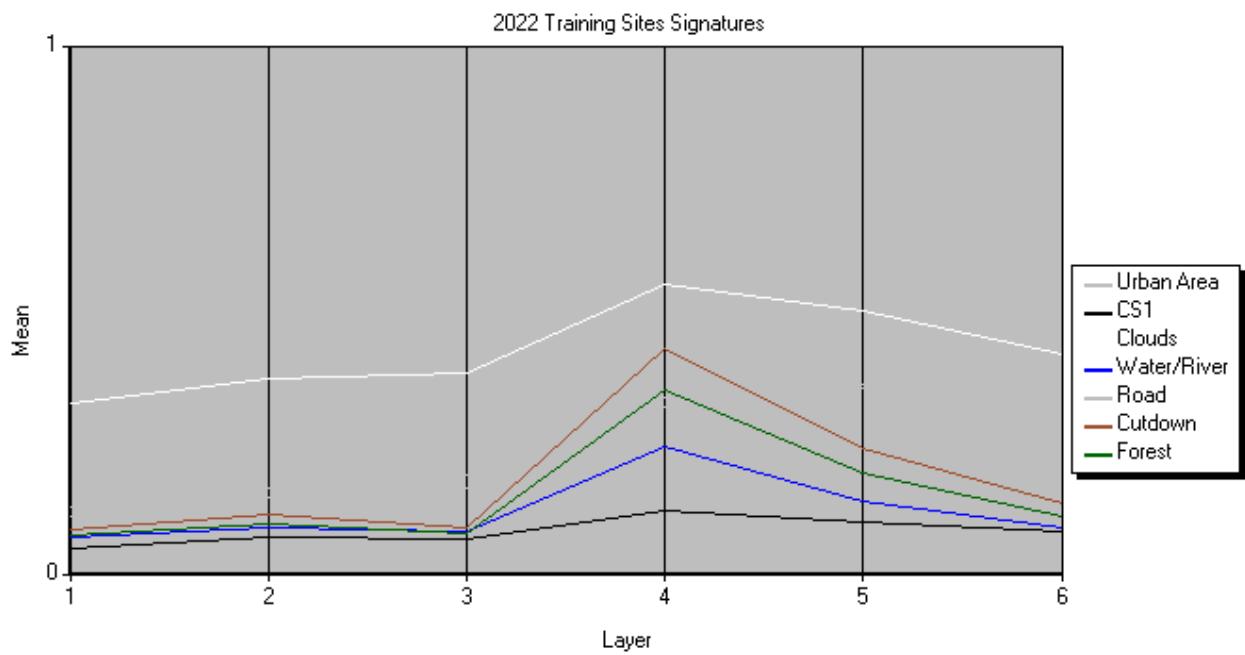
## 1. 2013



## 2. 2017

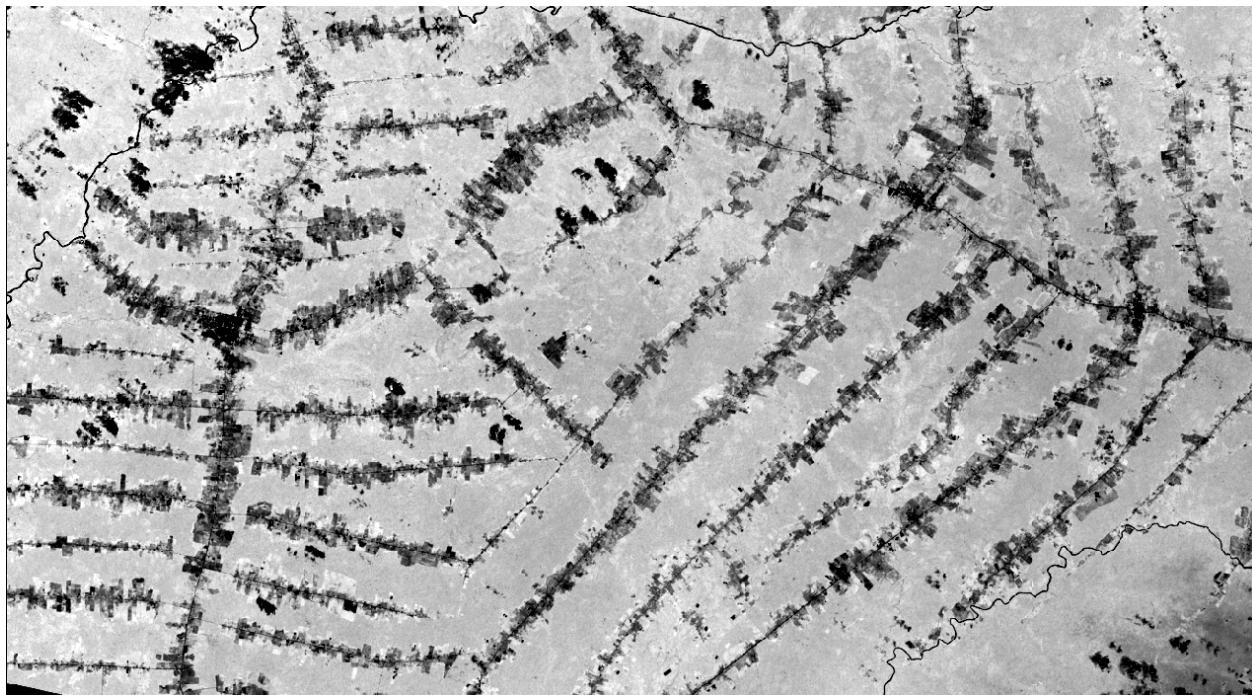


## 3. 2022

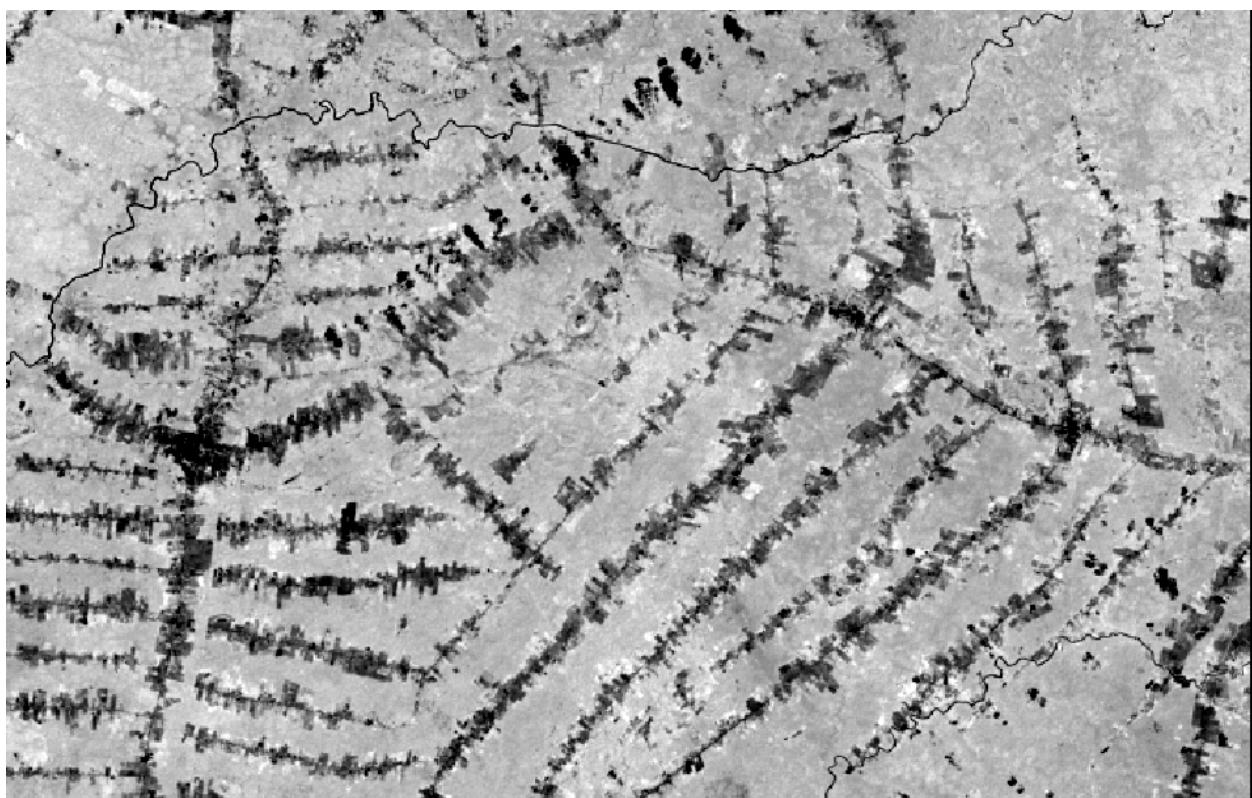


### **NDVI Analysis**

**2013**



**2017**

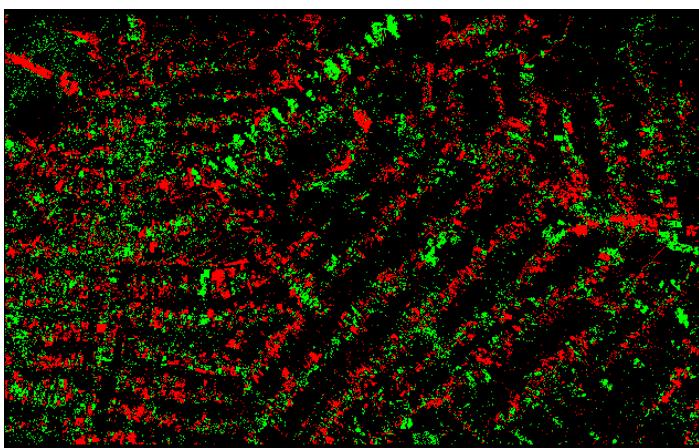


2022

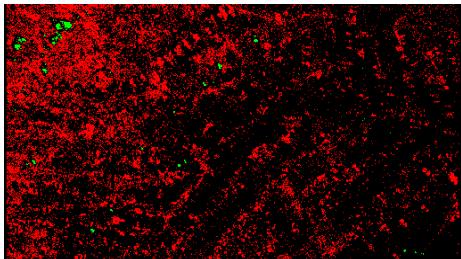


Ndvi Change Analysis

2017-2022

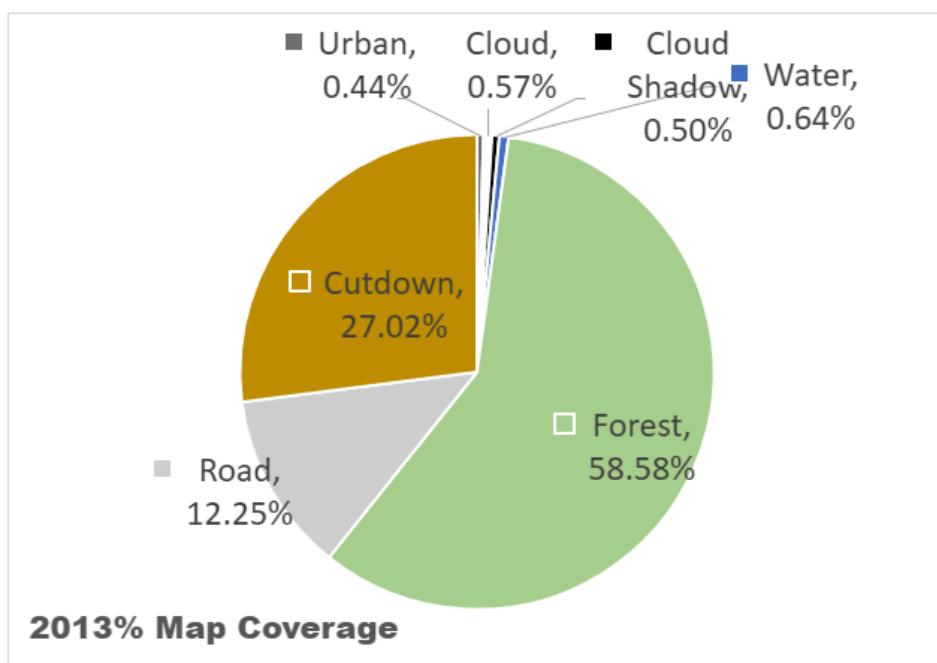


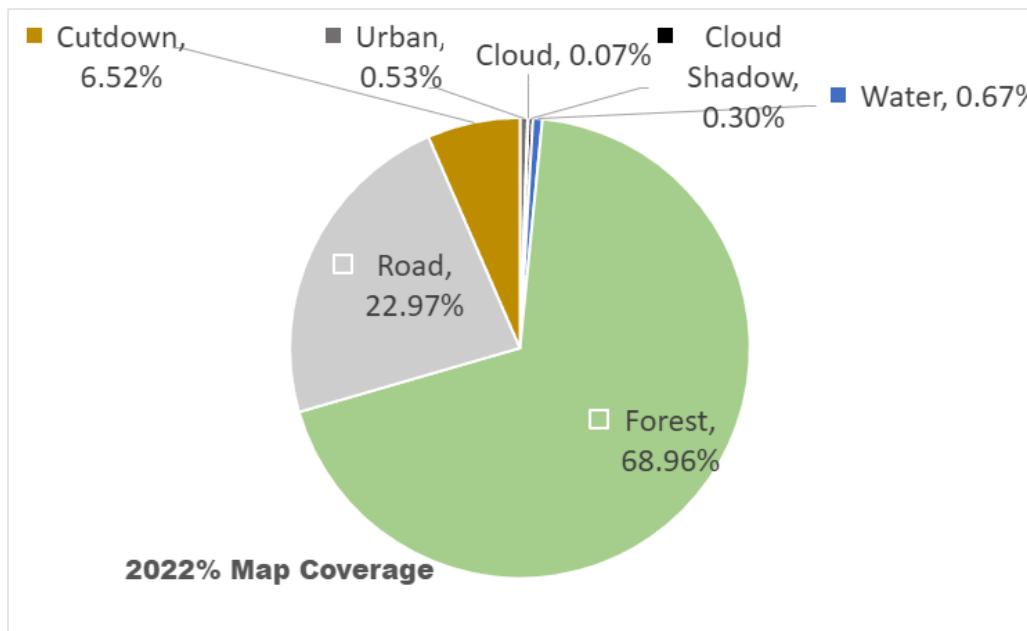
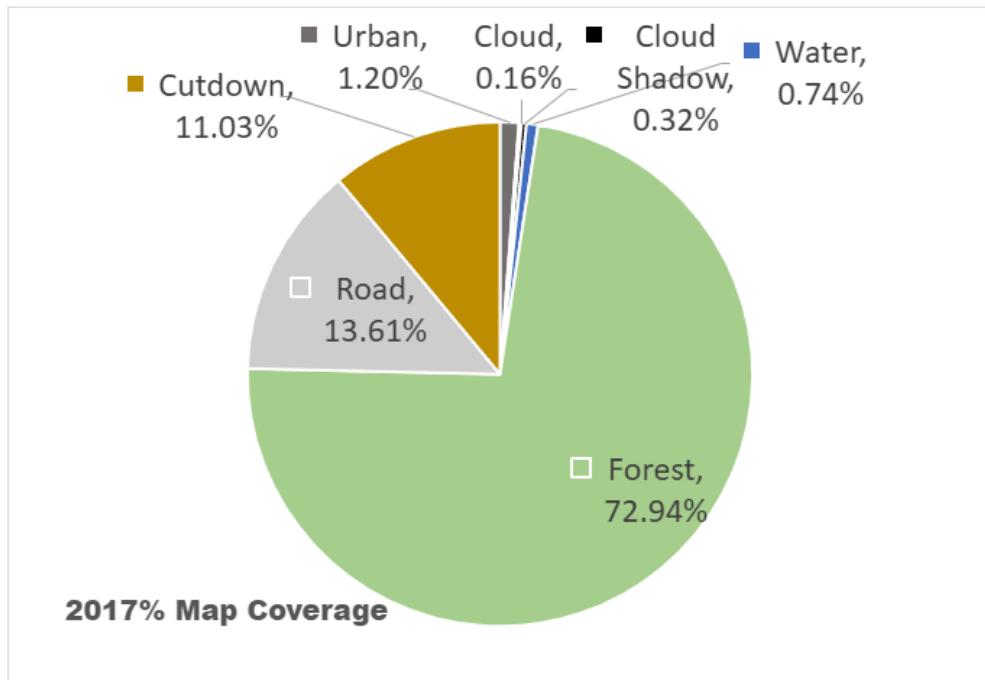
2013-2017



## **Accuracy Assessment**

## **Land Change Analysis (Pi Charts)**





## Conclusion

For our project, our area of study was the Brazilian Amazon and our goal was to find areas of deforestation over a 15 year duration. Through the process of remote sensing we were able to find exactly where this deforestation occurred, how much deforestation occurred, and how the land changed over time. First, we had to enhance our images so that we were able to clearly identify the different aspects of the landscape such as

vegetation and agricultural land. Once classifying the different landscapes, we completed a supervised classification on all three images in order to be able to separate all the landscapes and get detailed information as to how much of the area was covered by different types of crops, and other aspects such as clouds and their shadows. After comparing the areas of vegetation we saw a decline in forest and an increase in soil and crops showing how deforestation occurred in our specific area of the Amazon. There were a few components that were being misclassified such as shadows, clouds, and urban areas. (MENTION WHAT ISSUES WE FACED). Creating the training sites and performing the supervised classification was the most challenging part of the project since we had to create numerous training sets and make sure that the final image came out properly and showed all parts of the landscape. In the end we found why the deforestation occurred and we believed it was due to more people coming into the Amazon resulting in the need for more agriculture. This conclusion came from the change analysis because it proved that over the span of 15 years, vegetation and forests declined whereas agriculture, and urban areas increased in a fishbone pattern.

### New Conclusion

In our project, we delved into the Brazilian Amazon, aiming to track deforestation over a 15-year period from 2013 to 2022. Utilizing remote sensing techniques, we pinpointed deforested areas, tracked changes in the landscape, and assessed the extent of vegetation loss. Initially, we enhanced image clarity to discern landscape features such as vegetation and agricultural land. Subsequently, employing supervised classification across three images, we differentiated various landscapes and gathered detailed data on crop coverage and other features like clouds and shadows. Despite facing challenges such as misclassification of shadows, clouds, and urban areas, we persisted. Establishing training sites and executing supervised classification proved to be the most demanding tasks, ensuring the accurate portrayal of the landscape. Our analysis revealed a decline in forest cover and a rise in agricultural land, indicating deforestation in our study area of the Amazon. We attributed this trend to increased human activity, particularly agriculture. This inference was supported by change analysis, which demonstrated a gradual shift over the 15-year period from vegetation to agriculture and urbanization, resembling a fishbone pattern.

### True color

2013



2022



- 
- Urban Area
  - Cloud Shadow
  - Clouds
  - Water/River
  - Road
  - Cutdown
  - Forest