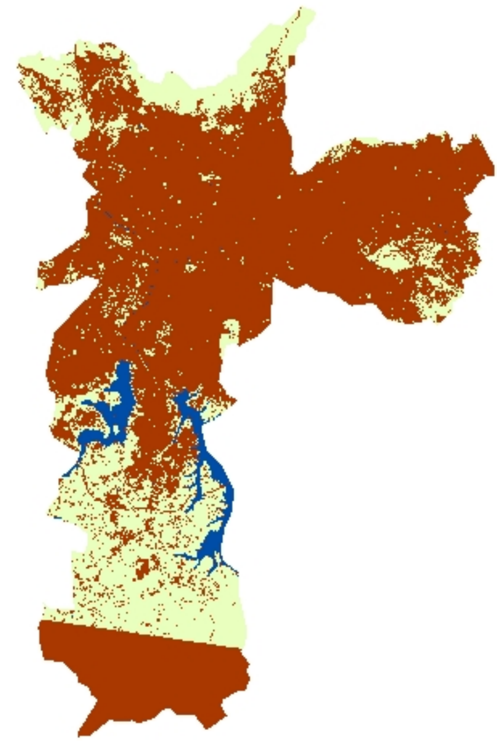
Remote Sensing & Land Use Efficiency in Sao Paulo, Brazil

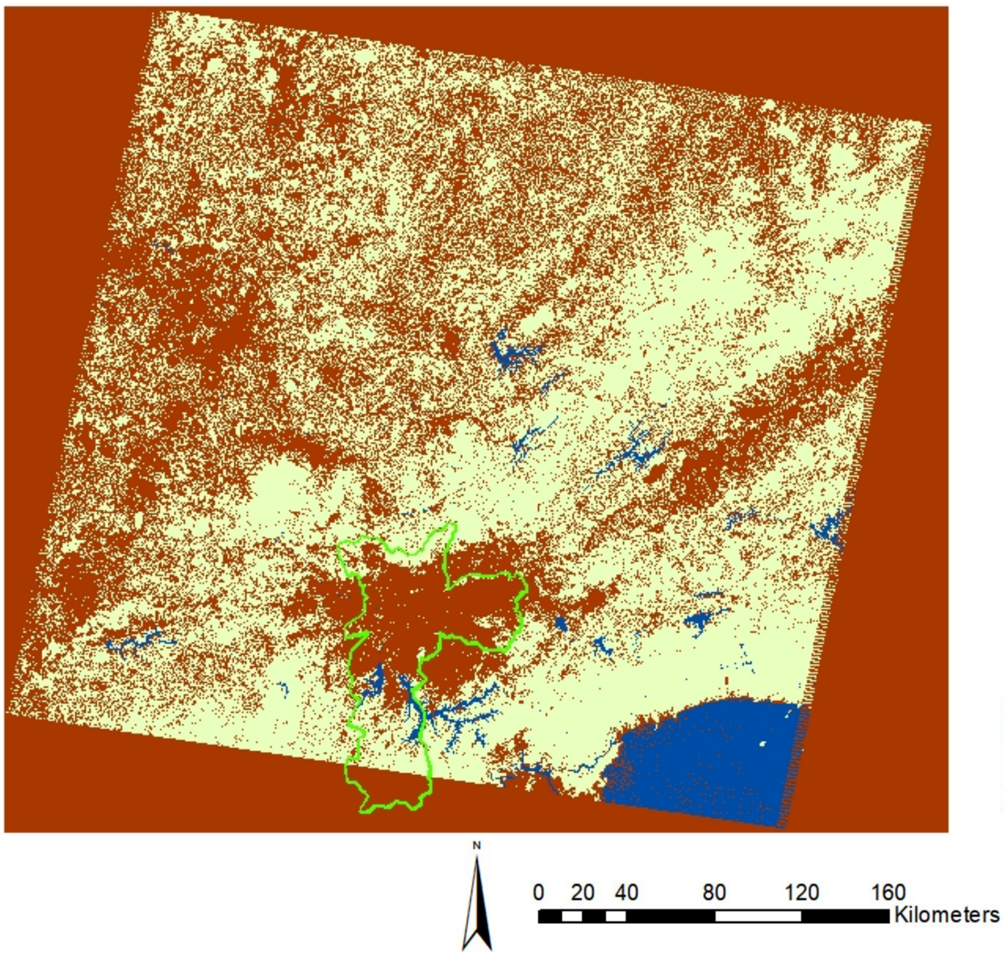
Overview: This analysis quantifies how the city of Sao Paulo, Brazil has sprawled over time relative to its population growth using LANDSAT imagery. Upon creating a normalized difference vegetation index (NDVI) to visualize areas of high and low vegetation (urbanized areas), it uses supervised classification classify land cover types in three typologies – urban vegetation and water. It studies change over time between 2008 and 2018 by using a land use efficiency ratio, which relates the rate of change in land relative to the rate of change in population.

Software used: ESRI ArcGIS

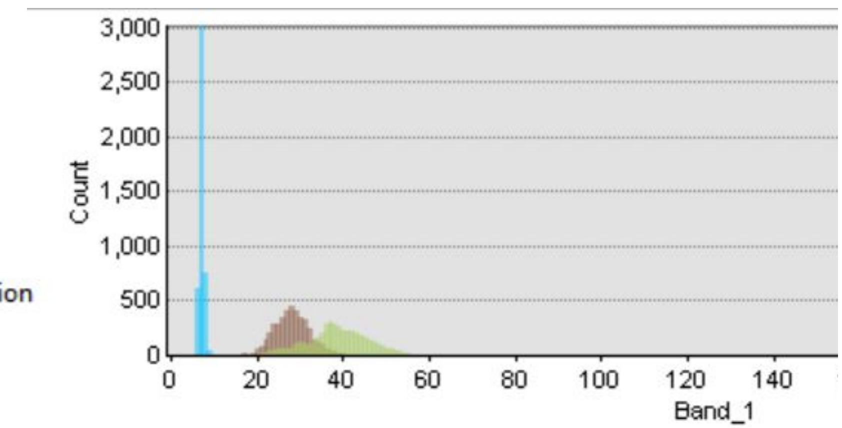
2008 Sao Paulo,Brazil



An NDVI was initially created in order to understand the areas of high vegetation and low vegetation (urbanized areas). Supervised classification was used to classify the land cover types in three typologies – urban, vegetation and water. Since the image data was clear with almost no cloud, the cloud typology was omitted. The labeled training data created a predictive model to analyze the rest of the satellite imagery, resulting in the map shown below and to the right. The center of the city of Sao Paulo is located towards the lower half of the satellite image – one can see how a large portion of the city is heavily urbanized with more vegetated landscape towards the south.

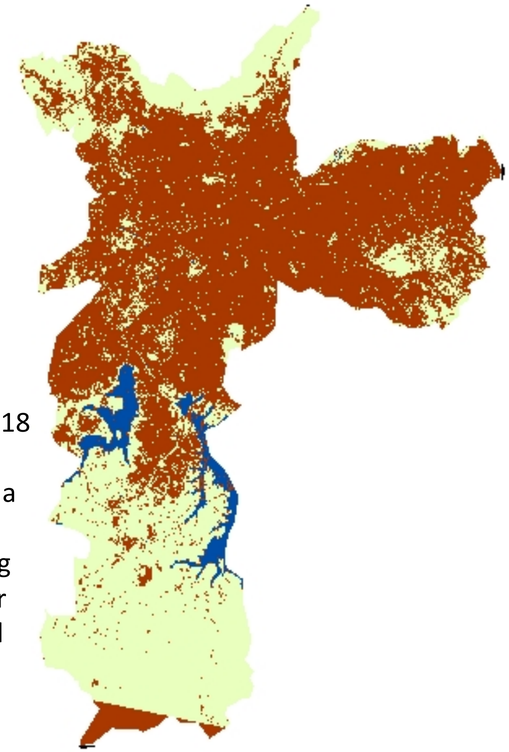


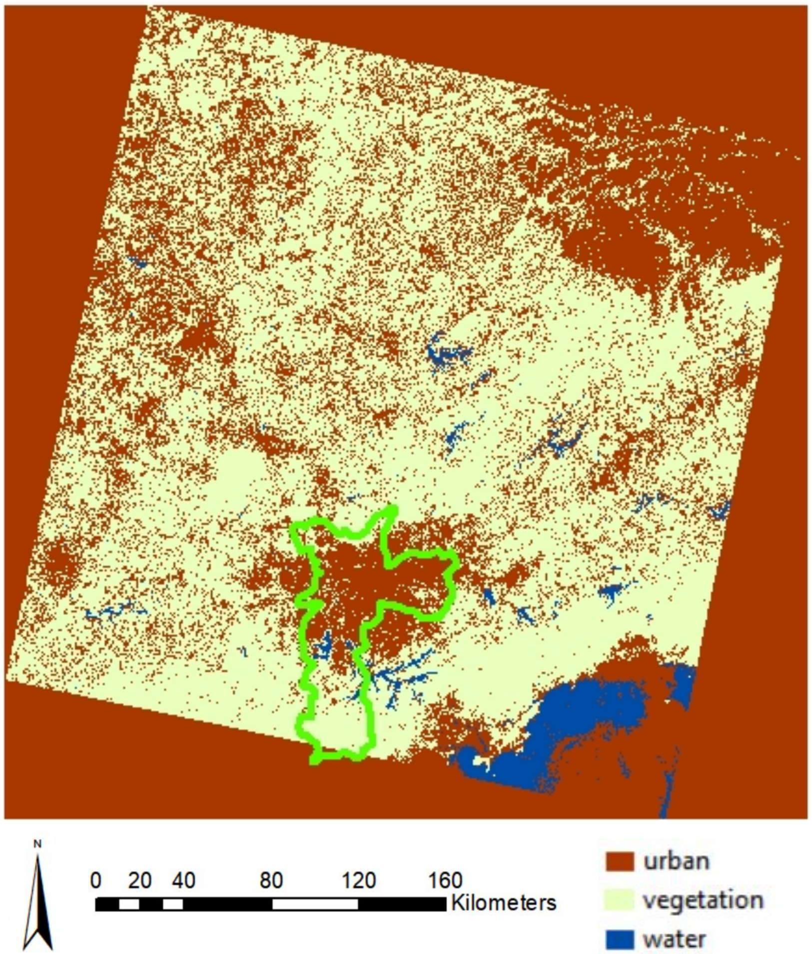
The histogram used for the classification shows the distribution and variance of the different typologies analyzed in the LANDSAT 5 data of the city of Sao Paulo. The signature band used was the infrared (Band 4). It is possible to see that the water characteristic has a lower value range as opposed to the urbanized land and vegetation values, which are more dispersed throughout the band values along the x-axis.



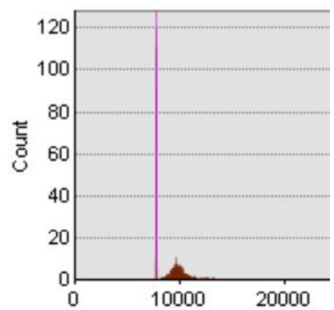
2018 Sao Paulo,Brazil

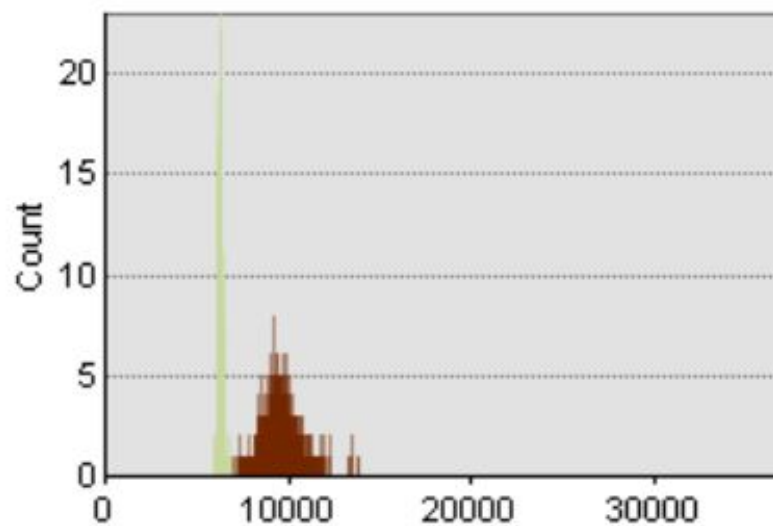
The same NDVI and supervised classification technique was used to compare the same location ten years later. This data however, had some cloud coverage found in the Northeast and Southeast corners of the satellite image. For the purposes of keeping consistency with the typology classification previously used, and since the clouds did not significantly interfere with the main area of analysis, the cloud attribute was not considered. Nonetheless, it is important to keep in mind that the training data may cause some inconsistencies and errors when classifying the pixels into the different typology categories defined, which could influence the final area calculations for understanding rate of change in new urban development and ultimately the land use efficiency.





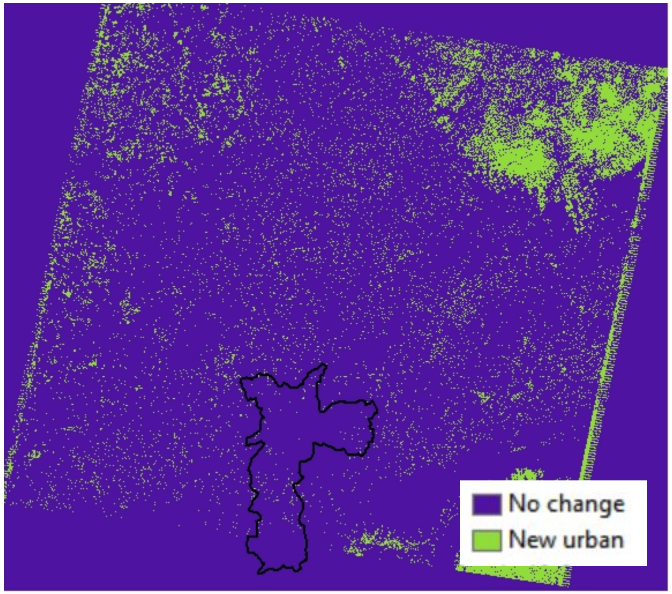
Similar to the graph from 2008, the histogram for 2018 showed similar patterns. Water showed the least variance in band values, causing it to spike and have a high pixel count, unbalancing the histogram overall (see small histogram to the left). Without considering the water classification, it is possible to have a better view of the distribution of band values for urban and vegetated land. One approach that was taken differently when making a training data for the 2018 data was that the composite image visualized the infrared layer (Bands 5,4,3 instead of 4,3,2).





2008 - 2018 Change Over Time

Ratio of land consumption rate to population growth rate: $\frac{Rate\ of\ change\ in\ new\ urban\ development\ between\ 2008 \sim 2018}{Rate\ of\ population\ change\ between\ 2008 \sim 2018}$



Land Percent Change:

$$\frac{(Urban\ land\ 2018\ -Urban\ land\ 2008)}{(Urban\ land\ 2018)}$$

	2008	2018
Urban land cells	31,433,073	31,648,280
Land area* (km^2)	28289.77	28483.45

Considering a 30 x 30 (meter) cell size from the data source properties, the land area was calculated into km^2 .

$$\frac{(28483.45\ -28289.77\ )}{(28483.45\ )}$$ = 0.68% increase

Population Percent Change:

$$\frac{(Population\ 2018\ -Population\ 2008)}{(Population\ 2018)}$$

	2008	2018
Population	19,100,000	21,730,000

United Nations, Department of Economic and Social Affairs, Population Division (2014). World Urbanization Prospects: The 2014 Revision, CD-ROM Edition.

$$\frac{(21{,}730{,}000 - 19{,}100{,}000)}{(21{,}730{,}000)}$$ = 21.1% increase

Efficiency Ratio = $\frac{0.68}{21.1}$ = 0.032

The first approach taken to find out where new urbanization occurred was to reclassify the "Likelihood Classification" layers from 2008 and 2018 into 0 and 1 values where 0 represented not urban and 1 represented urban. By subtracting 2008 from 2018, I would keep 1 values which are those pixels that became urban during the ten year period. The resulting change is reflected in the map above. As previously stated, the Northeast and Southeast corners where "land became urbanized" should not be fully relied on, as those are the areas where cloud cover was present in the 2018 data.

Following, I attempted to show the urbanized pixels change in the original map by creating a composite layer combining the 2008, 2018 and "urbanized land." One of the challenges to this approach was that the changed lands were not in a continuous pattern. Rather, the pixels were spread throughout in very little areas which made it hard to create a training data big with enough so the "Likelihood Classification" method would better predict the classification for the rest of the image. The result is shown on the left and although not all the pixels were accurately calculated, the green zones highlight some of the clustering that perhaps hint at fastest urbanizing regions.