Urbanization in Far Northwest San Antonio, 2013-2022

rodrigo.davilacastillo@my.utsa.edu

Rodrigo Davila Castillo

Department of Computer Science, The University of Texas at San Antonio, San Antonio, TX 78249

Introduction

Endless strip malls, lane expansions, and mass housing developments — these are just some of the features that have continued to paint the landscape of San Antonio in the past decade, as urbanization projects dominate much of the city, especially in its outer districts. These projects have a variety of environmental, social, and economic impacts; so, it's important to measure the rate and extent of urban development in the city to study its effects, a task made possible with remote sensing analysis techniques.

As such, this research project will make use of several RS techniques — band indices, transformations, and surface temperature monitoring — to measure the changes that have impacted areas around the far northwest area of the city in the past decade, specifically focusing on a study area containing Government Canyon State Natural Area and several housing subdivisions and commercial areas.

Background

As a resident of this area for the past decade, the amount of urban development around me hasn't gone unnoticed, and I can describe the changes from memory. But to make more scientific assessments on the extent and effects of urbanization here, RS techniques may be used to study urbanization patterns in San Antonio. For instance, visual inspection of true-color images may produce qualitative assessments on the progression of development; band indices and transformations may be used for data-guided observations on general vegetation health (NDVI) or urban sprawl (NDBI); and surface temperature readings can produce quantitative findings on the temperature side-effects of urbanization (i.e., changes in the extent and intensity of the UHI).

Therefore, these methods were used to study urbanization in an area of far NW San Antonio, with the hypothesis that these methods would reflect the patterns of urbanization in this area; over time, NDVI values should skew closer to -1, NDBI values should skew closer to 1, the number of high-brightness values in Tasseled Cap images should increase, and average surface temperature should increase over time.

Methods

ENVI 5.6 was used to assemble, analyze, and quantify the values of the study images. NDVI, NDBI, Tasseled Cap (Yale Center for Earth Observation 2014) and surface temperature values were analyzed in ENVI.

Table 1. A list of the Landsat 8 images used in the study.

Landsat Product ID L2	Date Captured	Scene Cloud Cover (%)
LC08_L2SP_027040_20131103_20200912_02_T1	2013-11-03	1
LC08_L2SP_027040_20141021_20200910_02_T1	2014-10-21	1.29
LC08_L2SP_028039_20151015_20200908_02_T1	2015-10-15	3.09
LC08_L2SP_027040_20161010_20200905_02_T1	2016-10-10	0.56
LC08_L2SP_027040_20171029_20200902_02_T1	2017-10-29	0.13
LC08_L2SP_027040_20181101_20200830_02_T1	2018-11-01	0.05
LC08_L2SP_028039_20191026_20200825_02_T1	2019-10-26	0.01
LC08_L2SP_028039_20201028_20201106_02_T1	2020-10-28	5.16
LC08_L2SP_027040_20211008_20211018_02_T1	2021-10-08	1.11
LC08_L2SP_028039_20221018_20221031_02_T1	2022-10-18	45.4

A study area was drawn using the boundaries of Bandera Rd. (SH-16), North Loop 1604, Culebra Rd. (FM 471), Old F.M. 471, and SH-211; Government Canyon SNA dominates the area, serving as a control region. The shapefile defining the 119 km^2 study area's boundaries, whose lines were derived from the U.S. Census Bureau's 2022 TIGER/Line shapefiles, was drawn in ArcGIS Pro 3.0 (2022 Sep 1).

Methods (cont'd.)

Image data was captured by Landsat 8, and was processed and retrieved from the Level 2, Collection 2 dataset, published by the USGS's EROS Center (2020 Nov 27). Images with low/no cloud cover were selected, with capture dates from late October to early November. In addition, other images from the candidate dataset were eliminated based on whether a severe weather event occurred before its capture date (Austin/San Antonio Weather Forecast Office 2022). Final study images were then narrowed down to those listed in Table 1.

Results

First, simple visual inspection of the true-color images confirmed a pattern of urbanization and development in certain parts of the study area, showing the development of new subdivisions in the southern areas of the study area, between Culebra Rd. and Culebra Creek (Figure 1). This does confirm that the images do, in fact, show an area with increasing urban sprawl; however, other data-driven analysis methods did not produce similar expected results.

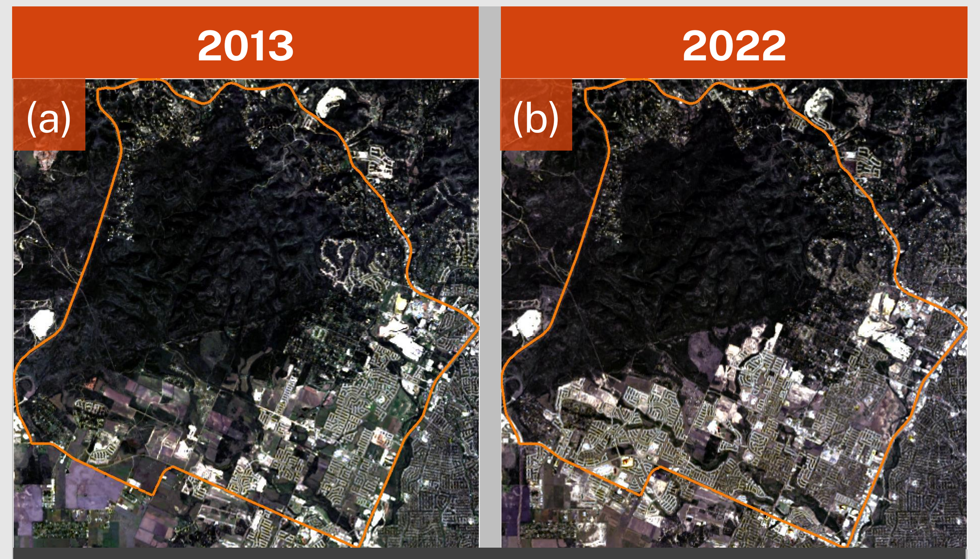

Figure 1. A comparison between true-color images from 2013 (a) and 2022 (b), with the study area's boundaries drawn in orange.

The progression of **NDVI** band index values over time were inconsistent with the hypothesized pattern; the predicted leftward shifts and lower curves in the graphs over time — which correspond to decreasing vegetation levels in the landscape — did not consistently appear from year to year. While the two individual 2013 and 2022 NDVI plots did show this leftward shift, plots in the in-between years did not change in a consistent pattern (Figure 2). There is no consistent shift from the right to the left.

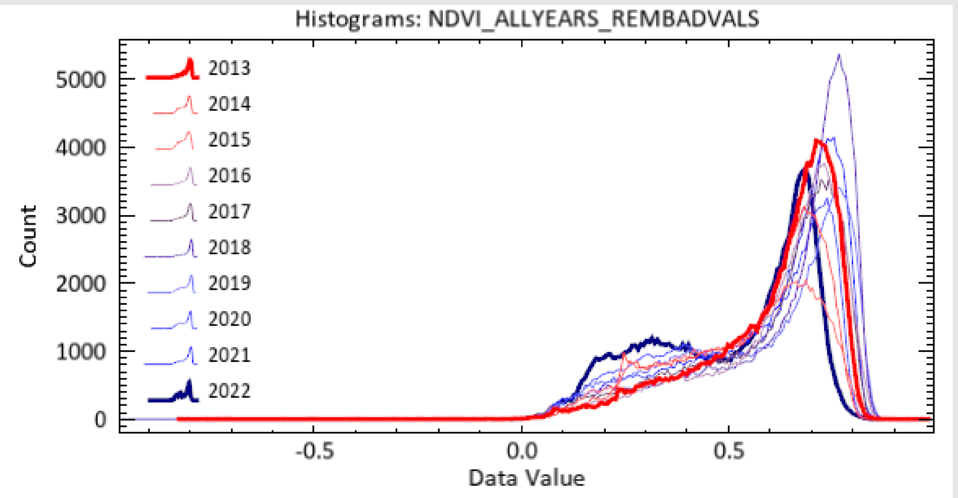

Figure 2. Graphs of NDVI values within the study area for each study year; 2013 and 2022 are drawn with thick red and blue outlines respectively, and years in between are drawn with thin outlines in a color spectrum from red to blue.

Similarly, the **NDBI** index statistics also showed an inconsistent pattern over time. It was expected for the plot curves to have shifted rightward, corresponding to increases in the extent of urban sprawl; instead, the plot curves' variations prevented any pattern from appearing over time. As previously seen in the NDVI plots, the 2013 and 2022 curves, in isolation, did align with the predicted behavior — but the years in between showed far too much variation to confirm the existence of the predicted pattern in the study data.

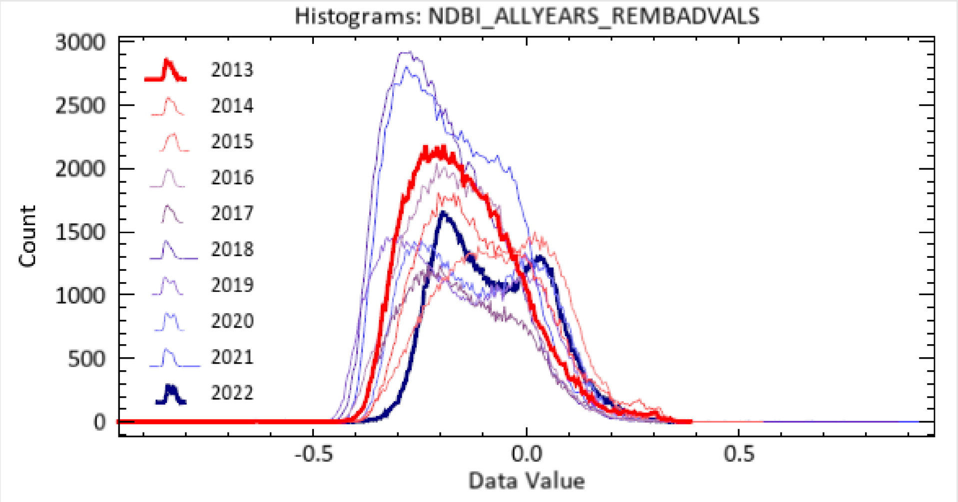

Figure 3. Plots of year-by-year NDBI values within the study area; 2013 and 2022 are drawn with thick red and blue outlines respectively, years in-between are thinly outlined from red to blue.

Results (cont'd.)

Other analysis methods were also subject to the same issues — for instance, the **Tasseled Cap** band transformation should have shown increases in the number of pixels with higher values in the **brightness** band, as man-made structures will tend to have higher brightness values. However, the plots for each year vary wildly — as seen by the fact that the largest spikes in brightness occur in wildly different years, 2015 and 2020 (Figure 4).

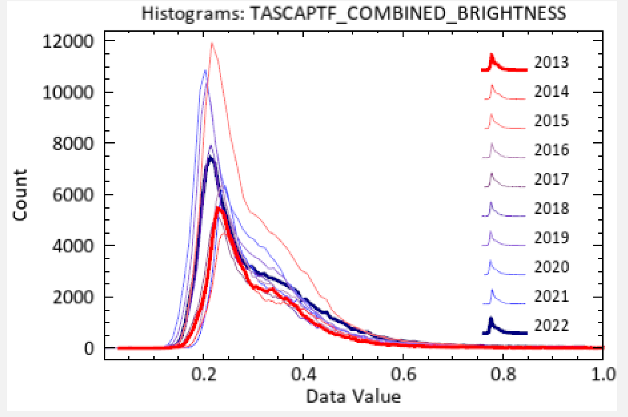

Figure 4. Plots of yearly Tasseled Cap brightness values within the study area. Thick outlines are for 2013 and 2022, and in-between years are drawn in thin outlines.

Lastly, **surface temperature** values also showed variations that hindered the ability to find a pattern over time. It was hypothesized that mean surface temperature values would increase over time, as the Urban Heat Island effect intensifies as a result of urban expansion into previously rural areas — a phenomenon that has been measured in the past in San Antonio (Xie *et al.* 2005). However, the mean values for each study image didn't show consistent increases over time, and the plot shows no discernible yearly trend (Figure 5).

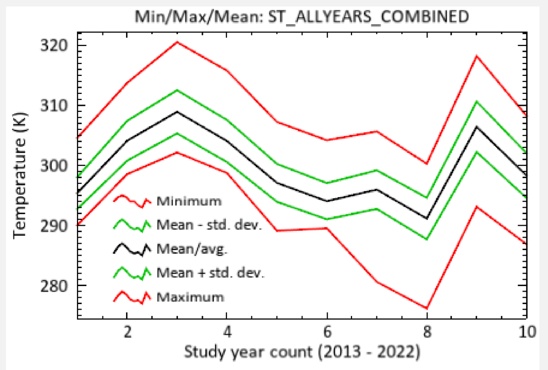

Figure 5. Plots for each year's minimum, mean ± one standard deviation, mean, and maximum values.

Conclusions

- NDVI values were expected to shift leftward, and more values were expected to be found in the lower parts of the NDVI spectrum as vegetation cover decreases from urban sprawl. **However, the study images did not find a consistent yearly pattern.**
- NDBI values were expected to shift rightward, as more values were expected to be found in the higher parts of the spectrum as the extent of built-up areas increased over time. **However, the study images did not find a consistent yearly pattern.**
- The Tasseled Cap transformation's brightness band was expected to see increases in the number of values in its higher range, as more pixels with higher brightness values (i.e., those defining urban structures) were expected to appear over time. **However, the study images did not find a consistent yearly pattern.**
- Mean surface temperature was expected to increase yearly, as the increasing extent of urban sprawl was expected to increase the extent of the urban heat island of San Antonio, which would increase the extent of high-surface temperature areas. **However, the study images did not find a consistent yearly pattern.**

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What Can Go Wrong in RS Analysis

A case study of *Urbanization in Far Northwest San Antonio, 2013-2022*

rodrigo.davilacastillo@my.utsa.edu

Rodrigo Davila Castillo

Department of Computer Science, The University of Texas at San Antonio, San Antonio, TX 78249

Introduction

A lot can go wrong in remote sensing analysis, even from the very beginning of one's own research; analysts may be faced with broken images, a lack of data, or an overly complex topic that requires more resources and knowledge than what they may have at hand.

However, other issues can arise further in the process of performing a study—issues in processing images may produce unexpected results, or the chosen analysis method may turn out to be unsuitable. Perhaps the most frustrating issue, though, is in the form of getting unexpected results—results that don't align with the hypothesis, or worse, one that seems to contradict the laws of physics.

Nevertheless, in such a situation, it's important to step back and consider the factors that may produce unexpected, inconsistent, or nonsensical results. User error, limitations and errors in study data, and natural phenomena can all converge and prevent an analyst from finding trends in data.

In the *Urbanization in Far Northwest San Antonio* study, several known and potential issues were identified to have limited the analysis, likely leading to the inconclusive results for the study; in other words, these issues created a critical flaw in the analysis, which led to my inability to find a sensical yearly pattern for the phenomena that should have been affected by urban spread.

Background

The *Urbanization* study was performed on a series of study images, captured by Landsat 8 from 2013 to 2022. 4 different factors were used to attempt and study the effects of urban sprawl in an area in far northwest San Antonio: two band indices (NDVI and NDBI), a tasseled cap transformation, and a simple analysis of surface temperature values from Band 10 of the Landsat 8 OLI sensor. However, none of these analysis methods produced a consistent yearly pattern (such as the varying shifts in plot curves for the NDBI graphs, seen in Figure 6), leading to an inconclusive result. Several issues have been identified to have affected the analysis, and others are proposed as potential issues, which should be addressed before attempting another urbanization study.

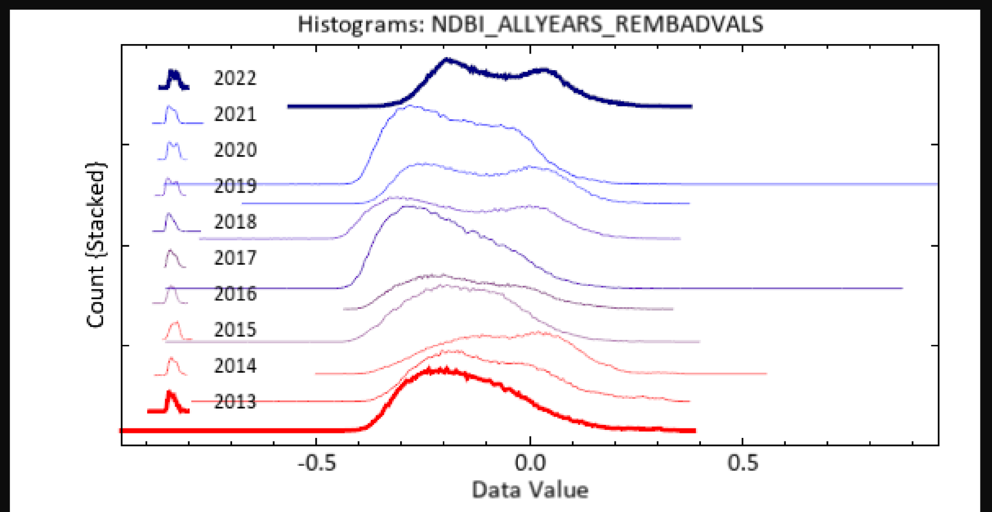

Figure 6. Stacked plots of NDBI values within the study area for each study year; 2013 and 2022 are drawn with thick red and blue outlines respectively, and years in between are drawn with thin outlines in a color spectrum from red to blue.

Known issues and acknowledgements

- Statistical analysis values may be slightly affected by the existence of NoData values in the bands, which were interpreted as having a reflectance of -20%, as well as other outlying values.
  - These values were filtered out in the NDVI and NDBI images (values outside of the -1 to 1 range were excluded) and in the surface temperature images (values of 149 degrees Kelvin were filtered out of analysis, though these were outside of the study area mask), through either the Replace Bad Values tool or with an image mask.
  - However, the Tasseled Cap Transformation did not exclude outlying values, though this should not affect the overall shape of the yearly graphs (seen in Figure 4).
- Images were captured from an overly broad range of dates—while most images were kept to late October and early November, some images fell outside of this range. The following 2 outlying date images make up **20%** of the dataset:
  - 2021's image, captured on October 8.
  - 2016's image, captured on October 10.

Potential contributing factors

There are several categories of factors that must be considered as potential contributors to the inconclusiveness of the report.

- **User error**
  - An **unsuitable analysis method** may have been chosen for the subject of this study. For instance, to better understand the actual changes in the *extent* of urban sprawl, it may have been more suitable to generate a classified image for each study date, as such an image will not be as affected by environmental factors.
- **Effects caused by man-made structures/development**
  - The progression of the construction of new subdivisions may have affected yearly vegetation and NDBI values. This is due to the process of developing a subdivision, which is as follows:
    - Untouched vegetation exists on the land
    - The plot is cleared out, wiping out vegetation in the area to be developed.
    - Homes are constructed, and plants and trees are planted to make the neighborhood appealing.
    - Therefore, vegetation values on an image (such as those from NDVI or tasseled cap greenness images) won't simply decrease over time—they'll dip down and partially recover, which makes it more difficult to measure the effects of urbanization in year-by-year images.

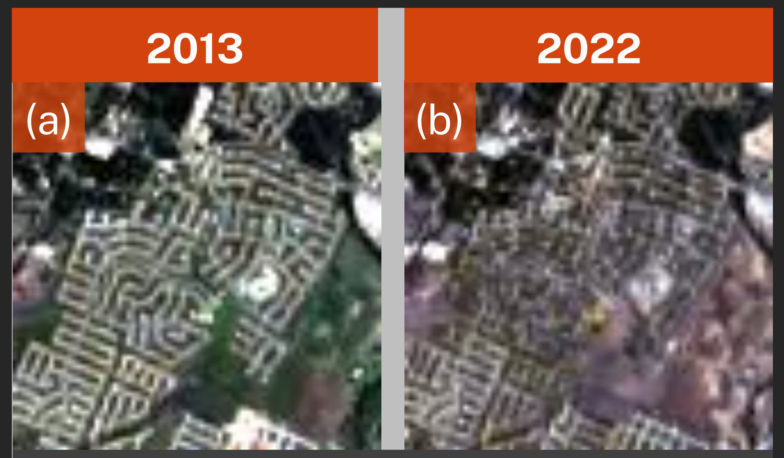

Figure 7. A comparison between a residential area in true-color images from 2013 (a) and 2022 (b).

Potential contributing factors (cont'd.)

  - Similarly, maturing vegetation in already-developed districts can affect overall measured vegetation levels in an image. Figure 7 illustrates how maturing vegetation can end up obscuring man-made structures—which, throughout an entire image, can also obscure the patterns of vegetation loss with urban sprawl.
- **Effects caused by natural phenomena**
  - Weather and climate patterns may affect measured vegetation levels (especially with indices such as NDVI); this external factor can make it more difficult to see actual patterns of man-made vegetation loss in an image.
    - For instance, drought may affect an area and cause temporary vegetation loss in one part of an image—but that's not the same as cutting down a chunk of a forest to build homes.
  - External factors that affect wildlife (such as plant disease) may end up also causing vegetation loss and attributing such vegetation loss to urbanization cause a faulty conclusion.

Conclusions and potential solutions

In the conclusion of our first lab report, I said that "it's easy to reach the conclusion that remotely sensed image analysis is *hard*," and that there's "many considerations that an analyst must keep in mind when attempting to get something meaningful out of their data" (Davila Castillo 2022, p. 10). That's certainly true—and despite all of the aforementioned factors, it's still possible to work through the limitations of RS data and put together a meaningful conclusion. Some possible strategies include:

- Using a large enough dataset that negates the effect of outliers and variations in climate patterns within a single year
  - In addition, this allows for the removal of outliers without significantly modifying the dataset.
- Using a control area to normalize values and reduce variation in the entire dataset.
- Select a more suitable analysis method for the study's subject.
- Use a more suitable sensor platform for the specific type of analysis
  - In Xie *et al.*, MODIS data was used to measure the UHI effect, and images from day/night conditions were processed to perform a more sophisticated analysis on the UHI of San Antonio.

Remotely sensed image analysis *is* hard—and it's easy to be in over your head when things go wrong. However, it's just as important to know how things can (and do) go wrong as it is to know how to actually do RS analysis. Consider them when performing a study, you'll be more likely to perform a successful study—hopefully reaching an important conclusion in the process!

References

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