

# Identifying Optimal Pixel Values for Swimming Pool Detection.

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## **Abstract**

The development of a workflow that will allow one to identify a particular feature in an aerial image offers a multitude of future applications. In the context of this project, several iterations of a workflow were tested to identify the optimal RGB pixel value range in order to identify as many swimming pools in an area of interest image as possible while still maintaining a minimum amount of extraneous feature and noise selection. A random sample set of 10 RGB pixel values was created from predetermined swimming pool features. This project determined that by extending the range of the original values by a total value of 5 resulted in the most efficient feature selection with minimal noise. Efficiently identifying features from an image quickly allows for future work such as the creation of training data sets for machine learning applications. This type of tedious manual work can be expedited with a selection process such as this.

## **Introduction**

The basis of this work was inspired by the work of Rohit Singh. As the Development Lead of ArcGIS API for Python, Singh detailed at the Esri UC 2018 Plenary session detailed workflow showing the capabilities of combining machine learning with ArcGIS Pro for the purpose of object identification with the use of artificial intelligence. His approach took a step ahead of the traditional object identification with reclassification by introducing the Python library of PyTorch. The hallmark of any project utilizing machine learning means that a training data set must first be created and prepared in order for the network to learn what it must do. Singh detailed this in his presentation, describing how he and his team had to manually create a data set of over 2,000 labeled swimming pools. Though he does not go into much more detail in regards to this step of the project, utilizing the power of image processing would allow one to quickly identify many swimming pools, or any other object, very quickly and would allow for the creation of even larger data sets within the same amount of time. Creating larger data sets will lead to even more intelligent machine learning models.

## **Project Objective**

The goal of this project is to discover the optimal range that should be allowed in order to identify as many swimming pools in an image as efficiently as possible. The process of manually scanning through many different images in order to identify pools by sight can be very tedious, especially when attempting to build a data set comprising of thousands of examples. By applying an image processing technique, it would be possible to vastly cut down on possible locations of pools in a given image.

## Materials and Methods

This project will be utilizing an image derived from the ESRI World Imagery basemap, the same data used by Rohit Singh. All processing was conducted with native ArcGIS Pro tools.



Area of Interest (subsection of city of Atlanta, GA)

1. The initial step was to isolate an urban area containing several swimming pools that could be tested. For this project, an image exported from the ESRI basemap was utilized. The individual bands for Red, Green, and Blue were then added for further analysis.
2. The next step was to collect a series of sample pixel values. 10 sets of Red, Green, and Blue were collected by identifying pools within the image with the naked eye.

R	G	B
112	192	197
104	171	182
113	203	201
98	174	178
143	223	227
74	149	156
93	159	172
128	194	195
107	196	205
83	142	158

	Minimum	Maximum	Mean
R	74	143	105.5
G	142	223	183
B	156	227	188.5

Here are the original 10 sample values collected for analysis as well as the determined minimums, maximums, and means for each band.

- After an initial set of RGB values was created to serve as a baseline, 2 more sets were created. The first reduced all minimum values by 2.5 and increased all maximums by 2.5, effectively increasing the value range for each band by 5. The second set was created by subtracting 5 from each minimum and adding 5 to each maximum value of the original set. Increasing the band value range by 10.

set 2 (+-2.5)			Set 3 (+-5)		
	Minimum	Maximum		Minimum	Maximum
R	71.5	145.5	R	69	148
G	139.5	225.5	G	137	228
B	153.5	229.5	B	151	232

- Once all three value sets were created, the Raster Calculator tool was used. The following conditional statement was used when running raster calculator. The tool was ran a total of 3 times, once for each value set. “R”, “G”, “B” stands for the individual bands created from original image. This created 3 binary images showing pixel selections within each respective range.

```
Con(("R" >= min) & ("R" <= max) &
("G" >= min) & ("G" <= max) &
("B" >= min) & ("B" <= max), 1, 0)
```

- After creating three raster outputs for the selected features, the raster to Polygon tool was used to convert these outputs into shapefile in order to select individual features. By default, these initial outputs lacked an area or geometry attribute in which to select features. The Calculate Geometry tool was used in order to create an area attribute in which to select the created features. The output is a binary color image with features highlighted in yellow.

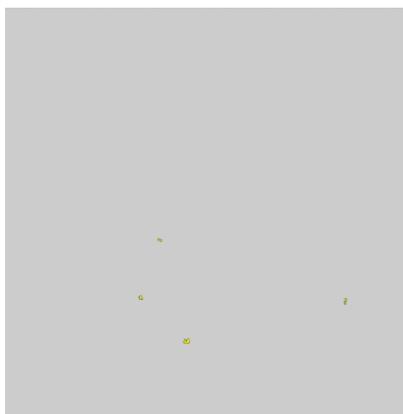


Set 1 output

Set 2 output

Set 3 output

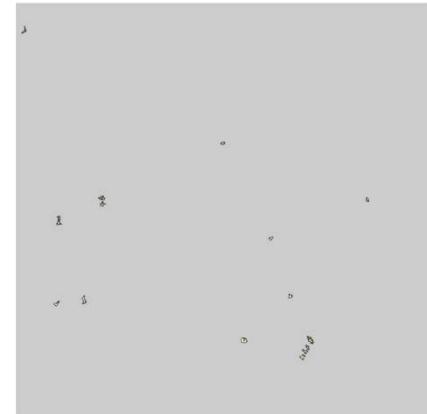
6. As can be seen above, progressively more features are selected as the RGB range extends. The next step is to eliminate all “noise”. In this case, noise was considered any selected features with an area size ranging from 3-20. Above this level most features present were larger and represented large portions of actual buildings or other objects that were not pools. The smallest area size that included the smallest swimming pool was 102 square meters of selected pixels, so this was used as the selective threshold. All other features smaller than this were deleted.



Set 1 output after deletion



Set 2 output after deletion



Set 3 output after deletion

7. Once all features smaller than 102 square meters have been deleted, any remaining features that are highlighting objects that are not swimming pools must be manually selected and deleted. This is best done by turning the background base color to transparent and overlaying the new features over the original image in order to identify each feature.
8. The final output will be a feature set showing locations of swimming pools.

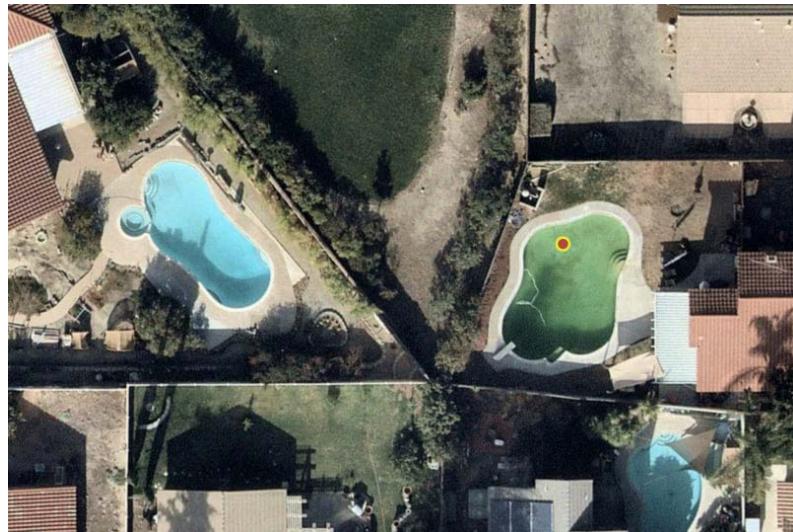
## Results and Discussion

After running the raster calculator in step 4 with the 3 different value sets, we see a progression in the number of pixels that are selected. The output of the first set shows several larger features, including 3 of the 4 noted swimming pools. There is also some minimal noise present. The set 4 output shows a much larger selection of pixels as the RGB range has been extended. But we see that a fourth swimming pool has now been highlighted due to the extended value range. The final output with the largest range in RGB values has also selected the fourth swimming pool, but it has also accumulated the largest amount of noise as well as unrelated larger features. What this means is that more manual inspection and deletion must occur in step 6 in order to produce a valid data set. Since the goal of this project is to minimize the amount of manual inspection required to identify swimming pools, the second set of values would be ideal to use for this particular area of interest. The second output selected a total of 13 large features at step 6, identifying 4 swimming pools. Output 3 selected 14 features and 4 swimming pools.



## Conclusion

Final results of this project show that a relatively small pixel value range extension of 5 increases pool identification by a margin of 25% for the area of interest. This is a significant improvement over the original value sets. Increasing the pixel range to 10 enters into a region of diminishing return, where there were no more pools located, but substantially more noise was generated. This simple process could lead to time savings in preexisting workflows and can be easily adapted to find any object necessary within an image. One consideration to make however is the color and conditions of swimming pools.



This image provided by Rohit Singh shows the stark difference in color that swimming pools can exhibit. It would be possible and likely necessary to sample values of derelict pools in order to create a more wide-ranging data set for machine learning applications. It may be possible to combine this process with an edge detection process in order to narrow down more potential swimming pools.

## References

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