Hurricane Michael Damage Assessment

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4360K Digital Image Processing
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Abstract:
In this study I attempt to quantify and symbolize the extent of damage caused by hurricane Michael in Mexico Beach Florida. I use a color-based extraction model to determine areas of damage from nondamaged areas. This method is applied to NOAA's post storm imagery which was collected the day after hurricane Michael made landfall. However, this imagery contains errors that prevent it from being used as a comparison to other ortho-imagery, such as NAIP. The post processing applied to this imagery also inhibited analysis due to image noise. As a result, the imagery had to be resampled to a larger spatial resolution, thus losing fine detail. To make the color-based feature extraction more uniform, I conducted an object-based image classification. This segmentation grouped pixels based on their neighbor's pixel value. The result was the color-based feature extraction was more complete in determining debris from nondamaged areas. This method, however, needs refining. While the extraction was good at determining the difference between damage and a road, for example, it struggled when trying to extract debris from vegetation or sand. This study was a preliminary step toward creating a damage assessment map from high spectral resolution imagery using only color values and will need to be iterated upon to further its capabilities. Future studies with this method include combining the results presented here with other image processing transformations and conducting an accuracy assessment.

Keywords: digital image, hurricane Michael, image segmentation, damage assessment

1. Introduction:

On October 10, 2018 hurricane Michael made landfall in the Florida panhandle near Mexico beach. With sustained winds at nearly 160 mph, Mexico Beach Florida was almost completely wiped out (NOAA, 2018). In the wake of this storm the focus for emergency personnel and law enforcement shifted from preparations to search and rescue. Due to the severity of the storm, the first responders needed a way to prioritize areas to focus their efforts. Damage assessment maps have always been done on site, several days after a storm has passed. As a result, these damage assessment maps are not utilized by first responders during the search and rescue efforts post storm. Given the immense amount of high-quality imagery and the ease of obtaining high spectral resolution with instruments like drones, I believe we can create simple damage assessment maps remotely within hours of a storms passing.

One of the most complete ways to survey the amount of damage done by a storm to a specific area is the use of active remote sensing instruments like Light Detection and Range (LiDAR). An ice storm hit the Oklahoma City metropolitan area in 2007 and LiDAR was used to measure the damage to the urban tree canopy (Rahman and Rashed, 2015). Using both pre and post storm Airborne Laser Scanners (ALS), Rahman and Rashed (2015) were able to construct an NDSM for both the pre and post datasets and determine the amount of damage to the tree canopy. After the tornadoes in Tuscaloosa Alabama and Moore Oklahoma in the 2010s, LiDAR in combination with onsite analysis was used to determine the areas of highest wind damage (Crawford, 2014). The results from both studies prove the power of LiDAR and how it along with on site evaluation can create a very detailed damage assessment. While active remote sensing techniques are useful for getting a three-dimensional representation of an affected area, passive techniques can be just as viable. Satellite imagery, like the Landsat program, provides a year-round constant supply of imagery to use in damage analysis. At a spatial resolution of 30 meter, the Landsat imagery is not as good for focusing on a small area of damage, but instead is more applicable to study a large storm system that has moved through a large swath of land. Ontario in 1998 experienced such an event with a widespread ice storm. To conduct their damage analysis, Olthof et al. (2003) used Landsat 5 TM spectral bands 1-5 and 7. Supplemental data consisted of elevation data, slope, aspect and metrological data for freezing rain amounts (Olthof et al., 2003). In total four different classification method's accuracy was compared to see which one was the strongest at determining damaged forested areas. These different models where; multiple regression, linear discriminant analysis, maximum likelihood, and neural networks (Olthof et al., 2003). In the end the neural networks proved to be the most successful in detecting damage. However simply having high quality data is not enough, this is where image processing can play a role by adjusting an image with use of algorithms to enhance it. A common transformation applied to a digital image is the Sobel filter. The sobel filter is an edge detection transformation that is meant to enhance the transitions in an image. But according to Zhang et al. (2018) this process can be inefficient and time consuming. By changing the gradient calculation template and the gradient calculation implementation, this new sobel filter is more efficient but also creates a clearer edge detection (Zhang et al., 2018).

For this study I will combine both remote sensing-based techniques to reclassify an area damaged by a storm and utilize low level image processing to extract those damaged areas based on their color. While this method utilizes a simple 3 x 3 smoothing filter to reduce noise it does not take advantage of other image transformations like a sobel edge detection or a Fourier series transformation, but future studies will implement these filters. The objective of this study is to utilize high resolution imagery and construct a simple damage assessment map. Unlike other damage assessment surveys, this analysis can be done remotely allowing for a quicker response. Hopefully in the future damage assessment maps such as what is presented in this study can be used by first responders and other rescue personnel to help in search and rescue

2. Materials and Methods:

This study focuses on the costal town of Mexico Beach Florida where hurricane Michael made landfall. The town almost was almost completely destroyed due a combination of the nearly 160 mph winds and 3-5 feet of storm surge (NOAA, 2018). For the imagery used in this study I took advantage of the Emergency Response Imagery database provided by the NOAA Remote Sensing Division. This imagery was collected on October 11, 2018, one day after Michael made landfall. It has a spatial resolution of 25 cm and contains 4 spectral bands in the RGB color model at bit depth of 8. For pre-storm imagery comparison I used the National Agriculture Imagery Program (NAIP) provided by the USDA collect on October 24, 2017. The spectral resolution of the NAIP imagery is 1 m and contains 4 individual bands at an 8-bit depth. The shapefile which contains the city limits for all towns and cities in Florida was provided by the USDA's Geospatial Data Gateway. Figure 1 shows the pre-storm appearance of Mexico Beach from the NAIP imagery, and Figure 2 shows post-storm Mexico Beach from the NOAA imagery.

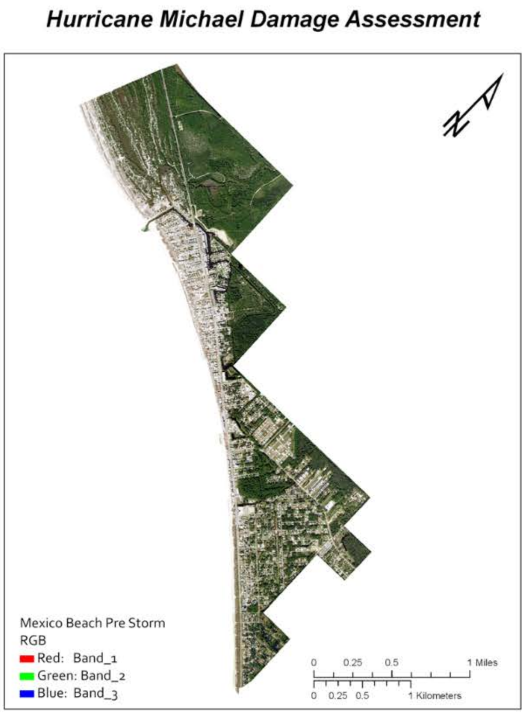

Figure 1: Mexico Beach before hurricane Michael

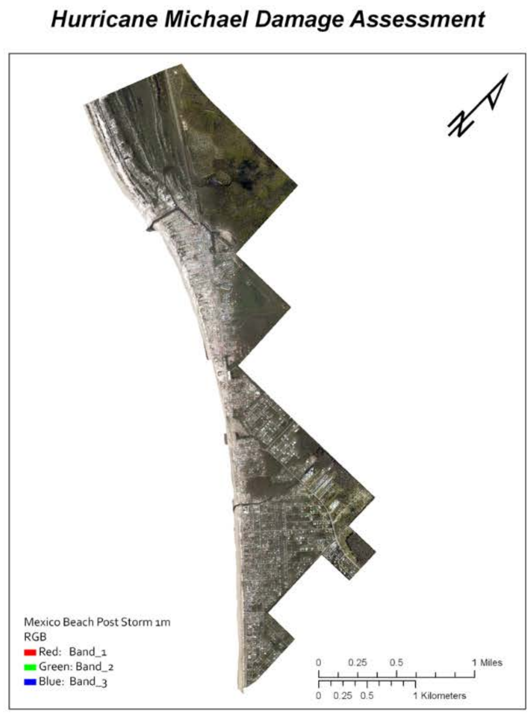

Figure 2: Mexico Beach after hurricane Michael

The first step for this study was I added all the data to a new ArcPRO project. The NOAA post sstrom imagery comes as individual tiles due to its high spatial resolution. I made the city limit vector have no fill and visually selected the tiles from the NOAA imagery that were contained within the limt for Mexico Beach. I then used the Mosaic to New Raster tool with the NOAA imagery and called the output post_storm. From the Florida city limit shapefile, selected Mexico Beach and then exported the selection to a new feature called mexico_beach. This would be used to clip the rasters to just my study area. Using the post_storm raster as the input I used the Extract by Mask tool to clip the post_storm raster to the mexico_beach feature and named the output mexico_beach_post. Because I wanted to compare the pre-storm conditions to the post storm, I ran the Mosaic to New Raster tool again but with the NAIP imagery and called the new raster, naip I then ran the Extract by Mask tool again on the naip layer with the mexico_beach feature as the clipping extent and called output, mexico_beach_pre. After I had both the pre and post storm imagery I needed to resample the mexico_beach_post raster from the 25cm pixel size to 1m, to match the mexico_beach_post layer. I named the new resampled raster, resampled_mexico_beach_post.

Because the post storm raster was noisy I applied a 3x3 smoothing filter to the resampled_mexico_beach_post raster. I then exported the raster to the project's geodatabase and called it smoothed_resample_1m_post. Figure 3 shows the new smoothed post-storm layer. To make color extraction easier, I ran the Segmentation Classification on the smoothed_resample_1m_post raster with a 17 spectral detail, 17 spatial detail and the minimum segment cell size in pixels to 10. I then exported the segmentation output as a new raster called segmented_mexico_beach to the geodatabase, shown in Figure 4. Using the explore function I collected the R, G and B reflectance values on 16 areas of high damage from the segmented_mexico_beach raster, shown in Table 1. I created a new excel spreadsheet and recorded those 16 samples and determined the minimum and maximum value for R, G, and B. Then I added the individual bands of the segmented_mexico_beach raster and named band 1 as "R", band 2 as "G" and band 3 as "B". Using the Raster Calculator, I constructed a conditional statement that selects all the values in between the max and min of the recorded R, G, and B values and sets it equal to 1, all other values become 0. I called this raster as con_seg_post:

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Con(("R" >= 159) & ("R" <= 212) & ("G" >= 131) & ("G" <= 191) & ("B" >= 113) & ("B" <= 184), 1, 0)
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After creating the con_seg_post raster, I used the Raster to Polygon tool to convert the conditional raster to a polygon based on the field 'Value' and named it con_poly, shown in Figure 5. I then used select by attributes on the con_poly feature to select all instances of gridcode = 0, and then deleted them because I just wanted the areas that were damaged. I visually inspected the con_poly layer for any obvious false positives and manually deleted them. The result is Figure 6, a map that highlights the damaged areas in red overlaid on top of the post storm imagery.

Figure 3: The smoothed post-storm imagery. A 3x3 smoothing filter was applied.

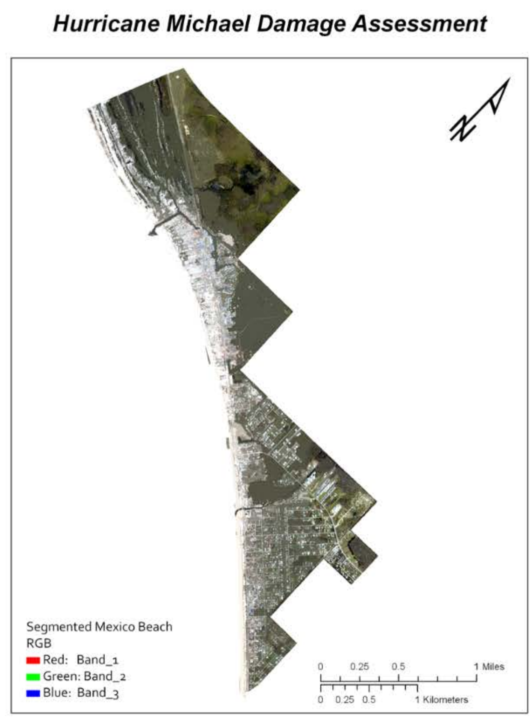

Figure 4: The object-based image segmentation, many areas of damage are now smoothed into a uniform color

Table 1: An example of the sample points used to determine the min and max spread of debris color

	Sample 1:	Sample 2:	Sample 3:	Sample 4:	Sample 5:	Sample 6:	Sample 7:	Sample 8	Sample 9:	Sample 10:	Sample 11:	Sample 12:	Sample 13:	Sample 14:	Sample 15:	Sample 16:	Max:	Min:
R:	165	170	164	192	184	182	165	196	176	160	197	201	212	159	197	194	212	159
G:	150	159	152	177	168	155	144	170	161	131	178	176	191	133	180	189	191	131
B:	141	153	142	169	155	140	134	149	147	113	169	161	174	122	168	184	184	113

Figure 5: This is the resulting raster from the conditional statement, with 0 being non-damaged areas and 1 being damage

Figure 6: The final product, all areas in red represent damage overlaid onto the post-storm dmage imagery

3. Results and Discussion:

Mexico Beach has a total land area of 1,487 acres, according to this study 96 of those acres were severely damaged. The strongest hit areas were, unsurprisingly, along the coast. The homes and businesses closest to the water have been completely wiped off their foundation. US Highway 98 impassable in many areas throughout Mexico Beach, and has been covered in a layer of sand for most of its length. The northwestern portion of the town was significantly harder hit by the storm compared to the south. This is due with the eye of Michael passing over Tyndall Air Force Base which is directly northeast of Mexico Beach. The storm surge was 3 to 5 feet in Mexico Beach according to NOAA (2018) which explains the severity of the damage and why there are piles of debris resting against the larger buildings along US Highway 98.

The color-based extraction used in this study performed well. It was able to detect the larger piles of debris, mentioned earlier, but also the wider damage field. It was most successful at detecting damage piles that were against other structures or that were on surfaces that caused a high contrast, like roads visible in Figure 7. This method was also successful at distinguishing damaged but still standing structures, for example holes in roofs. Many of the larger buildings in Mexico Beach were not completely destroyed but still suffered catastrophic damage, however this system still highlighted many of these structures for the damage the did suffer.

Basing this damage extraction method off color has proved to be a challenging obstacle. While the system does perform well overall, there are areas where it fails. Wood damage is among the most common when simply visually inspecting the imagery, but wood looks the same when damaged or still part of a structure. This method would often flag a deck that is part of an undamaged house as being debris, when that wasn't the case. There were also several instances of roofs that had been removed from there houses and ended up still relatively intact in other places that were not being categorized as damage. Sand proved to be a big issue as well. Due to the storm surge sand covered a large portion of roads close to the coast, and this system detected this as damage. While an argument can be made that sand covering a road is not damage, I think the fact that this system classified it as damage was correct. But the bigger issue relating to sand is the location of this study. At a beach sand is everywhere, not only at the coast. The soil makeup of coastal areas is majority sand and that can be seen in pre-storm imagery. This system however classified the sandy soil in Mexico Beach as damage when that is not accurate.

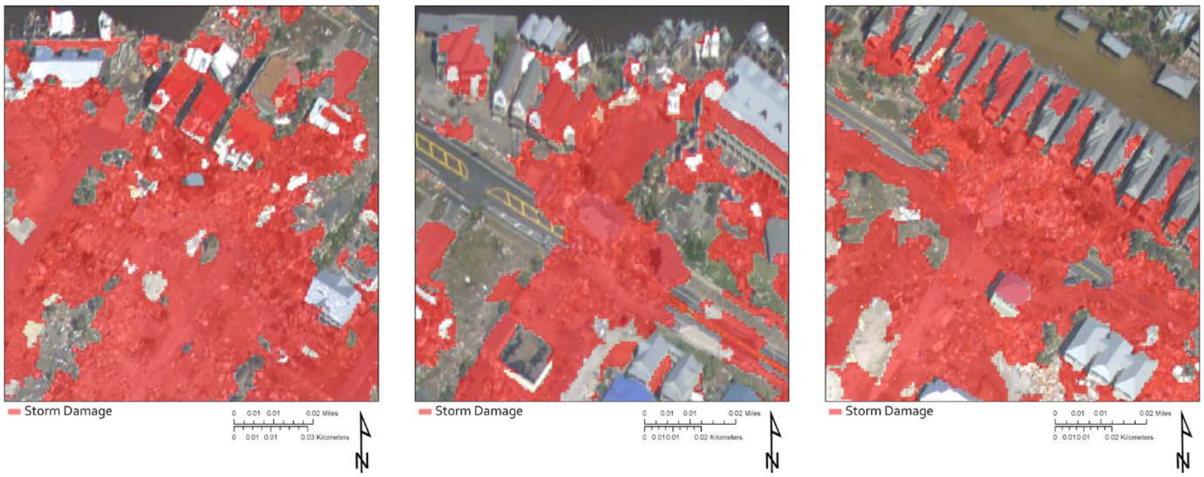

Figure 7: Examples of the color-based classification extracting storm damage

While this system did perform well in a large number of situations, the areas it did falter prevent it from being a viable quick response remote based damage assessment tool. There were also several limiting factors about this study that have contributed to it not performing as well as it could. First there were a couple of problems with the NOAA imagery. It was very high resolution, but it was taken at an oblique angle. This prevented a direct comparison with the pre-storm NAIP imagery. It was also very noisy which necessitated the smoothing filter. The imagery was taken the day following the storm, so their priority was simple to get the imagery. The way the imagery was mosaiced also was an issue, there were several spots where there was no data. Ultimately the imagery was not compromise to the point of it being unusable. Another issue with this study is the accuracy. I did not conduct an accuracy assessment of this method as this study was more a proof of concept, but one will need to be done to validate the results. To further test the accuracy of this method, multiple different locations and storm types should be used. Testing this method on different types of storm damage could further reveal its strengths and weaknesses. Finally, utilizing more image processing tools will improve the results. Using a Fourier transformation on the post storm imagery could possible match or exceed the results of this analysis. Combing that with an object-based classification could result in the best results.

4. Conclusion:

This study attempted to extract damage caused by hurricane Michael on the town of Mexico Beach Florida using a color-based classification. Using high spatial resolution imagery provided by NOAA’s Remote Sensing Branch, I was able to construct a method that looked at the color of the damage area and classify it as damage. The imagery needed to first be resampled to 1 m from the 25 cm native resolution because of comparisons to pre-storm conditions NAIP imagery. The imagery also needed to have a smoothing transformation applied to it due to high noise. The results were positive in the fact that large groups of debris were extracted from the non-damaged areas, especially in locations of high contrast. But this method falters with distinguishing non-damaged materials from damaged materials, wood for example.

Sand also was a common false positive as its color is very similar to a destroyed structure. Further refining of the method is needed to ensure higher accuracy. Future studies utilizing this method should consider the vast array of image processing tools available, like the Fourier transformations. Taking advantage of the improved sobel filter developed by Zhang et al. (2018) could also deliver better results. Also utilizing imagery with more bands could also improve results. Lambert et al. (1995) found that using an images infrared bands provided the most accurate classification of forest damage. Combing the use of infrared and thermal bands could work with this method.

While this method needs further testing and refining to ultimately be accurate enough to use, it still succeeded as a proof of concept. The goal of study was to see if it was possible to take advantage of amount of high-quality imagery available and construct a damage assessment remotely quickly after a storm. Even with the before mentioned issues with this method, this study proves that this indeed can be accomplished. This method can be applied not only to large scale storms like a hurricane, but also smaller storms like tornadoes. Where using active remote sensing techniques will always be more accurate, this method can a first step to creating a damage assessment map (Crawford, 2014). I plan to continue to refine this method in hopes to accomplish the ultimate goal of this study.

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