**NASA DEVELOP National Program**



Wise County Clerk of Court’s Office and NASA Langley Research Center

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Virginia Water Resources II

Utilizing NASA Earth Observations to Monitor the Extent of Harmful Algal Blooms in Lower Chesapeake Bay Watersheds

 **Technical Report**

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DEVELOP Wise County Clerk of Court’s Office

Arika Egan (Project Lead)

Jakub Blach

Zachary Tate

DEVELOP NASA Langley Research Center

Jessica Jozwik

Tyler Rhodes

Dr. Kenton Ross, NASA DEVELOP National Program (Science Advisor)

Bob VanGundy, University of Virginia’s College at Wise (Science Advisor)

Dr. DeWayne Cecil, Global Science and Technology, Inc. (Science Advisor)

Previous Contributors:

Sara Lubkin

Cassandra Morgan

# I. Abstract

Harmful Algal Blooms (HABs) in the Chesapeake Bay Watershed have an increasingly negative effect on the ecosystems in which they grow. They deprive their ecosystem of oxygen, produce harmful toxins, and mechanically damage other organisms. This disrupts the natural water chemistry and causes large-scale fish mortality events. Scientists from the Virginia Institute of Marine Science (VIMS) and Old Dominion University (ODU) monitor HABs and their effect on the water quality; however, the Chesapeake and its estuaries are geographically too large for the groups to continuously monitor HABs. This limits the group’s ability to monitor up-to-date locations of HABs and the water quality associated with them. To remedy this, surface reflectance data from Landsat 8 obtained from the USGS Earth Explorer, bathymetry imagery collected from NOAA CoastWatch, and *in-situ* data from VIMS and ODU were used to create a tool that produces a map of algal hotspots in the Chesapeake Bay area. Data were collected from August 17th, 2015. This tool will allow scientists at VIMS and ODU to identify the location of algal hotspots using current Landsat 8 data, as well as give them the ability to assess the timing, magnitude, duration, and frequency of HABs in the Chesapeake Bay Watershed.

**Keywords**

Remote Sensing, James River, York River, Landsat 8 OLI, Chlorophyll-a

# II. Introduction

The population around the Chesapeake Bay Watershed has doubled since 1950 and is currently approaching 18 million people (Chesapeake Bay Program 2015). As a result, increases in urban and agricultural land use have led to higher concentrations of nutrient runoff into the Chesapeake Bay and its estuaries (Ondrusek et al 2012). High concentrations of nitrogen and phosphorus in the water trigger the excessive growth of algae, known as Harmful Algal Blooms, or HABs (Ondrusek et al 2012). HABs have costly, negative impacts on water quality in the Chesapeake Bay. They form a film on top of the water, thus blocking sunlight necessary for photosynthetic activity in other beneficial organisms (Gilbert et al 2005). Additionally, as the algae die and decompose, they drastically decrease dissolved oxygen in the water (Gilbert et al 2005). By blocking sunlight and decreasing dissolved oxygen, entire ecosystems are negatively impacted and thrown out of balance by HABs.

HABs pose a threat to human health and well-being as well. They produce harmful, unpleasant smelling toxins that mutate underwater organisms and contaminate shellfish and oysters, making them unsafe for human consumption (Backer and McGillicuddy 2006). HABs often require beach closures to ensure safety. Communities also report massive fish mortality events during the bloom season from July to September, and oyster larvae are less likely to survive when HABs are present (Reese 2015). As fishing, oyster harvesting and tourism are three major economic industries for Virginia’s coastal communities, HABs pose serious threats to the economic security of the area (Chesapeake Bay Foundation 2015).

Decision makers on the local, state, and federal level are all concerned with the degrading water quality of the Chesapeake Bay. The Clean Air and Water Act of 1972 and President Obama’s Chesapeake Bay Executive Order of 2009 set water quality parameters and highlights the importance of restoring the health of the Chesapeake Bay. On the state level, an HAB Task Force, comprised of representatives from the Virginia Department of Health, Virginia Institute of Marine Science (VIMS), Virginia Department of Environmental Quality (DEQ), the Marine Resource Commission, and Old Dominion University (ODU), is tasked with identifying, monitoring, and researching HABs in an attempt to improve the water quality of the Chesapeake Bay. They focus on Virginia’s Chesapeake Bay, the James River, the York River, the Elizabeth River, and Mobjack Bay (Department of Environmental Quality 2015).

The HAB Task Force maintains 20 fixed testing stations throughout the region where various water quality parameters (chlorophyll-*a* content, salinity, temperature and turbidity), genetic molecular analysis, and HAB/phytoplankton identification tests are conducted monthly from May to November (Department of Environmental Quality 2015). Additionally, community members are encouraged to utilize a 24-hour HAB hotline that has been established to report suspicious colors, smells, or fish kills (Virginia Institute of Marine Science 2015). When a HAB is detected or reported, the response team collects samples that are analyzed at different institutions, depending on the nature of the report. Then, the VA Health Department determines future actions based on guidelines set by the Clean Water Act and State of VA Water Quality Standards (Department of Environmental Quality 2015).

While these resources exist, the total area of the Bay is too large to continuously monitor, and current methods do not allow for the desired real-time monitoring of the area. A more efficient and cost-effective method of identifying and studying HABs is necessary to assist local, state and federal agencies, and research institutions in their efforts to protect the Chesapeake Bay.

The objective of this project was to provide a method of identifying HABs in real time to the HAB Task Force using remote sensing technology. Building upon the work done by the Virginia Water Resources project from summer 2015 of NASA DEVELOP, this project attempted to utilize Landsat 8 OLI images, and historical *in situ* data to create a python tool that highlights high concentrations of chlorophyll in the Chesapeake Bay and its estuaries. Historically, researchers have utilized the Normalized Difference Vegetation Index to locate chlorophyll concentrations based on the amount of red and near infra-red light plants reflect (Shen et al 2012). Other band combinations, such as mid-infrared, near infrared, and red, have also been traditionally used to visualize chlorophyll (Horning 2004). Since vegetation absorbs nearly all red light, a red band can be helpful in visualizing chlorophyll. Near infrared helps differentiate between land and water. Since water absorbs nearly all light, the dark water is contrasted with bright reflectance of soil and vegetation on land. Finally, mid infrared is sensitive to moisture and is historically used to monitor vegetation. By combining these three bands, past researchers have been able to visualize chlorophyll concentrations on both land and water (Horning 2004).

The tool applied these remote sensing concepts specifically to areas in the Chesapeake Bay. Our partners will be able to locate and monitor the timing, magnitude, duration and frequency of HABs quickly and efficiently, and identify areas of the Bay that need additional testing. This project addresses NASA’s Earth Science Water Resources application area and aligns with the goals of President Obama’s Chesapeake Bay Executive Order to target resources, define tools, strengthen scientific support for decision making, and develop focused and coordinated research programs to improve water quality of the Chesapeake Bay.

# III. Methodology

**Data Acquisition:***Ancillary Data*  
*In situ* water sampling data were provided by Dr. Kim Reese from the Virginia Institute of Marine Science (VIMS). Samples were obtained from a data collection cruise on August 17th, 2015, occurring between 10:00am and 12:00pm. The data cruise collection provided detailed measurements of various water quality parameters, including turbidity, temperature (°C), *in vitro* chlorophyll measurements (µg/L), pH, and salinity (ppt).

*Landsat 8 OLI*  
Landsat 8 surface reflectance data products were obtained from the United States Geological Survey’s (USGS) EarthExplorer August 17th, 2015. This date was selected in order to combine it with available *in situ* data also from August 17th, 2015. This date was also selected because it was a particularly cloudless day. Path 15, Row 34 was used as the search criteria. A cloud mask, called the “CFmask”, is provided from the USGS EarthExplorer when surface reflectance products are ordered.

*Bathymetric Data*  
Bathymetric data for the Chesapeake Bay at 30 m resolution was downloaded as a DEM from the National Oceanic and Atmospheric Administration’s (NOAA) estuarine bathymetry website.

**Data Processing:** *Landsat 8 OLI*The pixel values in the Landsat 8 OLI data were given in integer values. This means that the outputs of any mathematical operations applied to them will default to integer values. Depending on the operation performed, resolution of the pixel values can be lost. Thus, true reflectance composites were compiled by dividing the pixel values by 10,000 for bands 1-7 of the Landsat 8 OLI data:

This converted the integer values into floating point values, and the resolution was conserved.

Next, land pixels were removed from each of the rescaled bands. This was achieved through the use of a normalized difference vegetation index (NDVI). The NDVI is calculated with the following formula:

Pixels with a value less than 0 corresponded to water and were reclassified to 1. All other pixels were reclassified to “NoData” using the conditional evaluation tool (watermask = Con(ndvi,1,"","VALUE < 0"). The watermask was applied to all rescaled floating point Landsat 8 OLI bands using the “Extract By Mask” tool in ArcMap. This removed pixels corresponding to land, and pixels corresponding to water were extracted.

The cloud mask, or cfmask, provided by the Landsat 8 surface reflectance product, was used to remove clouds and cloud shadows. Table 1 describes the pixel values and their interpretation, as provided by USGS Product Guide for the Provisional Landsat 8 Surface Reflectance Product.

|  |  |
| --- | --- |
| **Pixel Value** | **Interpretation** |
| 255 | Fill |
| 0 | Clear |
| 1 | Water |
| 2 | Shadow |
| 3 | Snow |
| 4 | Cloud |

**Table 1.** Description of the pixel values and their interpretation of the cfmask, as provided by the USGS Product Guide for the Provisional Landsat 8 Surface Reflectance Product.

Using the “Conditional Evaluation” tool in ArcMap, pixels valued 0 or 1 were reclassified to “1”. All other pixels were reclassified to “NoData”. This image became the cloud mask and was applied to the water-only rescaled bands using the “Extract by Mask” tool in ArcMap.

Cannizzarro and Carder (2005) report stark differences in chlorophyll estimation between optically shallow and optically deep water. They developed a technique that classifies data as optically shallow or optically deep and created two different chlorophyll estimation algorithms. For this reason, pixels corresponding to a depth of 2 meters or less were removed from the Landsat 8 OLI data. Shallow pixels reflect more light and produced what were believed to be false positives in our final product. Thus, a bathymetry mask was produced to remove these pixels.

NOAA bathymetry data were available as three DEM tiles. The tiles were joined as a mosaic in ArcMap and saved as a TIFF file. The bathymetry mask was created to remove pixels corresponding to a depth of 2 m or less from the Landsat 8 OLI data. The mask was created using the “Conditional Evaluation” tool in ArcMap. Pixels in the NOAA data with a value of -2 or greater were reclassified to “NoData” and all other pixels were reclassified to “1”. This image was saved as a bathymetry mask. It was applied to the land and cloud removed rescaled bands using the “Extract By Mask” tool in ArcMap.

Pixels corresponding to high sediment concentrations were removed. Like shallow water, it was suspected that high sediment concentrations were producing false positives when identifying areas of high chlorophyll concentration (Tebbs et al 2013). Lacaux et al (2007) describes a method for differentiating clear water from turbid water, or water filled with sediment. This was done by calculating an index called the Normalized Difference Turbidity Index (NDTI) using the following formula:

For Landsat 8 OLI, this becomes

Somvansh et al (2011) uses the mean and the standard deviation of the NDTI to classify regions of sediment concentration (Table 2).

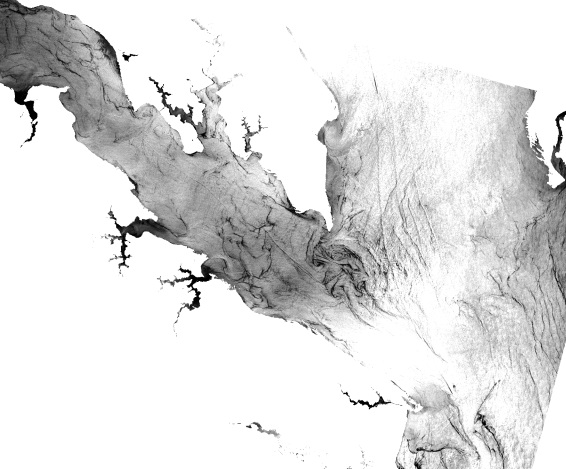
|  |  |
| --- | --- |
| **Sediment Classification** | **Formula** |
| Low | Mean – Standard Deviation |
| Moderate | Mean + Standard Deviation |
| High | More than Moderate |

Table 2. Regions of sediment concentration, as defined by Somvanshi et al (2011).

The standard deviation and mean of the NDTI were calculated from the image. Values corresponding to the “High” sediment classification were reclassified to “NoData” using the “Conditional Evaluation” tool in ArcMap. All other values were reclassified to “1”. This image was used to remove pixels with a high sediment concentration.

This final image, with land, cloud, shallow and high sediment concentration pixels removed, was used in our data analysis (Figure 1).

Figure 1. Before and after image processing. A raw Landsat 8 OLI band 1 image from August 17th is on the left, and the same image with land, cloud, shallow, and sediment pixels removed.



*Ancillary Data*The VIMS data file came in an excel spreadsheet and was imported into ArcMap. The coordinate system was set to the GCS\_WGS\_1984 geographic coordinate system. The data were then exported to a shapefile to allow Landsat 8 OLI pixel values to be exported to it. This was done using the “Extract Multi Values to Points” tool in ArcMap. Bathymetric values from the NOAA bathymetry mosaic data were also extracted to the VIMS shapefile.

There were a few data points from the VIMS shapefile that had no corresponding Landsat 8 OLI values. These missing pixels were most likely removed when shallow and cloud pixels were removed. Corresponding VIMS data values were removed by selecting all the points with a missing data in the Landsat 8 OLI data columns in the shapefile attribute table. Additional data points removed were those near any bridges and boats in the Landsat 8 OLI images. Data points near those features reflected extra light and produced artificially high reflectance values.

This collection of data was analyzed in the statistical analysis program R. To make the data readable in R, the VIMS shapefile was exported to a dBASE file. This dBASE file was opened in Microsoft Excel and then saved as a CSV. This CSV was used in R during the data analysis.

**Data Analysis:**  
*First Method*The Landsat 8 OLI processed data used for this method had the land, cloud, and shallow pixels removed. A separate CSV file was created with the extracted Landsat 8 OLI data and the VIMS data. The CSV file with the processed Landsat 8 OLI and VIMS data cruise data was imported into R. A correlation analysis was run on the data, attempting to find a relationship between chlorophyll measurements and the processed Landsat 8 OLI band pixel values. One hundred and seventy one different regression models were run on the data, including linear-linear, linear-log, and linear-exponential relationships. The success of the correlations was determined by the R2 value (Table 3).

|  |  |  |  |
| --- | --- | --- | --- |
| **Formula** | **R2** | **Formula** | **R2** |
| ~exp(b1/b2) +b1+ b2+ b3+b4 | 0.1868 | ~exp(b4/b3) +b1+ b2+ b3+b4 | 0.1889 |
| ~exp(b1/b2) +b1+ b2+ b3+b5 | 0.1796 | ~exp(b4/b3) +b1+ b2+ b3+b5 | 0.1884 |
| ~exp(b1/b2) +b1+ b2+ b3+b6 | 0.1613 | ~exp(b4/b3) +b1+ b2+ b3+b6 | 0.1905 |
| ~exp(b1/b2) +b1+ b2+ b3+b7 | 0.1621 | ~exp(b4/b3) +b1+ b2+ b3+b7 | 0.1902 |
| ~exp(b1/b2) +b1+ b2+b3+b4+b5 | 0.1872 | ~exp(b4/b3) +b1+ b2+b3+b4+b5 | 0.1893 |
| ~exp(b1/b2) +b1+ b2+b3+b4+b6 | 0.1878 | ~exp(b4/b3) +b1+ b2+b3+b4+b6 | 0.1909 |
| ~exp(b1/b2) +b1+ b2+b3+b4+b7 | 0.1877 | ~exp(b4/b3) +b1+ b2+b3+b4+b7 | 0.1907 |
| ~exp(b1/b2) +b1+ b2+b3+b4+b5+b6 | 0.1959 | ~exp(b4/b3) +b1+ b2+b3+b4+b5+b6 | 0.2011 |
| ~exp(b1/b2) +b1+ b2+b3+b4+b5+b7 | 0.1962 | ~exp(b4/b3) +b1+ b2+b3+b4+b5+b7 | 0.2009 |
| ~exp(b1/b2) +b1+ b2+ b3+b4+b5+b6+b7 | 0.1968 | ~exp(b4/b3) +b1+ b2+ b3+b4+b5+b6+b7 | 0.202 |

Table 3. Table of a selection of attempted regression models in the statistical program R. R2 value was 0.202, which is not a strong enough correlation to provide a good predictive model

The best R2 value out of all regression models run was 0.202, which was not a strong enough correlation to provide a good predictive model. As explained in the results section, a second analysis of the data in ArcMap provided evidence that the VIMS data cruise data and the Landsat 8 OLI data did not match up as they should.

Due to time constraints arising when this data inconsistency was realized, a second, more visually based methodology was developed to produce chlorophyll concentration choropleth maps.

*Second Method*  
The Landsat 8 OLI processed images for this method included the removal of high concentrations of sediment pixels as well as the removal of land, cloud, and shallow pixels. Two final choropleth maps were created. The first is a color composition consisting of the near infrared, the red, and the green bands of the processed Landsat 8 OLI data, created with the “Composite Bands” tool in ArcMap. Pixels colored a deep red correspond to high chlorophyll concentration; pixels colored a lighter red can correspond to mature or unhealthy growth; blues correspond to water, with lighter blues being shallower water and deeper blues being deeper water.

The second map was an NDVI map, created using the NDVI formula given previously. The values of the pixels are all negative, as expected when calculating an NDVI over water. However, values at the less negative end of the spectrum refer to areas of high chlorophyll concentration.

# IV. Results & Discussion

*First Method*  
This study attempted to find a regression model comparing *in situ* data to Landsat 8 OLI reflectance values. An analysis of the *in situ* data and a color composite meant to identify chlorophyll showed several areas where the two data sets were inconsistent with each other (Figure 2).

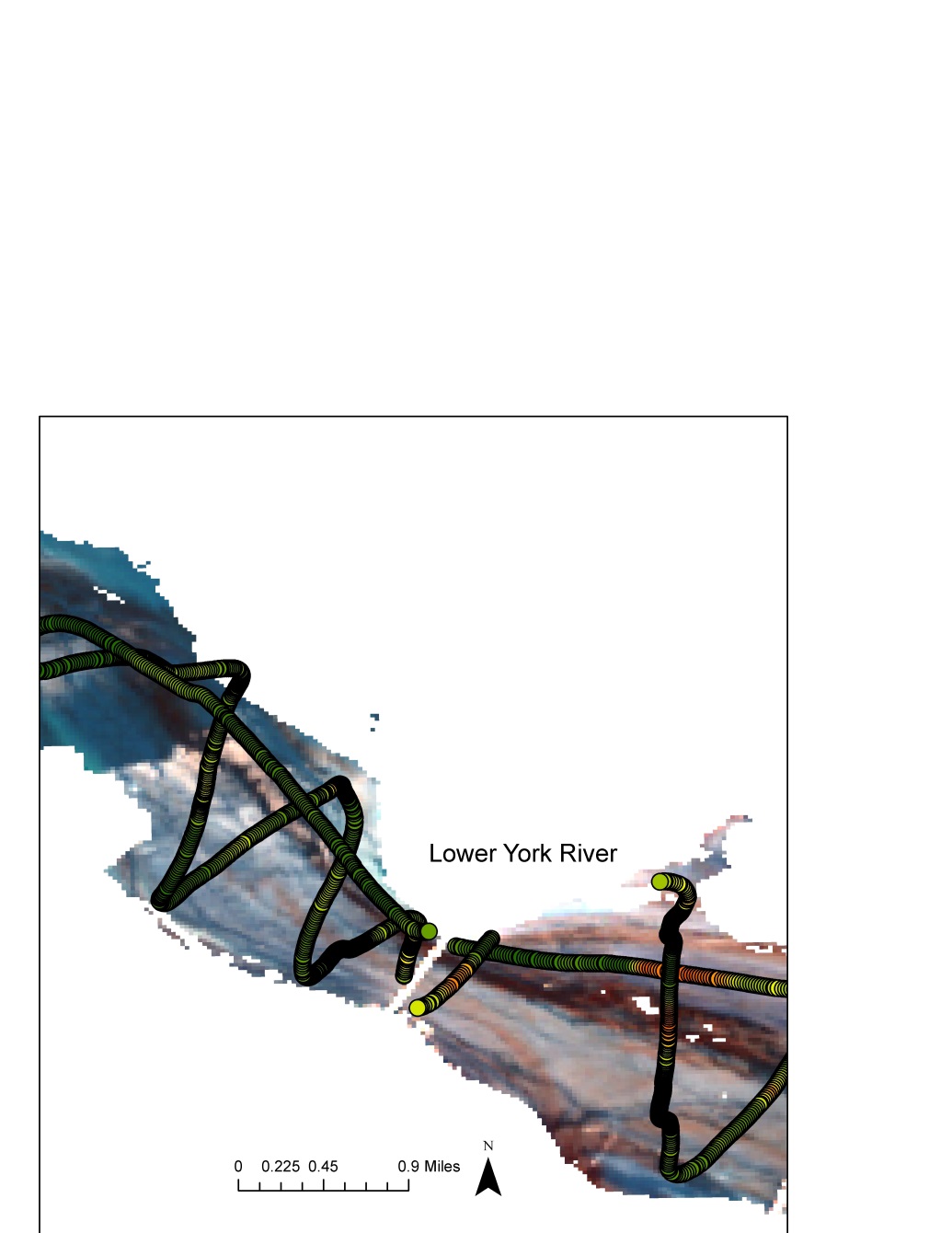
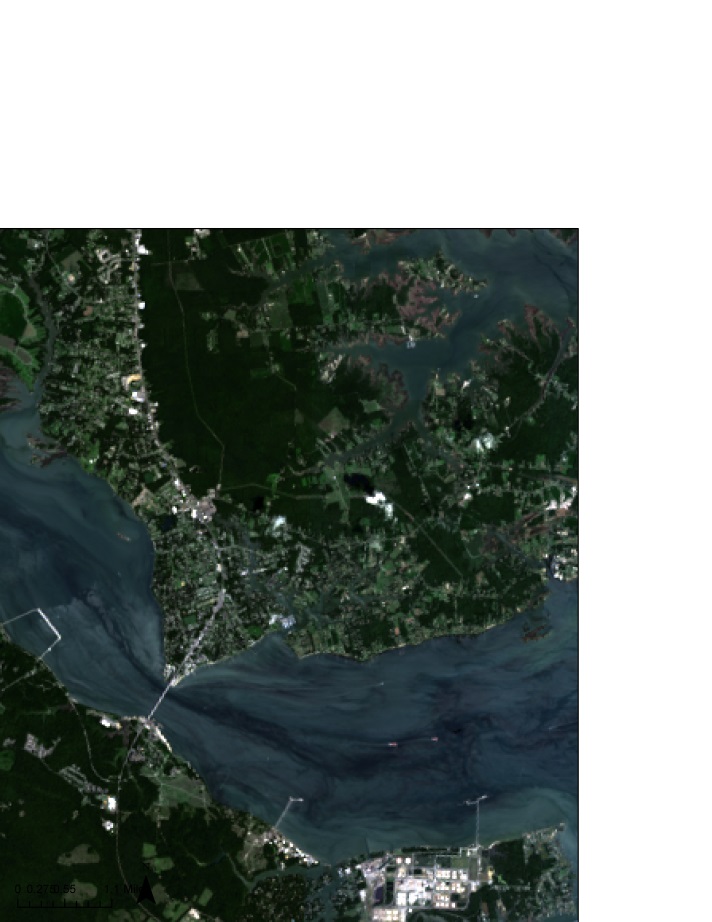


Figure 2. Image of a NIR, R, and G color composition used for displaying chlorophyll levels overlaid with the VIMS data cruise path. The data points are colored according to chlorophyll level, with green being low and red being high. The four circled areas highlight inconsistencies in the image and the cruise data, including inconsistencies in measurements where the data overlaps, where chlorophyll exists in the image but not in the cruise data, and vice versa.

These inconsistent values were removed, leaving 500 data points, and another attempt was made to find a regression model. The same 171 models from the first regression round were used in R, but no strong correlation was found. The best R2 value produced was 0.35, which was not considered to be a strong correlation. For this reason, the project team resorted to the second method to create the python tool.

There are several reasons why finding a correlation was not possible. One possible explanation is the presence of currents and water vehicles in the bay at the time the data was taken. The Chesapeake Bay is host to a number of commercial and private boats, several of which can be seen in the Landsat 8 OLI images. The movement of these boats as they traveled throughout the Bay may have disturbed the location of the algal blooms between the times when VIMS collected the *in situ* data and when Landsat 8 flew over the Bay (Figure 3). Thus, the locations VIMS reported having high concentrations of algae may not have been where the Landsat 8 OLI data reported the locations.

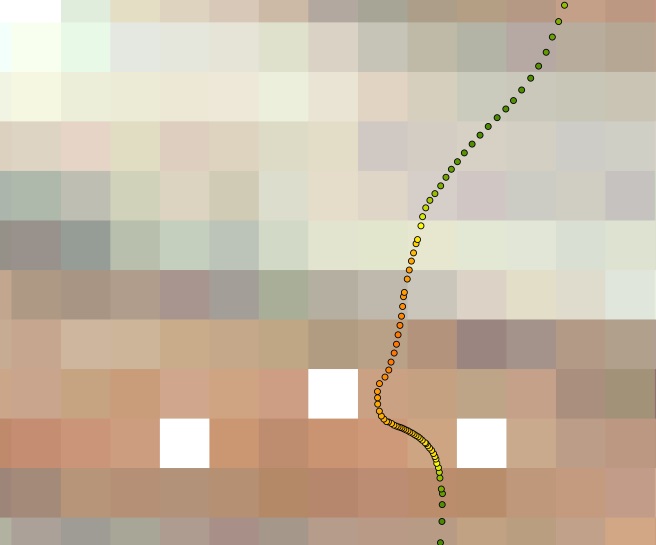


Another possible reason for the inconsistencies was the resolution of the Landsat 8 OLI data and that of the cruise data (Figure 4). There are several cruise data points per Landsat 8 OLI pixel, though the amount per pixel is not consistent. This variability in distribution may have produced extra data points where none should have existed, thus skewing the true correlation of Landsat 8 OLI data and VIMS chlorophyll measurements.

**Figure 3.** A true color composition of the Lower York River, created from Landsat bands 4, 3, and 2. Circled in red are three boats that were traveling in the river at the time the Landsat 8 OLI captured the image. The movement of boats like these in the water may have shifted the location of algae in the water, and thus affected the locations of detected chlorophyll in the Landsat 8 OLI data and the VIMS data cruise data.

Additionally, a discussion with representatives from VIMS led to the discovery that the equipment taking measurements of chlorophyll in the water was situated about a foot beneath the surface, whereas Landsat 8 OLI data takes reflectance values from the surface of the water. An inconsistency existed between the regions of the Chesapeake Bay that data was being collected from.

**Figure 4.** Close up of the VIMS data cruise data on a 543 color composite of fully processed Landsat 8 OLI data. The boxed pixel at the top has 3 data points in it, while the bottom boxed pixel has 18 data points in it. The amount of data points in each pixel is a result of the speed of the boat collecting the data. The excess and dearth of cruise data possibly skewed the data used for finding a good regression model.



Furthermore, it’s possible that the models we attempted to find did not account for other factors which affect algae growth, like depth, salinity, and turbidity. While shallow water pixels were accounted for with the removal of pixels corresponding to a depth of 2 meters or less, the range of depths in the Chesapeake is dynamic, with a maximum depth of 174 feet (CBF 2015).

*Second Method*  
The second method involved the creation of two chlorophyll concentration maps: near infrared, red, and green (543 color composition) color composition map and the NDVI map. Each map displays similar regions of high chlorophyll concentration (Figure 5). Thus, they have similar abilities to provide the locations of regions of high chlorophyll concentration and harmful algal blooms.

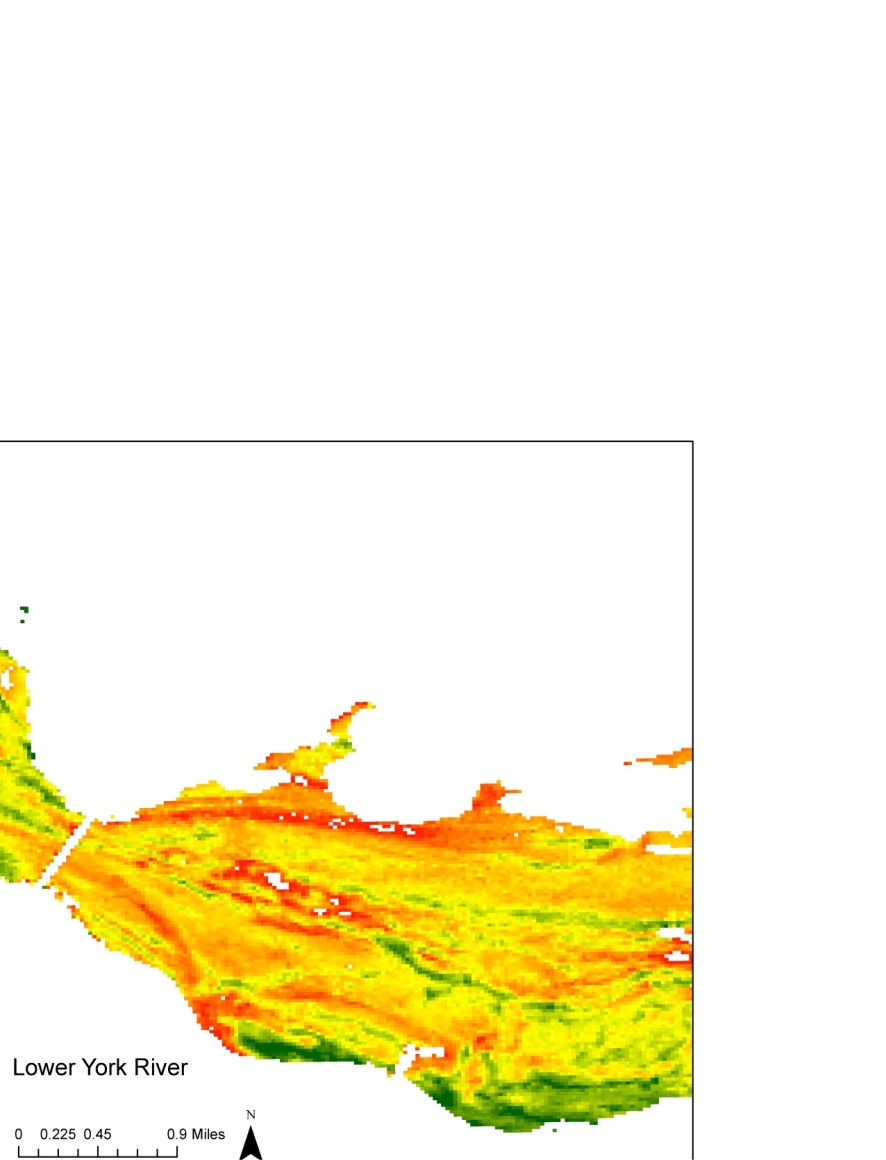
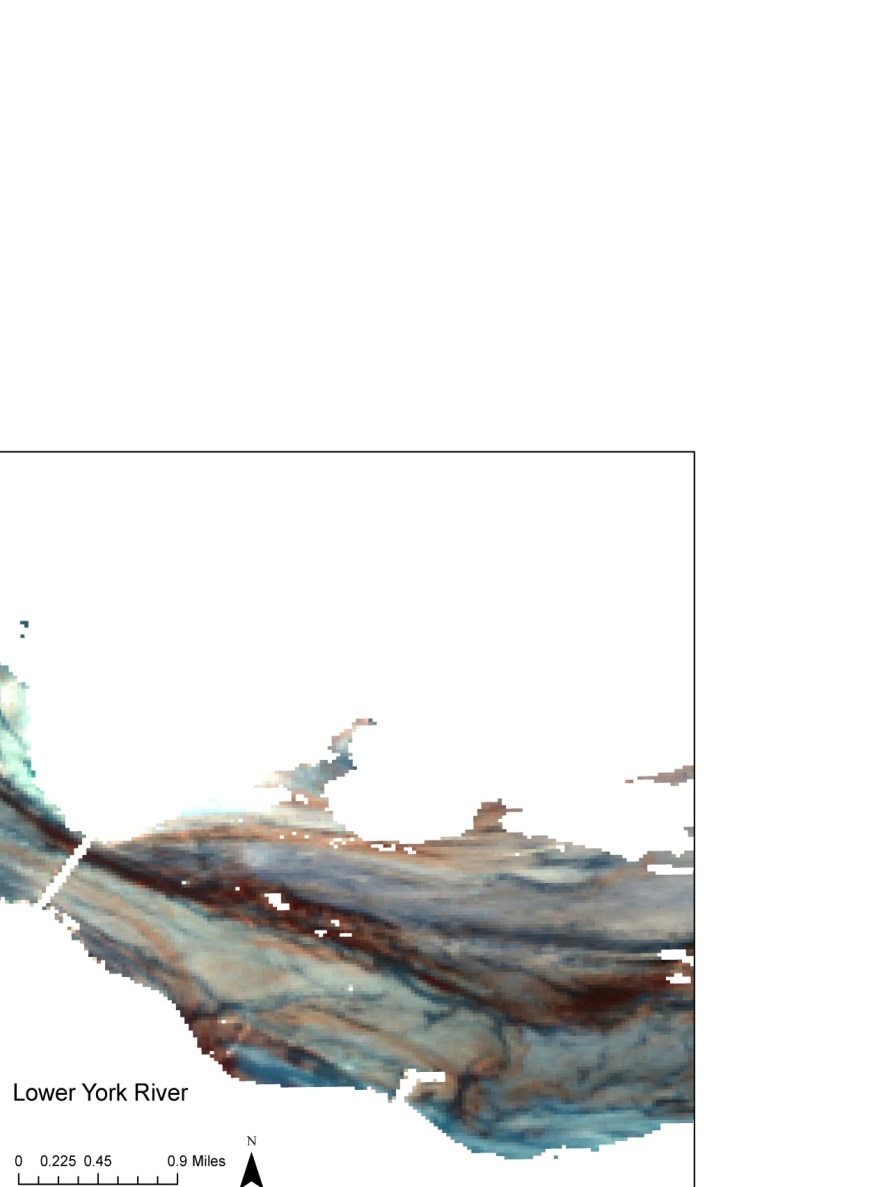
Some differences in the visual displays of the images are important to point out. First, areas in light red on the 543 composition map are marked as bright red on the NDVI map. The large streak of dark red in the 543 color composition is also not entirely present in the NDVI image.

Figure 5. These images are the final results of the code created for this project. The image on the left is a 543 color composition meant to display chlorophyll. Dark red pixels correspond to areas of high chlorophyll and light red pixels correspond to mature or dying vegetation. Light blue pixels correspond to shallower water and dark blue pixels correspond to deeper water. The image on the right is an NDVI with a 20% min percent clip and a color ramp applied to it. Pixels in red correspond to areas of relative high concentrations of chlorophyll and areas in green correspond to areas of relative low concentrations of chlorophyll.

The NDVI image displays only relative vegetation concentration. This means that if the entire region contains a very low algal bloom, regions with concentrations at the higher end of the spectrum will be displayed as red. To better use this map, it’s necessary to have calibrating data to produce a prediction of what the range of chlorophyll values is. The best stretch for the NDVI map is also uncertain. It’s possible to display the map with an extremely polarized gradient, but it’s also possible to stretch it with a more linear and gradual color ramp.

The 543 composition image provides a visual difference between actively blooming chlorophyll (and thus algae) and mature or dying chlorophyll, through the different shades of red. This is potentially more useful than the NDVI image and is an important distinction to make, as it allows the users of these maps to track the active causes of the active bloom, rather than arriving at a mature bloom and conducting guess work.

Since these differences exist and the maps are not calibrated with *in situ* data, it’s uncertain which map is better for identifying harmful algal blooms through high chlorophyll concentrations. Both are provided to the user, so whichever they choose to use is up to their discretion.

The python tool created during this project takes the raw Landsat 8 OLI data, carries out the data processing procedure outlined in the Data Processing section, and outputs two maps. The tool is called the Chesapeake Bay Chlorophyll Hotspot Identifier, or the CBCHI.

*Future Work*  
Among the reasons the first method did not produce good results is the quality of the data. It’s necessary to obtain data that is more consistent between the images and the *in situ* in order to find a good regression model. Another possibility is the size of our data set. Compared to the study area, the data available covered just a fraction of the whole region (Figure 6).

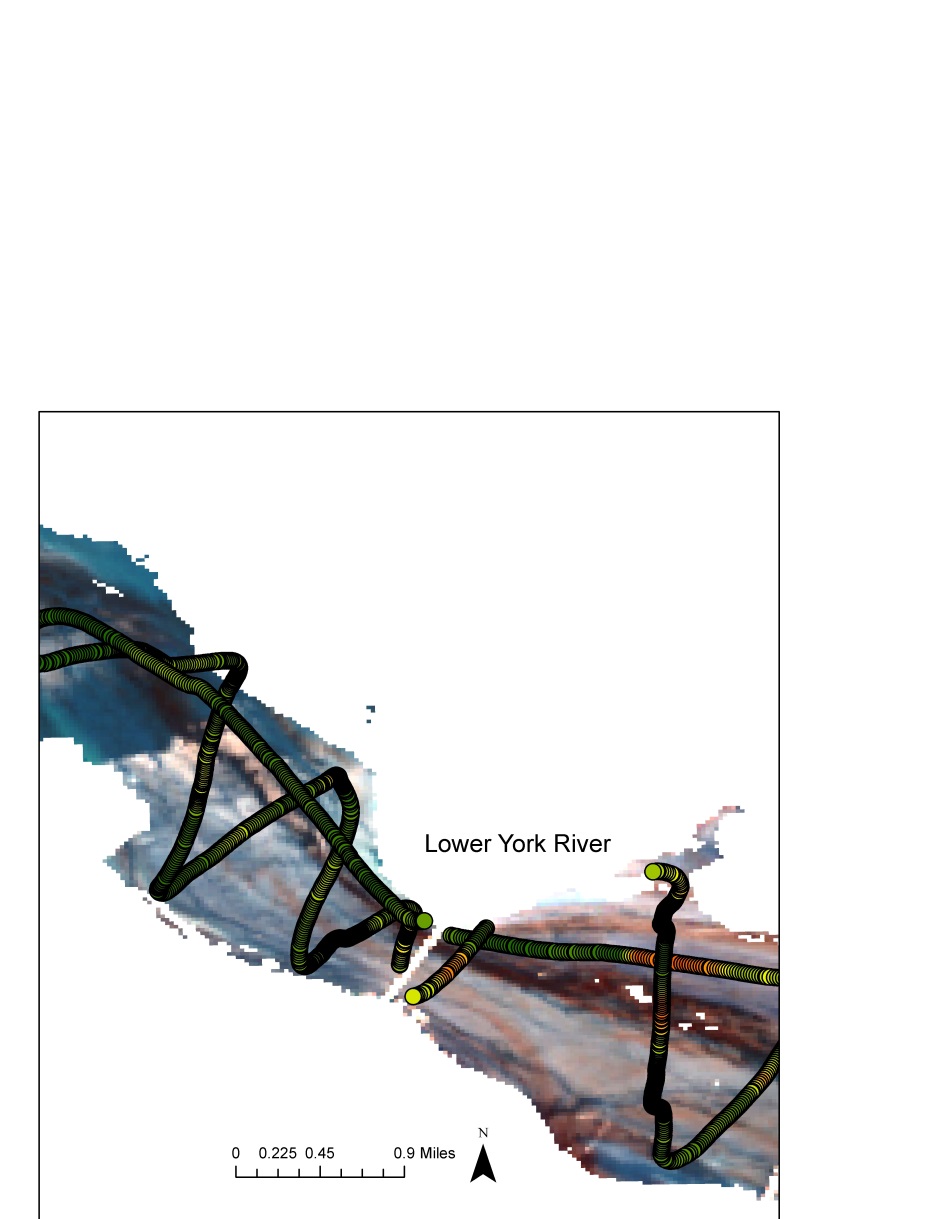


Figure 6. Map of the Chesapeake Bay area this project was supposed to address and the region of the Lower York River *in situ* data were collected from. The data area is extremely small and concentrated, and could cause problems when trying to find a regression model that will be applied to the entire Chesapeake Bay.

One method that might prove interesting to try addresses the resolution of the Landsat 8 OLI data and the VIMS data cruise data. The method involves averaging the chlorophyll values of multiple cruise data points in one pixel of the Landsat 8 OLI. This would be an attempt to reduce the potential skewing of the regression model due to the inconsistent distribution of the original Landsat 8 OLI and cruise data. This would produce one cruise data point per Landsat 8 OLI pixel and might produce a better regression model.

# V. Conclusions

The objective of this project was to create a tool that takes in Landsat 8 OLI data and produces a map providing estimations of chlorophyll concentration for the Chesapeake Bay Watershed. This tool was to be created in python. It would first process the Landsat 8 OLI data by removing land pixels, cloud pixels, pixels corresponding to a depth of 2 meters or shallower, and pixels with high sediment concentration. The tool would be incorporated with a regression model obtained by the correlation of Landsat 8 OLI surface reflectance images and *in situ* data provided by the Virginia Institute of Marine Science from a data cruise along the Lower York River. The tool would apply the regression model to the processed Landsat 8 OLI data and produce a map with predictions of chlorophyll concentrations.

The values of the data were inconsistent between Landsat 8 OLI and the VIMS cruise data. Thus, a model producing chlorophyll estimations could not be produced. The python tool instead produces two maps meant for highlighting relative chlorophyll concentration. The first map is a near infrared, red, and green color composition of processed Landsat 8 OLI data, created using processed Landsat 8 OLI bands 5, 4, and 3 respectively. The second map is an NDVI map created from bands 5 and 4 of the processed Landsat 8 OLI data.

While the tool provides maps with visual representations of chlorophyll concentration instead of numerical predictions, it is a good first step into identifying HABs in the Chesapeake Bay. There is currently no reliable method of real-time monitoring of HABs in the entire Chesapeake Bay. This tool provides maps of the entire Chesapeake Bay, allowing users of the CBCHI to have access to information the size of the bay normally precludes.

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* Russ Baxter, Virginia Deputy Secretary of Natural Resources for the Chesapeake Bay
* Will Hunley, Hampton Roads Sanitation Department
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Others:

* Dr. Sarah Lubkin, University of Mary Washington (previous contributor)
* Cassandra Morgan, NASA DEVELOP (previous contributor)
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# VII. Content Innovation

**Nomenclature**

CBCHI – Chesapeake Bay Chlorophyll Hotspot Identifier

DEM – Digital Elevation Model

HAB – Harmful Algal Bloom

ODU – Old Dominion University

OLI – Operational Land Imager

NDVI – Normalized Difference Vegetation Index

NDTI – Normalized Difference Turbidity Index

VIMS – Virginia Institute of Marine Science

**Glossary**

Chlorophyll

A biomolecule found in plants which allows them to absorb energy from light. It is a strong absorber of blue and red light, and a weak absorber of green and near infrared light.

Choropleth Map

A map shaded in proportion to a statistical variable.

Harmful Algal Bloom

An excessive growth of algae. Harmful effects include blocking sunlight from other organisms in water, reduce oxygen available to other organisms, and producing toxins harmful to aquatic and human life.

Landsat 8 OLI Surface Reflectance Product

Landsat 8 Operational Land Imager images corrected for affects created by the atmosphere.

Normalized Difference Turbidity Index (NDTI)  
 An index of how “cloudy” a body of water is, or how much sediment s is suspended in water, used to differentiate between clear and murky water.

Normalized Difference Vegetation Index (NDVI)

An index of how “green” a plant is, or how much photosynthetic activity is present in plants, used to determine the density of green in a satellite image.

**Brochure for Public Outreach**

2015Fall\_WC-LaRC\_VirginiaWaterII\_Brochure\_FD.ppt

**Recipe Cards**

2015Fall\_WC\_LaRC\_VriginiaWaterResourcesII\_RecipeCard\_Masks.docx

2015Fall\_WC\_LaRC\_VriginiaWaterResourcesII\_RecipeCard\_R.docx