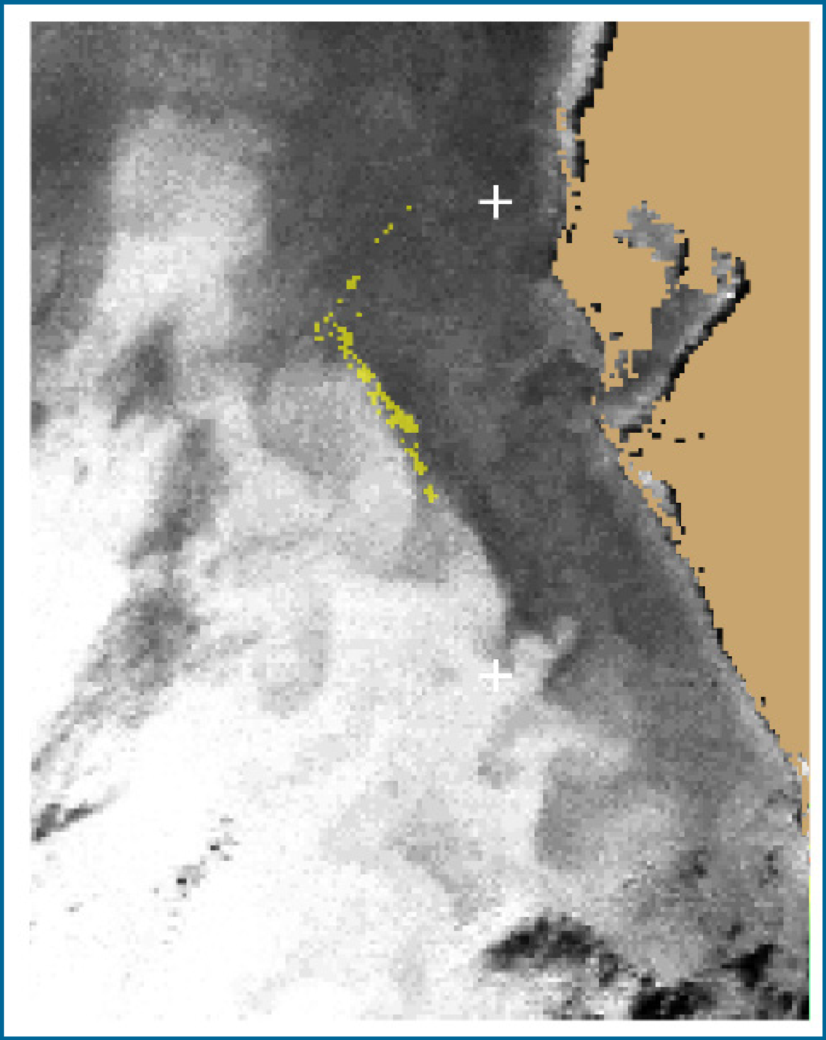
DOI: 10.25923/606t-m243

Harmful Algal Bloom Forecasting Branch Ocean Color Satellite Imagery Processing Guidelines

2021 Update



Authors
Timothy Wynne,
Andrew Meredith,
Richard Stumpf,
Travis Briggs,
and Wayne Litaker

June 2021

NOAA TECHNICAL MEMORANDUM NOS NCCOS 296

NOAA National Centers for Coastal Ocean Science

Citation for the Report: Wynne, T.T., A. Meredith, T. Briggs and W. Litaker. 2018. Harmful Algal Bloom Forecasting Branch Ocean Color Satellite Imagery Processing Guidelines. NOAA Technical Memorandum NOS NCCOS 296 48 pp. DOI: 10.25923/606t-m243

Harmful Algal Bloom Forecasting Branch Ocean Color Satellite Imagery Processing Guidelines

Harmful Algal Bloom –Forecasting Branch Stressor

Detection and Impact

National Centers for Coastal Ocean Science National

Ocean Service

National Oceanic and Atmospheric Administration

2018 Publication/2021 Update

Table of Contents

Harmful Algal Bloom Forecasting Branch Ocean Color Satellite Imagery Processing Guidelines

1. Introduction

The Harmful Algal Bloom - Forecasting Branch (HAB-FB) is a research group within the National Oceanic and Atmospheric Administration (NOAA), National Centers for Coastal Ocean Science (NCCOS) tasked with forecasting and monitoring HABs. One of the more effective ways to do so is through satellite based monitoring, which provides a synoptic view at high temporal resolution. The HAB-FB has established a routine and automated processing capability for satellite-derived products pertaining to the color of water. Water color can be used as proxy for various biogeophysical parameters, such as chlorophyll-*a* (Chl-*a*), turbidity, and water depth. All of our products are generated from mapped reflectance products, which will be referred to in this document as "level 3 products (see Section 3 for more details regarding how level 1-4 products are defined). Most of the level 3 products are derived from level 1B calibrated radiance data obtained from NASA or the European Space Agency (ESA) through our SeaDAS Automated Processing System (SAPS), based on NASA's SeaDAS software package (Baith et al., 2001). Some of our level 3 products originate from NASA or ESA level 2 unmapped reflectance and some standard NASA or ESA ocean color products. This technical memo describes (1) the most used level 3 products produced by the HAB-FB group, (2) the algorithms employed, and (3) the various setting, parameters, flags, etc. used by SAPS to generate each product. This suite of products is used for a variety of applications. These include assessing cyanobacterial blooms in Lake Erie and other water bodies in collaboration with the U.S. EPA and production of NOAA's Lake Erie HAB Operational Forecast System. Other products support interests by numerous states, including Maryland, Virginia, North Carolina, Florida, Ohio, and California in detecting blooms, and products as well as supporting NOAA's Office of Protected Species, and some of NOAA's National Marine Fisheries Science Centers.

The HAB-FB is primarily dedicated to research and does not a serve as a data depository. Consequently, experimental products will not be covered here primarily as their efficacy has yet to be proven, and these experimental products are not generally externally disseminated. When a research product becomes more widely used and or has been published in the primary literature, efforts will be made to update this document to include said products. This document is intended to serve as a blue print on how the processing is done, provide a metadata source for end-users, and more formally document the processing steps used within the branch at the time of publication.

2. Satellites from which Data are obtained

The HAB-FB has used a number of different sensors from disparate satellites since its inception in 2001. These satellites and sensors are summarized below. Various sensor characteristics can be found in Appendix A, and information on various flagging techniques for each sensor can be found in Appendix B.

2.1. SeaWiFS

The Sea-viewing Wide Field of View Sensor (SeaWiFS) was the first ocean color sensor to deliver routine, near-real time data. SeaWiFS was launched on the SeaStar satellite by Orbital Sciences Corporation in August 1997, and continued operation until 2010. The sensor had a daily revisit time, and a Global Area Coverage swath width of 45 degrees, with a sun synchronous orbit at 705 km. Specifications are found in Appendix A1.

2.2. MODIS

The Moderate Resolution Imaging Spectroradiometer (MODIS) is one of the key instruments that is onboard two NASA polar orbiting satellites, Terra (launched in 1999) and Aqua (launched in 2002). As of 2018, both the Terra and Aqua sensors are still functional and orbit at 705 km. Terra has a descending node (black line in Figure 1) and has an image acquisition time at ~10:30 AM local time, while Aqua has an ascending node (blue arrow in Figure 1) with an image acquisition time at ~1:30 PM local time. Both sensors have 36 bands, which are detailed in Appendix A2. About ½ of these bands are used for atmospheric or temperature analyses. Each satellite collects data about 5-6 days a week over the continental United States (CONUS).

Figure 1. Shows the difference between Terra (descending node, black arrow) and Aqua (ascending node, blue arrow) orbits.

2.3. MERIS

Data from the Medium Resolution Imaging Spectrometer (MERIS), flown on the Envisat-1 spacecraft, has been used in house since it was launched in April 2002 and ceased operations 10 years later in April of 2012. MERIS, was built and operated by European Space Agency (ESA) had a swath width of 1150 km, and additional specifications are listed in Appendix A3. There are two spatial resolutions of the data, full resolution (FR) which is at a 300-meter spatial resolution, and a reduced resolution (RR) at 1200-meter spatial resolution. The RR data sets were collected routinely for the globe, with about 3-4 days per week over CONUS. The data was originally accessed from the European Space Agency (ESA) as level 2 files in RR formats. These were later supplemented with Level 1 files from NASA at FR. Prior to 2008 the MERIS FR data sets for North America area were only partially recorded, so frequency of data acquisition varies, both between years and regions. Coverage was between 1 and 3 days per week. Routine direct downloads of data to Canada began in 2008. This increased coverage generally to 3-4 days a week, although southern Texas and California may have slightly less coverage.

2.4. OLCI

The Ocean Land Color Imager (OLCI) was launched by ESA as a follow to MERIS and is onboard the Sentinel-3 spacecraft. OLCI was initially launched on the Sentinal-3A spacecraft on February 16, 2016 and Sentinal-3B was launched on April 25, 2018. The OLCI has a slightly larger swath width relative to MERIS at 1270 km as well as better radiometric resolution. The revisit time is 3.8 days at the equator and 2.8 days at 30º latitude. It has a spatial resolution of 300 meters. Additional sensor specifications are provided in Appendix A4.

2.5. MSI

The Multispectral Instrument (MSI) is currently carried on two different Sentinel-2 spacecraft, which are operated by ESA. The first satellite, Sentinel-2A was launched on June 23, 2015, and the second, Sentinel-2B was launched on March 7, 2017. Both satellites are identical and have a 20.6° field of view with 209 km swath-width, a combined revisit time of 5 days, and a 10:30 AM local time descending node. The spatial resolution is band dependent and can be found in Appendix A6.

2.6. Landsat

Landsat is the world's longest running Earth observing satellite mission. The first Landsat satellite was launched in 1972. The Landsat Thematic Mapper (TM) sensor was first launched in 1982 and is the basic spectral design for all subsequent Landsat imagers. The most recent Landsat satellite, Landsat 8, was launched on February 11, 2013. Landsat 7 (launched April 15, 1999) and Landsat 8 are currently still in operations. Landsat 8 has two instruments on it, the Thermal Infrared Sensor (TIS) and the Operational Land Imager (OLI), which continues the TM capability. The TIS is for temperature studies and will be of limited use to the HAB-FB. The OLI, as well as Landsat 7 has ocean color bands and has shown to be effective in delineation of cyanobacteria blooms in western Lake Erie (Ho and Michalak, 2017). While the HAB-FS has not started routinely processing and pushing Landsat imagery as of 2020, there are plans to do so in the near future. Additional Landsat specifications are provided in Appendix A5. Landsat-7 has data gaps in all images due to a failure on the scan line corrector. This failure results in only the middle half of the swath retrieving useful data, so it is typically not used for water quality analysis.

2.7. VIIRS

The Visible Infrared Imaging Radiometer Suite (VIIRS) and is onboard the Suomi National Polar-orbiting Partnership (Suomi NPP) and the NOAA-NPOES suite, currently NOAA-20. The satellite was launched on October 28, 2011. VIIRS has a swath width of 3060 km and is polar orbiting at 829 km and takes images nearly daily over the CONUS. While VIIRS is not one of the key satellites used within the HAB-FB, some data is incorporated through HAB operational forecasts by NOAA's Center for Operational Oceanographic Products and Services (CO-OPS). VIIRS specifications are provided in Appendix A7.

3. Products

The HAB-FB outputs a number of standardized products. These products are used primarily to detect HABs indirectly through measuring proxies that primarily estimate Chl-*a* concentration. Some other products/optical proxies, which are designed for other applications can also be used for HAB detection, such as diffuse attenuation coefficient (K_d) and total suspended sediments (TSS). Data from MERIS and OLCI and MODIS are processed with clear water corrections found in Appendix C. This section will detail the standardized products that are commonly produced and disseminated by the HAB-FB.

Satellite data generally comes in several different levels, levels 0 to 4, as well as various products derived from the final level 4. Levels 0 through 2 originate from NASA or ESA:

1) Level 0 is raw, unprocessed instrument and payload data. These data need some level of processing to be useful for any application other than sensor calibration.
2) Level 1A is reconstructed unprocessed instrument data, which has been time referenced and annotated with ancillary information such as radiometric correction and absolute calibration coefficients are posted in ancillary data.
3) Level 1B data is Level 1A data that have been processed to sensor units (e.g. calibrated radiance, and have basic geometric corrections.
4) Level 2A have been systematically mapped into a standard cartographic projection, but still may have positioning errors.
5) Level 2B have additional georeferencing done and the files have been image rectified.

The level 3, 4 and subsequent products are generated from levels 0-2.

6) Level 3 are geophysical quantities (?) mapped in uniform geo-spatial scales with completeness and consistency. The level 3 files include primarily remote sensing reflectance, Rrs (sr^{-1}), and Rho_s (ρ_s; dimensionless or dl) corrected for molecular scattering (Rayleigh) and absorption due to certain atmospheric gases and water vapor (?). Some standard level 2 products, like Chl-*a*, that are generated by ESA or NASA, are also converted to level 3. When Rho_s are required for subsequent product production, we use NASA's l2gen software package to create reflectance, and we use ESA's Sentinel Application Platform (SNAP) for mapping. If we are using the standard level 2 ESA products, then we map the data, because the level 2 is already meaningful geophysical parameters, such as Rrs or Chl-*a*. These files are not distributed, owing to their large size. Level 3 processing currently takes about 20 minutes per tile but varies based on tile area and sensor resolution. Keeping Level 3 data on hand allows rapid production of new products as we add algorithms or change methods for flagging invalid data.
7) Level 4 includes all products derived from the level 3 and include masking and flagging for land, clouds, and invalid data (invalid meaning incorrect for the product of interest). We have a variety of products. The most commonly distributed products are as follows:

Product	Units
Rayleigh-corrected reflectance (ρ_s)	Dimensionless
Remote sensing reflectance (R_{rs})	sr^{-1}
Diffuse attenuation coefficient (K_d)	m^{-1}
Chlorophyll-*a* (*Chl-a*)	mg m^{-3}
Cyanobacteria Index (CI)	Dimensionless
Cyanobacteria Index (CI)	sr^{-1}
Red band difference (RBD)	Dimensionless

3.1. Cyanobacterial Index (CI)

Cyanobacteria, also known as blue-green algae, are one of most pressing environmental issues affecting freshwater ecosystems worldwide. The dominant freshwater cyanobacteria is *Microcystis,* which is capable of producing the hepatotoxin, microcystin that can severely affect domestic and wild animals as well as human health. By readily monitoring water bodies at-risk of cyanobacterial blooms, we may be able to negate some negative impacts of the organism as well as its associated toxin. The Cyanobacterial Index (CI) was first developed by Wynne et al. (2008) as the Spectral Shape around 681 nm (SS(681)) product, later renamed the Cyanobacteria Index by Wynne et al. (2010). The product was developed in Lake Erie using the MERIS data to detect large monospecific blooms of cyanobacteria, primarily *Microcystis aeruginosa*.

The CI is calculated using the following two equations:

$$SS = \rho_{\lambda 2} - \rho_{\lambda 1} + (\rho_{\lambda 3} - \rho_{\lambda 1}) \times \frac{(\lambda_2 - \lambda_1)}{(\lambda_3 - \lambda_1)} \qquad (1)$$

Where ρ_λ is the top-of-atmosphere reflectance measured at wavelength λ , and the subscripts 1 = 665 nm, 2= 681 nm and 3= 709 nm. From this point, the CI is calculated as:

(2)

Scaling equations can be found in the Appendix D.

False-positive CI's can occur in clear water. Therefore, a test is applied to identify clear water pixels. Any clear water pixels that will generate false-positive CI's are classified as non-detect (see Appendix D).

$$CI = SS \times (-1)$$

In addition to the standard product flags (no data, land, clouds, and saturated pixels), an additional adjacency flag is applied to MERIS and OLCI CI products when false-positive CI's are detected due to adjacency effects. Land is determined from a GIS database of land and water. Clouds are identified based on an algorithm oriented toward clouds. Invalid pixels are removed if they fail a series of masking procedures which include: excessive sunglint, presence of land or vegetation, or algorithm failure. Pixels are flagged for adjacency effects when a CI is registered but no MCI (see Maximum Chlorophyll Index section) is registered (see Appendix B2 for details).

3.1.1. CIcyano

This is a corrected version of the straight CI Index. Development of this product was driven by the observation that mixed phytoplankton assemblage yielded a positive CI value even when there were no reported occurrences of cyanobacteria. This issue was first noted in Chesapeake Bay, but has been observed elsewhere such as Green Bay and lakes throughout New England. This phenomenon occurs when eukaryotic algae do not fluoresce. It was determined that a correction was needed to parse areas where the chlorophyll signature was not dominated by cyanobacteria. Lunetta et al. (2015) proposed the following conditional equation to meet this requirement.

$$SS = \rho_{\lambda 2} - \rho_{\lambda 1} + (\rho_{\lambda 3} - \rho_{\lambda 1}) \times \left(\frac{\lambda_2 - \lambda_1}{\lambda_3 - \lambda_1}\right) \qquad (3)$$

Where ρ_λ is the top-of-atmosphere reflectance measured at wavelength λ, and the subscripts 1 = 620 nm, 2= 665 nm and 3= 681 nm. Matthews (2014) used this same condition to delineate blooms of cyanobacteria.

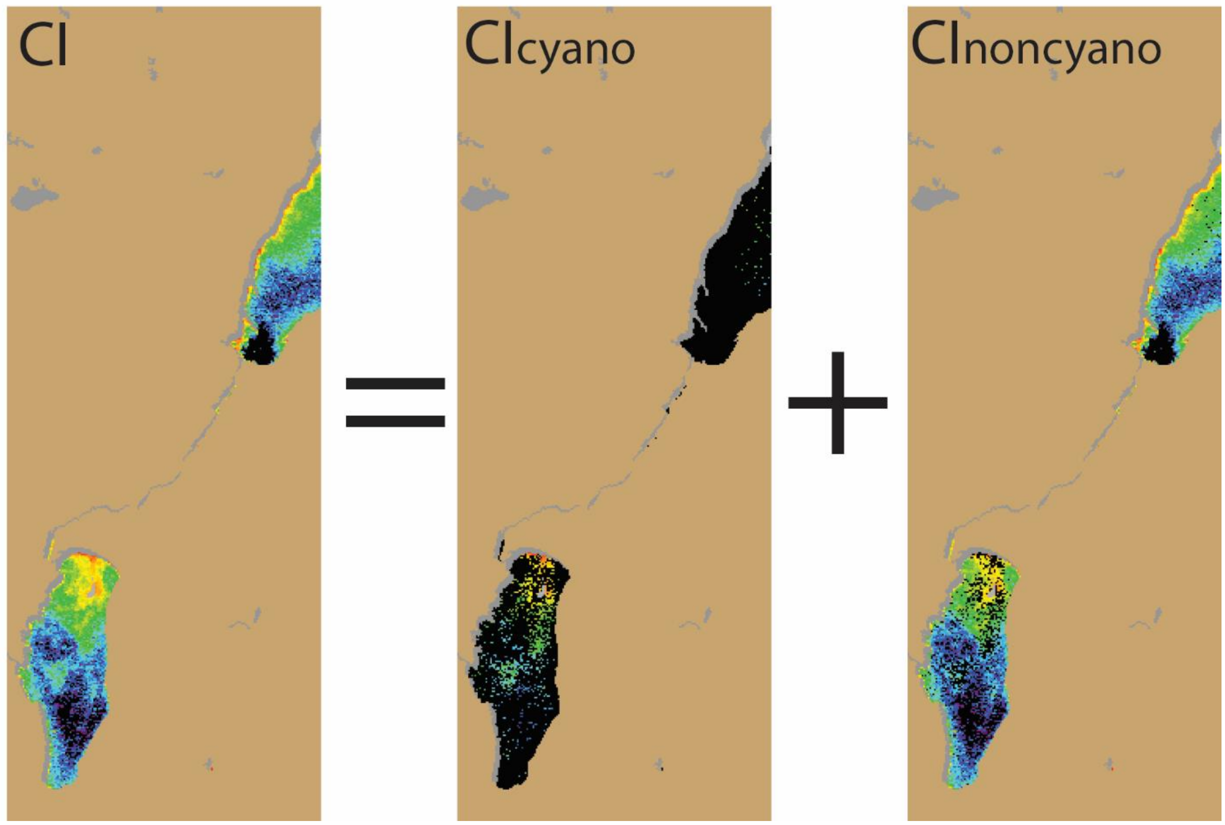


Figure 2. This example from Lake Winnebago, WI uses the MERIS FR imagery to illustrate the breakdown of the CI product.

If this quantity is positive, the representative pixel was determined to be cyanobacteria. If this quantity was negative, it was determined that the pixel was not cyanobacteria. If the quantity was cyanobacteria, the resultant product was called the CIcyano. The CIcyano is shown graphically in Figure 2.

In pixels where the CI was positive but the product in Eq. 4 was negative, the resultant pixel was determined to be not cyanobacteria, and the algorithm will register as a non-detect.

$$CI = CIcyano + CInoncyano \qquad (4)$$

3.1.1.1. MODIS Saturation

The CI for Lake Erie has units of per steradian (sr^{-1}) as a result of a historical artifact. The first MERIS L2 products had these units although they were regarded as dimensionless. MODIS was calibrated to MERIS by Wynne et al. (2013a), so this has been maintained. All Lake Erie CI products have units of sr^{-1} as of 2018.

Cyanobacteria can saturate MODIS imagery as seen in Figure 3(B and E), which was initially presented by Wynne et al. (2013a).

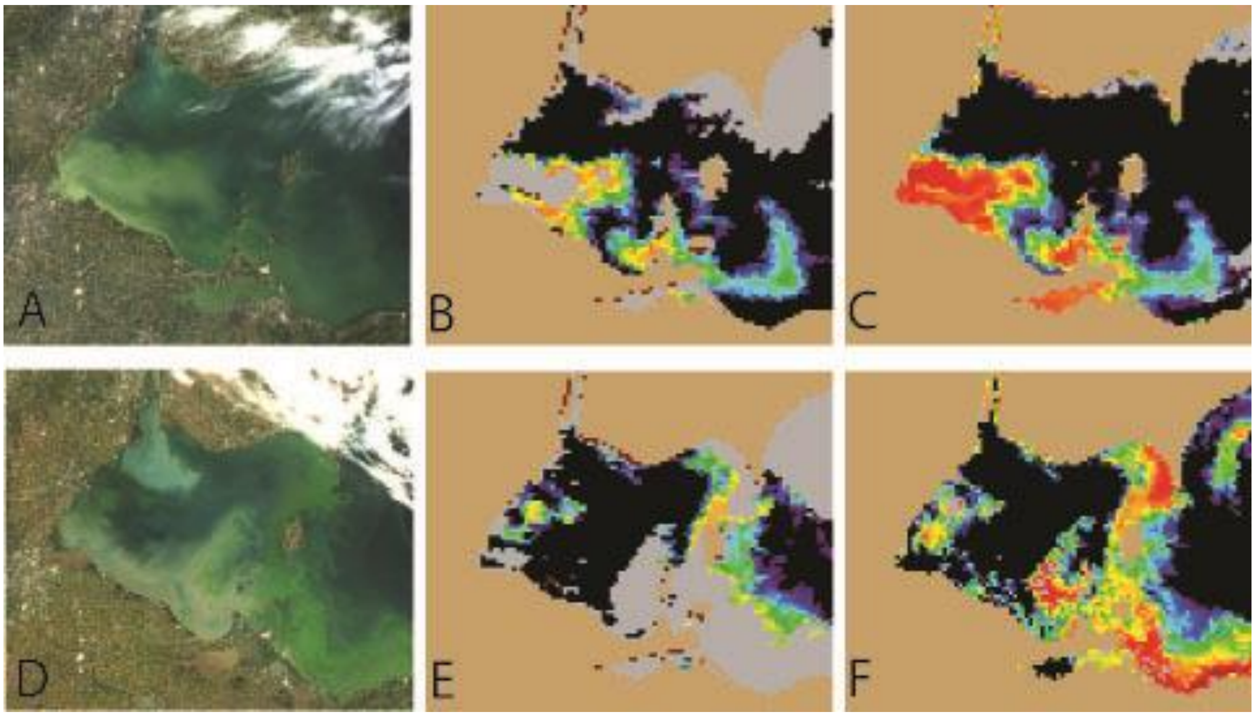


Figure 3. (A-C) is from 2 September 2008 and shows the MODIS Aqua true-color image, the CI from MODIS, and the CI from MERIS, respectively. (D-F) are from the 5 October 2011 image and show the MODIS Aqua true-color, the CI from MODIS, and the CI from MERIS, respectively. Note that the true color images are free of clouds, and that the CI from MODIS is shown as clouds but the CI from MERIS is clear and unsaturated.

This shows the need for a MODIS saturation correction. We have developed the following correction technique to replace any saturated pixels:

$$Saturation = 0.43 * (859\_peak + 0.0045) + 0.0008652 \quad (5)$$

where

$$859\_peak = \rho_{859} - \rho_{469} + (\rho_{469} - \rho_{1290}) * \frac{859-469}{1240-469} \quad (6)$$

Prior to this, the following equation was used in the 2013-2014 processing:

$$Saturation = 0.05 \times (\rho(859) - \rho(1240))^{0.5} \quad (7)$$

In the 2012, processing the following equation was used:

$$Saturation = \frac{\rho(645) - \rho(1240)}{\rho(869) - \rho(1240)} \quad (8)$$

1.1. Maximum Chlorophyll Index (MCI)

The MCI is a product used to detect high density patches of Chl-*a*. It was initially developed by Gower et al. (1999). The basic equation is the same as the initial step of the CI.

We use the Rayleigh-corrected reflectance from both the OLCI and the MERIS sensors.

$$SS = \rho_{\lambda 2} - \rho_{\lambda 1} + (\rho_{\lambda 3} - \rho_{\lambda 1}) \times \left(\frac{\lambda_2 - \lambda_1}{\lambda_3 - \lambda_1}\right) \quad (9)$$

Where ρ is the Rayleigh-corrected reflectance, λ is the wavelength of the band expressed in nanometers, and the subscripts 1 = 681, 2= 709 and 3= 754

The equation to go from 8-bit number to a 32-bit number is:

$$\text{32-bit} = 10^{(0.012 \times \text{8-bit} - 4)} \quad (10)$$

The equation to go from a 32-bit number to an 8-bit number is:

$$\text{8-bit} = round\left(\left(\frac{250}{3}\right) \times \left(4 + Log_{10}(\text{32-bit})\right)\right) (11)$$

The MCI will flag high Chl-*a* features whether they are cyanobacteria or from any other functional group (diatoms, dinoflagellates, etc.). An additional limitation is that the MCI will often report algae as present in waters with high concentrations of sediment. The standard set of flags used with this algorithm are no data, land, clouds, and invalid pixels (See Appendix B2).

1.2. Diffuse Attenuation Coefficient (K_d)

The diffuse attenuation coefficient (K_d) is a measure of how light dissipates with depth in water. K_d is an Apparent Optical Property (AOP), a property of water that changes with a changing light field, but is expressed in the same units (m^{-1}) as an Inherent Optical Properties (IOP), a property of water that does not change with a changing light field). The K_d product that is being processed here is a somewhat simplified version of the K_d proposed by Wang et al. (2009). The K_d is an indicator of the turbidity of the water column, and is directly related to the concentration of scattering particles into the water column. The K_d for the MODIS dataset is calculated by:

$$K_d = 2.8 \left[\frac{R_{rhos}(645) - R_{rhos}(858)}{R_{rhos}(469) - R_{rhos}(858)}\right] - 0.69 \qquad (12)$$

Where $R_{rhos}(\lambda)$ is the Rayleigh-corrected reflectance at wavelength λ (Tomlinson et al., 2019).

For the MERIS and the OLCI sensors, it is as follows:

$$K_d = 0.7 \times \left\{ \frac{\left[\frac{(\rho(620) + \rho(665))}{2}\right] - \rho(865)}{\left[\frac{(\rho(442) + \rho(490))}{2}\right] - \rho(865)} \right\} \qquad (13)$$

At this point, the respective K_d numbers can be used to calculate a calibrated K_d in Eq. 14

$$K_d calibrated\ (m^{-1}) = (2.8 \times K_d) - 0.69 \qquad (14)$$

The standard set of algorithms used in the K_d algorithm are: no data, land, clouds, and invalid pixels (See Appendix B for more details).

1.3. Chlorophyll-*a*

Chl-*a* is the dominant pigment used in aquatic photosynthesis. It is not specific to any one functional group of phytoplankton as it is ubiquitous to all of them. It is used as a general measure of overall phytoplankton biomass presence within one optical depth (i.e. one secchi depth) of the water column. There are many Chl-*a* algorithms in literature. We will touch on just a few of the ones that are part of the standard processing system.

1.3.1. OCx

The OCx algorithm is the standard NASA global Chl-*a* algorithm. It is the basic form of a Chl-*a* algorithm developed from SeaWiFS data which became available in the late 1990s (O'Reilly et al., 1999). This is a band-switching algorithm, which takes the largest value of the blue reflectance (this could be four bands or three bands depending on the sensor) and divides it by the green band. The highest blue band will be the maximum Chl-*a* absorption and then green band will be the minimum Chl-*a* absorption. It then places this into a quadratic equation to solve for the solution.

MODIS is based on 3 blue bands and is the OC3 algorithm. For MERIS the OCx is processed for the FR imagery but not the RR imagery in the same form as the NASA OC_3 algorithm.

For OC4 and OC3, Chl-*a* (*C*) is calculated as produced as L2 files by SeaDAS as:

$$\text{Chl-}a\,(mg/m^3) = 10^{(a0 + a1\times R + a2\times R + a3\times R)} + a4 \qquad (15)$$

SAPS uses OC_4 and OC_3 produced by level2 imagery in SeaDas. The coefficients can change with reprocessing but as of 2018 the R for SeaWiFS OC_4 were:

$$R = \log[(Rrs(443) > RRS(490) > RRS(510]/RRs(555)] \qquad (16)$$

In 2018, the coefficients for the OC_4 algorithm is a_0 = 0.4708; a_1= -3.8469; a_2 = 4.5338; a_3=-2.4434; a_4=-0.0414

For OC_3 the algorithm R is expressed as below:

$$R = \log[\frac{(Rrs(443) > RRS(488)]}{RRs(555)}] \qquad (17)$$

And the coefficients are defined by NASA in 2018 as: a0 = 0.3483; a1 = -2.9959; a2 = 2.9873; a3 = -1.4813; and a4 = -0.597.

The limitations for successfully retrieving a good model from OCx algorithm is a reliable atmospheric correction. Standard product flags are no data, land, clouds, and invalid pixels.

1.3.2. ESA alg1 and alg2

For the MERIS (and eventually the OLCI imagery), ESA has two standard level-2 Chl-*a* products, algal_1 and algal_2 (which have been renamed CHL_OC4ME and CHL_NN in ESA OLCI level 2 files). Algal_1 has the same general form as the OCx algorithm. Specifically, it is based on the band ratio of the blue to green as provided below.

$$log_{10}(Chl - a) = a_0 + \sum_{i=1}^{4} a_i \left(log_{10} \left[\frac{max(R_{rs}(443), R_{rs}(490), R_{rs}(510))}{R_{rs}(560)} \right] \right)^i , \qquad (18)$$

where a_0 (0.4502), a_1 (-3.2594), a_2 (3.5227), a_3 (-3.3594), and a_4 (0.9495) are MERIS sensor-specifc regression coefficients (ESA, 2012).

This is used for "case-1" waters, where the water’s optical properties co-vary with the concentration of phytoplankton biomass and their pigments. Algal_1 is an iterative equation that will eliminate the influence of bi-directionality on the Chl-*a* estimate and as an iterative equation, the final form is not publishable (ESA, 2006). The algal_2 algorithms is based on a neural network and is used for "case-2 waters", where the water optical properties don't co-vary with phytoplankton pigments and often dominated by inorganic mineral particles and colored dissolved organic matter (CDOM) (Doerffer and Schiller, 2007). The algal_1 and algal_2 algorithms are only produced from the ESA level 2 files which are only routinely processed in RR format. Standard flags for these algorithms are no data, land, clouds, and invalid pixels. These products when produced by the HAB-FB use the ESA L2 files.

1.3.3 Gilerson Chlorophyll

Chl-*a* concentration determined by a near-infrared to red ratio as described by Gilerson et al. (2010). We implement a modified version of equation 17.2 that uses rho_s instead of Rrs.

R2 = (rhos_709 - rhos_885) / (rhos_665 - rhos_885)

chl = [(35.75 * R2) - 14.3]^1.124

A minimum chl value of 0.5 is assigned when (35.75 * R2) - 14.3 < 0.5. It was noted that the waters off south Florida did not register a chl value, so the offset coefficient of 19.3 was changed to 14.3 thereby increasing chl approximately 5 ug/L.

1.3.4 Relative Fluorescence

Red band difference or RBD is used as a proxy of relative chlorophyll-s fluorescence and is calculated as the difference between two red bands.

RBD = (rhos_681 - rhos_665)

1.4. True Color

For MERIS and OLCI the true color Red, Green, Blue (RGB) composite is based on: R = ρ(665), G = ρ(560), B = ρ(490). For MODIS the true color RGB composite is based on: R = ρ(645), G = ρ(555), B = ρ(469).

True color composite imagery can be useful to do a quick QA/QC on the image flagging, as certain features (ice, snow, sun glint, etc.) can be relatively easy to see in RGB images. Furthermore, there are times when it is advantageous to have a "pretty picture" for dissemination to a wider audience. Additionally the true color images show the land, and features that go with land (as opposed to having all land masked out), so it can be advantageous to show these features at times.

1.5. Scumcolor

Scumcolor is a product used to locate areas where cyanobacteria) scums are present. Factors like low turbulence levels, long day-light, high water temperatures and the buoyant capacity of cyanobacterial cells, and prevailing winds can all contribute to the development of scums. These scums appear as a very bright target on the surface of the water and the MODIS sensor's bands that are generally used for water color become saturated and do not record a valid value. As a result the so-called "land-bands" are needed (these are bands 1-7 in Appendix A2). These bands do not saturate as readily as water targets are generally much darker relative to land targets; so that they are calibrated to pick up a greater and high dynamic range of reflectance values. Three of the high-resolution land-bands are used to determine where there is scum. This method uses three bands the blue, near infrared (NIR), and red in a three band image, with blue assigned to the first band, red to the second band, and NIR to the third band. The algorithm creates a false color composite such that: $band_1 = \rho(645)$, $band_2 = \rho(859)$, $band_3 = \rho(469)$.

For MODIS, dark/purple color in *Scumcolor* product is interpreted as water without scum, whereas green color is interpreted as water with scum. Vegetation appears as bright green at the shore when the land mask and the image are not aligned properly.

1.6. Rrs665

This product is the remote sensing reflectance (Rrs) in the commonly used red band centered at 665 nm, which provides an estimate of sediment laden turbidity (Stumpf and Pennock, 1989). *Rrs* contains the spectral color information of the water body (below the sea surface). *Rrs*, is conceptually shown in Figure 4 and is the ratio between water-leaving radiance ($L_w(\lambda)$, above the sea surface) and downwelling irradiance ($E_d(\lambda)$, above the sea surface). $L_w(\lambda)$ can be estimated from above-water radiometric measurements, in this case reflected skylight must be removed using a "surface reflectance factor".

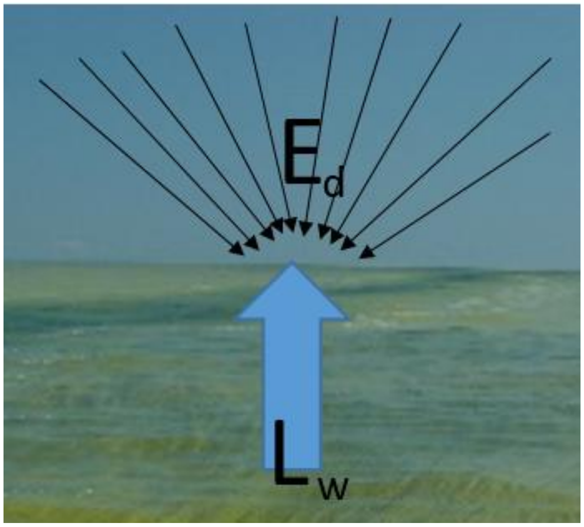


Figure 4: R_{rs} is the ratio of the light leaving the water, L_w (water leaving radiance) to light travelling down through the sky to the water surface, E_d (downwelling irradiance).

R_{rs}(665) is calculated by:

$$Rrs(665) = \frac{L_w(665)}{E_d(665)} \qquad (19)$$

Where L_w is water-leaving radiance propagated through the surface of the water, and E_d is the downwelling irradiance at the surface. The band is routinely used for a measure of water clarity and sediment resuspension as the red light is quickly and readily absorbed by pure water (Wynne et al., 2005).

Backscattered light is directly correlated with the concentration of inorganic sediments. For the sediment concentration levels found in this environment, backscatter can be linearly approximated by the reflectance in red wavelengths (Stumpf and Pennock, 1989). Remote sensing reflectance in the 665 nm band (Rrs_{665}), where absorption by the water molecules is much greater than backscatter, can be approximated by equation (20).

$$Rrs(665)\ \alpha\ \frac{bb(665)}{a(665)} \qquad (20)$$

Where b_{b665} and a_{665} are defined as the backscatter and the absorption coefficients measured at 665 nm band, respectively. Backscatter is defined by the following equation:

$$b_{b665} = b_{bw}(665) + b_{bp}(665) \qquad (21)$$

Where the subscripts of w, and p, indicate contributions to backscatter from: water molecules and particulate matters respectively. b_{bp} can further be partitioned into backscattering from sediments or non-algal particulates (b_{bnap}) and phytoplankton (b_{bph}). The backscatter is related to sediment concentration, S, by:

$$b_{b,nap} = b'_{b,nap} * S \qquad (22)$$

Where $b'_{b,nap}$ is the specific backscatter coefficient for non-algal particulates or sediments. Absorption at 665 nm is defined as following:

$$a(665) = a_w(665) + a_g(665) + a_d(665) + a_p(665) \qquad (23)$$

Where the subscripts of w, g, d, and p indicate contributions from water, colored dissolved organic material (CDOM), detritus, and plankton pigments, respectively. In general, $a_w >> a_g + a_d + a_p$ in the red wavelength region, and $b_{bs} >> b_{bw} + b_{bsp}$, so that reflectance in the red-NIR spectral region is proportional to b_{bs} / a_w. By combining this proportionality with Eq. 3, it is apparent that the red reflectance (R_{670}) is a surrogate for sediment concentration (S). At shorter wavelengths, the total absorption is not a constant, so reflectance cannot be used to approximate the sediment concentration. As the sediment load in the water column increases, the reflectance in the 670 nm wavelength will increase.

2. Processing

SAPS is a package of custom python modules (see Appendix E) that facilitate the downloading and processing of the level 0, 1, or 2 input files for one or more pre-defined geographic regions. The processing steps are shown in a flowchart in Appendix F. It uses NASA's SeaDAS software package including the OceanColor Science Software (OCSSW), distributed as part of SeaDAS or ESA's Sentinel Application Platform (SNAP), including both the Sentinel-2 and Sentinel-3 toolboxes, to standardize processing of low level input files to a standard level 3 GeoTiff. OCSSW's ***l2gen*** program creates level 2 NetCDF-4 files with the SAPS defined list of products. Level 2 files are mapped and converted to a standard multi-band level 3 GeoTiffs using the ***Reproject*** operator in SNAP's Graph Processing Tool (GPT). Remotely sensed data is collected from the satellite in a swath, a portion of a swath is called a granule. Data from the same day overlapping a geographic region are composited using a custom python compositing script. Level 3 GeoTiffs are input to our custom product generation scripts that apply specific algorithms to output single band GeoTiffs for each product.

SAPS processing runs nightly to process the previous day's available near real-time data from Sentinel-3's OLCI and Aqua and Terra's MODIS sensors. Sensor specific configuration files control what SAPS pre-defined geographic regions are processed and what products are generated. When refined ancillary data becomes available for Aqua and Terra input files or non-time critical L1B files for OLCI, SAPS processing is re-run and the previous near real-time L3 files and products are replaced.

2.1. Product format

The products from the HAB-FB have a consistent internal format. Products are distributed as single band GeoTiffs with pixel values ranging between 0-255. The following table describes the standard pixel value meaning (this information is also included within the internal metadata as described later in this section):

Value	Description from 2018 on	Description before 2018 reprocessing
0	No detect	No Data
1-249	Valid data (scaled from original value as described in product section)	Valid data
250	Saturated	Saturated
251	Adjacency	Not Used
252	Land	Land
253	Cloud	Cloud

254	Invalid or mixed	Not Used
255	No data	Not Used

Table 1. Defines 8-bit data flags in standard products used by the HAB-FB.

SAPS specific metadata is created during product creation. It is stored internally within the GeoTiff metadata record. The metadata contains information about product scaling, interpretation of flags and version. SAPS metadata are prefixed with "SAPS_".

The metadata may be display using a number of commonly available command line utilities including ***tiffinfo*** and ***gdalinfo*** (. The SAPS script ***run_saps_file_info.py*** may also be used in-house. Sample metadata is listed in Appendix G.

2.2. Product file naming

Products have a standard file naming convention as described below:

<sat>.yyyyjjj.mmdd.HHMM[...HHMM]C.L3.<areacode>.<srccode><l2genversion>_<SAPSVersion>_<AlgoscriptVersion>.<productname>.tif

Where:

Value	**Description**
<sat>	name of satellite
yyyy	4-digit year
jjj	julian day (zero-prefixed)
mm	month of year (zero-prefixed)
dd	day of month (zero-prefixed)
HHMM	hour & minute (both zero-prefixed) for each granule or swath included in same-day composite
<areacode>	3-digit areacode representing the geographic region covered

Value	Description
<srccode>	level 2 source code (v=SAPS-l2gen,n=NASA,e=ESA,E=SAPS-SNAP)
<l2genversion>	level 2 generating software version
<SAPSversion>	SAPS software version
<Algoscriptversion>	version of script generating product
<productname>	standard product name

For example: sentinel-3a.2017365.1231.1606C.L3.LE3.v8103_1_1.chloc4e.tif would be from the Sentinel-3a spacecraft, on December 31, 2017 at 16:06 GMT. It is a level 3 (L3) file that is from the OC4 Chl-*a* algorithm.

2.3. Level 3 GeoTiff format

The standard SAPS level 3 GeoTiff contains a band for each product generated by SAPS. The bands are all 32-bit floating point numbers in the units of the product. The internal TIFFTAG_IMAGEDESCRIPTION contains an ordered "|"-separated list of the band (i.e. product) names.

The GPT utility that converts the level 2 NetCDF file to a GeoTiff, packages the NetCDF metadata into a specialized XML metadata record within the GeoTiff. SeaDAS and SNAP read and use this information when loading a level 3 file. Among other things, this includes product properties such as units and spectral wavelength and parameters used by ***l2gen***. The XML metadata may be displayed using the ***tiffinfo*** utility.

2.4. Flags

Many pixels are routinely subjected to unwanted effects. These pixels are invalid for six main reasons (listed in each subsequent subsection in this portion of this memorandum) and need to be removed so that meaningful analysis can take place. Most of the satellite imagery used here is high temporal resolution but course spatial resolution. If one of these issues affects even a portion of a pixel, the entire pixel may be deemed invalid. As a result the pixels must be flagged as a bad data value and removed from further analysis. Appendices B1-B3 show the flags used for SeaWiFS, MERIS, and MODIS respectively.

2.4.1. Clouds

If clouds are present passive remote sensing platforms (such as all sensors described here, rely on natural sunlight) cannot detect the surface of the water and must be removed. Sometimes usable data can be gathered through some thin cirrus clouds for a daily image, but the data is generally not sufficient for climatological datasets.

The custom cloud flagging described below is only applied if the SAPS Level 3 file used to generate the product was created from Level 1 or Level 0 inputs. These can be identified from the filename as the ***srccode*** is "v" or "E" (see Product file naming section). SAPS Level 3 files with a different ***srccode*** use the default internal cloud L2_flag for flagging clouds.

2.4.2. Glint

Sun glint, or glint, occurs when sunlight is reflected off the surface of the water at the same angle that a satellite views the water. If a pixel is affected by sun glint the pixel is not usable. This occurs most often near the summer solstice when the sun angle is higher. An example of sun glint is provided in figure 5.

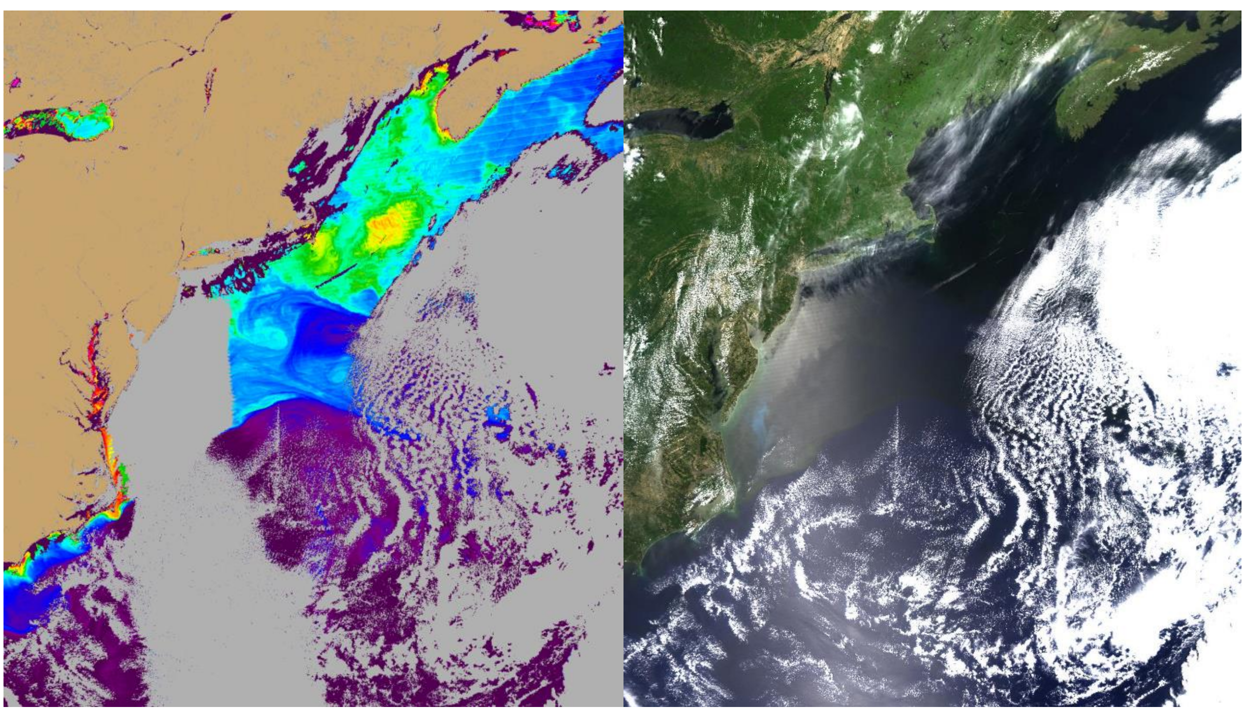


Figure 5. Shown here is an example of sun glint, to the left is an aqua Chl-*a* image from June 1, 2014. To the right is the true color image from the same date. Note that the sun glint appears as clouds.

2.4.3. Snow and Ice

Snow and Ice will present a host of issues and cannot be used in the vast majority of ocean color algorithms. As a result pixels containing ice must be removed from further analysis.

$$MDSI = \frac{\rho(865) - \rho(885)}{\rho(865) + \rho(885)} \qquad (24)$$

Where MDSI is the MERIS Differential Snow Index. The MDSI can incorrectly flag pixels in dense bloom conditions so with the assumption that snow and ice pixels show little variation in the visible bands, the coefficient of variation calculated in the blue, green and red bands for each pixel is tested against a maximum threshold. A minimum brightness in the NIR band is also required for snow and ice flagging.

This currently used snow and ice algorithm will need improvements. Snow and Ice flagging is currently only implemented for MERIS and OLCI products.

An example of ice is shown in Figure 6.

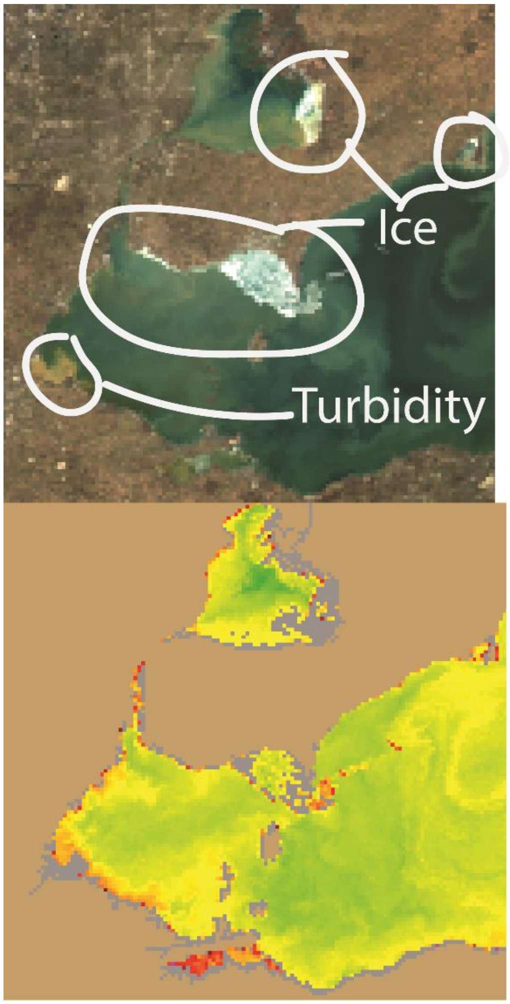


Figure 6. Shown here is a RGB composite on the top and the derived Chl-*a* concentration from an aqua image from January 1, 2014 in western Lake Erie. The majority of the ice and the turbidity in the western most portion of the lake has been flagged; however, some of the ice was not flagged. This ice does appear to have retrieved consistent values with the rest of the image.

As can be seen in Figure 6, the limitations are the type of ice. Some thin ice may have reliable retrievals. Some thicker ice may not.

2.4.4. Sensor Saturation

The MODIS sensor's ocean color bands have a more limited dynamic range than all other sensor and bands discussed in this document. As a result they saturate over bright targets. Commonly clouds, land, turbid water or hazy atmospheric conditions can cause saturation.

2.4.4.1. Algorithm Saturation

Some combination of water turbidity and atmospheric conditions, particularly hazy or slightly glinty conditions, may cause saturation in band ratio algorithms, such as the OCx suite of algorithms. An example of saturation from algorithmic failure is seen in Figure 7.

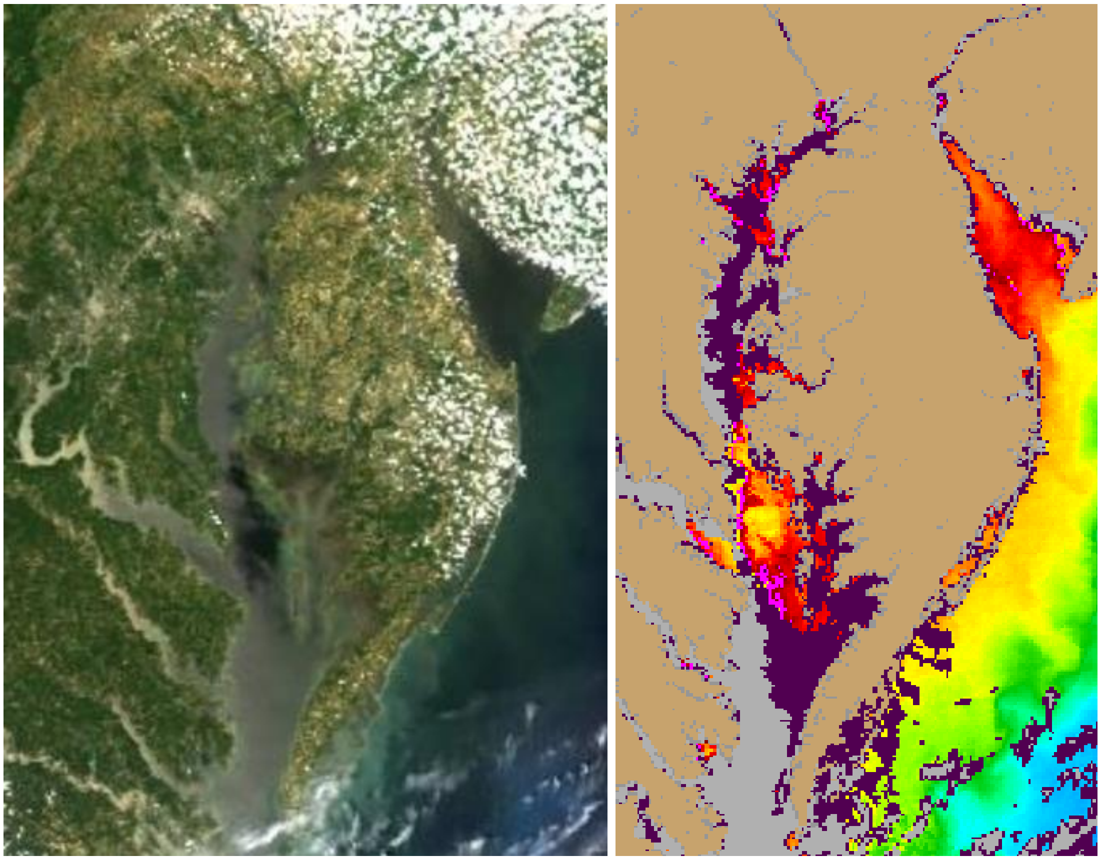


Figure 7. To the left is a true color image from the aqua sensor of the Chesapeake Bay from June 6, 2014. To the right is the derived Chl-*a* concentration from the same image. In the center portion of the bay, where the dark water is in the true color image shows up as realistic Chl-*a* concentrations. Where the light colored water is, (high turbidity) is flagged as such and no values are returned in the Chl-*a* image to the right.

2.5. Land and Dry Lake Bed

We are only concerned with water and not with land in these applications. As a result, all land must be removed. This is obviously most problematic near the coastline. Additionally if the water is shallow enough (< 1 meter), the bottom will be visible and the pixel may have to be removed.

$$Mixed\_pixel = [\rho(885) > \rho(620)] and [\rho(885) > \rho(709)] and [\rho(885) > \rho(754)] and [\rho(885) > 0.01]$$

$$Mixed\_pixel = [\rho(620) > \rho(560)] and [\rho(560) > 0.015] and [\rho(885) > 0.15]$$

Where a mixed pixel is a pixel that has elements of both land and water in it.

3. Georeferencing

Products are generally released as a georeferenced tagged image file format or (GeoTIFF). Low resolution products (i.e. 1km) have a custom Albers Equal Area projection with the *latitude of center* and *longitude of center* defined at the tile center. Albers is a conic projection that uses two parallels. Higher resolution products have a Universal Transverse Mercator (UTM) projection.

4. Dissemination

While having a suite of available products is certainly advantageous as a research tool but this should not be the end goal. The National Academy of Sciences (2005) said this: “Much of the federal science and technology investment is intended to help build the base of scientific and technical knowledge and expertise used by government and industry to address important national goals, such as national defense, space exploration, economic growth, and protection of public health and the environment.” In order to do this data must be effectively distributed to various user groups. In this section, the mechanisms in which products are disseminated are discussed.

4.1. Website

The HAB-FB has a strong web presence. The home page is https://coastalscience.noaa.gov/research/stressor-impacts-mitigation/hab-monitoring-system/ where many of the products are readily and freely accessed by anyone with a web browser. Different products are distributed into different regions. These include: Green Bay, Saginaw Bay, Lake Pontchartrain, Albemarle Sound, and Lake Okeechobee for cyanobacteria blooms. There is also southwest Florida monitoring for the toxic dinoflagellate, *Karenia brevis*. Finally there are predictive models of *Alexandrium catenella* in the Gulf of Maine. There is an NCCOS K_d(490) product distributed by Coastwatch here: https://coastwatch.chesapeakebay.noaa.gov/cw_k490_hires.php.

4.2. HAB bulletin

The HAB bulletin has been effective in producing periodic forecasts in a variety of different locations put out on short term forecasts (< 1 week). The forecasts are typically developed within NCCOS, and experimentally produced within NCCOS for a number of years and then the capability is put to NOAA's Center for Operational Oceanographic Products and Services (CO-OPS) which will produce the forecasts in an operational basis. Examples of forecasts developed within the NCCOS HAB-FB and then transferred to CO-OPS are *Karenia brevis* blooms in the west Florida Shelf (Stumpf et al., 2003); *Karenia brevis* blooms along the Texas coast (Wynne et al., 2005), and Cyanobacteria blooms in western Lake Erie (Wynne et al., 2013). These forecasts are emailed directly to thousands of subscribers via a pdf document. The forecasts are available on the internet at https://tidesandcurrents.noaa.gov/hab/lakeerie.html for Lake Erie and https://tidesandcurrents.noaa.gov/hab/gomx.html for the Gulf of Mexico region.

Additionally the HAB-FB has produced seasonal forecasts on cyanobacteria blooms in Lake Erie since 2012 (Stumpf et al., 2012; Stumpf et al., 2016). These forecasts are disseminated as press release on the NOAA webpage and are picked up by various other news outlets. They are also delivered at a press event at the Ohio State University Stone Laboratory. An example of the most recent press release can be found at NOAA, 2017.

4.3. Other

Products can be disseminated in other outlets on demand as needed. For example, we have been contacted by the USGS to provide them estimates of cyanobacterial concentration for a bioenergetics model to approximate if there are adequate food source to sustain a population of invasive bigheaded carps. This data was delivered onto the USGS ftp server.

5. Future work

We will add additional sensors and satellite missions. Landsat and Sentinel-2 would be of particular interest. Further dissemination products would also be used and described herein.

References

Amin, R., J. Zhou, A. Gilerson, B. Gross, F. Moshary, and S. Ahmed. 2009. Novel optical techniques for detecting and classifying toxic dinoflagellate Karenia brevis blooms using satellite imagery. Opt. Express 17, 9126-9144.

Baith, K., R. Lindsay, and C.R. McClain. 2001. SeaDAS, a data analysis system for ocean color satellite sensors. EOS Transactions of the American Geophysical Union. 82: 202.

Doerffer, R. and H. Schiller. 2007. The MERIS case 2 water algorithm. International Journal of Remote Sensing. 28: 517-535.

ESA. 2006. MERIS Product Handbook. Accessed online June 20, 2018 at: https://earth.esa.int/pub/ESA_DOC/ENVISAT/MERIS/meris.ProductHandbook.2_1.pdf.

ESA. 2012. MERIS 3rd data reprocessing Validation report. Accesses online on June 21, 2018 at: https://earth.esa.int/documents/700255/707222/A879-NT-017-ACR_v1.0.pdf/6fa86bec-9945-4e39-808e-3801f2e3962b

Gilerson, A., A. Gitelson, J. Zhou, D. Gurlin, W. Moses, I. Ioannou, and S. Ahmed. 2010, Algorithms for remote estimation of chlorophyll-a in coastal and inland waters using red and near infrared bands. Opt. Express 18, 24109-24125.

Gower, J.F.R., R. Doerffer., and G.A. Borstad. 1999, Interpretation of the 685 nm peak in water-leaving radiance spectra in terms of fluorescence, absorption, and scattering, and its observation by MERIS. International Journal of Remote Sensing, 20, 1771-1786.

Ho, J.C. and A.M. Michalak. 2017. Phytoplankton blooms in Lake Ertie impacted by both long-term and springtime phosphorus loading. Journal of Great Lakes Research. 43: 221-228.

Lunetta, R.S., B.A. Schaeffer, R.P. Stumpf, D.L. Keith, S.A. Jacobs, and M.S. Murphy. 2015. Evaluation of cyanobacteria cell count detection derived from MERIS imagery across the eastern USA. Remote Sensing of Environment. 157: 24-34.

Matthews, M.W. 2014. Eutrophication and cyanobacterial blooms in South African inland waters: 10 years of MERIS observations. Remote Sensing of Environment. 155:161-177.

National Academy of Sciences (US) Committee on Criteria for Federal Support of Research and Development. Allocating Federal Funds for Science and Technology. Washington (DC): National Academies Press (US); 1995. Supplement 1: The Evolution and Impact of Federal Government Support for R&D in Broad Outline. Available from: https://www.ncbi.nlm.nih.gov/books/NBK45556/

NOAA, 2017. https://coastalscience.noaa.gov/exit/?url=https%3A%2F%2Fnccospublicstor.blob.core.windows.net%2Fhab-data%2Fbulletins%2Flake-erie%2Fcurrent%2Fbulletin_current.pdf Accessed online 1/9/20018.

O'Reilly, J.E., Maritorena, S.,Mitchell, B. G., Siegel, D. A., Carder, K. L., Garver, S. A., Kahru, M., & McClain, C. R. (1998). Ocean color chlorophyll algorithms for SeaWiFS, Journal of Geophysical Research 103, 24937-24953

Stumpf, R.P. and J.R. Pennock. 1989. Calibration of a general optical equation for remote sensing of suspended sediments in a moderately turbid estuary. Journal of Geophysical Research. 94: 14,363-14,371.

Stumpf, R.P., M.E. Culver, P.A. Tester, M. Tomlinson, G.J. Kirkpatrick, B.A. Pederson, E. Truby, V. Ransibrahmanakul, M. Soracco. 2003. Monitoring *Karenia brevis* blooms in the Gulf of Mexico using satellite ocean color imagery and other data. Harmful Algae. Vol. 2. Pages 147-160.

Stumpf, R.P., L.T. Johnson, T.T. Wynne, and D.B. Baker. 2016. Forecasting annual cyanobacterial bloom biomass to inform management decisions in Lake Erie. *Journal of Great Lakes Research*. 42: 1174-1183.

Stumpf, R.P., T.T. Wynne, D.B. Baker, and G.L. Fahnenstiel. 2012. Interannual variability of cyanobacterial blooms in Lake Erie. *PLoS ONE*. . 7(8): e42444. doi:10.1371/journal.pone.0042444.

Tomlinson, M.C., R.P. Stumpf, and R.L. Vogel. 2019. Approximation of diffuse attenuation, Kd, for MODIS High resolution bands. International Journal of Remote Sensing and Remote Sensing Letters. 10: 178-185.

Wang, M. and W. Shi. 2007. The NIR-SWIR combined atmospheric correction approach for MODIS ocean color data processing. Optics Express. 15 (24): 15722.

Wang, M., S.H. Son., and L. W. Harding. 2009. Retrieval of diffuse attenuation coefficient in the Chesapeake Bay and turbid ocean regions for satellite ocean color applications. Journal of Geophysical Research: Oceans.114 (C10).

Wynne, T.T.; Stumpf, R.P.; Tomlinson, M.C.; Warner, R.A.; Tester, P.A.; Dyble, J.; Fahnenstiel, G.L. 2008. Relating spectral shape to cyanobacterial blooms in the Laurentian Great Lakes. International Journal of Remote Sensing. 29: 3665–3672.

Wynne, T.T., R.P. Stumpf, M.C. Tomlinson, V. Ransibrahmanakul, and T.A. Villareal. 2005. Detecting *Karenia brevis* blooms and algal resuspension in the western Gulf of Mexico with satellite ocean color imagery. Harmful Algae. Volume 4, Issue 6, pages 992 - 1003.

Wynne, T.T.; Stumpf, R.P.; Tomlinson, M.C.; Dyble, J. 2010. Characterizing a cyanobacterial bloom in western Lake Erie using satellite imagery and metrological data. Limnology and Oceanography. 55: 2025–2036.

Wynne, T.T., R.P. Stumpf, and T.O. Briggs. 2013a. Comparing MODIS and MERIS spectral shapes for cyanobacterial bloom detection. International Journal of Remote Sensing.

Wynne, T.T.; Stumpf, R.P.; Tomlinson, M.C.; Fahnensteil, G.L.; Schwab, D.J.; Dyble, J.;

Joshi, S. 2013b. Evolution of a cyanobacterial bloom forecast system in western Lake Erie: Development and initial evaluation. Journal of Great Lakes Research. 39, 90–99.

Acronyms Used:

HAB = Harmful Algal Bloom

HAB-FB = Harmful Algal Bloom Forecasting Branch; a branch within NCCOS.

Kd = diffuse attenuation coefficient

NCCOS = National Centers for Coastal Ocean Science

NOAA = National Oceanic and Atmospheric Administration

Rrs = Remote Sensing Reflectance

Appendices

Appendix A: Sensor Characteristics

A1. SeaWiFS band characteristics

Band	Band width	Spatial Resolution	Application
1	402-422	1100 meters	Yellow Substance
2	433-453	1100 meters	Chl absorption max
3	480-500	1100 meters	Chl and other pigments
4	500-520	1100 meters	Sediment and red tides
5	545-565	1100 meters	Chl absorption minimum
6	660-680	1100 meters	Chl absorption
7	745-785	1100 meters	Ocean color /phytoplankton/biogeochemistry
8	845-885	1100 meters	Ocean color /phytoplankton/biogeochemistry

A2. MODIS band characteristics from Section 1.2

Band	Bandwidth (nm)	Spectral radiance	Spatial Resolution	Primary Use
1	620-670	21.8	250 meters	Land/cloud aerosol boundary
2	841-876	24.7	250 meters	Land/cloud aerosol boundary
3	459-479	35.3	500 meters	Land/cloud aerosol properties
4	545-565	29.0	500 meters	Land/cloud aerosol properties
5	1230-1250	5.4	500 meters	Land/cloud aerosol properties
6	1628-1652	7.3	500 meters	Land/cloud aerosol properties
7	2105-2155	1.0	500 meters	Land/cloud aerosol properties
8	405-420	44.9	1000 meters	Ocean color /phytoplankton/biogeochemistry
9	438-493	41.9	1000 meters	Ocean color /phytoplankton/biogeochemistry

10	483-493	32.1	1000 meters	Ocean color /phytoplankton/biogeochemistry
11	526-536	27.9	1000 meters	Ocean color /phytoplankton/biogeochemistry
12	546-556	21.0	1000 meters	Ocean color /phytoplankton/biogeochemistry
13	662-672	9.5	1000 meters	Ocean color /phytoplankton/biogeochemistry
14	673-683	8.7	1000 meters	Ocean color /phytoplankton/biogeochemistry
15	743-753	10.2	1000 meters	Ocean color /phytoplankton/biogeochemistry
16	862-877	6.2	1000 meters	Ocean color /phytoplankton/biogeochemistry
17	890-920	10.0	1000 meters	Atmospheric water vapor
18	931-941	3.6	1000 meters	Atmospheric water vapor
19	915-965	15.0	1000 meters	Atmospheric water vapor
20	3660-3840	0.45	1000 meters	Surface/cloud temperature
21	3929-3989	2.38	1000 meters	Surface/cloud temperature
22	3929-3989	0.67	1000 meters	Surface/cloud temperature
23	4020-4080	0.79	1000 meters	Surface/cloud temperature
24	4433-4498	0.17	1000 meters	Atmospheric Temperature
25	4482-4549	0.59	1000 meters	Atmospheric Temperature
26	1360-1390	6.0	1000 meters	Cloud water vapor
27	6535-6895	1.16	1000 meters	Cloud water vapor
28	7175-7475	2.18	1000 meters	Cloud water vapor
29	8400-8700	9.58	1000 meters	Cloud properties
30	9580-9880	3.69	1000 meters	Ozone
31	10780-11280	9.55	1000 meters	Surface cloud temperature
32	11770-12270	8.94	1000 meters	Surface cloud temperature
33	13185-13485	4.52	1000 meters	Cloud top altitude
34	13485-13785	3.76	1000 meters	Cloud top altitude
35	13785-14085	3.11	1000 meters	Cloud top altitude

36	14085-14385	2.08	1000 meters	Cloud top altitude

A3. MERIS band characteristics from Section 1.3

Band Number	Band Center (nm)	Band Width (nm)	Application
1	412.5	10	Yellow substance
2	442.5	10	Chl-*a* absorption maximum
3	490	10	Chl-*a* and other pigments
4	510	10	Sediment and red tides
5	560	10	Chl-*a* absorption minimum
6	620	10	Suspended sediment
7	665	10	Chl absorption
8	681.25	7.5	Fluorescence peak
9	708.75	10	Fluorescence; atm correction
10	753.75	7.5	Vegetation and clouds
11	760.625	3.75	O2 absorption band
12	778.75	15	Atm. Correction
13	865	20	vegetation and water vapor
14	885	10	Atm correction
15	900	10	Water vapor and land

A4. OLCI band characteristics from section 1.4

Band Number	Band Center	Band Width	Application
1	400	15	Aerosols
2	412.5	10	Yellow substance
3	442.5	10	Chl absorption max
4	490	10	Chl other pigments
5	510	10	Sediments, red tide
6	560	10	Chl absorption minimum
7	620	10	Sediment loading

8	665	10	Chl absorption, sediment
9	673.75	7.5	Chl fluorescence baseline
10	681.25	7.5	Chl fluorescence
11	708.75	10	Chl fluorescence baseline
12	753.75	7.5	O2 absorption
13	761.25	2.5	Aerosol correction
14	764.375	3.75	Atm correction
15	767.5	2.5	Cloud detection
16	778.75	15	Atm correction
17	865	20	Atm correction
18	885	10	Water vapor
19	900	10	Water vapor
20	940	20	Water vapor
21	1020	40	Atm aerosol correction

A5. Landsat-8 OLI specifications

Spectral Band	Wavelength (nm)	Spatial Resolution
1	433-453	30 meters
2	450 – 515	30 meters
3	525 – 600	30 meters
4	630 – 680	30 meters
5	845 – 885	30 meters
6	1560 – 1660	30 meters
7	2100 – 2300	30 meters
8	500 - 680	30 meters
9	1360 – 1390	30 meters

A6. MSI band characteristics from Section 1.5

Band	Central Wavelength	Spatial Resolution	Bandwidth

1	443	60	20
2	490	10	65
3	560	10	35
4	665	10	30
5	705	20	15
6	740	20	15
7	783	20	20
8	842	10	115
8A	865	20	20
9	945	60	20
10	1375	60	20
11	1610	20	90
12	2190	20	180

A7.VIIRS band characteristics from Section 1.6

VIIRS Band	Central λ (nm)	λ range (nm)	Primary Uses	Spatial Resolution
M1	412	402-422	Pigment detection	750 meters
M2	445	436-454	Pigment detection	750 meters
M3	488	478-488	Pigment detection	750 meters
M4	555	545-565	Pigment detection	750 meters
M5(B)	672	662-682	Pigment detection	750 meters
M6	746	739-754	Atm correction	750 meters
M7(G)	865	846-885	Atm correction	750 meters
M8	1240	1230-1250	Atm correction	750 meters
M9	1378	1371-1386	Atm correction	750 meters
M10	1610	1580-1640	Atm correction	750 meters
M11	2250	2230-2280	Atm correction	750 meters
M12	3700	3610-3790	Atm correction	750 meters
M13	4050	3970-4130	Atm correction	750 meters
M14	8550	8400-8700	Atm correction	750 meters
M15	10763	10260-11260	Atm correction	750 meters

M16	12013	11540-12490	Atm correction	750 meters

Appendix B: Flags

B1. SeaWiFS flags

Sensor-Seawifs	
Mask	Python Implementation

Cloud Mask	# first correct for turbid water
	numreal = rrs_red.copy()
	numreal[(chl >= 0)] = rrs_red[(chl >= 0)] * (0.45 + chl[(chl >= 0)] * 0.005) / 4.3
	numreal[(rrs_red < 0)] = 0
	
	#need to capture nan's
	
	numreal[np.isnan(numreal)] = 0
	
	#create cloud mask and set all pixels equal 0
	
	cld = np.zeros(cldalb.shape, dtype=np.uint8)
	cld[(cldalb - numreal) > 0.027] = 1

Mixed/Invalid Pixel Mask	mixed_pixel = np.zeros(rhos_443.shape) mixed_pixel[(rhos_865 > rhos_443) & (rhos_865 > rhos_555) & (rhos_865 > rhos_670) & (rhos_865 > 0.01)] = 1

B2. MERIS/OLCI flags

Sensor-MERIS/OLCI	
Mask	Python Implementation

Cloud Mask	#if L2 created in SNAP has no cloud_albedo product substitute rhos_865
	if not l3_file.bands_in_file('cloud_albedo'):
	    cldalb = rhos_865
	
	numreal = (rhos_620 + rhos_665 + rhos_681) - 3.0 * rhos_443 - (rhos_754 - rhos_443) / (754 - 443) * (620 + 665 + 681 - 3.0 *443)
	idx = (numreal > 0)
	cldtmp = cldalb.copy()
	
	#switch to rhos_865 where cldalb fails
	cldtmp[(np.isnan(cldalb))] = rhos_865[(np.isnan(cldalb))]
	cldtmp[idx] = cldalb[idx] - 3 * numreal[idx]
	
	#create cloud mask and set all pixels equal 0
	cld = np.zeros(cldalb.shape, dtype=np.uint8)
	
	cld[cldtmp > 0.08] = 1

Cloud Mask (Scum)	#to deal with scum look at relative of NIR and blue for lower albedos cld[((rhos_754 + rhos_709) > (rhos_443 + rhos_490)) & (cldalb < 0.1)] = 0 cld[((rhos_754 + rhos_709) - (rhos_665 + rhos_681) > 0.01) & (cldtmp < 0.15)] = 0 cld[(((rhos_754 + rhos_709) - (rhos_665 + rhos_681)) / cldtmp) > 0.1] = 0 cld[(rhos_665 > 0.1) & (cldalb > 0.15)] = 1
Cloud Mask (Glint)	#flag high glint cld[(rhos_865 - cldalb) > 0.25] = 1
Mixed Pixel Mask	# original test conditions:

	mixed_pixel[((rhos_885 > rhos_620) & (rhos_885 > rhos_709) & (rhos_885 > rhos_754) & (rhos_885 > 0.01))] = 1
Mixed Pixel Mask (dry lake)	# test dry lake condition: mixed_pixel[((rhos_620 > rhos_560) & (rhos_560 > 0.15) & (rhos_885 > 0.15))] = 1
Mixed Pixel Mask (snow/ice)	# test snow/ice condition: # MERIS differential snow index mdsi = (rhos_865 - rhos_885) / (rhos_865 + rhos_885) # exclude potential bloom conditions (use coefficient of variation in visible bands) cv = (np.nanstd(np.array([rhos_443, rhos_490, rhos_510, rhos_560, rhos_620, rhos_665, rhos_681]), axis=0) / np.nanmean(np.array([rhos_443, rhos_490, rhos_510, rhos_560, rhos_620, rhos_665, rhos_681]), axis=0)) mixed_pixel[((mdsi > 0.01) & (rhos_885 > 0.15) & (cv < 0.1))] = 1

Adjacency Mask	ci = calc_ci(rhos_665, rhos_681, rhos_709)
	ci = apply_kd_corr(ci, rhos_442, rhos_490, rhos_510, rhos_560, rhos_620, rhos_665, rhos_709, rhos_865)
	
	mci =calc_mci(rhos_681, rhos_709, rhos_754)
	
	#create mask and set all pixels equal 0
	mask = np.zeros(rhos_490.shape, dtype=np.uint8)
	
	#flag adjacency pixels
	adj_mask[((ci>0) & (mci<0))] = 1

B3. MODIS flags

Sensor-MODIS	
Mask	Python Implementation
Cloud Mask	numreal = rrs_red.copy() idx = (chl >= 0) numreal[idx] = rrs_red[idx] * (0.45 + chl[idx] * 0.005) / 4.3 # first correct for turbid water numreal[rrs_red < 0] = 0 # need to capture nan pixels numreal[np.isnan(numreal)] = 0 # create cloud mask and set all pixels equal 0 cld = np.zeros(cldalb.shape, dtype=np.uint8) cld[(cldalb - numreal) > cloudthr] = 1
Cloud Mask (Non-Water Check)	# non-water check 1240 is bright relative to 859 & the combination is bright # this may hit glint by accident, need to be checked. cld[((rhos_1240 / rhos_859 > 0.5) & (rhos_1240 + rhos_2130 > 0.10))] = 1

Cloud Mask (Glint)	# now try to correct for glint
	numreal = rhos_645 - rhos_555 + (rhos_555 - rhos_859) * (645 - 555) / (859 - 555)
	
	# need to capture nan pixels
	numreal[np.isnan(numreal)] = 0
	
	numreal_1 = cldalb + numreal

	[((cldalb > 0) & (numreal_1 < cloudthr))] = 0 cld[(rhos_859 / rhos_1240 > 4)] = 0
Cloud Mask (Scum)	# scum areas cld[((rhos_859 - rhos_469 > 0.01) & (cldalb > 0) & (cldalb < 0.30))] = 0 cld[((rhos_859 - rhos_645 > 0.01) & (cldalb > 0) & (cldalb < 0.30))] = 0 idx = (rhos_1240 < 0.2) numreal_1[idx] = (numreal_1[idx] - (rhos_859[idx] - rhos_1240[idx]) * np.abs(rhos_859[idx] - rhos_1240[idx]) / cloudthr)
Cloud Mask (water areas)	# water areas numreal_2 = numreal_1.copy() idx = (numreal_1 < cloudthr * 2) numreal_2[idx] = numreal_1[idx] - (rhos_555[idx] - rhos_1240[idx]) numreal_2[~idx] = numreal_1[~idx] - (rhos_469[~idx] - rhos_1240[~idx]) cld[(cldalb > 0) & (numreal_2 < 1)] = 0
Mixed Pixel Mask	mixed_pixel = np.zeros(rhos_469.shape) mixed_pixel[(rhos_859 > rhos_469) & (rhos_859 > rhos_555) & (rhos_859 > rhos_645) & (rhos_859 > 0.01)] = 1 mixed_pixel[(rhos_1240 > rhos_555)] = 1

B4. MSI flags

Sensor-MSI	
Mask	Python Implementation
Cloud Mask	#if L2 created in SNAP has no cloud_albedo product substitute rhos_865 if not l3_file.bands_in_file('cloud_albedo'):

	cldalb = rhos_865
	numreal = rhos_665 - rhos_443 - (rhos_740 - rhos_443) / (740 - 443) * (665 - 443)
	
	idx = (numreal > 0)
	cldtmp = cldalb.copy()
	
	#switch to rhos_865 where cldalb fails
	cldtmp[(np.isnan(cldalb))] = rhos_865[(np.isnan(cldalb))]
	cldtmp[idx] = cldalb[idx] - 3 * numreal[idx]
	
	#create cloud mask and set all pixels equal 0
	cld = np.zeros(cldalb.shape, dtype=np.uint8)
	
	cld[cldtmp > 0.08] = 1

Cloud Mask (Scum)	#to deal with scum look at relative of NIR and blue for lower albedos cld[((rhos_740 + rhos_704) > (rhos_443 + rhos_492)) & (cldtmp < 0.1) & (rhos_560 > rhos_665)] = 0 #no rhos_681, so replace with rhos_665 cld[((rhos_740 + rhos_704) - (rhos_665 + rhos_665) > 0.01) & (cldtmp < 0.15) & (rhos_560 > rhos_665)] = 0 cld[((((rhos_740 + rhos_704) - (rhos_665 + rhos_665)) / cldtmp) > 0.1) & (rhos_560 > rhos_665)] = 0 cld[(rhos_665 > 0.1) & (cldtmp > 0.15)] = 1
Cloud Mask (Glint)	#flag high glint cld[(rhos_865 - cldalb) > 0.25] = 1
Mixed Pixel Mask	# original test conditions: mixed_pixel[((rhos_865 > rhos_665) & (rhos_865 > rhos_704) & (rhos_865 > rhos_740) & (rhos_865 > 0.01))] = 1

Mixed Pixel Mask (dry lake)	# test dry lake condition: mixed_pixel[((rhos_665 > rhos_560) & (rhos_560 > 0.15) & (rhos_865 > 0.15))] = 1

Appendix C: Clear water correction

CI: MODIS clear water correction

<table>
<tr><th colspan="2">Sensor-MODIS</th></tr>
<tr><td>Threshold</td><td>Python Implementation</td></tr>
<tr><td>0.51</td><td>#calculate standard Kd for correction
kd =calc_kd_rhos(rhos_469, rhos_645, rhos_859)

#expect a 560 peak with cyano blooms
ss_555 = (rhos_555 - rhos_469 + (rhos_469 - rhos_645) * (555 - 469) / (645 - 469))

ci[(kd < kd_min_threshold) & ((rhos_859 <= rhos_469) | (rhos_859 <= rhos_645)) & (ss_555 < 0.01)] = 0</td></tr>
</table>

C2: MERIS/OLCI clear water correction

<table>
<tr><th colspan="2">Sensor-MERIS/OLCI</th></tr>
<tr><td>Threshold</td><td>Python Implementation</td></tr>
<tr><td>0.31</td><td>#calculate standard Kd for correction
kd = calc_kd_rhos(rhos_442, rhos_490, rhos_620, rhos_665, rhos_865)

#calculate Kd using rhos_709 instead of rhos_620 & rhos_665
kd_709 = calc_kd_rhos(rhos_442, rhos_490, rhos_620, rhos_709, rhos_865)
#709 switching modification for scum conditions
kd[(kd_709 > kd)] = kd_709[(kd_709 > kd)]

#expect a 560 peak with cyano blooms
ss_560 = (rhos_560 - rhos_442 + (rhos_442 - rhos_620) * (560 - 442) / (620 - 442))</td></tr>
</table>

	ci[(kd <kd_min_threshold) & (kd > 0) & ((rhos_865 <= rhos_490) | (rhos_865 <= rhos_665) | (rhos_865 <= rhos_709)) & (ss_560 < 0.01)] = 0

Appendix D: Scaling Factors

The scaling factors are needed to go from a geophysical value (such as Chl-*a* concentration in µg L-1) to a scaled number from 0-255 for an output product. Additionally the scaling factor can be seen in the metadata from each product using the gdal utility found in Appendix G (gdalinfo <ProductName*.tif> | grep "SAPS")

Product	**Scaling**
CI	**Scaled = (83.3)*(Log10(CI + 4.2))**
MCI	**Scaled = (250 / 3)*(4 + Log10(MCI))**
Chl (coastal)	**Scaled = (275 / (1 + 13.46374 / chl))**
Chl (global)	**Scaled = (250.0 / 3.0) * (1.3 + Log10(chl))**
Kd	**Scaled = 325 / (1 + 2.71828 / Kd)**
Rrs	**Scaled = (270 / (1+0.00609675 / Rrs665))**
RBD	**Scaled = 150 * (4 + Log10(rbd))**

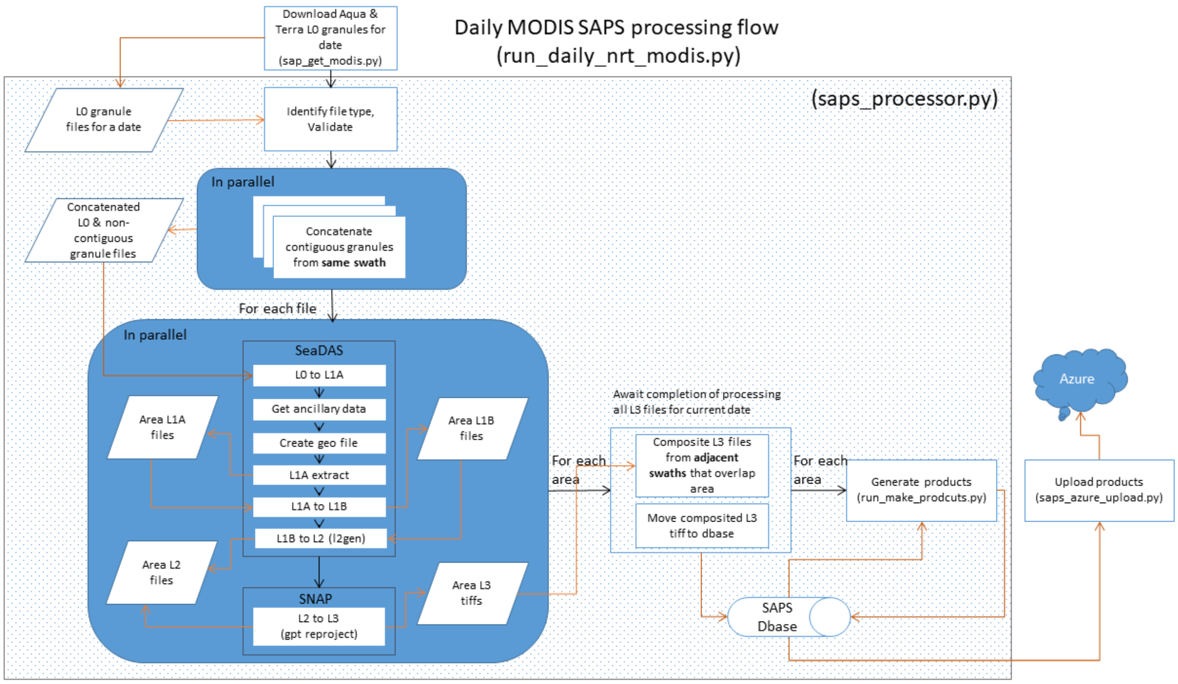
Appendix E: SAPS script listing

S.N.	**Script**	**Description**
1	create_metadata.py	Create metadata file for a list of SAPS products
2	create_saps_colorbars.py	Add colorbar to SAPS product or create standalone colorbar for product
3	get_sentinel_data.py	Search for and download S3 OLCI or S2 MSI data
4	meris_third.py	Download MERIS L1B FRS or RR data
5	run_compare_products.py	Utility module to compare SAPS products
6	run_daily_nrt_modis.py	Run MODIS daily near real-time processing
7	run_daily_nrt_olci.py	Run OLCI daily near real-time processing
8	run_olci_reprocess.py	Reprocess OLCI using non-time critical L1B inputs

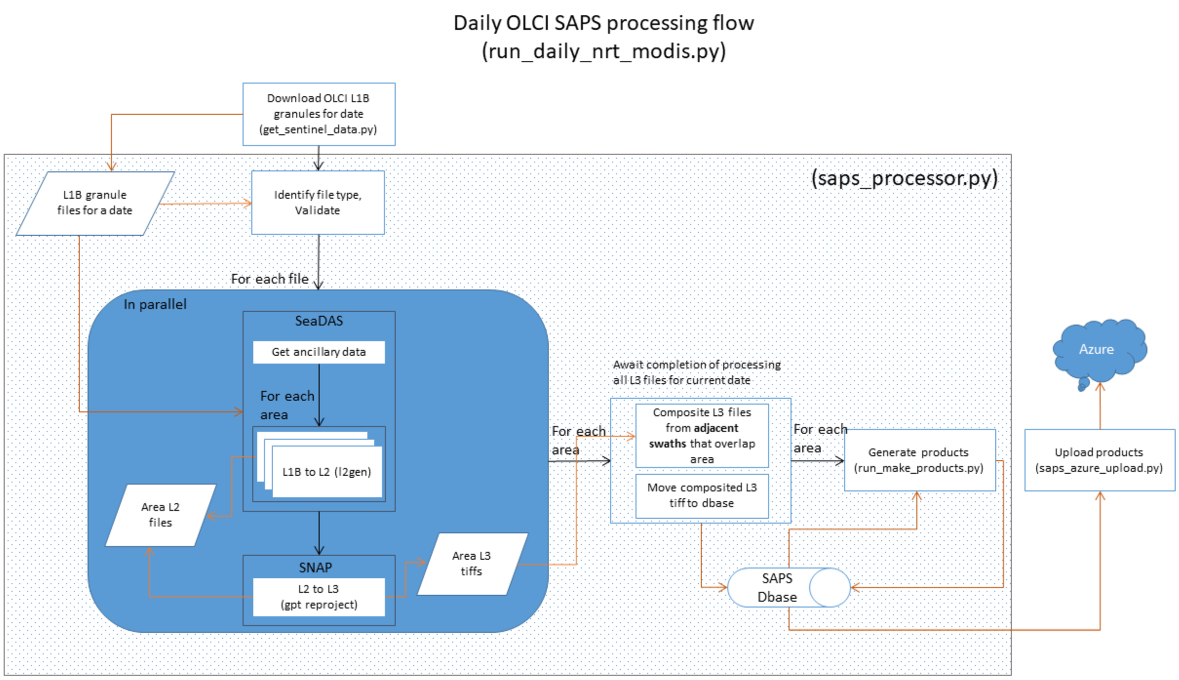
9	run_modis_reprocess.py	Reprocess MODIS with refined ancillary and calibration inputs
10	run_make_custom_products.py	Test and run custom products from SAPS L3 files
11	run_make_products.py	Creates products from SAPS L3 files
12	run_make_default_products.py	Create default products based on SAPS area config file
13	run_saps_file_info.py	Display internal SAPS product metadata
14	saps_azure_upload.py	Upload products to Azure storage
15	atlas_azure_upload.py	Upload products to Azure storage from Atlas
16	saps_get_modis.py	Download MODIS L0 data
17	saps_make_area_landmask.py	Utility module to create a SAPS landmask
18	saps_ngs_upload.py	Upload products via FTP
19	saps_processor.py	Run all processing steps to generate both SAPS L3 and product files for list of input files
20	saps_show_products.py	Utility module to display information about product algorithms
21	saps_zonal_stats.py	Utility module to generate zonal statistics
22	swap_colortable.py	Utility module to replace color table in SAPS GeoTiFF product
23	saps_setup_env	Define command line environment to run SAPS modules

Appendix F: Processing flowcharts

F1. MODIS processing flowchart



F2. OLCI processing flowchart



Appendix G: Sample metadata extract

The *gdalinfo* utility distributed as part of the gdal open source software package (https://gdal.org/) can be used to view internal metadata within SAPS GeoTiff products.

Here is an example of running the command in a linux window to display the SAPS specific metadata from envisat.2003364.1230.1844C.L3.CAN.v670_1_2.rrs665.tif (which we are assuming is in the currently directory:

[twynne@nccos-vs-haas 2003]$ gdalinfo envisat.2003364.1230.1844C.L3.CAN.v670_1_2.rrs665.tif | grep "SAPS"

SAPS_cloud_mask_desc=Meris SAPS cloud mask

SAPS_cloud_mask_name=meris_cloud

SAPS_cloud_mask_version=1.1

SAPS_mixed_pixel_mask_desc=Meris mixed pixel mask

SAPS_mixed_pixel_mask_name=meris_mixpix

SAPS_mixed_pixel_mask_version=1.1

SAPS_nodata_mask_desc=No data coverage mask

SAPS_nodata_mask_name=nodata

SAPS_nodata_mask_version=1.0

SAPS_product_created=20180905T0835

SAPS_product_desc=Turbidity based on rrs_665

SAPS_product_flag_cloud=253

SAPS_product_flag_invalid=254

SAPS_product_flag_land=252

SAPS_product_flag_nodata=255

SAPS_product_flag_nodetect=0

SAPS_product_flag_saturated=250

SAPS_product_lut_fn=viridis_red_v2.txt

SAPS_product_masking=CMDL

SAPS_product_name=rrs665

SAPS_product_rev_scaling=0.00609675 / ((270.0 / DN) - 1)

SAPS_product_scaling=np.round(270 / (1 + 0.00609675 / rrs_665[rrs_665>0]))

SAPS_product_src=envisat.2003364.1230.1844C.L3.CAN.v670_1.tif

SAPS_product_type=standard_prod

SAPS_product_version=1.0

Below is an example of the metadata from a SAPS CI file:

SAPS info:

SAPS_ci_adj_mask_desc = SAPS CI adjacency mask based on CI detect and no MCI detect

SAPS_ci_adj_mask_name = ci_adj

SAPS_ci_adj_mask_version = 1.0

SAPS_cloud_mask_desc = OLCI SAPS cloud mask

SAPS_cloud_mask_name = olci_cloud

SAPS_cloud_mask_version = 1.0

SAPS_mixed_pixel_mask_desc = OLCI mixed pixel mask

SAPS_mixed_pixel_mask_name = olci_mixpix

SAPS_mixed_pixel_mask_version = 1.1

SAPS_nodata_mask_desc = No data coverage mask

SAPS_nodata_mask_name = nodata

SAPS_nodata_mask_version = 1.0

SAPS_product_created = 20180417T1106

SAPS_product_desc = Chlorophyll Cyanobacteria Index with Kd clear water correction and CInoMCI adjacency flagging

SAPS_product_flag_adjacency = 251

SAPS_product_flag_cloud = 253

SAPS_product_flag_invalid = 254

SAPS_product_flag_land = 252

SAPS_product_flag_nodata = 255

SAPS_product_flag_nodetect = 0

SAPS_product_flag_saturated = 250

SAPS_product_lut_fn = viridis_red_v2.txt

SAPS_product_masking = CMADL

SAPS_product_name = CI

SAPS_product_rev_scaling = 10**(3.0 / 250.0 * DN - 4.2)

SAPS_product_scaling = np.round(83.3 * (np.log10(ci[ci>0]) + 4.2))

SAPS_product_src = sentinel-3a.2017220.0808.1526_1527C.L3.OH3.v8103_1.tif

SAPS_product_type = standard_prod

SAPS_product_version = 1.1

U.S. Department of Commerce

Wilbur L. Ross, Jr., *Secretary*

National Oceanic and Atmospheric Administration

Neil Jacobs, *Acting Under Secretary of Commerce for Oceans and Atmosphere*

National Ocean Service

Nicole LeBoeuf, *Acting Assistant Administrator for National Ocean Service*

The mission of the National Centers for Coastal Ocean Science is to provide managers with scientific information and tools needed to balance society's environmental, social and economic goals. For more information, please visit: **http://www.coastalscience.noaa.gov/**