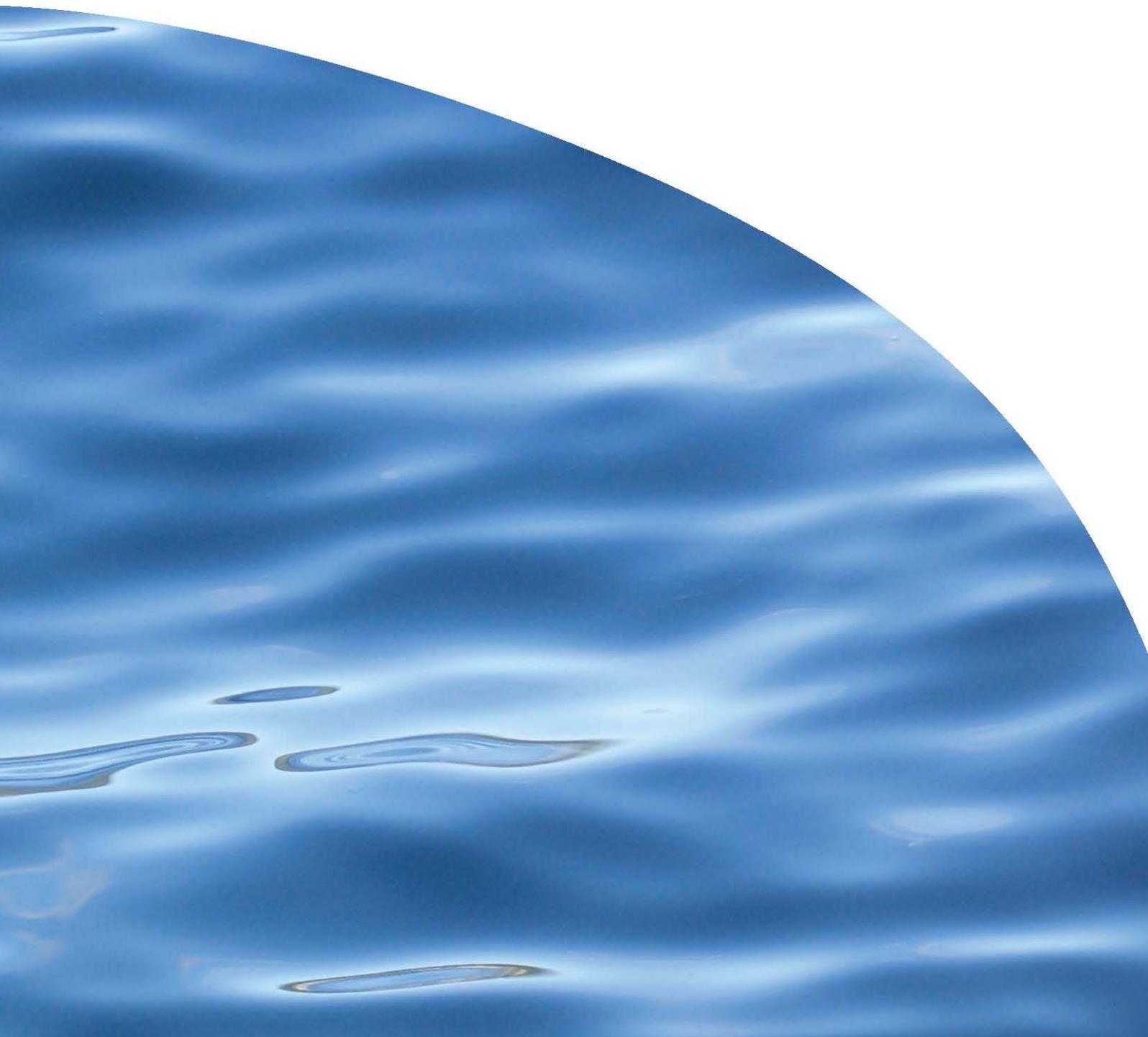




REPORT NO. 2443

**USE OF REMOTE SENSING TO MONITOR WATER  
QUALITY IN HAWKE BAY**





# USE OF REMOTE SENSING TO MONITOR WATER QUALITY IN HAWKE BAY

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## TABLE OF CONTENTS

1. BACKGROUND .....	1
1.1. Data sources .....	1
1.1.1. <i>Satellite data</i> .....	2
1.1.2. <i>In situ data</i> .....	3
2. METHODS .....	4
3. RESULTS .....	6
3.1. Production of a virtual 10-year HAWQi dataset .....	9
4. DISCUSSION AND CONCLUSIONS.....	11
5. ACKNOWLEDGEMENTS .....	13
6. REFERENCES .....	13
7. APPENDICES.....	14

## LIST OF FIGURES

Figure 1.	Moored data sites and state of the environment water sampled sites in Hawke Bay used in the study.....	2
Figure 2.	Quantile-Quantile plot of sample and theoretical quantiles showing no clear bias in the residuals.....	6
Figure 3.	Comparison of chlorophyll- <i>a</i> concentrations predicted from satellite data to concentrations measured at the HAWQi buoy site, using data omitted from the satellite chlorophyll model fitting process.....	7
Figure 4.	Time series comparison of satellite GLM predictions to <i>in situ</i> HAWQi mooring data ( $\Delta$ ) for chlorophyll- <i>a</i> over the period December 2012 to October 2013.....	8
Figure 5.	Comparison of observed chl- <i>a</i> concentrations (mg chl- <i>a</i> /m <sup>3</sup> ) from state of the environment monitoring around the Hawke Bay region to model predictions.....	8
Figure 6.	Virtual time series of chlorophyll- <i>a</i> at the HAWQi site based on the application of the customised satellite algorithm developed for the region.....	10
Figure 7.	Example screenshot of standard MODIS chlorophyll- <i>a</i> product displayed in SeaDAS 7.0.....	16
Figure 8.	Band Maths dialogue box.....	17
Figure 9.	Partial screenshot of the top left corner of the main SeaDAS window showing the new “HAWQi_Chla” variable.....	18
Figure 10.	Properties of the HAWQi_Chla variable.....	18

## LIST OF TABLES

Table 1.	Table from Jones <i>et al.</i> (2013) showing suitability and accuracy of some satellite sensors for a variety of regional council monitoring tasks.....	3
Table 2.	Coefficients fitted for the local implementation of the OC3M algorithm to HAWQi data.....	6
Table 3.	Performance of algorithm when compared to state of the environment monitoring data from sites located around the Hawke’s Bay region.....	9

## LIST OF APPENDICES

Appendix 1.	Additional summary information and performance of the satellite algorithm model generated by R.....	14
Appendix 2.	Additional summary information on the trend analysis generated by R.....	15
Appendix 3.	Basic instructions for the use of SeaDAS 7.0 for processing satellite images using the newly created chlorophyll- <i>a</i> algorithm.....	16

## 1. BACKGROUND

Cawthron Institute (Cawthron) has recently assisted the Hawke's Bay Regional Council (HBRC) to set up a dedicated buoy (referred to as HAWQi) to monitor water quality in the Bay. The buoy has been deployed in the Bay for almost a year and is located approximately 10 km NNE of Napier at a water depth of 20 m. Over this time an *in situ* sensor (located 5 m below the water surface) has recorded several high-chlorophyll-*a* (chl-*a*) events. Chlorophyll-*a* information is of particular interest to HBRC because their records indicate there was a red-tide event over the 2012 / 2013 summer period<sup>1</sup>.

In order to find out more about the historical variability and spatial extent of chl-*a* in the region, a small Envirolink proposal was submitted. This report is the outcome of that Envirolink application. The aim of the application was to investigate the potential for development of a customized algorithm for estimating surface chl-*a* from freely available satellite data and *in situ* data sources in the region (e.g. HAWQi).

### 1.1. Data sources

The study utilised one source of satellite data for algorithm development and several *in situ* sources of data, which included two datasets from moored installations at an Open Ocean Aquaculture (OOA) research site and the HAWQi buoy (Figure 1). Over 400 state of the environment (SOE) samples from around Hawke Bay were also used in the study (Figure 1).

---

<sup>1</sup> See e.g. "Algal bloom turns east coast sea red" – newspaper article 17/08/2012.

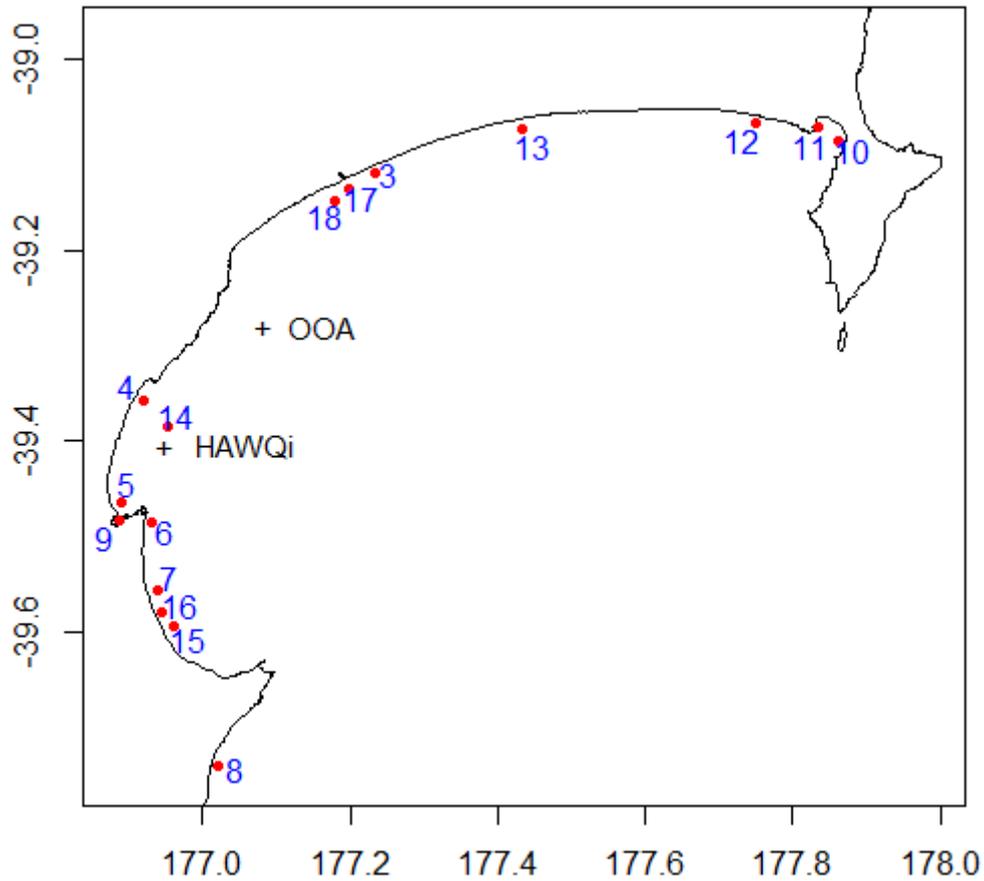


Figure 1. Moored data sites (Open Ocean Aquaculture [OOA] and HAWQi) and state of the environment (SOE) water sampled sites (numbered sites) in Hawke Bay used in the study.

**1.1.1. Satellite data**

A recent review of satellite data sources for the region undertaken for the Waikato Regional Council (WRC) showed that hyper spectral reflectance data from the MODIS satellite was the most appropriate for the region. This is because it is freely available, has the required wavelengths for chl-a sensing, longevity of data collection (2002 to present) and daily collection of data (see *e.g.* Jones *et al.* 2013; Table 1).

Data for the entire available period was compiled through the use of the Level 1 and 2 OceanColor Browse Tool<sup>2</sup>, for a region incorporating all of Hawke Bay.

<sup>2</sup> <http://oceancolor.gsfc.nasa.gov/cgi/browse.pl?sen=am>

Table 1. Table from Jones *et al.* (2013) showing suitability and accuracy of some satellite sensors for a variety of regional council monitoring tasks. Sensors are subjectively ranked in order of usefulness.

Sensor	SST	Suspended sediments	CDOM	Light attenuation	Chl-a (Case 2)	NPP	Phytoplankton speciation <sup>b</sup>	HABs <sup>b</sup>	Benthic habitat	Mangrove cover
MODIS	😊	😐	😐	😊	😊	😊	😊	😊	😞	😞
HICO	NA	😊	😊	😊	😊	😊	😊	😊	😐	😐
LandSat	😊	😐	😞	😐	😞	😞	😞	😞	😊	😊
MERIS	😊 <sup>a</sup>	😊	😊	😊	😊	😊	😊	😊	😞	😞
SeaWiFS	😊	😐	😐	😊	😊	😊	😐	😐	😞	😞
CZCS	😊	😞	😞	😐	😞	😐	😞	😞	😞	😞
VIIRS <sup>41</sup>	😐	😐	😐	😐	😐	😐	😐	😐	😞	😞
Accuracy Legend	High accuracy possible after validation.		Moderate accuracy possible after validation.		Low accuracy likely; improvement possible with research and algorithm development.			Poor accuracy likely even with validation; potentially able to validate into qualitative categories (e.g. high/mid/low).		

a. Product derived from radiometric sensor on same satellite berth as ocean colour instrument.

b. Extreme bloom events, particularly red tide events may be able to be detected by operational MODIS and HICO sensors.

### 1.1.2. *In situ* data

The *in situ* chl-a data were compiled from the following sources:

1. Recently acquired HAWQi mooring data for chl-a taken at a depth of 5 m, for a period of approximately eight months<sup>3</sup>
2. Historical Open Ocean Aquaculture (OOA) research mooring data (held by Cawthron) taken at depths of 10 m to 30 m from a location several kilometres north of Napier. This data covers a 3-year period.
3. State of the environment (SOE) sampling conducted throughout the Hawke's Bay region over 2002–2013.

Initial comparisons between the satellite surface measurements and the deep OOA measurements showed very little correlation. This suggested the latter were not suitable for surface water algorithm development so the OOA data were excluded from further use in the study.

The available SOE sample data were also excluded from the algorithm development. This data was used however, as a final cross-check of the algorithm for different areas of the Bay.

<sup>3</sup> <http://data.hbrc.govt.nz/hydrotel/cgi-bin/hydwebserver.cgi/points/details?point=3279>

## 2. METHODS

There are many options available to develop algorithms for estimating chl-a from satellite data. For this project the method selected was one that had been used previously in the Waikato region (Jones *et al.* 2013), where local data was fitted to a standard empirical OC3M algorithm (O'Reilly *et al.* 2000)<sup>4</sup> and to standard level 2 MODIS files (which are downloadable on request from the OceanColor website<sup>5</sup>). Whilst this approach did not produce a particularly good model fit ( $R^2 < 0.2$ ), when trained on 'spot measurement' samples<sup>6</sup> in the Waikato region, it was still one of the better results from the study.

The empirical OC3M method has the advantage that it is based on well-grounded optical theory (O'Reilly *et al.* 2000) and does not require a large effort to specially prepare satellite data for processing. The use of this method makes daily data generation more feasible for council staff. One of the main disadvantages, however, is that this method relies on reflectance measurements that may be affected by atmospheric effects. There are more complex methods that attempt to correct for atmospheric effects that may improve predictions, but these were considered outside the scope of the study.

The OC3M algorithm takes the form of:

$$\text{Log}_{10}(\text{Chl-a}) = a + b \cdot R + c \cdot R^2 + d \cdot R^3 + e \cdot R^4 \quad (\text{eqn. 1})$$

Where  $R = \max(R_{rs443}, R_{rs488}) / R_{rs555}$

$R_{rs}$  is the remote sensing reflectance for a given wavelength (given in nm, *i.e.*  $R_{rs443}$  is the remote sensing reflectance for a wavelength of 443 nm). The letters 'a' to 'd' refer to the coefficients that will be fitted to collected data to generate a customised algorithm for the region.

Because the method relies on a ratio of reflectance between two wavelengths, it will be less affected by atmospheric effects than some algorithms if it is locally calibrated. However local calibration could limit its use to areas with similar optical properties.

In order to ensure that an unbiased performance measure of the algorithm could be recorded, the data were separated into two-thirds of the data for training and one-third for testing, additional SoE samples were also used to test the generality of the model in different regions, times and depths. As mentioned in Section 1.1, only the HAWQi data was used to train the model.

<sup>4</sup> Additional information also available from: <http://oceancolor.gsfc.nasa.gov/REPROCESSING/R2009/ocv6/>

<sup>5</sup> <http://oceancolor.gsfc.nasa.gov>

<sup>6</sup> In this case 'spot measurements' were water samples taken at various sites in the Firth of Thames over several years.

Upon initial inspection of the HAWQi data, it was observed that spikes in the chl-*a* data were present. Discussions with HBRC staff revealed that the periodic spiking in the measurements was caused by a loose rope (attached to the mooring) interfering with the optical sensor. In order to reduce the effect of this spurious data, concentrations of chl-*a* above 10 mg chl-*a*/m<sup>3</sup> were removed from the dataset. Furthermore, because the HAWQi data were comprised of several measurements per hour, it was possible to temporally smooth the data. Smoothing of the data was undertaken to get a better representation of the concentrations of chl-*a* around the mooring on a given day for comparison to the 1 km resolution satellite data.

As the satellite reflectance measurements were for a 1 km x 1 km square, a 6-hourly moving average was applied to the raw HAWQi data. This averaging assumes an average constant water speed of ~4.5 cm/s over six hours would move ~1 km of water past the sensor.

After the HAWQi data was cleaned up and smoothed, *R* (from eqn. 1) was calculated from the available satellite reflectance data<sup>7</sup> and fitted to smoothed 'test' HAWQi chl-*a* data from the site. The model fitting to eqn. 1 was then undertaken via the generalized linear modelling (GLM) functionality in the R software package (R Core Team 2013), using closest matching times from both satellite and the smoothed HAWQi training dataset.

---

<sup>7</sup> Data was not always available due to impediments such as cloud cover and sun-glint *etc.*

### 3. RESULTS

The coefficients from the model fitting process for use at the HAWQi site are given in Table 2.

Table 2. Coefficients fitted for the local implementation of the OC3M algorithm to HAWQi data.

Coefficient from eqn. 1	Value ( $\pm$ Standard Error)
a	0.84350 $\pm$ 0.502
b	0.31949 $\pm$ 1.367
c	-1.87885 $\pm$ 1.255
d	0.85697 $\pm$ 0.460
e	-0.10961 $\pm$ 0.056

As a consequence of the model fitting process, the equation for calculating chl-a (in mg chl-a/m<sup>3</sup>) from satellite data was derived as:

$$\text{Chl-a} = 10^{(0.84350 + 0.31949 R + -1.87885 R^2 + 0.85697 R^3 + -0.10961R^4)} \text{ (eqn. 2)}$$

The final model explained 88% of the deviance in the data on which it was trained ( $R^2 = 0.88$ ) and no clear pattern was observed in the residuals (Figure 2), indicating that the model fitting process was successful.

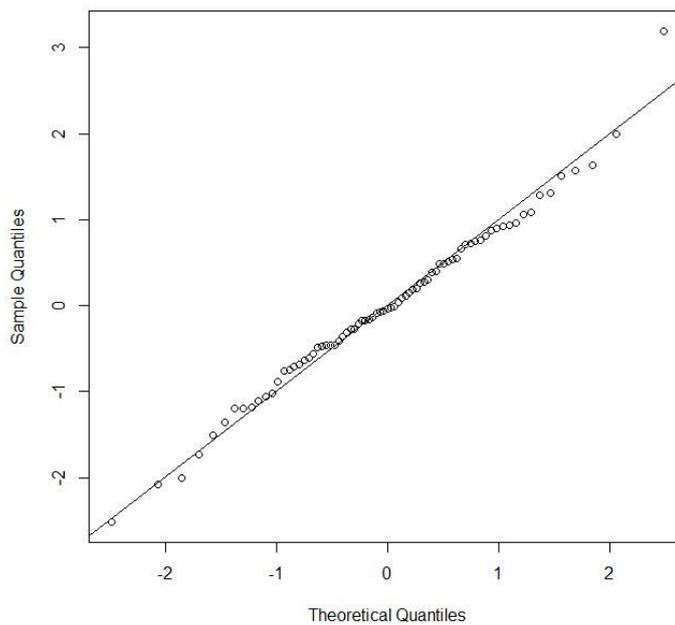


Figure 2. Quantile-Quantile plot of sample and theoretical quantiles showing no clear bias in the residuals.

Inspection of the test dataset, using one third of the total data that was withheld from the model-building process, showed that the fitted model also performed well (Pearson's correlation coefficient ( $r$ ) = 0.8). There was some evidence that the model was potentially less accurate at high chl-*a* concentrations in the test data (chl-*a* > 2 mg chl-*a*/m<sup>3</sup>), although the modelled accuracy appeared to be good for chl-*a* concentrations less than 2 mg chl-*a*/m<sup>3</sup> (Figure 3). However, the limited number of test samples (N=39) means that clear conclusions cannot be drawn from this assessment.

A temporal comparison of chl-*a* measured by moored instrumentation at the HAWQi site with the satellite-derived data shows the satellite data respond to increases in chl-*a* at the site, but that an underestimation of the algorithm at high chl-*a* concentrations occurs (Figure 4).

Application of the model to SOE samples (N=277) around the region, which were generally located in shallower water and closer to the coastline, showed a slight bias toward under-estimation (~ -8% bias) by the algorithm from samples distributed over the whole Bay (Figure 5; Appendix 2).

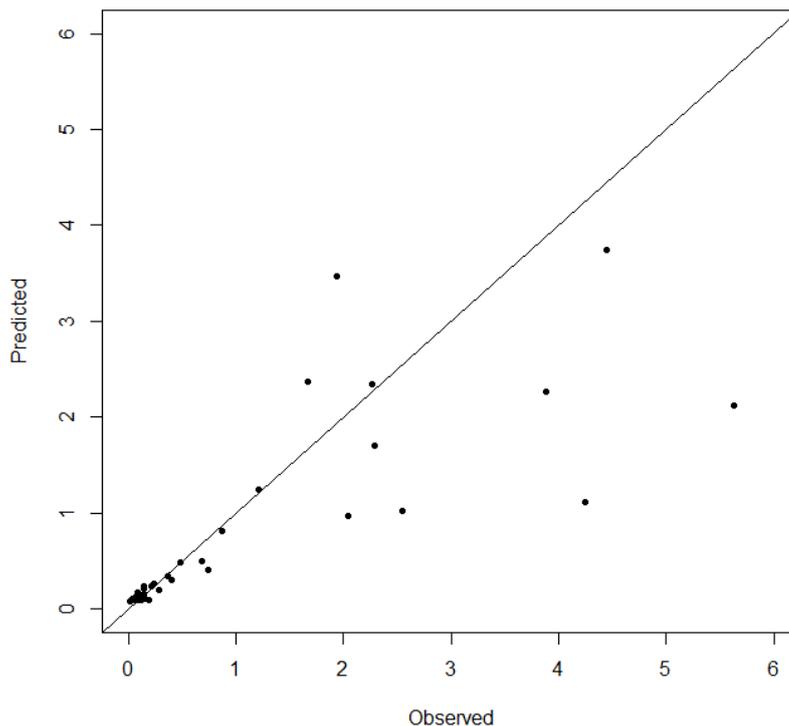


Figure 3. Comparison of chlorophyll-*a* (chl-*a*) concentrations predicted from satellite data to concentrations measured at the HAWQi buoy site, using data omitted from the satellite chlorophyll model fitting process. Pearson's  $r$  = 0.8.

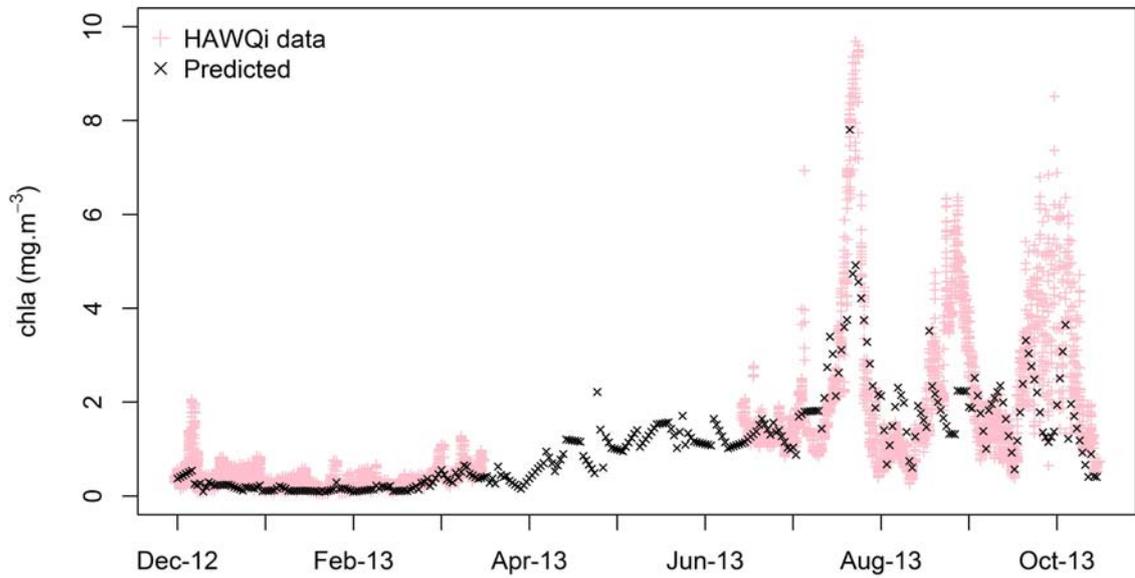


Figure 4. Time series comparison of satellite GLM predictions to *in situ* HAWQi mooring data for chlorophyll-a (chl-a) over the period December 2012 to October 2013.

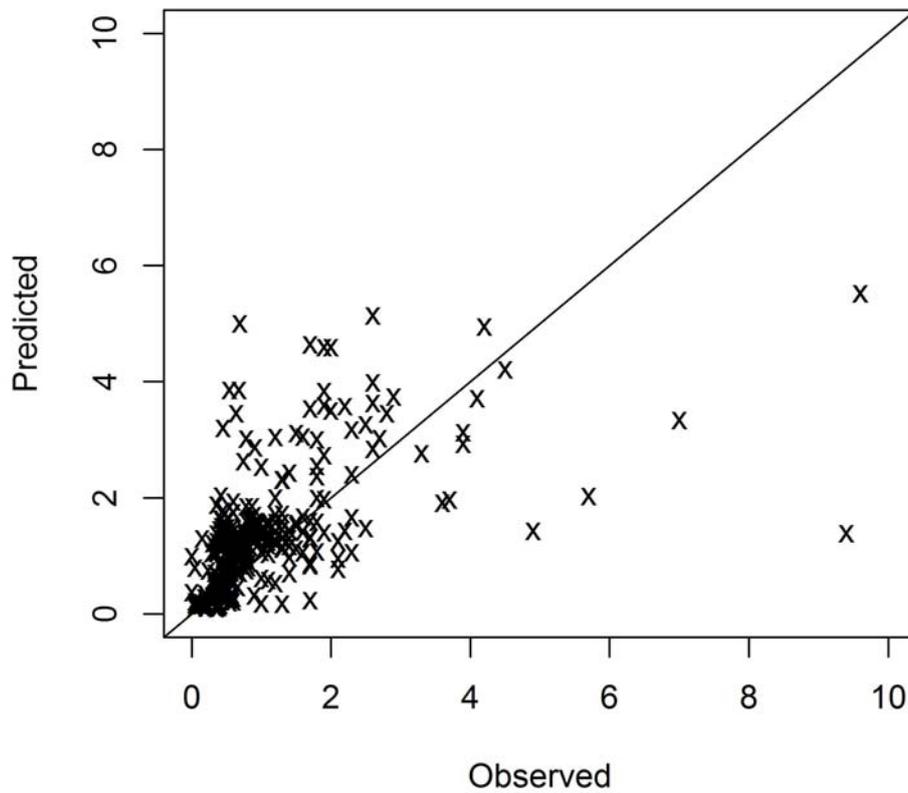


Figure 5. Comparison of observed chlorophyll-a (chl-a) concentrations ( $\text{mg chl-a/m}^3$ ) from state of the environment (SOE) monitoring around the Hawke Bay region to model predictions.

Model biases were also estimated by fitting a linear model between SOE monitoring observations and the modelled predictions with a zero intercept. Results from this analysis show the performance of the model varied by site with over- and under-estimation of chl-*a* from satellite (*i.e.* model slope) results (Table 3).

Table 3. Performance of algorithm when compared to state of the environment (SOE) monitoring data from sites located around the Hawke's Bay region. N is the sample size, Slope is a measure of the bias in the model and the Model Bias (1-Slope) is expressed as a percentage.

Site number	Longitude (°E)	Latitude (°S)	N	Slope	Model bias
All	NA	NA	277	0.927	-7%
3	177.2354	39.11934	37	0.684	-32%
4	176.9212	39.35812	34	0.621	-38%
5	176.8901	39.47424	30	0.691	-31%
6	176.9309	39.48555	36	0.718	-28%
7	176.9398	39.56657	33	1.362	36%
8	177.0214	39.74109	36	0.585	-42%
9	176.8876	39.48452	28	0.527	-47%
10	177.8627	39.08576	4	0.598	-40%
11	177.8353	39.07019	5	0.726	-27%
12	177.7502	39.0668	7	0.630	-37%
13	177.4325	39.07247	7	0.821	-18%
14	176.9535	39.38489	7	0.804	-20%
15	176.9623	39.59531	5	1.786	79%
16	176.946	39.58026	5	2.493	149%
17	177.1992	39.13685	1	0.810	-19%
18	177.1791	39.14936	2	0.627	-37%

### 3.1. Production of a virtual 10-year HAWQi dataset

The newly created satellite chl-*a* algorithm was applied to the full period of satellite measurements in the region to create a 10-year long time series. Inspection of these data shows clear seasonal signals with inter-annual variations (Figure 6). On examination of the smoothed time series, it appears that there is a slight increase in chl-*a* over the time period, with notably higher results in recent years.

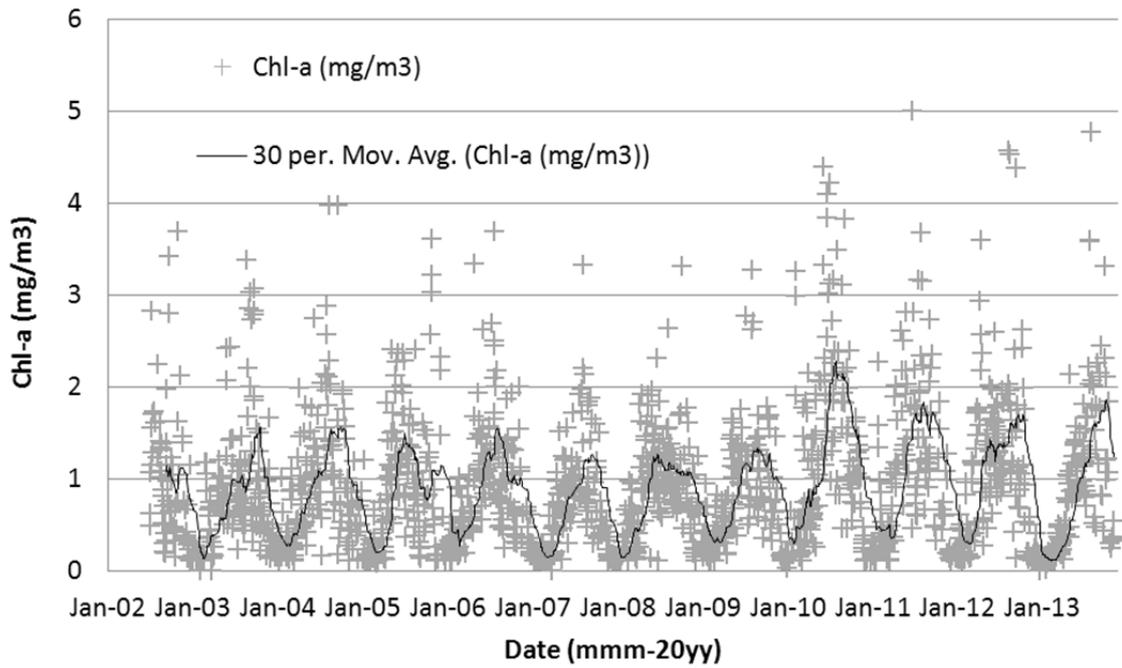


Figure 6. Virtual time series of chlorophyll-*a* (chl-*a*) at the HAWQi site based on the application of the customised satellite algorithm developed for the region. The + symbols are the raw data with the black line showing 30-day smoothed data.

Trend analysis shows a small but statistically significant increase in chl-*a* concentrations over the 10 year period ( $\sim +0.02 \pm 0.004$  mg chl-*a*/m<sup>3</sup>/yr; see R produced summary table in Appendix 2). Although this trend is small at an annual scale it may be relevant when considered over several years.

## 4. DISCUSSION AND CONCLUSIONS

A relatively simple satellite algorithm for Hawke Bay HAWQi mooring site has been developed. This shows that much value can be gained from moored instrument deployments over periods of less than a year for some coastal regions around New Zealand. Whilst the newly created model clearly exhibited biases outside of the depth and location it was trained for (*i.e.* 5 m depth at the HAWQi site), the model was particularly useful for hindcasting a 'virtual' HAWQi time series over a 10-year period.

Individual SOE monitoring samples from varying depths (over about 0 to 10 metres) and regions in the Bay were also used to assess model performance. In areas with a reasonable number of samples ( $N > 10$ ), there was a clear overestimation bias in the model at coastal sites (Table 3)<sup>8</sup>. However, when these data were aggregated, application of the new chl-*a* algorithm to all of the SOE monitoring samples ( $N = 277$ ) around the region (generally located in shallower water to that of the HAWQi site and closer to the coast), showed a slight bias toward under-estimation ( $\sim 8\%$  bias) over the Bay (Figure 5). This indicates that the model does not need to be limited to the HAWQi site, but could be widely applicable over a range of locations and depths in the Bay. However, the model is not perfect, and it needs to be recognised that some biases (generally over-estimates) exist in the comparisons between some coastal sites in the Bay.

As well as the collation of a large amount of raw satellite data for the region, a valuable time series of subsurface chl-*a* measurements over a multi-year period has also been retrieved and compiled. The Foundation for Research Science and Technology (FRST) funded project was set up to investigate the viability of open ocean aquaculture (OOA) in the region. Despite the OOA data not being particularly useful for estimating surface chl-*a*, the results of this study show that 'deeper' waters ( $> 10\text{m}$ ) of Hawke Bay appear to be independent of the surface waters. This apparent disconnection of 'deep' and surface waters suggests that future consideration should be given to the provision of chl-*a* sensors deeper than the current instrument at 5 m on the HAWQi mooring.

While satellite data is not necessarily as accurate as *in situ* data, it exhibits some clear advantages for trend analysis. For example, it is not prone to the fouling and associated measurement issues that can temporarily affect the accuracy of moored instruments. Application of the satellite-derived chl-*a* algorithm for the HAWQi buoy for a 10-year period shows some interesting results, with a small but significant annual trend observed.

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<sup>8</sup> The exception was site 7, which is located close to some of the major rivers in the region. This site had a reasonable number of samples ( $N = 33$ ) and was the only site to show a positive bias. This indicates that the algorithm tended to overestimate chl-*a* in this region.

The average predicted concentration for the HAWQi site was 0.88 mg chl-*a*/m<sup>3</sup> over the period, so an average trend increase over 10 years of 0.2 mg chl-*a*/m<sup>3</sup> (~20% of average) could be ecologically significant. However, the analysis conducted was basic and further research would be required to validate these initial results. Even if the trend is confirmed, it would not be possible to conclude from the available data what might have led to this increase; any increases are likely to be driven by a combination of ecological, climate and anthropogenic changes over the period.

The temporal analysis is an important aspect of coastal remote sensing studies, but it was also important to consider the spatial objectives of the study. Whilst the results from the algorithm will be most accurate for the region it was calibrated for (*i.e.* HAWQi site at 5 m depth), it is also possible to apply it to other areas of Hawke Bay. When compared to data from around the region some biases evident, but these are substantially less than generic oceanic water chl-*a* estimates in the region. Consequently we recommend that this algorithm be used as the preferred proxy for *in situ* chl-*a* estimates over alternative methods, such as the default chl-*a* estimates provided with freely available MODIS datasets..

In order for Council staff to be able to utilise the newly-created algorithm to investigate spatial patterns in the region on a day-to-day basis, instructions for its application in the freely available SeaDAS software package are provided in Appendix 3 of this report.

Given the demonstrated performance of this empirical approach for relatively little effort, it is concluded that there is potential for wide applicability of the approach presented here to many other coastal regions around New Zealand. While 10-years of satellite derived data is probably too short a period for robust analysis of some climate-driven cycles, this approach is still useful for strengthening data provision in poorly sampled areas and existing data pools. In the case of Hawke Bay, this approach has proven successful and will provide a useful resource for analysing chl-*a* trends in the region and responding to episodic phytoplankton events in future.

## 5. ACKNOWLEDGEMENTS

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- The Ministry of Business, Innovation and Employment — Science and Innovation funding provided through the Envirolink small advice grant (number 1436-HBRC199).
- Hawke's Bay Regional Council staff, in particular Oliver Wade and Anna Madararasaz-Smith, for the timely provision of data required for this project and comments while preparing this report.
- Waikato Regional Council staff, in particular Hilke Giles and Vernon Pickett, for supporting the initial work undertaken in Jones *et al.* (2013) that has formed the basis of this study.
- Ross Sneddon, Chris Cornelisen and Cherie Johansson are also thanked for their help in reviewing and editing this report.

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## 7. APPENDICES

### Appendix 1. Additional summary information and performance of the satellite algorithm model generated by R.

Additional summary information on the satellite algorithm model:

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	0.84350	0.50233	1.679	0.0975 .
R	0.31949	1.36689	0.234	0.8159 .
I (R^2)	-1.87885	1.25466	-1.497	0.1386 .
I (R^3)	0.85697	0.46051	1.861	0.0668 .
I (R^4)	-0.10961	0.05649	-1.940	0.0563 .

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.04383025)

Null deviance: 26.3183 on 76 degrees of freedom  
Residual deviance: 3.1558 on 72 degrees of freedom  
AIC: -15.465

Number of Fisher Scoring iterations: 2

R-square = 0.8800921

Additional summary information on the satellite algorithm performance when compared to all state of the environment monitoring data (N=277):

Call:

glm(formula = chl ~ chl.predict + 0, data = datc)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.9432	-0.6675	-0.1774	0.0804	13.0126

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
chl.predict	0.92681	0.04708	19.69	<2e-16 ***

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 2.199001)

Null deviance: 1459.12 on 277 degrees of freedom  
Residual deviance: 606.92 on 276 degrees of freedom  
AIC: 1007.4

Number of Fisher Scoring iterations: 2

## Appendix 2. Additional summary information on the trend analysis generated by R.

```

Call:
glm(formula = rlt ~ factor(month) + year, data = dataout)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.2376 -0.3286 -0.1105  0.1770  3.5970

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -42.909265    8.477461  -5.062 4.57e-07 ***
factor(month)2  0.075688    0.066476   1.139 0.255028
factor(month)3  0.216637    0.063124   3.432 0.000613 ***
factor(month)4  0.594526    0.066474   8.944 < 2e-16 ***
factor(month)5  0.951819    0.065739  14.479 < 2e-16 ***
factor(month)6  1.090553    0.065154  16.738 < 2e-16 ***
factor(month)7  1.146365    0.067043  17.099 < 2e-16 ***
factor(month)8  1.144896    0.065291  17.535 < 2e-16 ***
factor(month)9  1.006954    0.066762  15.083 < 2e-16 ***
factor(month)10 0.783257    0.066986  11.693 < 2e-16 ***
factor(month)11 0.416639    0.071470   5.830 6.54e-09 ***
factor(month)12 0.114427    0.071759   1.595 0.110972
year          0.021492    0.004222   5.091 3.92e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.3532859)

Null deviance: 1007.64 on 1866 degrees of freedom
Residual deviance: 654.99 on 1854 degrees of freedom
(2285 observations deleted due to missingness)
AIC: 3370.7

Number of Fisher Scoring iterations: 2

```

### Appendix 3. Basic instructions for the use of SeaDAS 7.0 for processing satellite images using the newly created chlorophyll-a (chl-a) algorithm.

In order to process satellite data using the new algorithm created for the Hawke's Bay region, it is necessary to use appropriate processing software. We recommend HBRC use SeaDAS 7 as a suitable platform for generating and analysing satellite data retrieved from the OceanColor website<sup>9</sup>. This software is freely available at no cost from: <http://seadas.gsfc.nasa.gov/installers/>

Once installed it should be possible to open a zipped HDF file retrieved from the OceanColor website and generate pre-processed variables. As an initial example, we explain the use of the tool on the default chlorophyll-a data provided in a downloaded MODIS HDF file.

#### Instructions

1. Open the 'Bands' folder in the top left box of the graphical user interface (GUI) and double click on the "chloro\_a" variable in the file (Figure 6).

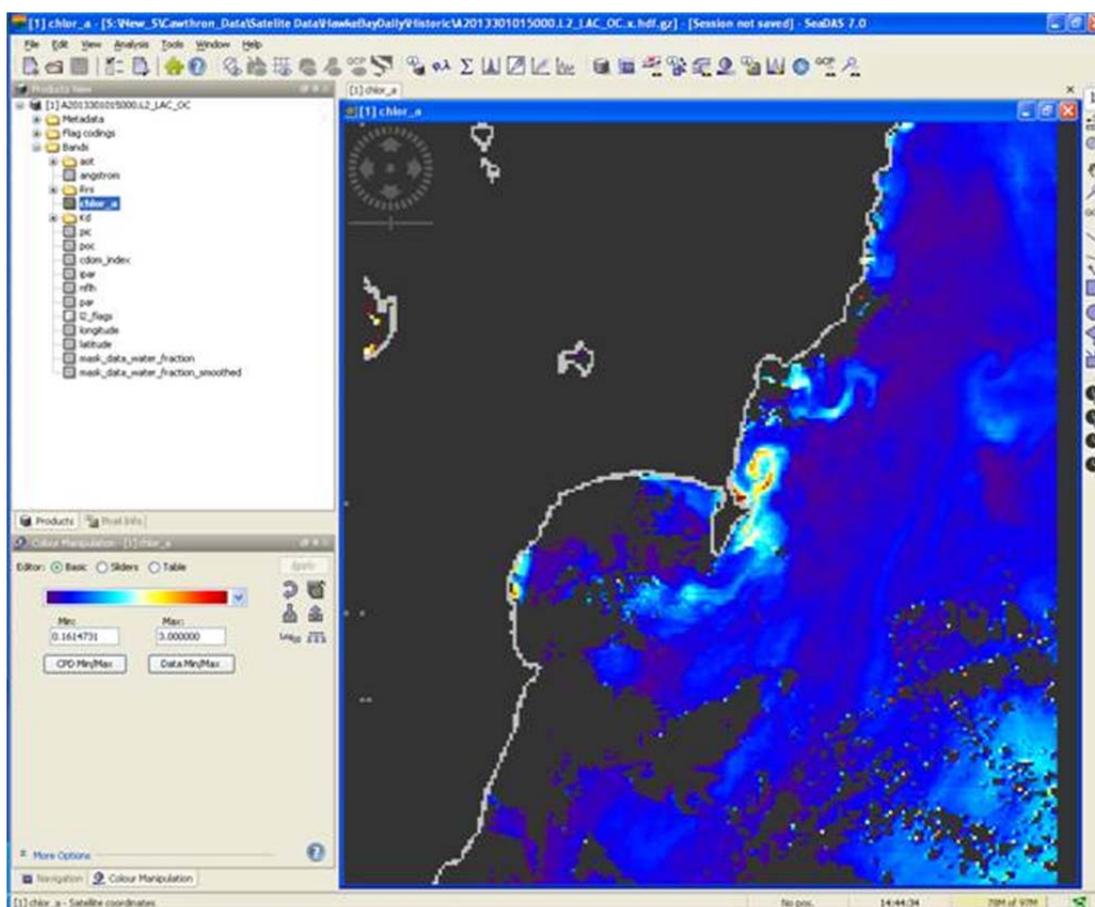


Figure 7. Example screenshot of standard MODIS chlorophyll-a product displayed in SeaDAS 7.0.

<sup>9</sup> <http://oceancolor.gsfc.nasa.gov/cgi/browse.pl?sen=am>

2. Select the 'Colour Manipulation' tab in the lower left corner and choose the required minimum and maximum range and colour scheme and then click the 'Apply' button (Figure 6).
3. Apply the newly created HAWQi algorithm presented in this report (once familiar with the basic plotting functionality) by using the 'Create Band-by-Band Maths' function under the 'Tools' menu. This opens the following 'Band Maths' dialogue box (Figure 7).

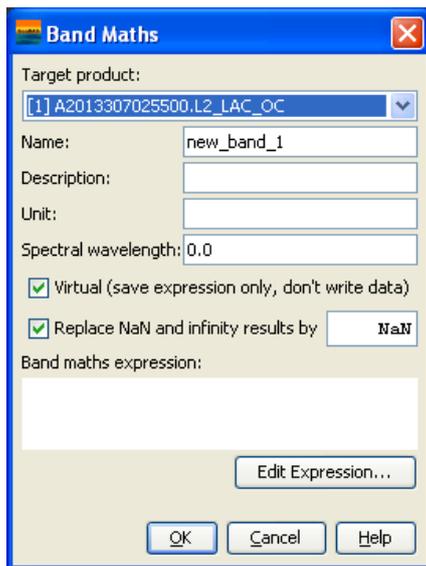


Figure 8. Band Maths dialogue box.

4. Enter 'Name' (e.g. HAWQi\_Chla), 'Description' and 'Unit' information in the relevant fields in the 'Band Maths' dialogue box.
5. Select the 'Edit Expression' button and enter the following text version of the chl-a algorithm:

```
pow(10 , 0.84350 + 0.31949 * max(Rrs_443 ,Rrs_488) / Rrs_555 - 1.87885 *
pow(max(Rrs_443 ,Rrs_488) / Rrs_555,2) + 0.85697 *
pow(max(Rrs_443 ,Rrs_488) / Rrs_555,3) - 0.10961 *
pow(max(Rrs_443 ,Rrs_488)/Rrs_555,4))
```

Note: It is important that all of algorithm is entered correctly. 'R' is also now defined in this equation as:

$$\max(\text{Rrs\_443}, \text{Rrs\_488}) / \text{Rrs\_555}$$

- Press 'OK'. The new variable will be visible under the 'Bands' folder (Figure 8). Right click and select 'Properties' to view the properties of this new variable (e.g. Figure 9). Double click to view the data and select the 'Colour Manipulation' tab to manipulate the colours displayed in the image.

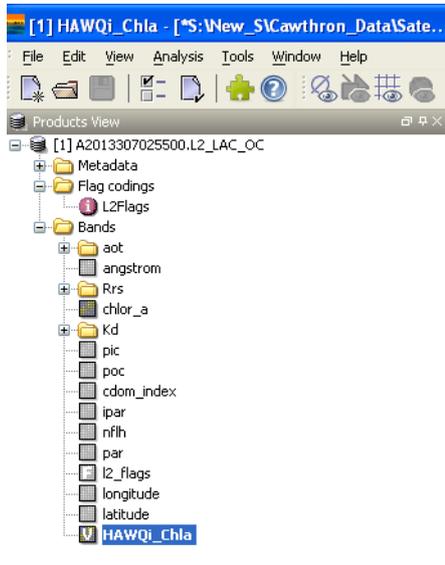


Figure 9. Partial screenshot of the top left corner of the main SeaDAS window showing the new “HAWQi\_Chla” variable.

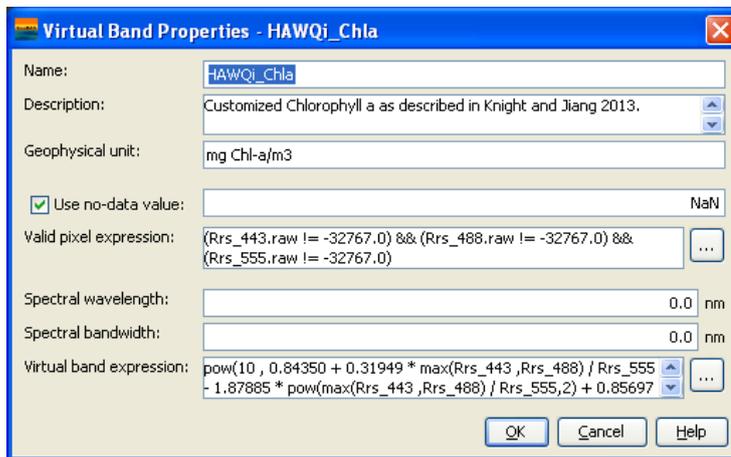


Figure 10. Properties of the HAWQi\_Chla variable.