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A Model For Remotely Estimating Water Quality Parameters In Inland Water Bodies Based On Landsat ETM+ Data

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Abstract

This work tries to explore how remote sensing could be used in monitoring selected water quality (WQ) parameters in small inland water bodies. Models were created based of Landsat 7 images taken in 6 samplings from May 2012 to september 2014 to estimate water quality parameters. The images used were scenes of WRS-2, path and row 191/25 as well as 190/25 respectively. Samples were taken from 13 water bodies, 9 water bodies (20-90 Ha) were used in modelling (some were removed due to clouds and imagery gaps). The water quality parameters were chlorophyll-a, Total Carbon, Total Organic Carbon, Total Nitrogen, Temperature, and Secchi Disk Depth. The 3×3 moving average window technique was used and a water only mask was used in order to limit the process to water areas only. The best models created based on surface reflectance (T based on TOA radiance) are as follows (model formula, r^2): SDD [cm] = 245.7(L1/L3)-194.4, 0.77. Chl-a [µg/l] = 33,66*(L3/L1)^3,405, 0.82. TC [mg/l] = 53.946*(L3/L1)+15.150, 0.83. TOC [mg/l] = 32.76*(L3/L1)-5.814, 0.87. TN [mg/l] = 10^(1.764*(L2/L1)-2.051), 0.78. T [°C] = 1.1203*L62-302.78, 0.88. The models and workflow created are intended to help institutions mandated in monitoring water bodies.

Abstrakt

Tato práce se zabývá možnostmi využití dálkového průzkumu Země v monitoringu vybraných ukazatelů kvality vody v menších vnitrozemských vodních plochách. Na základě snímků Landsat 7 pořízených v době šesti odběrů vzorků a měření, provedených od května 2012 do září 2014, byly vytvořeny modely pro odhad ukazatelů kvality vody. Byly použity snímky z WRS-2 umístění 191/25 a 190/25. Vzorky byly odebírány ze 13 vodních ploch, odběry z 9 vodních ploch (20-90 ha) byly využity pro vytvoření modelů (některé odběry byly vyloučeny kvůli oblačnosti a výpadkům v obrazových datech). Modelované ukazatele kvality vody byly chlorofyl-a, celkový uhlík, celkový organický uhlík, celkový dusík, teplota a průhlednost jako hloubka Secchiho desky. Pro omezení vlivu obrazového šumu byl použit posuvný obrazový filtr průměru z 3x3 pixelů s prostorovým vymezením maskou vodních ploch. Nejlepší modely vytvořené na základě povrchové reflektance (T na základě TOA radiance) jsou následující (rovnice modelu, r^2): SDD [cm] = 245,7 (L1 / L3) -194,4, 0,77. Chl-a [ug / l] = 33,66 * (L3 / L1) ^ 3,405, 0,82. TC [mg / l] = 53,946 * (L3 / L1) + 15,150, 0,83. TOC [mg / l] = 32,76 * (L3 / L1) -5,814, 0,87. TN [mg / l] = 10 ^ (1,764 * (L2 / L1) -2,051), 0,78. T [° C] = 1,1203 * L62-302,78, 0,88. Vytvořené modely a pracovní postupy mají pomáhat institucím pověřeným monitorováním vodních ploch.

Keywords

Landsat, Remote Sensing, Algorithms, Inland Water Quality, Water Monitoring, Model

Klíčová Slova

Landsat, dálkový průzkum země, algoritmy, kvalita vnitrozemské vody, monitorování vody, model

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Introduction

Water bodies, such as lakes and ponds, need to be carefully managed, as the water quality has a significant effect on the humans using it, aquatic organisms as well as the environment in general. There are numerous definitions that are usually used in defining inland water one of such is by Mishra [1] is a term that could be used for ecosystem unless it specifically termed. It is very essential for the quality of our water resources to be maintained. Their deterioration is a major global concern as it impacts the ecology and well as society. Some these inland water bodies are reservoirs, streams, Lakes (both natural and artificial). It must be noted that some these small inland water bodies serves as the main sources of drinking water, recreational purposes and the breeding of fish. Making sure these inland water bodies maintain a standard of quality can be tedious and costly [2]. It also requires constantly checking certain quality parameters in these water bodies. Measuring these parameters are mostly done in-situ or require taken samples to the laboratory for further analysis which makes it labour intensive and time consuming [3]. Example, more than $650,000 CAN was spent to collect and analyse *in situ* samples from 150 water bodies in the province of Quebec alone during 2009 [4].

Remotely sensed based methods for monitoring water quality parameters is one way of addressing this constraint that comes with water quality monitoring. Remote sensing could defined as the 'science of deriving information about an object based on measurement from a distance without actually coming in contact' [5]. This phenomenon can be seen in illustration 1.

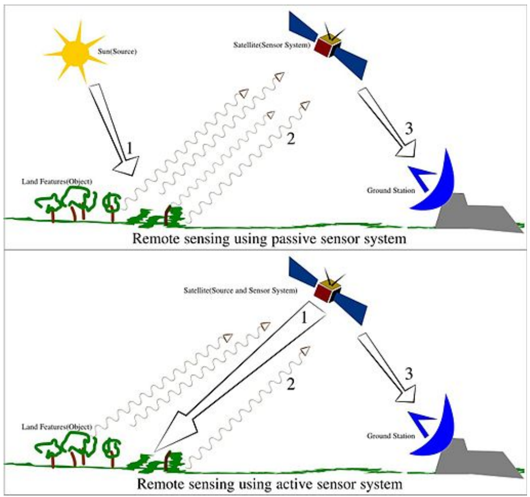

Illustration 1: Principle of Remote Sensing [36]

The quantity measured in present- day remote sensing systems is the electromagnetic energy emanating from objects of interest and although there are possibilities such as seismic waves, sonic waves and gravitational force, attention is mostly focused on systems which, measure electromagnetic energy. In estimating these parameters (water quality parameters), algorithms based on remotely sensed data can be used. In furtherance of this, many researchers have come up with possibilities based on the use of different satellite sensors to monitor water quality parameters [6] [7] [8] [9] [10]. Some of the Sensors used in remote sensing are LANDSAT, MODIS, MERIS, VIIRS, HySpIRI [11]. Through the use of these sensors we are able to measure colour of water in detail as well as it variables (water quality parameters). These parameters may include chlorophyll-a (Chl-a), total suspended sediment, coloured dissolved matter, temperature, total nitrogen, organic carbon and secchi disk depth (SSD) quantitatively observed [12]. Studies in this regard has come up with algorithms based on data collected from Landsat for the estimation of various water quality parameters under consideration [13] [14] [15] [16] [17] [18] [19] [20]. Some of these are elucidated below. These algorithms could be single band-ratio or combinations of bands combinations based. Hadjimitsis used ratios based on empirical relationship between blue band (450 – 500 nm), green band (500 – 600nm), red band (600 – 700 nm) to remotely estimate the seasonal patterns of chlorophyll-a levels in inland water bodies[21]. In the case of Harding an algorithm was created in estimating the seasonal patterns of chlorophyll levels in the Chesapeake Bay [9].

$$log_{10}\,[Chl_a]=a+b(-log_{10}\,(G)) \tag{1}$$

where a and b are empirical constant derived from in situ measurements and G is

$$G=\frac{R_2^2}{R_1^2 \cdot R_3^2} \tag{2}$$

where R1 is radiance at 460 nm, R2 is radiance at 490 nm, and R3 is radiance at 520 nm.

Rundquist et al. [8], estimated Chl-a by using, remote measurement of algal chlorophyll in surface waters looked at hyper spectral signatures, in the visible and near-infrared, associated with two experiments conducted outdoors in large water tanks; one involving relatively low amounts of chlorophyll over a narrow range and a second involving relatively high amounts over a wide range. The principal finding was that the commonly used near-infra red ratio is best for estimating pigment amounts when the concentration of chlorophyll is relatively low, and the first derivative of reflectance around 690 nm is best when the concentration is relatively high.

In choosing a specific sensor to use, consideration was given to spatial, temporal and spectral resolution with regard to images. Therefore Landsat ETM+ was chosen as the inland water bodies under consideration are small in size. Landsat ETM+ fitted better in terms of spatial resolution as compared to sensors like MODIS, MERIS, OCM-2 [12]. In addition the following reasons also attributed to Landsat ETM+ being chosen,

1. economical reasons (freely available)
2. easy and quick to access to Landsat data from United States Geological Survey (USGS)
3. it's extent of reach (coverage)
4. availability of already processed images.

The outline of this research work is to

1. use remote sensing as a tool to estimate the levels of water quality parameters in small inland water bodies in the Pardubice and Hradec Kralove region by

   constructing a model based on multiple water bodies as well as multiple sampling dates using Landsat ETM+ data
2. effect of 3×3 window averaging on data used
3. the effect of atmospheric correction on the data used.

The water bodies sampled for this work are relatively small ones in relation to those cited in the modelling articles espoused earlier. As it is also an objective of this work to examine the reliability of using 30m Landsat data for such small water bodies.

Aside the creation models for SDD and Chl-a, this research also tries to estimate total organic carbon (TOC), total nitrogen (TN) and temperature (T) based on the same method. The purpose for exploring how well TOC as a water quality parameter would relate with other parameters such Chl-a based on satellite modelling. It must be noted that it is believed that TOC and Chl-a are easier to measure as they correlate with algae content in water and it is also used as an indicator of the overall eutrophication of water. In the case of TC, this was considered as it is measured in the laboratory alongside TOC. Total nitrogen (TN) as a parameter is measured by the use of an analytical instrument and consist of both biomass and nutrient which as well correlate with algae and eutrophication. Based on computing of land surface temperature or brightness temperature from thermal bands we are able to estimate temperature (T) [22] [23]. In furtherance the application of regression analysis between satellite bands and measured parameters was adopted.

1 Methodology

The under consideration centred on water bodies around Pardubice (50°02′19″N 15°46′45″E) and Hradec Kralove (50°12′34″N15°50′00″E). The water bodies around these two areas that are the focus of this work, are mostly lakes created as a result of sand winning and fishponds (illustration 2). The sizes of these water bodies are relatively small and range from 8 to 90 hectares. These water bodies especially the fishponds were constructed in the middle ages as described by Kukla [24]. Regarding the lakes emanating from sand winning these are relatively new as some of them do not have a surface inlet and outlet. Their usage is for recreational purposes (swimming) and for fishing.

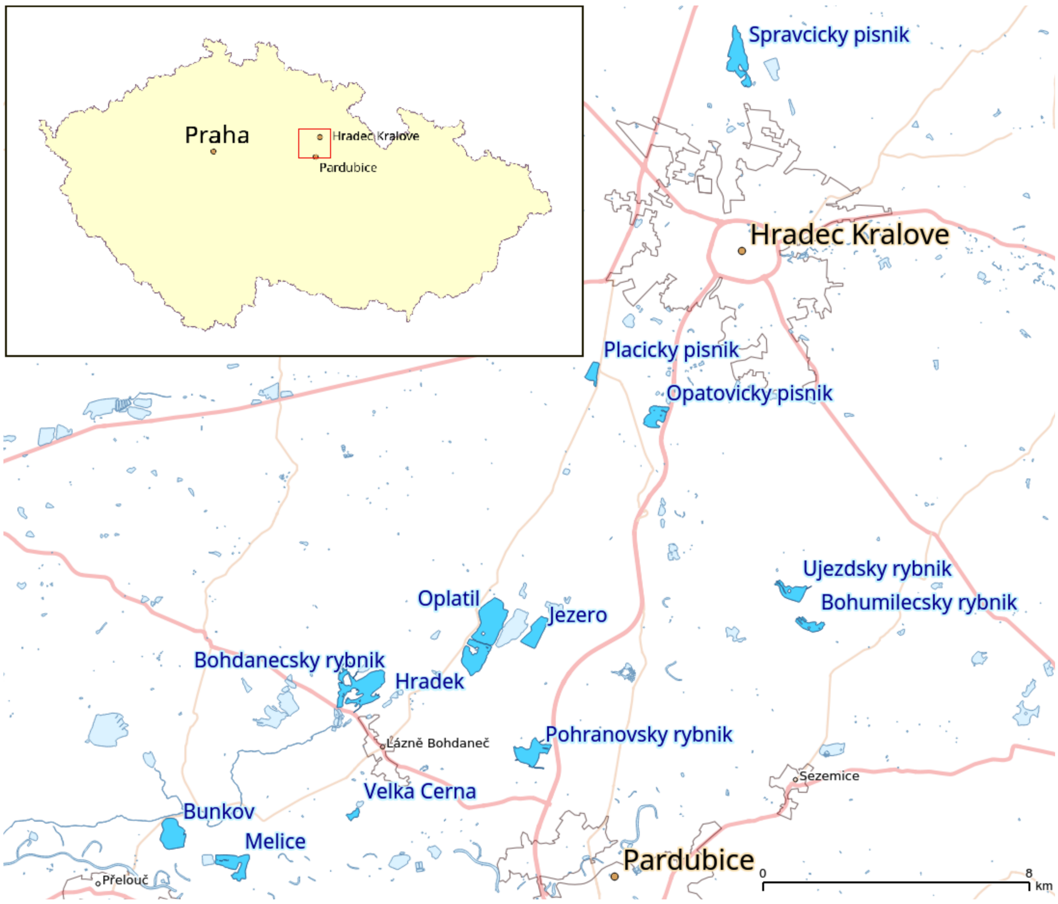

Illustration 2: Study Area

1.1 In Situ and Laboratory

Samples for this research work were taken from autumn of 2011 to the spring of 2015. In all 13 inland water bodies were covered during field measurement. These field measurement were done on or close to the day and time of satellite overpass over the Czech Republic as much as possible. A GPS unit Trimble Juno SB was used for recording the geo-location to identify the coordinates of sampling points. The samples taken were from about 10cm approximately and kept in a cooling box with dark conditions effectively making sure the samples were not destroyed. 1.5 litres of each of the water bodies sampled were collected. Readings of temperature were made using a digital thermometer like wise the Secchi disk depth was done using a 20cm diameter Secchi disk. The inland water bodies sampled are *Bohdanecsky rybnik, Bohumilecsky rybnik, Bunkov, Hradek, Jezero, Melice, Opatovicky pisnik, Oplatil, Placicky pisnik, Pohranovsky rybnik, Spravcicky pisnik, Ujezdsky rybnik, Velka Cerna.*

The weather conditions that prevailed during the times of sampling were quite calm and had intermittent cloudy conditions, whilst visibility (general atmospheric clarity) was generally good.

Ground collection of data has been suggested by some researchers to done nearly simultaneously with Landsat overpass as this reduces the errors when calibrating algorithms[18] [25] [26]. Other researchers have suggested that measurements made 10 days before or after the satellite overpass is acceptable [2], a day before or after the satellite overpass is also suggested by some researchers as they believe it brings better correlation but if the revisit time may bring some loss in correlation [26]. In this research work in situ measurements were mostly made a day of satellite overpass. Situations where not possible, they were taken a day before or after the overpass.

Analysis of Chl-a was always done in the laboratory in consonance with ISO-10260 [28] and a Fisher micro fibre with 0.7 μm pore size. Regarding pigment extraction this was done by grinding the filter in ethanol of 90%. Then the extract was hot water bathed at a temperature of 75 ºC for 5 mins and afterwards allowed to cool for 15 mins before been put in a refrigerator for another 30 mins minimum. Refrigerating it was concentrate the chlorophyll-a spectrophotometric determination. Using a TOC/TN analyser, Total Organic Carbon (TOC) and Total Nitrogen (TN) were analysed directly using collected samples. In situ measurements made are summarised in table 1.

The samples and measurements that did meet the quality check done on the satellite data in the location of measurement points were all removed. Thus not all the point were used in the model creation. Within the table all the empty cells shows that no measurement was made for that particular water quality parameter.

Table 1: In situ measurement, mean and standard deviation (std dev)

Date	Samples	Chl-a	TC [mg/l]	TOC [mg/l]	TN [mg/l]	T [°C]	SDD [cm]
2011.09.15	9	1.5-71				19.5-20.9	
2011.09.26	9	0.2-29					
2012.05.29	9	2.2-31.9	53.31-58.9	16.0-18.1	0.16-0.18	21-23.4	21.5-480
2012.06.22	4	2.9-36.3	34.2-71.5	8.48-21.31	0.1-0.16	24.2-26.3	62-186
2012.07.31-01.08	8	0.7-9.7				26.3-28.4	44.5-228
2012.09.18	3	3-68.9	31.2-84.11	6.15-30.63	0.1-0.19	19.5-22.2	15-220
2012.11.14	6	2.2-8		4.16-6.86		8.3-9.2	240-635
2013.04.23	6	3.9-7.3	38.16-43.16	4.55-9.53	0.11-0.15	11.5-13.8	123-184
2013.05.09	4	0.4-20.9	35.01-60.81	6-19.06	0.31-1.68	18.7-22.7	52-620
2013.06.19	10	0.2-65.7	39.19-72.23	7.7-34.85	0.36-3.19	25.1-29.9	19-364
2013.07.29	9	0.5-49.5	26.8-99.55	5.41-43.86	0.36-3.52	26.6-29.9	22-485
2013.08.12	8	0.4-4.7	26.8-45.48	4.63-12.2	0.5-1.23	24.7-52.2	65-499
2014.05.21	8	0.7-8.1	31-52.81	8.18-14.96	0.62-1.4	18.8-21.6	125-275
2014.07.23	7	0.2-34.9	35.7-95.58	6.4-42.17	0.59-3.35	24.6-25.8	23-325
2014.09.16	6	1.9-39.1	33.96-85.22	5.8-30.92	0.59-2.54	20.3-21	24-490
2015.04.21	8	5.1-35.6	34.49-46.24	7.08-15.51	0.78-1.57	11.9-15.1	66-255
Mean		**12.42**	**48.12**	**13.82**	**0.94**	**21.65**	**207.26**
Std Dev		**16.53**	**19.18**	**10.1**	**0.85**	**6.08**	**168.02**

1.2 Satellite Data, Processing & Smoothing

Images from Landsat 7 ETM+ for this work was with a spatial resolution of 30 by 30m. The area of study is fully covered by both Landsat 7 ETM+ scenes of WRS-2, path row 190/25 and 191/25. This had an average revisit time of 8 days. The images used were downloaded from earth explorer (http://earthexplorer.usgs.gov). The data analysed was from individual sample dates. There was an issue of missing data strips in Landsat 7 ETM+ imagery [29]. This issue was resolved by removing all affected measurements from the processing. Spectral bands used were Landsat 7 ETM+ bands 1 to 8 (450nm – 2350nm) and this falls within blue to mid-infrared nominal spectral location and has radiometric resolution of 256 digital numbers [30] [31].

There were issues with cloud cover and shade. This had impact on some of the images that had to be processed for this work. In dealing with this issue identification of the areas affected by haze and clouds was by using RGB combination [26]. With the RGB combination, bands 1,6,6 (illustration 3) was used to identify all areas affected by clouds and haze. Based on this tool these areas affected were relatively hazy. Furthermore by using the true colour imagery adapting a fixed colour interpretation it also helped in checking problematic sample points were identified as all images used were checked. All the sample points identified to be problematic were then removed.

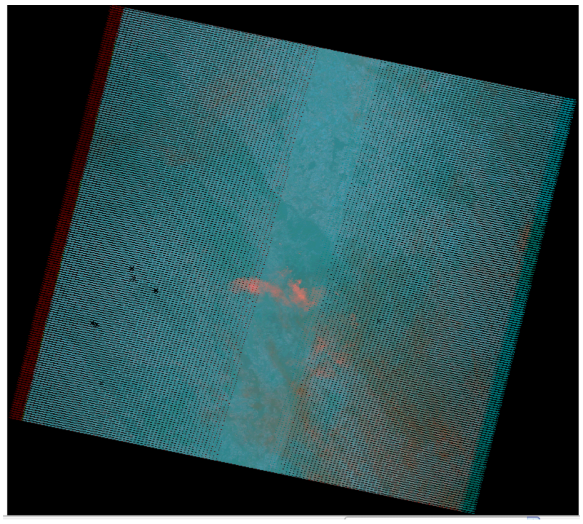

Illustration 3: RGB combination 1,6,6

Different levels of processing were applied to satellite data as model development were initiated. Firstly the DN extracted from Landsat 7 ETM+ were converted to TOA (Top of Atmosphere) reflectance. Aside DN data, surface reflectance (SR) product by USGS (http://earthexplorer.usgs.gov) was downloaded and used. Band 6 of ETM+ (10400-12500 nm) is the thermal infrared band. DN's were converted to top of atmosphere radiance, since this band is not available as atmospherically corrected [32].

To reduce the negative impact of noise in the imagery on the models, image smoothing was used. A water only mask was created based on a detailed vector map of inland water bodies in Czech Republic (illustration 4) and used first to mask out the area that the averaging 3×3 window was used.

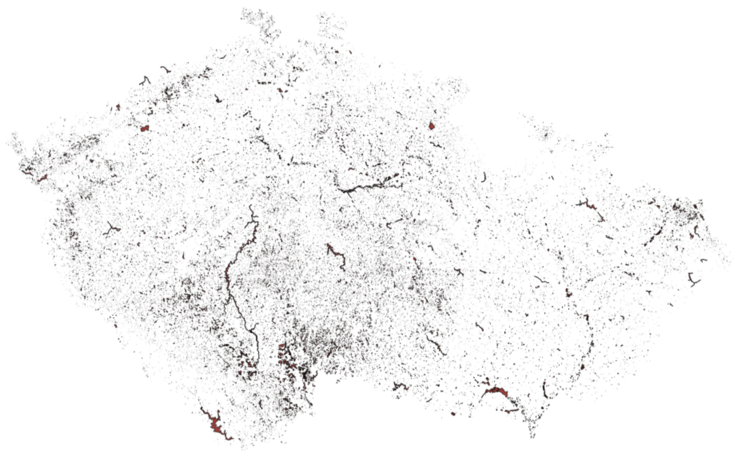

Illustration 4: Water areas only in the Czech Republic

The effect of noise was limited by the use of the smoothing technique, non-water areas such as vegetation along these water banks were eliminated by the water only mask. Using the 3×3 averaging window (illustration 5), the images were filtered spatially by convolving the image through a small window or the mask. Regarding the pixels of the original image, each pixel was replaced by a weighted average based on the window as well as the neighbouring pixels [33].

Title: 3x3 average, non-null data only
Matrix 3
1 1 1
1 1 1
1 1 1
Divisor: 0
Type: P

Illustration 5: 3x3 averaging window

As a result of this process the resultant values of the pixels within the new image were expressed based on the following,

$$DN_{new} = \sum_{i=1}^{9} Z_i \, DN_{i_{orig}} \qquad (3)$$

Where the *DN* represent the brightness values of the pixels and Zi is divisor, which equals to inverted number of values in the averaging window matrix (here Zi = 1/9). The same formula applies to DN, TOA and SR imagery.

In achieving the above the following steps were followed:

Step 1. Using r.mask command in Grass GIS, a mask was created based on the water areas map. Non water areas were masked out.

Step 2. Using map calculator in Grass GIS, an open water mask was created based on band 7 threshold (Band7<210). This way water areas affected by water vegetation, surface algae cover, accumulated sediment, etc. are masked out (in addition to the mask created in step 1.).

Step 3. Using the r.mfilter in Grass GIS a filter was ran to smooth the open water pixel values using the 3×3 average window.

Effectively, the high and low values are averaged out reducing extreme values, which eliminates possible artificial or unusual correlations that may arise from noise in the imagery [31] [33].

1.3 Developing Models

Monitoring inland water quality through the measurement of the various quality parameters are done based on the changes of their optical properties within the water column [31] [34]. Selection of spectral bands and band ratios for the creation of models for the parameters under consideration was done by evaluating all possibilities with the available bands based on linear r^2 between the measured parameter and every band as well as band combination.

Bands and band combinations that produced relatively good correlation with specific water quality parameter were used to develop the models. The models developed and their outliers showed in the charts that were created were rechecked based on the maps. Through this those that were problematic was removed from the processing.

In assessing the performance of created models, three indices were used in doing so. These were coefficient of determination (r^2), root mean square error (RMSE), normalized root mean square error (NRMSE). The measured parameters were checked as against the estimated values derived from the models. Using these indices and how close the model 1:1 line in the model performance charts, models with the best performance were chosen. These best performance models were then applied to satellite imagery to get the maps of the specific water quality parameters with regard to water surface visible imagery.

2 Results and Discussion

2.1 Spectral Bands Selected for Model Creation and Analysis

In all only with 0.6 and more were considered after the measured parameters were plotted as as against the smoothed extracted values from the Landsat 7 ETM+ image's spectral bands. All the other parameters were considered based on the extracts except temperature (T).

As seen in the table (2) most of the measured parameters had good correlations with either bands L1 (0.450-0.515nm), L2 (0.520-0.605nm), L3 (0.630-0.690nm) or their combinations (ratios). The table shows in terms of Chl-a that Landsat 7 ETM+ bands L1/L3, its inverse or logarithm gave the best correlation. In the case of SSD, L1, L2, L3, their combination (ratios), inverse and their logarithm as was the case in Chl-a gave the best correlations. With regard to TC and TOC they also had the same bands and their ratios as Chl-a and SDD. Though the logarithm of some band combinations gave high correlations does not necessarily mean the models emanating from them would be better. Therefore its worth noting not to compare different modes of correlation based on different regression analysis, example linear and logarithm correlations should not be directly compared. Bands L1 and L2 combination gave the best correlation vis a vis TN.

Table 2: Bands and band combinations considered for the creation of models

Parameter	**Band**	**r^2**	**Parameter**	**Band**	**r^2**
SDD	L1/L2	0.64	TOC	L1/L2	0.62
SDD	L1/L3	0.77	TOC	L1/L3	0.75
SDD	L2/L1	0.69	TOC	L2/L1	0.78
SDD	L3/L1	0.75	TOC	L3/L1	0.90
Log(SDD)	L3	0.71	Log(TOC)	L2	0.71
Log(SDD)	L1/L2	0.61	Log(TOC)	L3	0.64
Log(SDD)	L1/L3	0.80	Log(TOC)	L1/L2	0.73
Log(SDD)	L2/L1	0.74	Log(TOC)	L1/L3	0.76
Log(SDD)	L3/L1	0.90	Log(TOC)	L2/L1	0.81
Chl-a	L1/L3	0.61	Log(TOC)	L3/L1	0.85
Chl-a	L2/L1	0.64	TN	L2/L1	0.75
Chl-a	L3/L1	0.80	TN	L3/L1	0.68
Log(Chl-a)	L3	0.77	TN	L4/L1	0.60
Log(Chl-a)	L1/L3	0.86	Log(TN)	L1/L2	0.70
Log(Chl-a)	L2/L3	0.74	Log(TN)	L2/L1	0.79
Log(Chl-a)	L3/L1	0.80	T	L1	0.88
Log(Chl-a)	L3/L2	0.74	T	L61	0.87
TC	L2	0.67	T	L62	0.88
TC	L3	0.74	T	L1/L61	0.89
TC	L1/L3	0.75	T	L1/L62	0.89
TC	L2/L1	0.62	T	L61/L1	0.90
TC	L3/L1	0.83	T	L62/L1	0.90
Log(TC)	L2	0.66	Log(T)	L1	0.91
Log(TC)	L3	0.73	Log(T)	L61	0.84
Log(TC)	L1/L3	0.77	Log(T)	L62	0.86
Log(TC)	L2/L1	0.63	Log(T)	L1/L61	0.92
Log(TC)	L3/L1	0.84	Log(T)	L1/L62	0.92
TOC	L2	0.71	Log(T)	L61/L1	0.87
TOC	L3	0.69	Log(T)	L62/L1	0.87

From the analysis it proved that bands in the visible region of the spectrum are best suitable for Chl-a analysis. To this extent some researchers have buttressed this point as showed in Bonansea [31], Brezonik [18], Hellweger [13] demonstrated by using Landsat TM and ETM+ bands L2 (0.520-0.625nm) and L3 (0.630-0.690nm) in developing models for Chl-a.

For analysis for temperature (T) was done based on TOA radiance as atmospherically corrected Landsat 7 ETM+ images with thermal infrared bands were not available anymore. Based on linear regression the best correlation for temperature came for the individual thermal band L61 and L62 but as equally surprising was L1 which is usually not the case.

2.2 Models Created and their Performance

All the correlation were analysed which involved the various bands I relation to the measured parameters that are under consideration. Also the different regression models in relation to the measured parameters that were done in situ were constructed. The performance of the models created were tested by checking r^2, RMSE, NRMSE associated with of the model there were created. The ones with the high levels based of the three techniques adapted were considered.

The table 3 shows the best two performing models from each of the parameters under consideration. The range means minimum and maximum measured value of the parameter used in model development, n is the number of measurements used in model development. Based on the predictive models the various parameters were estimated after which performance charts were created for them. These charts showed the relationship between the estimated values of the parameters and the measured (in situ) values of the parameters. Similar charts were created for several models of each water quality parameter and best model was chosen based on the parameters in table 3 and the charts.

Table 3: The best two models of each of the water quality parameters created

Parameter	**Models**	$r2$	**RMSE**	**NRMSE**	**Range**	**n**
SDD [cm]	245.7(L1/L3)-194.4	0.77	102	16.6%	19-635	32
SDD [cm]	10^(-1.819(L3/L1)+3.347)	0.77	105	17.1%	19-635	32
Chl-a [ug/l]	33,66*(L3/L1)^3,405	0.82	8.4	12.8%	0.2-65.7	30
Chl-a [ug/l]	10^(-0.8330(L1/L3)+2.331)	0.82	8.5	12.9%	0.2-65.7	30
TC [mg/l]	53.946*(L3/L1)+15.150	0.83	7.5	13.2%	29.1- 85.2	25
TC [mg/l]	10^(-0.1640*(L1/L3)+1.988)	0.81	8.1	14.3%	29.1- 85.2	25
TOC [mg/l]	33.58*(L3/L1)-6.0159	0.90	3.5	11.5%	4.2-34.8	25
TOC [mg/l]	10^(0,9279*(L3/L1)+0,4906)	0.87	4.2	13.5%	4.2-34.8	25
TN [mg/l]	10^(1.764*(L2/L1)-2.051)	0.78	0.47	15.2%	0.09-3.19	25
TN [mg/l]	3.257*(L2/L1)-2.294	0.75	0.49	16.0%	0.09-3.19	25
T [°C]	0.0154*(L62/L1)-27.05	0.90	1.7	8.0%	8.3-29.9	36
T [°C]	1.1203*L62-302.78	0.88	1.9	8.8%	8.3-29.9	36

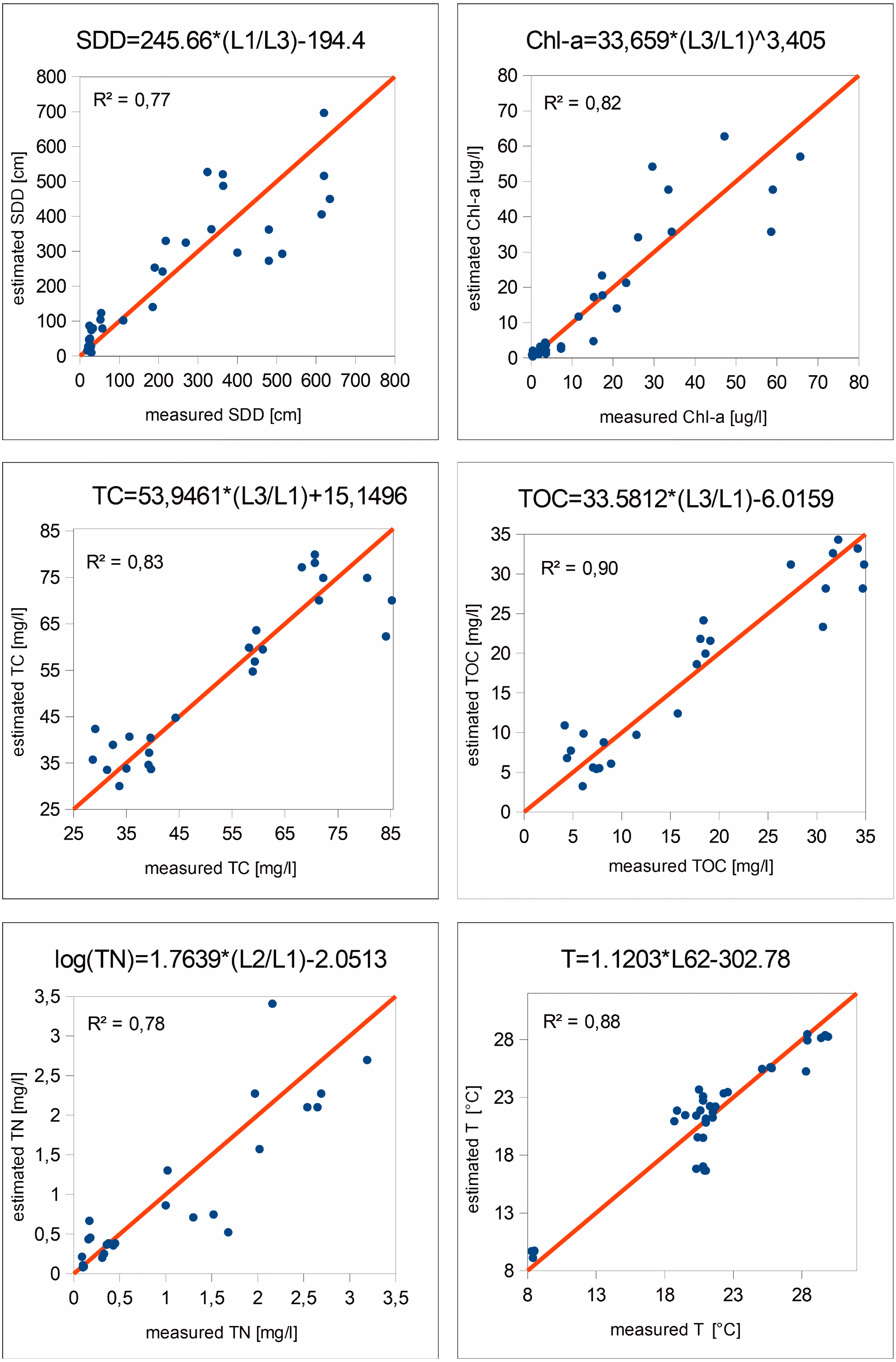

Illustration 6: Performance charts of the best models created

2.3 Chlorophyll-a Model Application

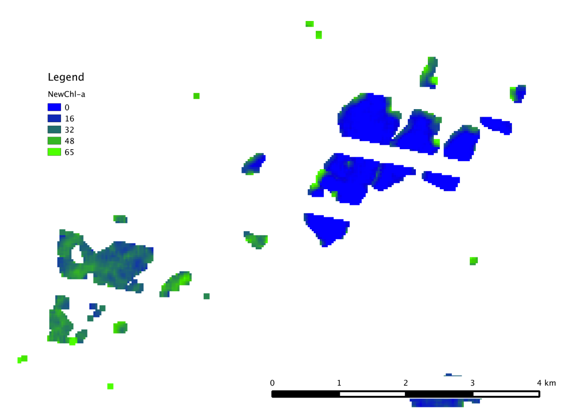

Illustration 7: Chl-a on Oplatil and Bohdanecsky rybnik on 2012.06.23

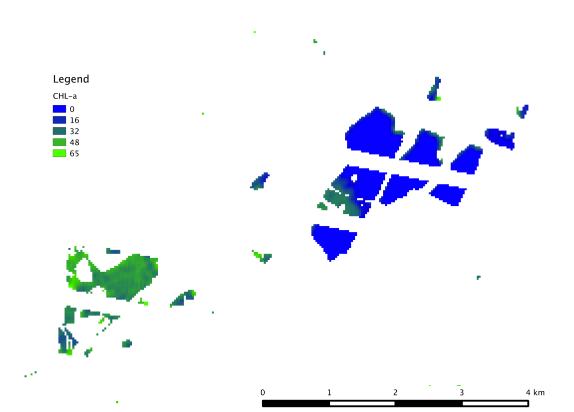

Illustration 8: Chl-a on Oplatil and Bohdanecsky rybnik on 2012.05.29

In the application of the models created the chlorophyll-a levels on Oplatil and Bohdanecsky rybnik were estimated on different seasons of the year from May to November, 2012 (compare with illustration 1 to identify the water bodies by shape). Also visible are two smaller water bodies to the east of Oplatil and several very small ones scattered in the area. The estimated levels of Chl-a were based on the model 33,66*(L3/L1)^3,405. Bohdanecsky rybnik is a protected national reserve as it serves as a breeding habitat for numerous species of birds. Based on models that have been developed the various water quality parameters of such water bodies could be estimated without disturbing the habitat of these birds. The average levels of Chl-a for the Bohdanecsky rybnik and Oplatil were computed based on the model. This was to estimate time line of Chl-a for the two water bodies, showing an example of how model could be used. It should be noted, that Chl-a levels could be estimated also for all the smaller water bodies visible in the map. The average for Oplatil and Bohdanecsky rybnik for June the average Chl-a concentrations as per the model were 4.9 ug/l, 64.4 ug/l (illustration 6). For the 23rd of 29th of May 2012 was 3.5 ug/l and 33.6 ug/l (illustration 7), respectively.

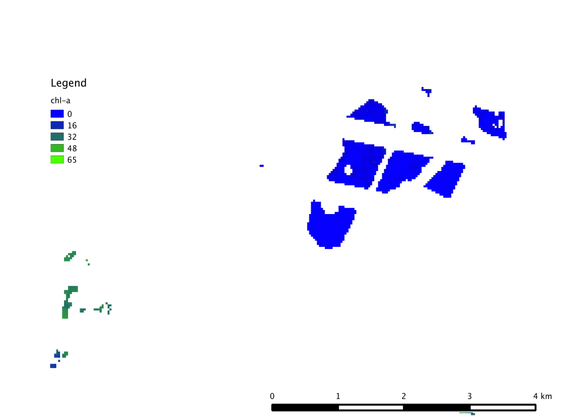

Illustration 9: Chl-a on Oplatil and Bohdanecsky rybnik on 2012.09.11

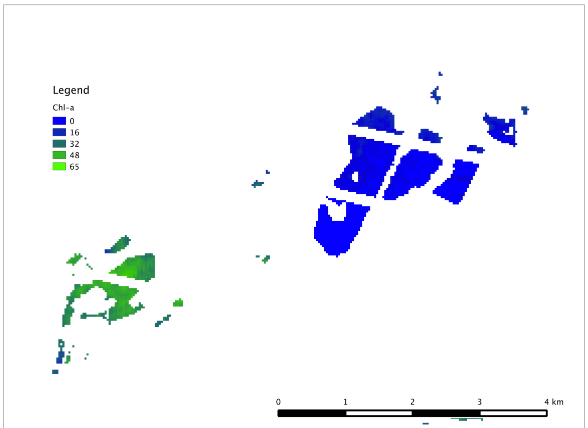

Illustration 10: Chl-a on Oplatil and Bohdanecsky rybnik on 2012.08.01

The next date (11th of September, 2012) showed 4.1 ug/l, 52.4 ug/l (illustration 8) for Oplatil and Bohdanecsky rybnik. That for 1st of August averages for the two water bodies were 2.8 ug/l and 39.6 ug/l (illustration 9). 18th of september showed averages of 5.3 and 42.3 illustration 10) respectively. For the 14th of november the average Chl-a were 1.9 ug/l for Oplatil and 27.0 ug/l for Bohdanecsky rybnik illustration 11)

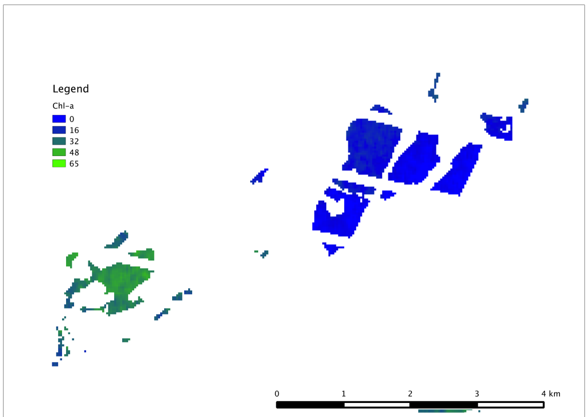

Illustration 11: Chl-a on Oplatil and Bohdanecsky rybnik on 2012.09.18

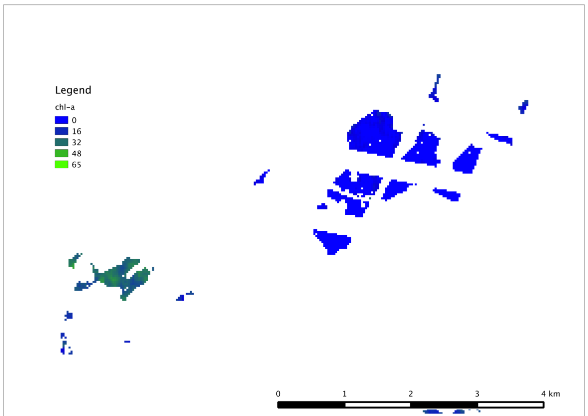

Illustration 12: Chl-a on Oplatil and Bohdanecsky rybnik on 2012.11.14

Bohdanecsky rybnik and Oplatil water were measured based on the model developed (60.3921*L3/L1-25.5008) for Chl-a. This was to estimated time line of Chl-a for the two water bodies, showing how the models really work. The average for Bohdanecsky rybnik and Oplatil for 9th of May 2012 was 34.84 ug/l and 5.48 ug/l (illustration 12) respectively. For the 22nd of June the average measurements as per the model were 8.71 ug/l, 47.58 ug/l (illustration 12). The next date(1st of August, 2012) showed 6.96 ug/l, 43.27 (illustration 12) for Oplatil and Bohdanecsky rybnik. That for 11th of september averages for the two water bodies were 3.63 ug/l and 37.86 ug/l (illustration 12). 18th of september showed averages of 9.59 and 39.08 (illustration 3.30) respectively. For the 14th of november the average Chl-a were 0.61 ug/l (illustration 12) for Oplatil and 31.08 ug/l (illustration 12) for Bohdanecsky rybnik. The highest average for Bohdanecsky rybnik was in June whereas that of Oplatil was in september.

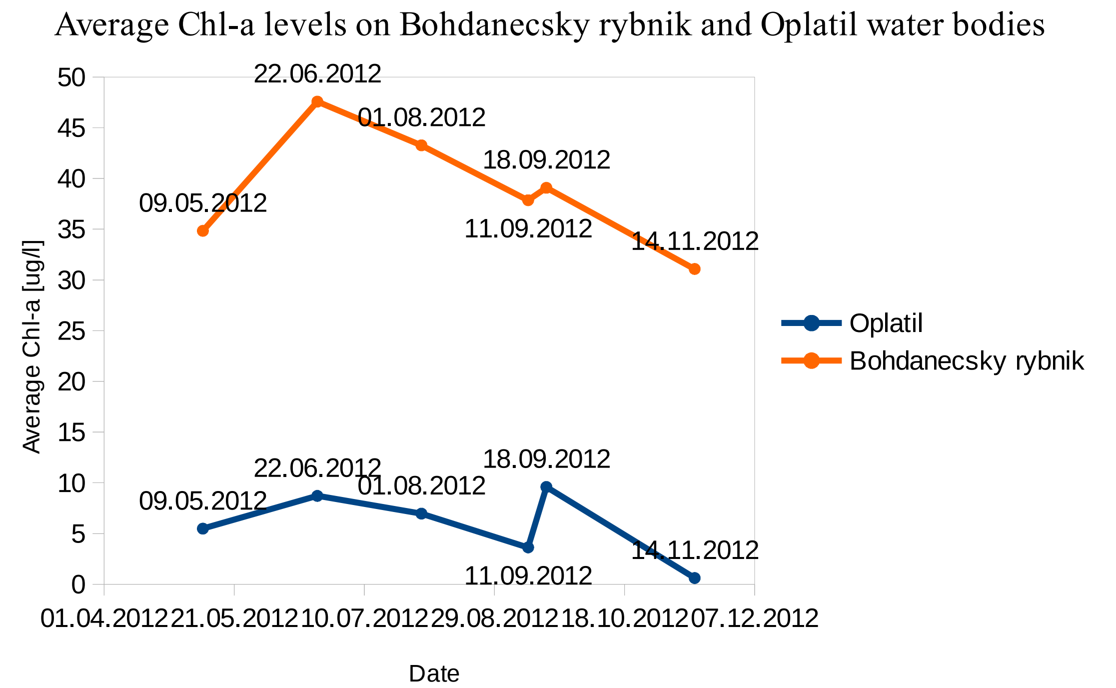

Illustration 13: Average Chl-a levels for Bohdanecsky rybnik and Oplatil in 2012 based on Model developed for Chl-a

Conclusion

In this era where water quality and security has become an issue. The effective monitoring of all available inland water resources is of much importance. The process of monitoring these water bodies by relying solely on traditional methods (in situ, laboratory) for are very expensive, time consuming and tiring. Therefore the need for other likely methods for monitoring inland water bodies can not be over emphasised. Mostly bigger inland water bodies such as lakes, ponds, reservoirs that catch the attention of the public and environmental authorities eye are the bigger ones.

In looking at the use of remote sensing as a tool for monitoring inland water bodies the following objectives were set. First to create a model for estimating the levels of inland water quality parameters based on Landsat ETM+ data. Secondly to access the effects of smoothing on the models developed because of the sizes of the water bodies that were to be monitored. Three the effects of atmospheric correction on the models that were developed.

In analysing data statistically Toar and atmospherically corrected were those that were considered. The use of RGB band combination did aid the identification of areas covered by hidden clouds, cloud shade and haze. This made it possible to identify and remove sample points which were affected by these phenomenon.

The effect of noise on remotely sensed images is an issue. Even so are the sizes of the inland water bodies that were sampled. When dealing with bigger water bodies its easier to reduce the impact of noise on the images. Masking out non water areas made smoothing effective. This buttresses the point that smaller water bodies can still be smoothed if an effective mask is used as seen in illustration 4. All non water areas were masked to avoid contamination of the water pixels by nearby land covers because of the use of 30m resolution satellite data. Smoothing can also make the models worse but in this case it didn't and instead brought about improvements. Atmospheric correction did also improve the overall data though in some situations it reduced correlation as visible. Atmospherically corrected Landsat ETM+ images request from USGS. These images were corrected based on the 6S algorithm as expounded by Masek et al [35].

From the models its evident that most of the water quality parameters had varied r^2 values though in some it was low vis a vis bands and band combinations that falls within the range 450 (blue) – 900 (Near infrared) nm with the exception of temperature which clearly shows in table 2. For the substantive water quality parameters, Chl-a the combination of bands 3 (Red 630 – 690 nm) and l (Blue 450 – 515 nm) gave the best fit for the models with r^2 value. SDD had the best fit based on band combination L3/L1 just as Chl-a. TC likewise had the best fit based on the band combination L3/L1. Band combination L3/L1 (Red 630-690/Blue 450 – 515 nm) gave TOC the best fit. Temperature whose model was developed based on thermal band. Based on the just enumerated results showed there was to an extent some inter-correlation amongst the various water quality parameters (TC, TOC, TN, Chl-a, SDD).

The reliance on Landsat data helped in creating models that cover the various water bodies that were monitored for the various water quality parameters (TC, TOC, TN, Chl-a, SDD, T) that were measured. There exists a huge potential in the use of remote sensing as a tool in the monitoring of inland water quality. Though mostly small sized inland water bodies monitored in this research it showed clearly that Landsat ETM+ data can be relied on for monitoring of inland water quality parameters as shown by the models developed. Though data for smaller inland may be a bit problematic smoothing, when a right water only mask is adapted this can be possible. Regarding inter-correlation between Chl-a and the other inland water quality parameters, it showed that to some extent there exist correlation. Especially Chl-a, TOC and SDD in most cases had similar band performances.

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