An Appraisal of the Potential of Landsat 8 in Estimating Chlorophyll-a, Ammonium Concentrations and Other Water Quality Indicators

Vassiliki Markogianni 1,*, Dionissios Kalivas 2 , George P. Petropoulos 3,4 ID and Elias Dimitriou 1 ID

Remote Sens. 2018, 10, 1018; doi:10.3390/rs10071018

Introduction

- Lake water is an essential renewable ecological resource and highly essential in the global economy since it is exploited for civil, industrial, recreational purposes…

- It is therefore imperative to consistently monitor both inland and Ocean Water quality for sustainable consumption(SDG6 & 14) to meet the growing population needs.

- Satellite RS esp. Landsat 8 OLI has demonstrated a great potential in inland water quality monitoring and intelligent decision making for sustainability.

- Further coupling this with *In-situ* sensors is highly cost-effective esp. when investigating long term multi-scale temporal analysis.

Problem

- The globally increasing population has negatively exerted anthropogenic pressure on natural resources and demand for fresh water thereby posing a global danger to the water quality of lakes.
- Moreover the effect of climate change (global warming) is further steering this.

- There's thus need to incorporate Satellite RS to improve inland water quality monitoring and Lake Management.

- Monitoring spectral variability info and indices on NIR, Red & Blue band can help estimate photosynthetic *Chl-a* concentration etc. to help make informed decisions on inland water body quality.

Study Area

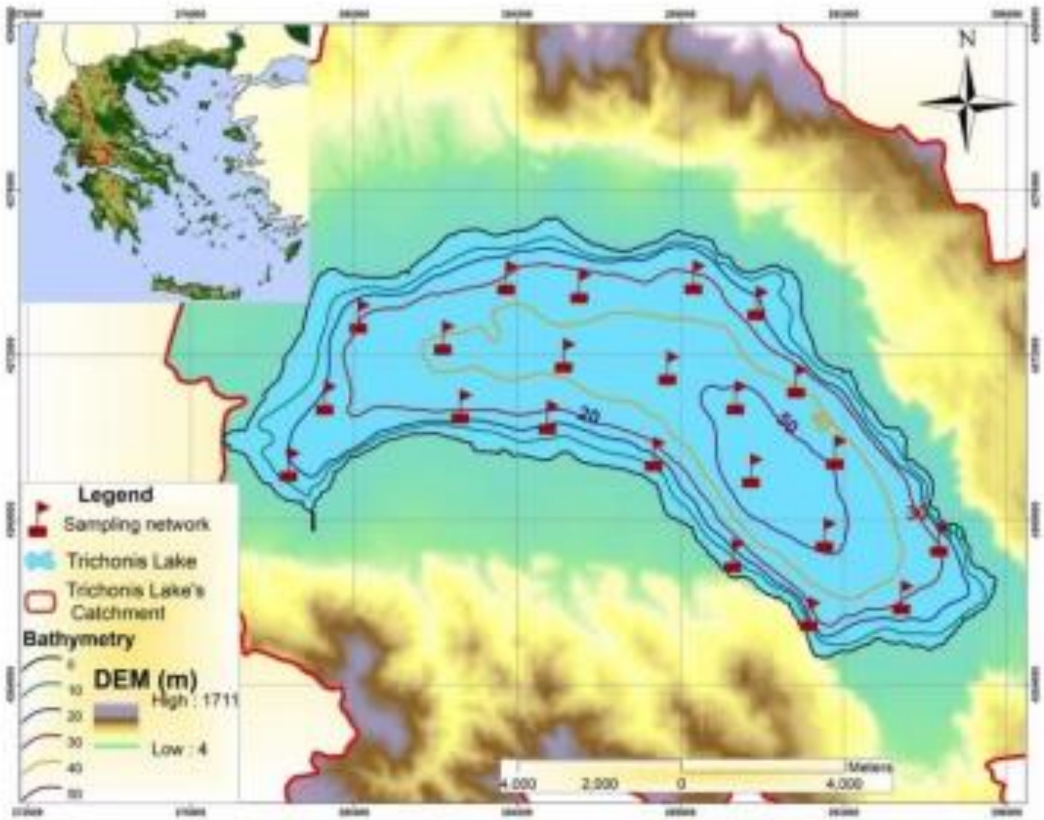


Fig 1.Lake Trichonis,-Greek bathymetry, chl-a and nutrients' samples, October 2013 and late August 2014.

Imagery Used

Table 2. Landsat 8 spectral bands, wavelengths and spatial resolution.

Bands	Wavelength (Micrometers)	Resolution (Meters)
Band 1—Ultra Blue (coastal/aerosol)	0.435–0.451	30
Band 2—Blue	0.452–0.512	30
Band 3—Green	0.533–0.590	30
Band 4—Red	0.636–0.673	30
Band 5—NIR	0.851–0.879	30
Band 6—Shortwave Infrared (SWIR) 1	1.566–1.651	30
Band 7—Shortwave Infrared (SWIR) 2	2.107–2.294	30
Band 8—Panchromatic	0.503–0.676	15
Band 9—Cirrus	1.363–1.384	30
Band 10—Thermal Infrared (TIRS) 1	10.60–11.19	100 × (30)
Band 11—Thermal Infrared (TIRS) 2	11.50–12.51	100 × (30)

Table 3. Selected spectral indices calculated, according to literature.

INDEX	EQUATION	Source
Enhanced Vegetation Index (EVI)	$EVI = G \times ((nir - red)/(nir + C1 \times red - C2 \times blue + L\_evi))$	[52]
Normalized Ratio Vegetation Index (NRVI)	$NRVI = (red/nir - 1)/(red/nir + 1)$	[53]
Normalized Difference Water Index (NDWI)	$NDWI = (green - nir)/(green + nir)$	[54]
Normalized Difference Water Index (NDWI2)	$NDWI2 = (nir - swir2)/(nir + swir2)$	[55]
Modified Normalized Difference Water Index (MNDWI)	$MNDWI = (green - swir2)/(green + swir2)$	[56]
Green Normalized Difference Vegetation Index (GNDVI)	$GNDVI = (nir - green)/(nir + green)$	[57]
Normalized Difference Vegetation Index (NDVI)	$NDVI = (nir - red)/(nir + red)$	[58]

Overall Methodology

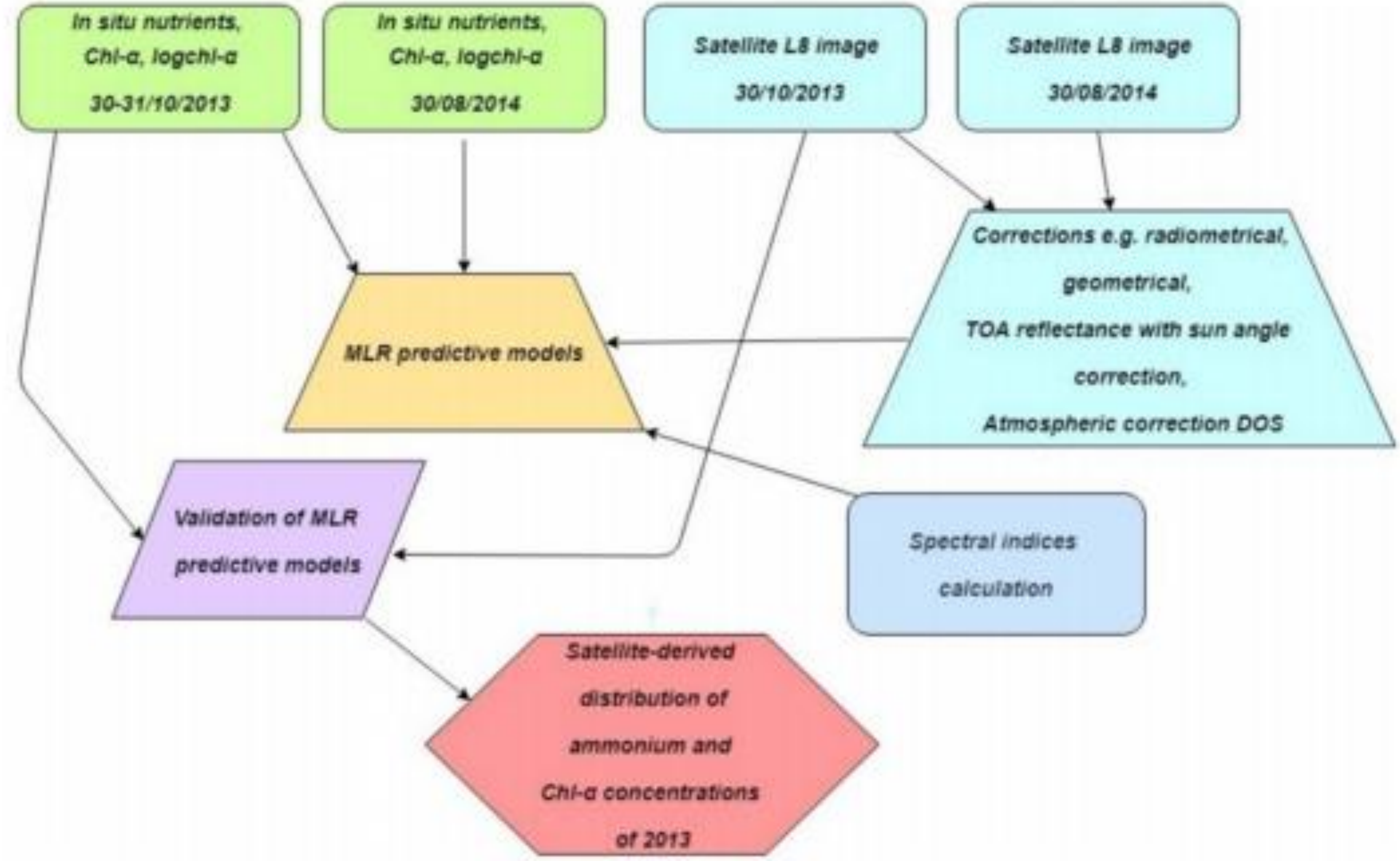


Figure 2. A flow chart summarizing the methodology adopted in this study.

Preprocessing Steps

- Geometric Corrections:

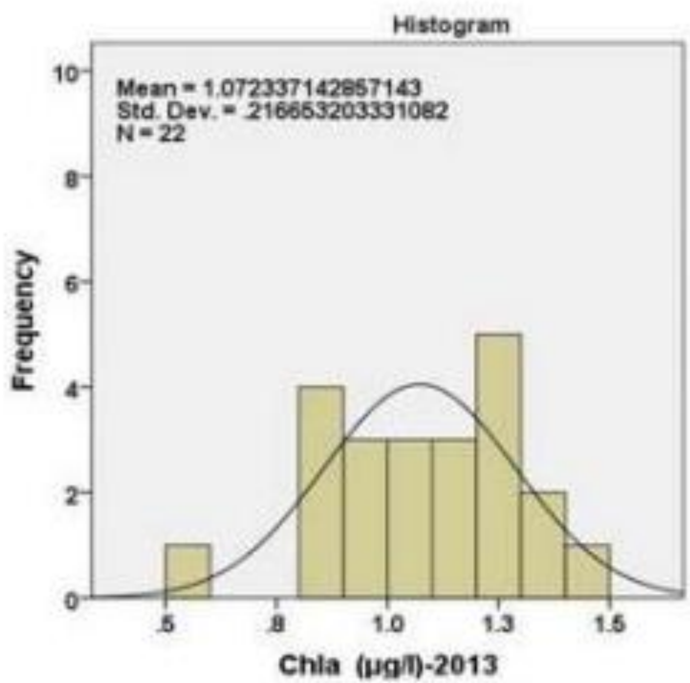
  -GCPs
- Radiometric Corrections:
  - Dark Object Subtraction(DOS)
  - Sun angle correction
  - Earth-Sun distance

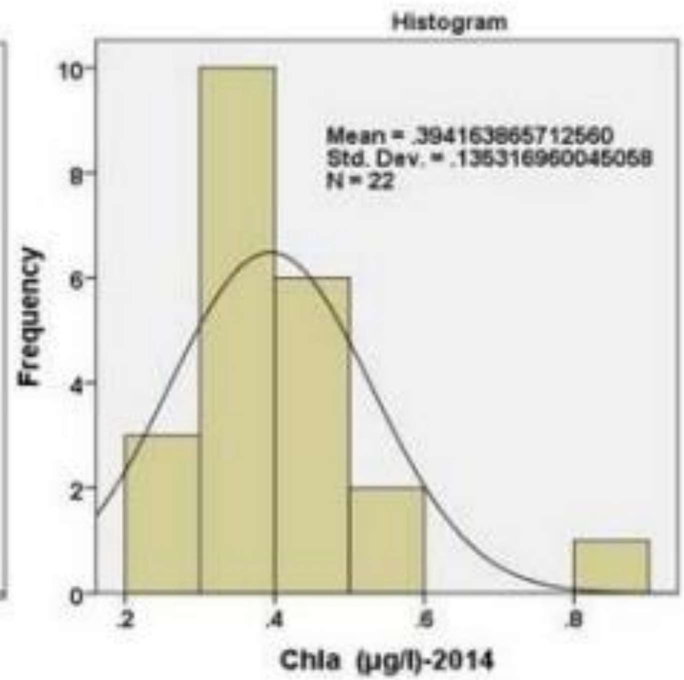
- Landsat 8 images clipped to study area
- *In-situ* data buffered to a zone of 90m form each sensor

Results 1

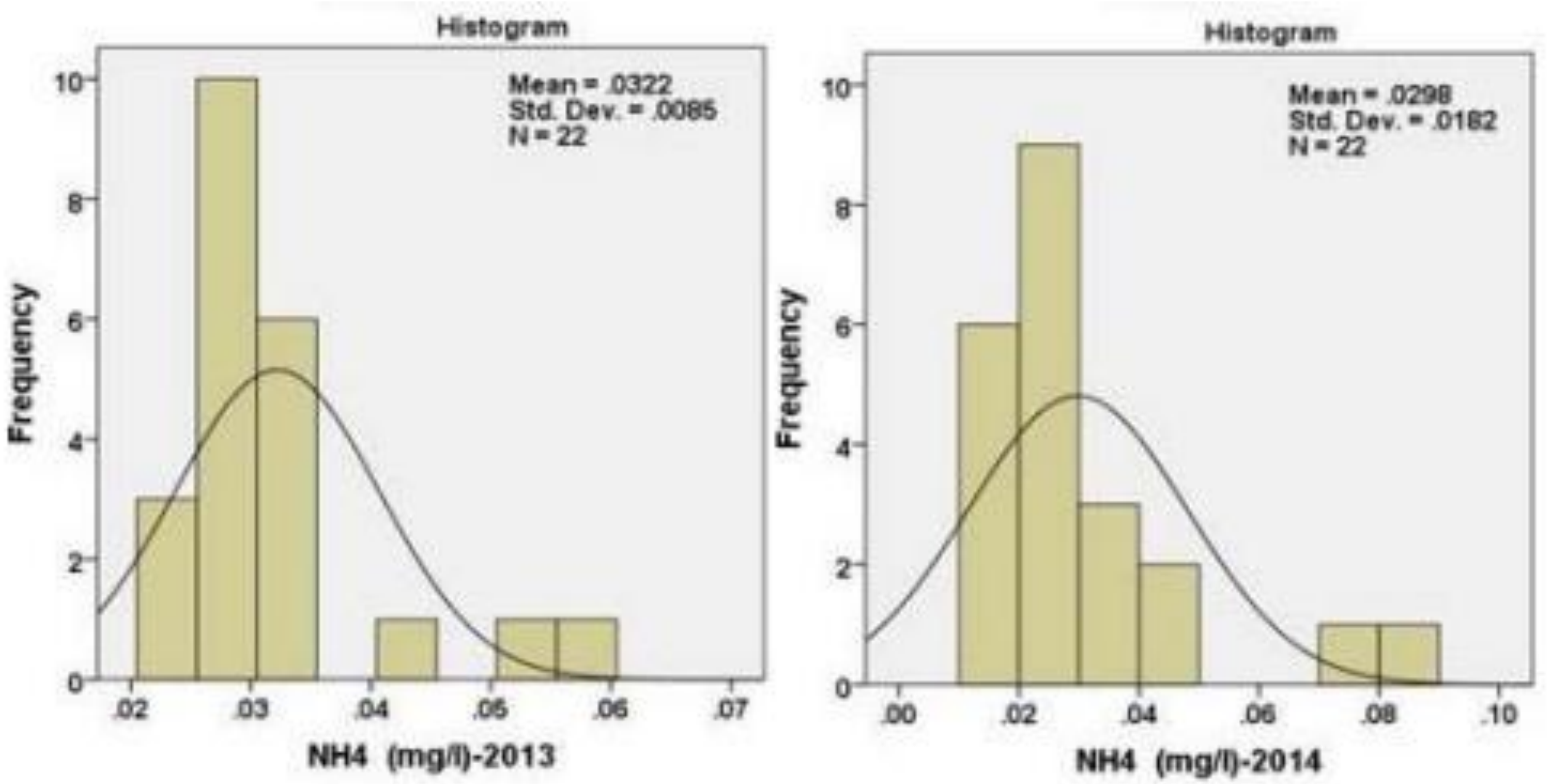
Statistical Summary of In-Situ Measurements and Water Quality Classification

- Frequency graphs presenting the distribution of the in-water constituents (Chl-a and NH_4^+) for both years
- Nitrate, nitrite, phosphate and total nitrogen were 2014 were lower than in 2013





Results 1…


Histogram
Mean = .0322
Std. Dev. = .0085
N = 22
Frequency
NH4 (mg/l)-2013
Histogram
Mean = .0298
Std. Dev. = .0182
N = 22
Frequency
NH4 (mg/l)-2014

Tabular In-situ Data Results for ‘13 & `14

Table 4. Descriptive statistics-Summary tables of in-situ Chlorophyll-*a*, Total phosphorus and ammonium concentrations of 2013 and 2014.

	Chl-*a* (µg/L)-2013	Chl-*a* (µg/L)-2014	TP (mg/L)-2013	TP (mg/L)-2014	NH_4^+ (mg/L)-2013	NH_4^+ (mg/L)-2014
N	22	22	22	22	22	22
Range	0.898	0.66	0.06	0.05	0.04	0.07
Minimum	0.53	0.22	0.03	0.01	0.02	0.01
Maximum	1.43	0.88	0.08	0.06	0.06	0.09
Mean	1.07	0.39	0.04	0.02	0.03	0.03
Std. Deviation	0.22	0.14	0.01	0.01	0.01	0.02
Variance	0.05	0.02	0.0	0.0	0.0	0.0
CV (%)	20.2	34.3	29.6	60.0	28.1	60.0
Skewness	−0.51	2.15	1.22	1.86	2.06	1.99
Std. Error	0.49	0.49	0.49	0.49	0.49	0.49
Kurtosis	0.19	7.42	2.12	3.71	4.59	3.88
Std. Error	0.95	0.95	0.95	0.95	0.95	0.95

Results 2:
M-Linear Regression Analysis and Predictive Models

The 2014 correlation analysis, between the Band Spectral reflectance & In-situ data, were more correlated as compared to data of 2013.

The spatial distribution of spectral indices, measured from satellite image of 2014, also indicated the greatest value range in NDVI values (0.0227) while the lowest is in the EVI index.

Chlorophyll-a can be measured initially by using vegetation indices based on the Green and SWIR bands of water indices (NDWI, MNDWI).

Statistical Summary of L8 Spectral Bands

Table 8. Descriptive statistics-Summary tables of selected spectral indices calculated from satellite image of 2014.

2014	N	Range	Min	Max	Mean	Std. Deviation	Skew-ness	Std. Error	Kurto-Sis	Std. Error
EVI	22	0.0001	−0.002	−0.002	−0.002	0.0	0.17	0.49	1.32	0.95
NRVI	22	0.0002	−1.002	−1.002	−1.002	0.0	−0.58	0.49	−0.3	0.95
NDWI	22	0.0064	0.86	0.87	0.87	0.002	0.46	0.49	−0.6	0.95
MNDWI	22	0.0021	0.94	0.94	0.94	0.0005	0.02	0.49	0.08	0.95
GNDVI	22	0.0218	−0.424	−0.4	−0.42	0.006	0.72	0.49	−0.08	0.95
NDVI	22	0.023	−0.29	−0.26	−0.28	0.006	0.797	0.491	0.46	0.953

Table 9. Regression analysis statistics and models' summary among multiple spectral indices and log-chlorophyll-*a* concentrations (dependent variable).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	0.578 [a]	0.334	0.126	0.12	0.334	1.608	5	16	0.214	
2	0.576 [b]	0.332	0.175	0.12	−0.002	0.054	1	16	0.819	
3	0.493 [c]	0.243	0.117	0.12	−0.089	2.275	1	17	0.150	
4	0.473 [d]	0.224	0.142	0.12	−0.019	0.449	1	18	0.512	2.235

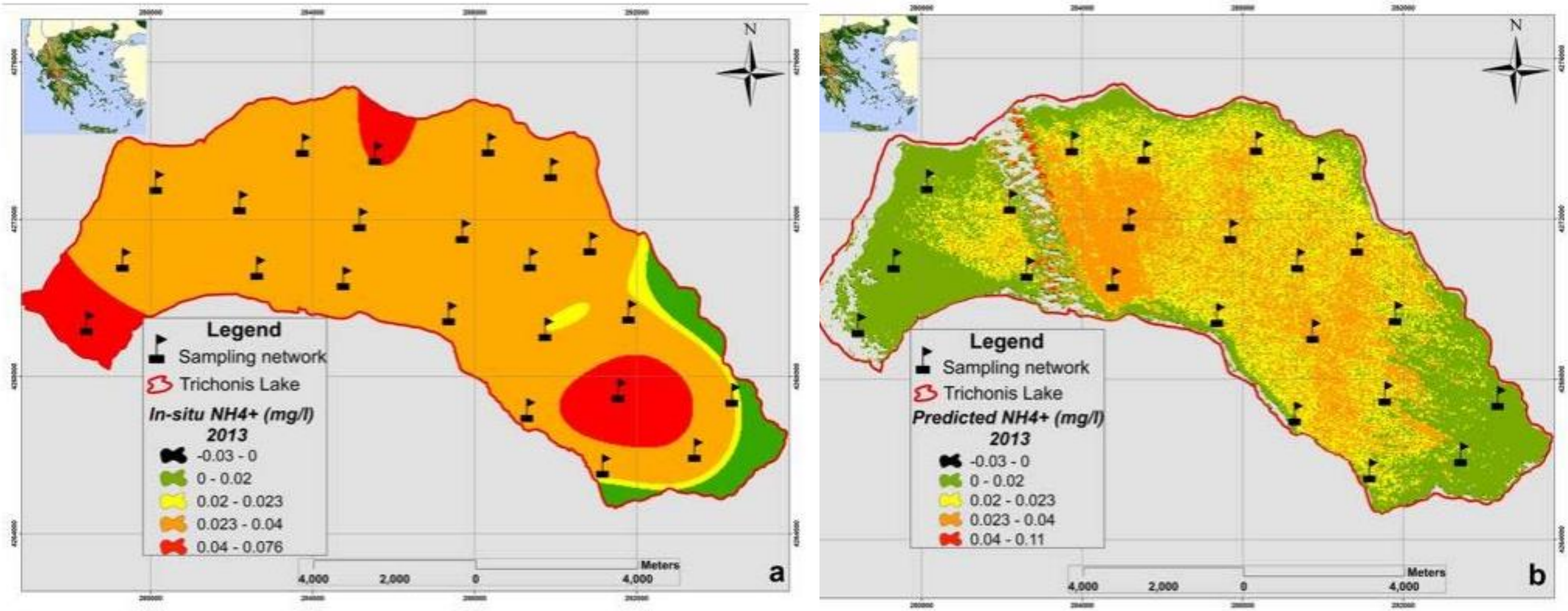
Dependent Variable: LOGCHL-A; [a] Predictors: (Constant), NDVI, MNDWI, EVI, NDWI2, NRVI; [b] Predictors: (Constant), NDVI, MNDWI, EVI, NDWI2; [c] Predictors: (Constant), NDVI, EVI, NDWI2; [d] Predictors: (Constant), NDVI, NDWI2.

Algorithm Validation

Ammonium concentration assessment model with R = 0.7, then *chl-a* cubic model 0.5 and finally *logchl-a* predictive model with similar values between cubic and quadratic models, 0.4 and 0.41

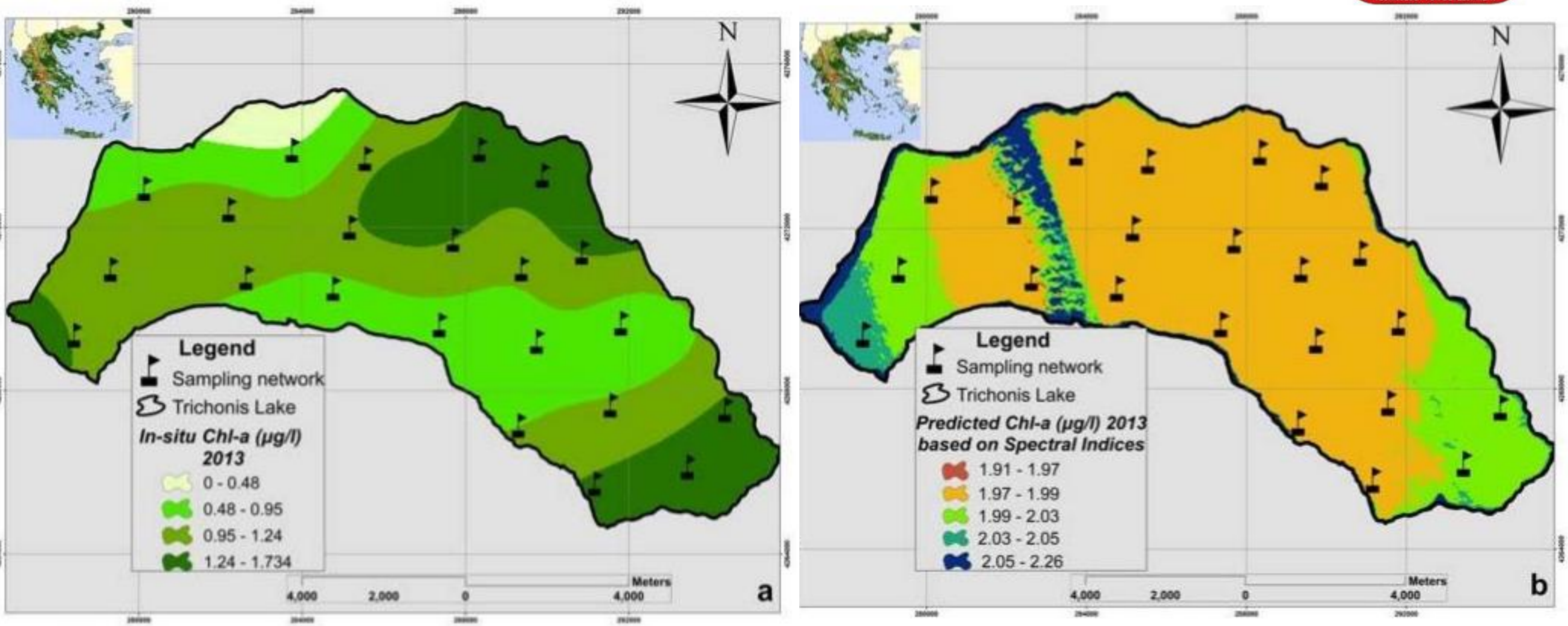
Chl-*a* (μg/L)			Model Summary						Parameter Estimates		
Equation	R^2	R	Std. Error of the Estimate	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.04	0.2	0.22	0.71	1	17	0.41	1.95	0.25		
Logarithmic	0.05	0.2	0.22	0.89	1	17	0.36	2.19	0.29		
Quadratic	0.2	0.44	0.21	1.92	2	16	0.18	−2.28	8.27	−3.72	
Cubic	0.2	0.5	0.21	1.99	2	16	0.17	−0.96	4.42	0.0	−1.18
Power	0.1	0.23	0.09	0.92	1	17	0.35	2.18	0.13		
Exponential	0.04	0.2	0.095	0.72	1	17	0.41	1.96	0.11		
NH_4^+ (mg/L)			Model Summary						Parameter Estimates		
Equation	R^2	R	Std. Error of the Estimate	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.11	0.33	0.01	2.36	1	20	0.14	0.03	−0.22		
Logarithmic	0.06	0.25	0.01	1.36	1	20	0.26	−0.001	−0.01		
Quadratic	0.37	0.61	0.01	5.67	2	19	0.012	−0.02	2.33	−31.7	
Cubic	0.47	0.69	0.004	5.42	3	18	0.01	0.09	−6.63	208.94	−2038.7
Power	0.18	0.42	0.379	4.31	1	20	0.05	0.001	−0.76		
Exponential	0.26	0.51	0.36	6.84	1	20	0.02	0.04	−24.2		
Chl-*a* (μg/L) (Spectral Indices)			Model Summary						Parameter Estimates		
Equation	R^2	R	Std. Error of the Estimate	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	0.11	0.34	0.016	2.54	1	20	0.13	1.96	0.03		
Logarithmic	0.09	0.3	0.016	1.91	1	20	0.18	1.99	0.02		
Quadratic	0.17	0.41	0.016	1.92	2	19	0.17	2.02	−0.11	0.07	
Cubic	0.17	0.4	0.016	1.22	3	18	0.33	1.998	−0.02	−0.03	0.03
Power	0.09	0.3	0.008	1.91	1	20	0.18	1.99	0.01		
Exponential	0.11	0.34	0.008	2.54	1	20	0.13	1.96	0.01		

Ammonium assessment model alongside RS



(a) In-situ NH4 + (mg/L) spatial distribution of 2013 and (b) Satellite derived NH4 + (mg/L) of 2013 applying the satellite-predictive algorithm.

Chl-a model alongside RS



(a) In-situ Chl-a (μg/L) spatial distribution of 2013 and (b) satellite derived Chl-a (μg/L) of 2013 after applying the satellite-predictive algorithm using L8 spectral indices

Conclusions

- Landsat 8 images & *In-situ* data acquired in 2013 and 2014 were able to monitor chl-a concentration and other water quality indicators for lake Trichonis , Greece.

- Weak correlations were detected among in-situ and satellite data esp. in 2013, while those correlations, particularly in autumn and summer, may also be due to the lake turnover effect.

- In-situ data were able to be transformed (using the log transform) in order to establish a relationship between the data and L8 surface reflectance and spectral indices data.

Proposed Further Studies

- Integrate Landsat 8’s low temporal Resolution with Modis Aqua for improved Temporal Resolutions.

- Use additional in-situ footprint monitoring stations for improved spatial distributions above the 22 used to gather more dataset.
- Investigate how the increasing poor water quality correlate with the health impacts.
- Further investigation is needed, on the incorporation of the SWIR band into *chl-a* estimation as there may be a relationship between SWIR reflection and algae/plant production.

Take home message

- Satellite RS data are key pieces of information for monitoring the effect of climate change on fresh water bodies.
- L8 spectral band indices have the potential to monitor Water quality.
- Logchl-a predictive model based on spectral indices incorporated OLI bands 2 (blue), 3 (green), 4 (red), 5 (NIR) and 7 (swir2) is capable of estimating chlorophyll-a in lakes and reservoirs and more particular vegetation indices.
- Thermal gradient in large water bodies induces mixing of surface and bottom waters, making remote monitoring difficult due to instability, hence weaker correlation between in-situ and RS.
- Sat. RS and In-situ sensors are potential warning indicators of water quality deterioration.

Applications in Kenya

- Assessing spatiotemporal change in Water Quality in fresh water Lakes e.g., L. Victoria by monitoring Chlorophyll-a, Ammonium Concentrations, etc.

- Assessing the impact of intensive floriculture and other anthropogenic activities to Lake Naivasha and impacts on Fish counts.

- Perform a spatial temporal analysis showing the decrease or increase in River Nairobi water quality and Turbidity.