Review on Water Scarcity Analysis Using Remote Sensing Technology

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Abstract: Remote sensing is increasingly used in various applications, including water quality analysis, tracking water uses, and water scarcity analysis in the country. Water is a significant natural resource to sustain life on the earth. Water exists in various forms on the planet, including freshwater, saltwater, vapor, cloud, snow, and ice. The total amount of 70% water, which includes 0.02 Percent freshwater, is available on the planet earth. Day by Day, increasing population and decreasing rainfall have to put a high amount of pressure on the water distribution. The agriculture sector highly consumes freshwater. The article discusses the potential role that algorithms could play with more advanced model-based algorithms in water remote sensing, especially for near real-time water-body monitoring. This article reviews water scarcity and surface water estimation using remote sensing technology.

***IndexTerms* - Waterbody, Satellites, Remote sensing, Water scarcity**

I. INTRODUCTION

Water is the most important thing for all living organisms. The water cycle is continuously running from evaporation, transpiration, condensation, precipitation & runoff. About 70% of the earth's surface is covered by water in the ocean; only a tiny area of the earth's surface presents groundwater. A significant amount of water is present in a glacier, and a small amount of water in steam, cloud, and precipitation. Water has economic importance, whereas 70% of freshwater is used for agriculture (UNESCO-WWAP, 2006). Similarly, it is also highly used for industrial and domestic purposes. The recent launch of many new satellite sensors, and advances in computer technologies, has greatly increased the range of successful water-related remote-sensing applications and improved real-time monitoring of water quality and the rapid detection of environmental threats such as eutrophication and harmful algal blooms (HABs) (Mertes 2002, Ritchie et al. 2003, Glasgow et al. 2004, Power et al. 2005).

Remote sensing sensors allow recording the color of a water body and its content, providing vital information on the water quality (Ogilvie et al. 2015, 2016). The watercolor spectrum is defined as an apparent optical property (AOP) of the water. It means that the color of the water is influenced by the angular distribution of the light field and by the nature and quantity of the substances in the medium (Sriwongsitanon 2011). Thus, the value of this parameter will change in the optical properties and concentrations of the optically active substances in the water, the inherent optical properties, or IOPS. The IOPS are independent of the angular distribution of light but are dependent on the type and substances present in the medium (Sriwongsitanon 2011). For instance, the diffuse attenuation coefficient of downwelling irradiance, Kd (often used as an index of water clarity or ocean turbidity), is defined as an AOP. In contrast, the absorption coefficient and the scattering coefficient of the medium are defined as IOPS (Gitelson 2008).

There are two different approaches to determine the concentration of optically active water components by studying the spectra. The first approach consists of empirical algorithms based on statistical relationships and the second approach consists of analytical algorithms based on the inversion of calibrated bio-optical models. (Gitelson 2008). Accurate calibration of the connections/models used is an essential condition for successful inversion of water remote sensing techniques and determining the concentration of water quality parameters from observed spectral remote sensing data. Thus, these techniques depend on their ability to record these changes in the spectral signature of light backscattered from the water surface and relate these recorded changes to water quality parameters via empirical or analytical approaches. Different parts of the spectrum will be analyzed depending on the water constituents of interest and the sensor used (Ritchie 2003). Table 1.0 shows the information of Satellite sensors primarily used for the water-related study.

Table 1. shows Satellite for water remote sensing

Sr	Satellite	Launch Date,	Sensors,	Resolution and Bands	Agency, Country
1	GeoEye's OrbView-2 (AKA SeaSta	1/08/1997 and 11/12/2010	SeaWiFs,	Spatial Res s 1.1 km (LAC), 4.5 km (GAC), Bands 8,	NASA , USA
2	Terra (EOS AM)/ Aqua (EOS PM)	18/12/1999	MODIS	Temporal resolution: 1-2 days, Spatial resolution: 250 m (bands 1–2) 500 m (bands 3–7) 1000 m (bands 8–36) 36 bands.	NASA,USA
3	Envisat-1	01/03/02	MERIS	spectral rang: 390 nm-1040 nm 15 bands	ESA, Europe
4	Suomi NPP	28/10/2011	VIIRS	Temporal resolution: 16 days, Spatial resolution: 750m 22 bands	Raytheon Company, USA
5	COMS-1	26/06/2010.	GOCI	Temporal resolution: 8 times a day Spectral range: 400-865nm,	KARI/KORDI, USA

				Spatial resolution:500m, 8 bands	
6	ISS	09/10/2009	HICO	spectral resolution: 5.7 nm R : 638.9 nm (band 42) G : 553.0 nm (band 27) B : 461.4 nm (band 11)	NASA, USA
7	EO-1	21/11/2000	Hyperion	Temporal resolution: 16 days Spatial resolution :30m Spectral range: 0.4 - 2.4 µm 220 Bands	NASA, USA
8	Landsat4-5	1982 and 1984	Landsat TM	Spatial resolution: 30m 7 bands	NASA, USA
9	Sentinel 3	16/02/2016	OLCI (Ocean and Land Colour Instrument)	Spectral Band 27	European Space Agency (ESA), Europe
10	SARAL – ALTIKA Satellite with ARGOS and ALTIKA (SARAL)	25/02/2013	4 PI sun sensors, magnetometer , star sensors	Ka band 35.75 Giga Hertz.	ISRO, India

II. LITERATURE SURVEY

In this research paper, we have studied various research articles from the reputed journal. The literature survey is an essential step to carrying out the experimental work, which helps select suitable techniques and algorithms. Similarly, it also helps to understand the recent progress in the targeted research domain. In other words, it is necessary to justify the lacunas of conducted research studies.

Table 2. shows the literature survey

No.	Author/Year	Study Area/Period	Satellite data	Technique.
1	Andrew Ogilvie et al. 2018	1999-2014) for 7 small reservoirs within the Merguellil catchment in Central Tunisia	Landsat Thematic Mapper (TM)5 , and Landsat OLI 8	Daily time series of surface area aggregated and converted into mean annual surface volumes are using landsat dataset.the MNDWI(Modified Normalised Difference Water Index) has used for identification of Water body in the study area R2 value =0.9
2	Gordana Jakovljević Banja Luka, Bosnia and Miro Govedarica & Flor Álvarez-Taboada, 2017	Spain	Sentinel 2 Landsat OLI 8,	Supported Vector Machine (SVM) classifier was adopted for waterbody extraction from Sentinel-2, Landsat 8 Operational Land Imager (OLI) and RapidEye satellite images., Regarding the performance between Sentinel-2 and Landsat 8 OLI, Sentinel-2 obtained the most accurate results (overall accuracy 94.49 vs. 94.17, commission error 1.34 vs. 1.87)
3	Yun Du et al. 2016	Venice coastland, Italy.	Sentinel-2 satellite	In the experiment, six water indexes, including 10-m NDWI, 20-m MNDWI and 10-m MNDWI, produced by four pan-sharpening algorithms, were compared. Three levels of results, including the sharpened images, the produced MNDWI images and the finally mapped water bodies, were analysed quantitatively
4	Fangfang Yao et. al. 2015	Aksu, Fuzhou, Hanyang, Huangpo and Huainan, China	ZiYuan-3 (ZY-3), China	Furthermore, UWEM has more stable performances than NDWI's in a range of thresholds near zero. It reduces the over- and under-estimation issues which often accompany previous water indices when mapping urban surface water under complex environmental conditions. Kappa coefficients improved by 7.87%
5	J.-F. Pekel et al 2014	Belgium	MODIS	The time series analysis of NDWI index has used for the research study, surface product with an independent dataset derived from high resolution imagery, showed an accuracy 25of 91.5% .
6	Li, Wenbo, et al . 2013	Yangtze River Basin inside Hubei province, China	Landsat 7	The accuracies of LSW maps derived from eleven NDWI models showed that five NDWI models of the ALI sensor have more than an overall accuracy of 91% with a Kappa coefficient of 0.78 of LSW maps at three test sites
7	Behera, M. D., et al , 2012	Raebareli district of Uttar Pradesh, india	ResourceSat 1	Satellite remote sensing was utilized to understand the periodic and seasonal dynamics of Samaspur wetlands using Landsat and RESOURCESAT-1 temporal data. Index-based (i.e., Normalized Difference Water Index (NDWI) and Normalized Difference Vegetation Index (NDVI)) classification resulted in meaningful iscrimination of wetland classes. Accuracy achieved 96.7%
8	Bortels, Liesbeth, et al, 2011	Amvrakikos Gulf, 15 years (1989–2004)	Landsat 7-ETM+	For the classification, a hybrid unsupervised–supervised method was used. Spectral classes were generated using an unsupervised method, the Iterative Self-Organizing Data Analysis Technique (ISODATA). Kappa = 0.8.
9	Sivanpillai, et al. (2010)	Powder River Basin in Wyoming,	Landsat 7	This study assessed the benefits of using higher spatial resolution ASTER image, in contrast to more commonly used moderate-resolution Landsat imagery, for detecting smaller water bodies in the Powder River Basin.
10	Carroll, M. L., et al. 2009	Gironde Estuary, France	MODIS AQUA(250m), SRTM	To address this issue a new water mask product has been created using theSWBD in combination with MODIS 250 m data to create a complete global mapof surface water at 250 m spatial resolution

11	Olmanson et al. (2008)	Poyang Lake, China	MODIS	Wu, 2008 has used MODIS data for turbidity and SD. Author has obtained R2 =0.88 using LT-MLR (Log-transformed multiple linear regression) technique.
18	Flink et al. (2001)	Lakes Erken and Märalen, Sweden	Sl. CASI MERIS	Flink et al. (2001) has used MERIS dataset for Chl-a analysis. Author has obtained R2 =0.94 accuracy using LR technique.

III. CLASSIFICATION TECHNIQUES

The literature survey was conducted for the identification of suitable techniques for the water scarcity analysis. The satellite-based water indices are essential for the water scarcity zone identification and its analysis. The water indices are the vital technique for feature extraction; they also provided significant parameters for water-related classification techniques.

Normalized Difference Water Index (NDWI)

The NDWI index is most appropriate for water body mapping. The water body has strong absorbability and low radiation in the range from visible to infrared wavelengths. The index uses the green and Near Infra-red bands of remote sensing images based on this phenomenon. The NDWI can enhance the water information effectively in most cases. It is sensitive to built-up land and often results in over-estimated water bodies. Values of water bodies are larger than 0.5.

Moreover, vegetation has much smaller values, which results in distinguishing vegetation from water bodies more accessible. Built-up features have positive values between zero and 0.2. The NDWI results from the following equation:

NDWI = (IR_factor * near_IR - mir_factor * middle_IR) / (IR_factor * near_IR + mir_factor * middle_IR) (1)

Also the processor computes an additional flags band called 'ndwi_flags' with the following bit coding:

Table 1. shows criteria of NDWI

Bit Position	Description
Bit 0	The computed value for NDWI is NAN or is Infinite
Bit 1	The computed value for NDWI is less than -1 (minus one)
Bit 2	The computed value for NDWI is greater than 1 (one)

Modified Normalised Difference Water Index (NDWI)

This index enhances open water features while suppressing noise from built-up land, vegetation, and soil. Xu (2006) reported that the MNDWI produced better results than the Normalized Difference Water Index (McFeeters 1996) in enhancing and extracting water from a background dominated by build-up land areas.

$$MNDWI = \frac{Green - SWIR}{Green + SWIR} \quad (2)$$

Here are some guidelines for interpreting MNDWI results in Open water has greater positive values than NDWI, as it absorbs more shortwave-infrared (SWIR) wavelengths than near-infrared (NIR) wavelengths; Built-up features have negative values; Soil and vegetation have negative values, as soil reflects more SWIR wavelengths than NIR wavelengths. The MNDWI was initially developed for use with Landsat TM bands 2 and 5. However, it will work with any multispectral sensor with a green band between 0.5-0.6 µm and a SWIR band between 1.55-1.75 µm. Also, the processor computes an additional flags band called 'ndwi_flags' with the following bit coding:

Table 3. shows criteria of NDWI

Bit Position	Description
Bit 0	The computed value for NDWI is NAN or is Infinite
Bit 1	The computed value for NDWI is less than -1 (minus one)
Bit 2	The computed value for NDWI is greater than 1 (one)

Second Normalised Difference Water Index (NDWI2)

The **second N**ormalized **D**ifference **W**ater **I**ndex algorithm was developed by McFeeters (1996) to detect surface waters in wetland environments and allow for the measurement of surface water extent. The NDWI2 results from the following equation:

NDWI2 = (green_factor * green - IR_factor * near_IR) / (green_factor * green + IR_factor * near_IR) (3)

Also the processor computes an additional flags band called 'ndwi2_flags' with the following bit coding:

Table 4. shows criteria of NDWI2

Bit Position	Description
Bit 0	The computed value for NDWI2 is NAN or is Infinite
Bit 1	The computed value for NDWI2 is less than -1 (minus one)
Bit 2	The computed value for NDWI2 is greater than 1 (one)

Normalized Difference Mud Index (NDMI)

This index highlights muddy or shallow water pixels. This index was originally designed as a filter to exclude those pixels and to improve the accuracy of QUAC (Bernstein 2012)

$$NDMI = \frac{(\rho_{795} - \rho_{990})}{(\rho_{795} + \rho_{990})} \quad (4)$$

Also the processor computes an additional flags band called 'ndwi2_flags' with the following bit coding:

Table 5. shows criteria of NDWI

Bit Position	Description
Bit 0	The computed value for NDMI is NAN or is Infinite
Bit 1	The computed value for NDMI is less than -1 (minus one)
Bit 2	The computed value for NDMI is greater than 1 (one)

WorldView Water Index (WV-WI)

This index uses WorldView-2 bands to highlight areas of standing water greater than one pixel in size.

$$WV\text{-}WI = \frac{(Coastal - NIR2)}{(Coastal + NIR2)} \quad (5)$$

Also the processor computes an additional flags band called 'ndwi_flags' with the following bit coding:

Table 6. shows criteria of WV-WI

Bit Position	Description
Bit 0	The computed value for WV-WI is NAN or is Infinite
Bit 1	The computed value for WV-WI is less than -1 (minus one)
Bit 2	The computed value for WV-WI is greater than 1 (one)

Normalized Difference Pond Index (NDPI)

The NDPI makes it possible not only to distinguish small ponds and water bodies (down to 0.01 ha), but also to differentiate vegetation inside ponds from that in their surroundings The NDPI results from the following equation:

NDPI = (green_factor * green - swir_factor * ShortWave_IR) / (green_factor * green + swir_factor * ShortWave_IR) (6)

Also the processor computes an additional flags band called 'ndpi_flags' with the following bit coding:

Table 7. shows criteria of NDPI

Bit Position	Description
Bit 0	The computed value for NDPI is NAN or is Infinite
Bit 1	The computed value for NDPI is less than -1 (minus one)
Bit 2	The computed value for NDPI is greater than 1 (one)

Normalized Difference Turbidity Index

The Normalized Difference Turbidity Index algorithm was developed by J.P Lacaux & al. (2006), allowing for water turbidity measurement. Wetlands are one of our most essential yet endangered and undervalued environments. Sustainable management of the wetland ecosystem is necessary as it serves important functions such as food storage, water quality maintenance, and habitat for different wildlife species. More than 75% of commercial fish species require wetlands to complete part of their life cycle. Many local and migratory birds also utilize coastal wetlands as breeding and roosting sites and provide food and habitat for many animal and plant species. Wetlands are also a valuable buffer against coastal erosion, storm surges, and flooding. The NDTI results from the following equation:

NDTI = (red_factor * red - green_factor * green) / (red_factor * red + green_factor * green) (7)

Also the processor computes an additional flags band called 'ndti_flags' with the following bit coding:

Table 8. shows criteria of NDPI

Bit Position	Description
Bit 0	The computed value for NDTI is NAN or is Infinite
Bit 1	The computed value for NDTI is less than -1 (minus one)
Bit 2	The computed value for NDTI is greater than 1 (one)

IV. Discussion

V. Remote sensing and GIS play an essential role in the estimation and mapping of surface water. In Addition, It is also used to assess the quality of the water. The pure water is a test less, odorless and colorless chemical compound which forms the chemical reaction of two Hydrogen molecule and one Oxygen molecule. The color of water appears blue due to the reflection of the sky. Most of the radiation is absorbed by water, including infrared and shortwave infrared wavelength. Solar radiation can penetrate pure water up to 1500 Feet (Ritchie et al. 1974). Various researchers worked with Normalised Difference Water Index (NDWI), Modified Normalised Difference Water Index (MNDWI) indices are based on multispectral satellite images. It helps the detecting weather impacts and other events relevant to ecology and agricultural analysis. The temporal resolution provided glimpses of trend analysis of water scarcity. Water is an integral element of the farming sector, where most of the cropland is based on the rainfed system. Indian agriculture is vulnerable to the drought disaster. Therefore it directly affects the agricultural yield of the nation. The government of India was using remote sensing for agricultural yield analysis using remote sensing and GIS.

VI. Conclusion.

Water is a vital driver element to sustain life on the planet; therefore, the natural ecosystem will collapse without water. This review paper has discussed the possibility of establishing a relationship between the spectral behavior of water and its parameter like CHl-a, TSS, CDOM, etc. Various satellite sensors like MERIS, SeaWiFS, MODIS, Landsat TM, Sentinel 3 datasets play an essential role in identifying and classifying water quality. The MODIS and MERIS dataset archive has included historical records essential for water pollution and water spectral behavior analysis-related study. Many researchers have studied quality attributes using LR, LT-MLR, and Polynomial techniques. LR and LT-MLR have shown the highest correlation between observed characteristics with the spectral response of water. The article concludes that satellite remote sensing is an essential technology for water quality estimation and analysis.

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