Measurement and Monitoring of TDS and TSS

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Total dissolved solids (TDS) and total suspended solids (TSS) have traditionally been analyzed and monitored through field or in situ sampling and laboratory testing generally classified as conventional methods. Field and laboratory measurements include grab sampling, filtering, and evaporating a sample through a fine filter paper followed by drying in an air oven which are collectively known as gravimetric methods. Conventional methods of monitoring of water quality parameters (WQPs) are, however, cost-prohibitive, labor-intensive, time-consuming, and, also not suitable for large-scale analysis.

airborne sensors hyperspectral multispectral optically active remote sensing (RS) satellite sensors

1. Introduction

Total dissolved solids (TDS) and total suspended solids (TSS) are two physical water quality parameters (WQPs) that impair the quality of water resources such as rivers and lakes [1][2][3]. Both TDS and TSS are fractional constituents of "total solids" of the same sample separated by filtration [4]. Total solids refers to "the material residue left in the vessel after evaporation of a sample and its subsequent drying in an oven at a defined temperature" [5].

The 23rd edition of the American Public Health Association Standard Methods for the Examination of Water and Wastewater, Section 2540 defines TDS as constituents of total solids in a water sample, which passes through 2.0 µm or less nominal pore size under specific conditions. Constituents of TSS in any given sample of water are retained by a filter with a 2 µm or less pore size measured by weighing the dried residue left on the filter [4][5]. Constituents of TSS encompass particulate matter including sediment, silts, and algae among other solid suspended particles. TSS, however, does not include colored dissolved organic matter (CDOM). The presence of these CDOM, phytoplankton, and non-algal particles (NAP) at various compositions often poses a challenge to the determination of WQPs such as TSS [2][6].

Increased concentrations of TDS and TSS in water bodies limit them from serving their purpose for drinking, power generation, industrial cooling, supporting biodiversity, ecosystem services, recreation, transportation routes, waste disposal, agriculture production, irrigation, energy production, regional planning, and fish farming [7][8][9][10][11][12][13][14][15][16][17]. Impairment of water bodies by parameters such as TDS and TSS is caused by climate change, development, and urbanization associated with surface imperviousness resulting from increased population, and contamination caused by rapid and uncontrolled environmental changes including drought, wastewater discharges, nutrient pollution, sediments, and changes in land use and land cover which results in negative impacts such as the proliferation of harmful blue-green algae, accelerated eutrophication, and extreme turbidity among others which have negative implications on the sustainability of the limited water resources [3][6][18][19][20][21][22][23][24][25][26][27][28][29].

Changes in the quality of water resources by these parameters can cause changes in the quality of recreational and commercial activities. There is a decline in boating, fishing, and swimming in these water bodies when they are impaired, which brings about significant economic losses. Swimming and boating in impaired water may also result in respiratory and gastrointestinal diseases [30][31]. A study performed through the use of biophysical modeling established that Virginia households are ready to pay as much as USD 184 million yearly to ensure there is an improvement in the quality of their water [31].

To protect and restore the quality of water resources, monitoring efforts and management strategies are key and need to be successful to achieve the desired results of a healthy water body in the ecosystem economy [32][33]. Monitoring and assessment of WQPs such as TDS and TSS are crucial to fully comprehending how changes in the natural environment and human activity affect water bodies [34]. TDS and TSS have been widely monitored using conventional or traditional methods such as laboratory analysis or grab sampling [2][19][35], these methods are, however, time-consuming, expensive, and need a lot of labor. As a prospective alternative to traditional methods for measuring TDS and TSS, remote sensing (RS) techniques have gained popularity in recent years and have proven to be cost-effective in monitoring these WQPs on local to global spatiotemporal scales non-intrusively [2][36][37].

2. Measuring TDS and TSS Using Conventional Approaches

2.1. Measurement of TDS

TDS or dissolved solids (DS) concentration is measured either directly or indirectly.

Direct TDS determination involves grab sampling which entails the collection of individual samples at specified times which are reflective of the water conditions at the moment the sample is collected [35]. These samples are prepared in the lab and oven-dried. TDS is then determined by weighing the residue that remains after the evaporation of a specific volume of a filtrate. TDS can also be analyzed in the field or lab by utilizing electrochemistry meters and probes developed to detect the dissolved solids in a sample [38].

One way to indirectly determine TDS involves the summing of measured concentrations of various constituents in the filtered water sample. Researchers in [39] have found strong correlations among various dissolved minerals such as TDS, electrical conductivity (EC), and chloride with $r > 0.8$ which makes the EC an effective tool for determining the salinity of water [40]. TDS can therefore be estimated indirectly by multiplying EC measured in micromhos per centimeter by an empirical factor that ranges from 0.55 to 0.9. The exact factor used in TDS estimation is influenced by the temperature and soluble components of the water which is determined by establishing repeated paired linear regressions of measurements of TDS and specific conductance for a specific water body. A high factor is used for saline water while a lower value is used for water systems with considerable hydroxide or free acid [4]. A value of 0.67 is often adopted for several natural water systems [4]. However, Ref. [41] used a correlation factor of 0.64 in their study to estimate and characterize physical and organic chemical indicators of water quality. Both TDS and EC are used to describe the salinity level in the water. EC measures the capacity of the water to conduct an electric charge and its ability to do so is influenced by the ionic strength, temperature of measurement, and concentrations of dissolved ions. The concentrations of these dissolved ions are measured as TDS. TDS analysis is said to offer a better understanding of groundwater quality and the effect of seawater intrusion compared with EC analysis. While the EC of water is inexpensive to measure and can be measured in situ through the use of a portable water quality checker, analysis and measurement of TDS are, however, more difficult, time-consuming, and expensive [42]. TDS estimation from EC using a correlation factor is based on the assumption that dissolved solids are mainly ionic species of low concentration needed to yield a linear EC–TDS relationship [43]. Chemical analysis is said to be the only reliable means to measure TDS. This method can, however, be time-consuming and costly. An indirect method is usually used to aid in the effort of salinity measurement. The direct method is performed through the measurement and establishment of empirical relationships between salinity and other physical properties of water such as conductivity, sound speed, refractive index, and density [4].

2.1.1. Measurement of TSS

Several researchers have monitored TSS in water bodies because it is key to ensuring the restoration of the integrity of water bodies, leading to the sustainability of water resources and ultimately protecting human and aquatic lives [44][45].

Water loaded with suspended sediments increases its turbidity, reducing its light absorption capability while allowing a greater amount of reflection. An increase in sediments and turbidity, therefore, causes an increase in the reflectance of light in the visible and the near-infrared (NIR) spectrum of the electromagnetic spectrum [46]. The remotely sensed estimation of sediment concentration (TSS) is influenced by particle parameters, including their size, shape, density, and color, dissolved and particulate color. Suspended particles originate from runoff, soil erosion, stirred bottom sediments, algal blooms, or discharges. The composition of TSS materials in inland waters includes components supplied by tributaries called allochthonous and components produced within the water column called autochthonous and resuspension [47]. Both TSS and turbidity are used as indicators to assess the clarity of water and are a macro-descriptor for water quality as they are directly related to other variables used in the management of inland waters such as the lake. The composition of suspended particles may differ in inland waters as they are governed by characteristics of the drainage basin, resuspension of bottom deposits driven by motion, and hydrology [47].

Researchers in [48] found a correlation between TSS and turbidity of 0.64. A sampling of TSS can be performed using multiple particle filtration systems (MuPFiSs), a system that has four filtration lines in parallel with water meters to measure the flow of water filtered over a period under pressure using appropriate filter pore sizes [49]. In a study performed by [50] to analyze WQPs including TSS in the effluent of a WWTP in Switzerland, an in situ UV spectrometer was applied to the effluent and calibrated using a multivariate calibration algorithm and partial least squares (PLS) regression. The accuracy of the TSS measurement was found to be unsatisfactory. This is because the spectrometer used did not cover a wavelength spectrum of up to 700 nm, which was said to give a better signal for TSS calibration owing to the strong correlation between TSS and turbidity.

Researchers in [51] estimated TSS concentrations using ML models coupled with several watershed factors rainfall depth, drainage area, percent of imperviousness, runoff volume, land use, and antecedent dry days for various storm events retrieved from 17 US states. The authors reported they found the random forest and the adaptive boosting regressors the best models for TSS estimations from these watershed factors with $R^2 \geq 0.64$ and Nash–Sutcliffe Efficiency (NSE) ≥ 0.62 from the training to the prediction steps of the models.

2.1.2. Strengths and Limitations of the Conventional Method for Measuring TDS and TSS

Strengths

Conventional methods [38], are well-established methods employed in laboratories and have been used for decades. They have been proven to produce reliable and accurate results and are widely understood by many experts and researchers in the field of water quality and water resources management.

There is a substantial body of literature on the subject in terms of reports provided by governmental and non-governmental institutions and companies [4][38][52][53].

Conventional methods also present details about instantaneous concentrations of TDS and TSS at a certain time. Additionally, conventional methods present standardized procedures for determining TDS and TSS which means the results from different measurements can be compared [4][35].

Limitations

Conventional methods of TDS and TSS measurement techniques can take a lot of preparation and analysis time. From sample preparation to oven drying in the case of TDS measurements, the conventional method requires significant time ranges from hours to days for their analysis [54]. The time required to collect samples, send them to a laboratory for processing, and receive findings can be long and particularly cumbersome when sampling at multiple locations [55].

Conventional methods of TDS and TSS measurement techniques can be laborious and require skilled personnel for effective and accurate measurements, analysis, and interpretation of results [54].

Some standard or conventional methods of measuring these WQPs require the use of dangerous chemicals and specialized equipment which can pose safety issues to researchers and laboratory technicians [4][54].

Conventional methods are limited by spatial and temporal resolution. Traditional approaches require physical sampling and are therefore confined to using the point measurements taken at certain times and locations, which may miss significant changes in water quality across time and space and are therefore not feasible for large or remote water systems [2][36][56][57][58].

2.2. Monitoring of TDS and TSS Using RS

2.2.1. Concept of TDS and TSS Interactions and Measurements Using RS

The basic underlying principle and concept of retrieving WQPs such as TSS and TDS from RS are based on the interaction of suspended and dissolved colored substances with light. Dissolved colored and suspended substances increase light absorption (dissolved) and absorption and scattering (suspended) in water and change the direction of the returned light. The spectral distribution of backscattered energy is affected by additional absorption by dissolved colored matter in the water column. SM on the other hand increases the backscattering of light and hence may increase the remote signal [59]. The interaction of light with SM produces a signal reflectance that is detectable from a distance. These signals can therefore be used to estimate the presence and the quantity of TSS. The strong backscattering property of TSS makes it possible to be detected by RS techniques [60]. The spectral properties of the water are categorized as the Inherent Optical Properties (IOPs) and the Apparent Optical Properties (AOPs). The IOPs which describe the spectral light absorption and backscattering are key components in linking reflectance measurements to the concentrations of water parameters such as TSS. The absorption coefficients of particles in optically complex waters such as inland, coastal, and estuarine are broken into components caused by phytoplankton and those caused by non-algal particles. While the IOPs can be quantified in the laboratory, the AOPs which include radiance and downwelling plane irradiance are only measured using the IOPs and depend on the IOPs and the geometric structure of the radiance distribution including the wind speed, surface water structure, and atmospheric conditions [47][61].

RS-based approaches for the estimation and retrieval of the TSS and TDS involve establishing relations between these WQPs and spectral properties of RS images. The approaches include empirical methods which utilize statistical relationships derived from measured RS spectral properties and these WQPs. These are simple and straightforward approaches which been used in the effective estimation and retrieval of these WQPs [10][62][63][64][65][66][67][68].

Another approach used is the analytical method which uses the IOPs including the scattering and absorption coefficient and the volume scattering function, and the AOPs such as the diffuse attenuation coefficient for downwelling irradiance and the irradiance reflectance to model and derive these WQPs [2][63][64][66]. Other studies are semi-empirical methods: which are a combination of the empirical and analytical methods for the retrieval of these WQPs [2][10][63][64][69][70][71]. In this approach, the spectral radiance is recalculated to above the surface irradiance reflectance and subsequently, through regression techniques related to the TDS and TSS. Over the years, studies have developed and improved these approaches leading to more recent use in the state-of-art artificial intelligence (AI) approaches such as machine learning (ML) models and deep learning which uses implicit algorithms to capture both linear and nonlinear relationships compared with the conventional statistical methods [2][63][72][73][74][75][76].

2.2.2. Optical Characterization of TDS and TSS

WQPs are categorized as optically active and inactive parameters for RS applications. Optical RS is based on the difference in spectral reflectance of water and land [77]. Optically active water parameters are those parameters that are likely to impact the optical characteristics measured by RS sensors while non-optically active parameters are those parameters that are less likely to influence the optical characteristics measured by the RS sensors [78]. TSS is an optically active parameter while TDS is an optically weak property. Optically active parameters such as TSS absorb light in the ultraviolet and visible wavelength range and influence the optical properties enabling them to be sensed from satellite observations. Optically active water parameters are also used to monitor several other processes aside from water quality. The high amount of sediment loads have the potential to reduce water clarity and block radiation needed for submerged aquatic vegetation growth. Sediments affect the optical characteristics of estuarine waters making a color in both in situ and RS a good indicator for monitoring phenomena, including run-off processes [79]. Studies have also found a good correlation between the SPM concentrations and water reflectance in the green and red regions of the electromagnetic spectrum for low to moderately turbid waters [69]. The reflectance in the 580–680 nm and 700–900 nm ranges of the electromagnetic spectrum have been reported to be most sensitive to TSM concentration changes and hence most ideal for the retrieval of TSM concentrations [63]. A study by [80][81] corroborated this assertion by finding SS concentration to be associated with an increase in reflected energy at longer wavelengths (630–690 nm).

A study was performed by [82] to estimate optical water parameters using a guided approach. The optical WQPs considered included TSM using the Ocean and Land Color Instrument (OLCI), and MSI data at Estonian and Finnish lakes and the Baltic Sea coastal area. The study used empirical algorithms. A high correlation ($r > 0.87$) was established for in situ measured optical WQPs and the parameters predicted by the optical water-type guided approach. The amount of SSC and turbidity affects the reflectance of light with the relationship between spectral reflectance and SSC or turbidity often described as a positive linear correlation or nonlinear regression in the visible and the NIR wavelengths [83][84].

Researchers [85] found an increase in reflectance in the NIR regions and reduced reflectance in red and SWIR due to high water absorption in the most turbid regions of the Río de la Plata estuary located in South America. Researchers [86], however, noted the NIR spectral bands to be less sensitive to the increase in TSM concentrations in highly turbid waters with TSM > 100 mg/L making the use of SWIR with a wavelength of 1000–1300 nm an alternative in such scenarios.

2.2.3. RS Sensors for Monitoring TDS and TSS

Microwave and optical RS technologies are two technologies used in the estimation of WQPs including TDS and TSS. Optical RS sensors collect data in the visible, near-infrared, and shortwave infrared regions of the electromagnetic spectrum, but microwave sensors use a longer wavelength (cm to m) which makes them able to penetrate through cloud cover, dust, haze, and all kinds of rainfall except the heaviest rains. The longer wavelengths of microwave sensors make them insusceptible to atmospheric scattering which impacts shorter optical wavelengths which makes it possible for them to detect microwave energy under all weather and environmental conditions at any time [87][88][89]. Microwave sensors provide cost-effective, reusable, reliable, and automatic water-sensing technologies to provide accurate real-time water quality measurements [90].

Microwave RS are categorized as active, also known as non-optical sensors, and passive sensors also called optical sensors. Optical sensors depend on the energy of the sun, unlike non-optical sensors which produce their energy. Although most studies have measured WQPs using optical RS, there is an opportunity to measure these parameters from the microwave region of the electromagnetic spectrum [87][88][91][92]. Passive microwave sensors detect the emitted energy within their field of view. Active microwave sensors are those sensors that provide their source of radiation to illuminate their target.

Optical RS sensors are mainly passive sensors that make use of the sun's energy. The USGS's Landsat, NASA's MODIS, the ESA's Sentinel-2, and the Medium Resolution Imaging Spectrometer (MERIS) among many others are some optical remote sensors that have been used by several scientists, including water researchers for monitoring and managing water resources [2][89][93][94]. Other known sensors used in studies include the Oceanic and Atmospheric Administration (NOAA) Advanced Very High-Resolution Radiometer (AVHRR) and the OrbView-2 Sea-viewing Wide Field-of-view Sensor (SeaWiFS) sensors [95].

Passive sensors can be either airborne or spaceborne sensors based on the platforms launched. Images from these sensors can be multispectral or hyperspectral, based on spectral and spatial resolutions. Multispectral systems collect data in 3–10 spectral bands in a single observation from the visible and the near-infrared range of the electromagnetic spectrum. The spectral bands of multispectral bands range from 0.4–0.7 µm for red–green–blue, and infrared wavelengths within the range of 0.7–10 µm, or more for near, middle, and far infrared [36][63][96]. The use of multispectral images is, however, restrictive because the spectral resolution of the images influences the quality and quantity of the information they can provide [97]. Hyperspectral RS applications offer an effective mechanism for frequent, synoptic water quality monitoring over a large spatial extent [98]. Hyperspectral sensors collect 200 or more bands enabling the construction of a continuous reflectance spectrum for all the pixels in the scene using cameras categorized as snapshot, pushbroom, or whiskbroom. The snapshot camera captures the whole image at one time. The pushbroom captures one line of the picture while the whiskbroom captures one point of the picture [2][99]. Multispectral and hyperspectral images have been used for the direct or indirect measurement of several WQPs including TSS and TDS or salinity [36][63][96]. Spaceborne sensors are those carried by satellites or spacecraft to areas outside the Earth's atmosphere. Examples of spaceborne sensors include Landsat satellite, Advanced Spaceborne Thermal Emission and Reflection Radiation (ASTER), Moderate Resolution Imaging Spectroradiometer (MODIS) Sensor, GeoEye, and IKONOS among others. Airborne sensors are mounted on platforms flown within the Earth's atmosphere. These platforms include boats, helicopters, aircraft, or balloons. Examples of airborne sensors used for capturing images for WQP monitoring include the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) manufactured by NASA Jet Propulsion Lab (Pasadena, CA, USA), the Airborne Prism Experiment (APEX) manufactured by VITO (Mol, Belgium), Hyperspectral Digital Imagery manufactured by the Naval Research Lab (Washington, DC, USA), Daedalus Multispectral Scanner (MSS) manufactured by the Daedalus Enterprise Inc (Ann Arbor, MI, USA), Compact Airborne Spectrographic Imager (CASI-1500) manufactured by ITRES Research Limited (Calgary, AB, Canada), and the Multispectral Infrared and Visible Imaging Spectrometer (MIVIS) manufactured by Daedalus Enterprise Inc., (Ann Arbor, MI, USA) [36].

2.2.4. RS Spectral Indices Used in Estimating TDS and TSS

RS indices combine information from two or more spectral bands. The incorporation of reflectance values from different bands through band ratios has been noted to improve the estimation of WQPs by reducing the effect of the atmosphere and further increasing the signal-to-noise ratio [62]

Several indices have been established and widely acknowledged as valuable tools in the identification of features of interest. Studies have developed indices for vegetation vigor, land use changes, and crop assessment [100]. Band ratios or indices have been used as model variables and have been found to produce good results [101]. For example, [100] used indices termed salinity indices, vegetation indices, and principal component analysis (PCA) to map and discriminate salt-affected, waterlogged areas/water bodies in Faisalabad, Pakistan. The indices used include salinity indices which are the square root of the product of the first and third bands and the normalized differential salinity index which utilizes band 3 and band 4. Additionally used were the Normalized Difference Vegetation Index (NDVI), and band ratio (Band 3/Band 4). The acquired images used were from the Linear Image Self-scanning Spectrometer (LISS-II) of the Indian RS satellite (IRS-1B). Additionally, ref. [102] found that the band ratio of 560/660 nm of radiometric data acquired with hyperspectral radiometers with a 3 nm resolution and bandwidths over the 400–700 nm range is the best ratio at $p < 0.005$ for the estimation of suspended mineral concentration for inland and coastal waters in the Vancouver Island of British Columbia, Canada.

Some of the commonly used indices include the Normalized Suspended Material Index (NSMI), the Normalized Difference Suspended Sediment Index (NDSSI), and the Band Ratio (BR) used in the analysis of suspended sediments [103][104][105][106]. Normalized Difference Salinity Index (NDSI), salinity indices, and TDS indices are used for the monitoring of TDS or salinity [56][107][108]. Indices utilized in the literature for monitoring TSS include the Water-Sediment Ratio Index (WSRI), the NDVI, the normalized difference water index (NDWI), and the Enhanced Green Ratio Index (EGRI) [100][106][109].

The following subsections highlight some of the indices that have been used in water quality monitoring.

TDS and Salinity Indices

Multiple spectral salinity indices have been established in various studies. Highly reflective spectral packages are used in understanding the relationship between WQPs and spectral bands. Three water body reflectances exist for assessing WQPs using band reflectance. These are surface reflectance, bottom reflectance, and volume reflectance. To demonstrate the properties of water, a spectral range with higher reflectance is adopted. Several salinity indices which are combinations of bands in the visible and NIR range of the electromagnetic spectrum have been reported in the literature [107][110][111][112]. Clear water (i.e., water with a depth greater than 2 m) likely exhibits low reflectance in a visible range of the electromagnetic spectrum (i.e., blue, red, and green bands) There is a characteristic trend of reduction in the spectral signature value of water reflectance with increasing wavelength in the visible (band 2) and NIR infrared band [107][113].

TSS and Sediment Indices

Indices used for the estimation of TSS indices include the Normalized Suspended Material Index (NSMI), the Normalized Difference Suspended Sediment Index (NDSSI), the Band Ratio (BR), and other established indices.

Values of NSMI and NDSSI range from −1 to +1. Lower values of NSMI correspond to clearer water. When the blue band has a higher value than the sum of the red and green bands, the equation gives a negative value, indicating the presence of clearer water. Higher values correspond to water with more SM. Sediment also increases the reflectance of the green range of the spectrum [104]. Higher values of NDSSI, however, indicate the presence of clearer water and lower values indicate the presence of more turbid water or land. BR ranges from 0 to infinity. The highest value indicates the presence of more suspended sediments. A study found NSMI to have a better performance in estimating TSS compared to NDSSI because the wavelength of visible bands as associated with NSMI have greater penetrating power in the water surface compared with infrared bands [105]. Another study by [104] utilized NSMI to identify SM by using Landsat 7 Enhanced Thematic Mapper (ETM+) satellite data on the coast of Cabo Rojo in Puerto Rico. Results obtained from the NSMI were compared to other indices, such as the NDSSI and BR, and found similar patterns and indications of validity of the results. Although the NSMI was found to be successful in distinguishing between clear water and suspended material in a study performed in Cabo Rojo in Puerto Rico, it was unable to identify suspended matter in shallow areas such as coral reefs and swamps.

2.2.5. Summary of Studies on TDS and TSS Estimation with RS Applications

RS applications have also been used in the analysis and estimation of TSS and TDS in water bodies. The impact of TSS concentrations on the reflectance is clear and substantial making it one of the most successful parameters to be measured using RS applications [47]. Satellite and airborne imagery have become valuable tools for scientists to map, assess, and monitor the spatial distribution of suspended sediments. RS is used in combination with in situ measurements to assess and monitor the distribution of WQPs such as TSM [114]. RS spectral indices have been used in determining suspended sediment distributions.

Empirical regression algorithms have been used in the determination of salinity or TDS using reflectance data obtained from spaceborne optical sensors such as Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI, and other satellite images [115][116][117]. Salt or ion accumulations affect the reflectance of electromagnetic radiation as it interacts with the water.

Microwave-based RS sensors used for monitoring salinity include the STARRS, SLFMR, and Nimbus-7 SMMR. The STARRS is an enhanced version of the Scanning Low-Frequency Microwave Radiometer. The STARRS sensor accepts input data and improves salinity retrieval accuracy [118]. Microwave sensors have been found to provide accurate measurements of ocean salinity and temperature because the emission measured by the microwave systems is sensitive to the dielectric constant or the permittivity, which is dependent on the water salinity and temperature [61]. The sea surface temperature and salinity are important in determining the density of seawater which is a critical indicator driving the currents of the ocean. Ocean circulation is a critical phenomenon to analyze global water balance, evaporation rates, and productivity forecast models [36]. Although the RS sensors are effective in the monitoring of water quality of ocean waters, their usage in fresh waters such as rivers and lakes may be limited due to very large pixel sizes (coarse spatial resolution) varying to kilometers [61], which are larger than many freshwater systems.

Studies have reported satisfactory performance using microwave sensors for the estimation of salinity/TDS and TSS in ocean waters. Examples include the study by [119] where ship-borne microwave radiometer data were used to develop improved sea surface microwave emission models or algorithms for the retrieval of sea surface salinity. The authors found root mean square error (RMSE) or differences between the in situ and retrieved sea surface salinity of around 0.4 Practical Salinity Units (PSU) which indicates good model performance. Another study by [120] measured the variability in sea surface salinity by the Aquarius and SMOS satellite missions using an assimilation scheme as described by researchers in [121] and obtained a RMSE of <0.1 PSU between derived and field surface salinity in most of the ocean with a global median value of 0.05 PSU. Additionally, the NASA Aquarius, in situ field, and Hybrid Coordinate Ocean Model (HYCOM) products were used to assess sea surface salinity in a study by [122]. The study found RMSE for Aquarius Level-2 and Level-3 data to be 0.17 PSU and 0.13 PSU, respectively, using triple point analysis.

Researchers in [123] used microwave SAR and thermal images and an inversion technique applied to the models of scattering to estimate WQPs including TDS and salinity in high-precision SAR and thermal images. Analysis of the results pointed to the potential of identifying WQPs with superior precision using microwave sensors. Researchers in [124] used an airborne scanning low-frequency microwave radiometer and in situ bio-optical variables to estimate WQPs including SS for Florida Bay located in the southern tip of the state of Florida, USA using empirical relationships or algorithms. The study found the average salinity for the outer and central bay stations to be 31.2 PSU and 23.6 PSU, respectively. The study also found that the concentration and variability of TSS were greater in the outer bay as compared to the central bay stations. Average TSS concentrations of 14.4 mg/L and 2.8 mg/L were recorded, respectively, for the outer and central bay stations. Inorganic composition counted for 70% and 15% of the TSS loads, respectively, for the outer and central bay stations. Results from the study demonstrate the significance of salinity measurement in delineating bio-optical regimes useful for the development of regional ocean color RS techniques for coastal waters.

TSS estimations have also been successfully carried out in rivers, reservoirs, and estuaries using empirical regression algorithms or analyses. These analyses are performed with in situ measurements and reflectance data from airborne RS and spaceborne optical sensors, including Landsat (4 and 5) TMs, (7) ETM+, (8) OLI, and other sensors. Airborne RS produces more accurate results in TSS estimations in rivers and reservoirs, owing to less atmospheric interference, fewer temporal restraints, and adaptable spatial resolutions [48][115][116][125][126][127].

The following paragraphs summarize some of the work that has been performed on the estimation of TSS and TDS using RS applications.

Researchers in [128] applied empirical neural networks in the estimation of WQPs, including SSC, in the Gulf of Finland using combined optical (Landsat 5 TM) and microwave data (ERS-2 SAR). Results indicated that the neural network was adequate in describing the nonlinear transfer function between the optical and microwave sensors and the water surface parameters as compared to the regression analysis. The optical bands produced an R^2 of 54% and 89% for regression and neural network analyses, respectively. The reported performance when optical and microwave bands were fused was slightly higher (55% and 91%, respectively, for regression and neural network analyses). Analysis of the results also showed a difference in RMSE between the optical and the optical/microwave fused bands of 0.01 mg/L and 0.007 mg/L, respectively, for the regression and neural network analyses. A similar study by [129] compared the results of MODIS-Landsat fusion to single-band algorithms for TSS estimations.

Researchers in [130] explored the possibility of using MODIS 250 m and 500 m resolution bands at 469 nm, 555 nm, and 645 nm for the monitoring of water quality indicators including TSS in Tampa Bay, FL, USA. Tampa Bay is the largest open-water estuary in the State of Florida, USA with an approximate area of 910 km^2. Field sampling conducted shows that Tampa Bay has Case-II waters (waters in which the parameters studied do not co-vary) with a salinity range of 24–32 PSU and TSS of 2 to 11 mg/L. The authors established a regression model for the total radiance measured by the MODIS and the WQPs, which were subsequently used to develop a synoptic map of suspended sediments. The authors found a significant R^2 of 90% for a sample size of 31 between TSS and the spectral RS reflectance value of the 645 nm band of the MODIS image using empirical regression.

Researchers in [131] also used the 250 m resolution to map concentrations of TSM in coastal waters located in the Northern Gulf of Mexico. The study established a linear relationship between in situ TSM measurements and band 1 of the MODIS Terra 250 m image with 620–670 nm wavelength and found an R^2 of 89% for a sample size of 52.

Researchers in [132] used reflectance band ratios to estimate suspended and dissolved matter concentration in the Tamar estuary located in the southwest UK using in situ hyperspectral remote-sensing reflectance measurements. The study obtained a strong R^2 of 96% between the NIR (wavelength of 850 nm) to visible reflectance (wavelength of 550 nm) (visible/NIR) ratio of the compact airborne spectrographic imager (CASI) and the TSM concentrations.

Researchers in [133] compared several ML algorithms including ANN, SVR, random forest, and cubist regression for the retrieval of WQPs including concentrations of suspended solids in the coastal waters of Hong Kong using in situ reflectance (CROPSCAN Multispectral Radiometer (MSR)) and satellite data (Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI). The authors found the ANN to be the model with the highest accuracy for estimating TSS with R^2 of 92% and 93% for the satellite data and in situ reflectance data, respectively.

Researchers in [134] used ANN to investigate and assess WQPs. The study establishes a relationship between the reflectance from Landsat 5 TM data for different bands (i.e., band 1 to band 7) and WQPs including suspended sediments for the Beaver Reservoir located in Arkansas, USA. The Beaver Reservoir is the main source of drinking water for more than 300,000 people in the northwestern part of the state of Arkansas with a surface area of 103 km^2 and with a depth ranging from 18 to 60 m. The study first linearly regressed the combination of bands termed as indices and found moderate predictions for estimations for most of the indices utilizing the first three bands (R values of 0.21 to −0.69). Further analyses were performed by feeding the bands and indices values into an ANN model for the estimation of WQPs. The ANN model produced an 81.6% to 98.2% efficiency for the estimation of suspended sediments with the highest efficiency coming from an ANN model using bands 1 to 4. This model was trained at an efficiency of 98%.

Researchers in [125] developed an RS-based index from Landsat 7 ETM+ to estimate and map SSC in a river and lake environment in the USA. The study explored the possibility of using RS Landsat images to estimate coefficients that could further predict SSC in periods where in situ field measurements become impossible due to extreme events using empirical relationships or algorithms. The authors found the model with power relations yielding R^2 of 73.8% to show potential for the estimation of SSC for the Mississippi River and Lake Pontchartrain located in Louisiana, USA for the Bonnet Carre Spillway opening event and before and after Hurricane Katrina. Results were compared with simulations from CCHE2D: a numerical model developed by the National Center for Computational Hydroscience and Engineering (NCCHE) for unsteady turbulent flow simulation. Results were in good agreement quantitatively and qualitatively [125].

Researchers in [135] retrieved the TSM and chlorophyll-a concentration using the Indian Remote-Sensing Satellite (IRS-P6). Analysis of the water quality data and satellite-received radiances signals using empirical regression and ANN models or algorithms. Results showed that the empirical models produced an R^2 of 94% for TSM. The performance accuracy improved significantly with the ANN model with R^2 of 98% for the TSM concentration. RMSEs produced were 15% and 7.5%, respectively, for the empirical and ANN models. Researchers in [136] developed an RS-based early warning system for monitoring TSS concentration in Lake Mead located in a water-scarce area in the US.

Researchers in [137] applied GIS and RS techniques for the monitoring of several WQPs including TDS and TSS using empirical linear regression in Lake Al-Habbaniyah, Iraq. The authors compared remotely sensed results from Landsat 8 OLI to in situ measurements and reported a variation of 147–1520 mg/L and 68–3200, respectively, for TDS and TSS. Results indicate a probable significant correlation between bands 2 and 3 with TDS for autumn and summer. TSS has a probable strong correlation with band 2 during the autumn. The study estimates the highest r in TDS (0.94 at p = 0.016) and the highest r (0.73 at p = 0.158) for band 2 reflectance.

Researchers in [95] performed a study to quantify surface river SS along a river-dominated coastline in Louisiana, USA using statistical models including correlation, linear and nonlinear algorithms or techniques. The study used data acquired by the NOAA AVHRR and the Orbview-2 SeaWiFS ocean color sensors. Field measurement samples used in the study were obtained using a helicopter, small boat, and automatic water sampler within a few hours of the satellite overpasses. The study used satellite and field measurements to develop statistical models for the estimation of near-SS and surface-suspended sediments. Analysis shows that the NOAA AVHRR Channel 1 (580–680 nm), Channel 2 (725–1100 nm), and SeaWiFS Channel 6 (660–680 nm) with a cubic, linear, and power model, respectively, were the best models for surface SSC predictions. The SeaWiFS Channel 5 (545–565 nm) was found to perform poorly. The authors attribute the inferior performance to reasons including the type of atmospheric correction technique applied, the shallow depth of the water samples collected, and the absorption effects from non-sediment water constituents.

Researchers in [98] developed an empirical algorithm using hyperspectral RS. The water irradiance reflectance spectra were acquired with dual Ocean Optic 2000 spectroradiometers (USB2000) with a sample size of 53 and about 2000 bands and a sampling interval and spectral resolution of approximately 0.3 nm and 1.5 nm, respectively. The study was carried out on the Patuxent River, a large tributary of Chesapeake Bay in the USA with a 2427 sq. km watershed area. The study developed empirical models using water reflectance for the retrieval of WQPs including TSS and found that the ratio of green to blue spectral bands was the best predictor of TSS (R^2 of 75% was established).

Researchers in [138] used a robust algorithm for the estimation of TSS in inland and nearshore coastal waters using a Statistical, inherent Optical property (IOP)-based, and muLti-conditional Inversion proceDure (SOLID) approach developed from semi-analytical, ML, and empirical models. To demonstrate the performance of the SOLID model, the model was implemented for images acquired by MultiSpectral Imager aboard Sentinel-2A/B over the Chesapeake Bay, San-Francisco-Bay-Delta Estuary, Lake Okeechobee, and Lake Taihu. It was established that the SOLID approach has the potential for producing TSS products in global coastal and inland waters. To obtain consistent, multi-mission TSS products, the model performance was extended and evaluated for other satellite missions including the OLCI, Landsat 8 OLI, MODIS, and VIIRS. Results obtained from statistical analysis showed the SOLID model improved retrieval performances offered by five widely used TSS retrieval methods for global and all water types. Comparing results to other models used in other studies shows improvement in the SOLID model to other models. For example for global waters, the statistical performance of the SOLID model had a median absolute percentage error (MAPE) of 49%, root means squared logarithmic error of 0.32, the mean absolute error (MAE) computed in log-space of 1.81, and log-transformed residuals (bias) of 1.09 compared with MAPE, MAE, RMSE, Bias of 58.82%, 2.56, 0.53, and 0.50, respectively, obtained by [131], MAPE, MAE, RMSE, Bias of 59.74%, 2.31, 0.46, and 1.26, respectively, obtained by [114][131], MAPE, MAE, RMSE, Bias of 57.71%, 2.17, 0.41, and 0.70, respectively, obtained by Petus et al. (2010), MAPE, MAE, RMSE, Bias of 68.38%, 2.28, 0.46, and 1.60, respectively, obtained by [79] and MAPE, MAE, RMSE, Bias of 52.73%, 1.92, 0.35, and 1.27, respectively, obtained by [69].

Researchers in [139] evaluated the radiometric and spatial performance of Chinese high-resolution GF-1 Wide Field Imager (WFI) data for monitoring SPM using inversion and regression models. Results obtained from GF-1 data were compared to outputs from the Landsat 8 OLI and MODIS (250 and 500 m) resolution bands. High consistency in spatial distribution and concentration of SPM maps was seen between the GF-1 and Landsat 8 OLI data. More than 75% of the spatial variations in turbidity were resolved by the GF-1 while only 40% were resolved by the MODIS band with 250 m resolution.

Researchers [140] used the NDVI to assess how catchment condition varies within and across river catchments in Zimbabwe. The study used a non-linear regression to check if the NDVI is significantly related to the levels of TSS. Results from the analysis showed a consistent negative curvilinear relationship between the NDVI derived from the

Landsat 8 OLI and TSS measured across the catchments under study. A total of 98% of the variations in TSS are explained by the NDVI in the drier catchments with 64% of the variations in TSS explained by the NDVI in the wetter catchments at the 0.05 significance level. The results showed a consistent negative curvilinear relationship between Landsat 8 OLI-derived NDVI and TSS measured across the catchments under study.

Researchers in [141] reported a linear relationship between reflectance and TSS at concentrations from 1 to 500 mg/L for a study conducted at the Didipio catchment located in the northern territory of the Philippines with a surface area of 39.25 km^2 using remote sensing images and empirical regression models. The catchment area is made of seven rivers (i.e., Dupit, Alimit, Surong, Camgat, Camgat-Surong, Didipio, and Dinauyan Rivers). The authors found that reflectance increases at a lower and variable rate in the concentration ranges of 500 to 3580 mg/L.

Researchers in [142] used Landsat 7 ETM+ and Landsat 8 OLI sensors to monitor WQPs, including TSM in a nutrient-rich (hypereutrophic) Qaraoun Reservoir in Lebanon. The study area has a surface area and median depth varying from 4 to 10 sq. km and 10 to 20 m, respectively. The reservoir has a maximum depth of 45 m. The study develops empirical algorithms to quantify the parameters of interest. In general, ETM+ sensors have improved performance compared to OLI sensors. R^2 was 81% for the ETM+ models and 58% for the OLI-based models. Results confirmed the effectiveness of using Landsat-based models to quantify WQPs in a semi-arid hypereutrophic reservoir, which presents the opportunity to improve the spatiotemporal coverage of data cost-effectively.

Researchers in [106] used Landsat 8 OLI RS spectral indices and empirical regression models for mapping SS in various dam impoundments located in South Africa. These dams include Spring Grove Dam, Midmar Dam, Nagle Dam, Albert Falls Dam, and the Inanda Dam. The indices considered were NSMI, WSRI, NDVI, and EGRI. The NSMI was the most effective index among the studied indices for the mapping of SS in the study area. Other spectral indices in the visible to shortwave infrared also produce reasonable estimations (R^2 of 70% at $p < 0.05$). The NSMI showed greater accuracy for the mapping of WQPs, as opposed to two-band spectral indices. The authors recommend comparing these results to other indices derived from high-resolution images such as Sentinel-2 and Ziyuan-3.

Researchers in [143] retrieved and mapped chlorophyll-a and TSS using Sentinel-2A images and Cubist ML models. Water samples used in the study were collected from water reservoirs within the southern part of the Czech Republic in Central Europe. The authors reported an R^2 of 80% for the accurate prediction of TSS. The study found dramatic temporal changes in the values of TSS in fishponds compared to sand lakes. Differences in the management practices in these water bodies were linked to the dramatic changes in TSS values over time.

Researchers in [144] assessed the impact of LULC on groundwater quantity and quality in Ajman City and its adjoining area located in the United Arab Emirates (UAE). The study correlated a Spectral Angle Mapper (SAM) and NDVI of Landsat 7 ETM+ and Landsat 8 OLI with WQPs including TDS. Analysis of the spatial extents revealed a sharp depletion in the quality and quantity of groundwater related to an increase in LULC. The mean TDS reported was about 24,210.5 mg/L with a groundwater depth of 14.8 m for 15 years.

Researchers in [145] used the NDWI indices of Landsat 8 OLI images as an effective tool to determine surface WQPs including TDS and TSS concentrations using step-wise regression-based models for the Bijayapur River flowing through Pokhara in Nepal. Reported TDS concentration ranges from about 244 to 1145 mg/L while TSS concentrations range from 0 to 750 mg/L.

Researchers in [146] used Landsat 8 OLI and forward regression analysis to develop models for the estimation of WQPs including TDS and TSS in the Tubay River located in the Philippines. The study found an R^2 of 96.8% for TDS and ≥24.4% for the regression models.

Another study by [147] developed an empirical regression algorithm to assess WQPs, such as TDS, EC, and water temperature, in the Tigris and Euphrates rivers in Iraq by using Landsat 5 TM. The stations used for the water quality monitoring were situated in Diyala and Baghad cities along the 120 km stretch of the Tigris River, and Ramadi and Karbala cities along the 277 km stretch of the Euphrates River. The model developed showed a significant correlation between models and WQPs with $R^2 > 0.83$. The measured and predicted TDS ranged from 350 to 550 mg/L.

Researchers in [111] also established a correlation between water extraction indices of Landsat 8 OLI and WQPs including TDS and TSS for the Tigris River for different type periods and found correlation of −0.808 between TDS and WRI and r of 0.651 for TSS and AWEI for the samples collected on 11 May 2017 in five stations in a stream of 15–20 m width. Field-measured TDS concentrations ranged from 450 to 646 mg/L while TSS ranged from 16 to 54 mg/L for the five stations on the said date.

Researchers in [148] correlated values of different Landsat 8 OLI sensor bands with the measured TDS and established a regression model for the estimation of TDS. The authors investigated the use of Digital Numbers (DN) of atmospherically corrected Landsat 8 OLI images in estimating TSS and TDS in Mosul Dam Lake located in Iraq using linear corrections between the reflectance values and the in situ field measurements. Bands 1, 5, and 6 were found to correlate to TSS for summer, spring, and autumn, while bands 3, 6, and 7 significantly correlated to TDS for autumn, summer, and spring. The highest R^2 values of 31% and 41% were obtained for TSS and TDS, respectively, in July.

Researchers in [26] utilized several ML models for estimating WQPs including TDS in Lake Tana located in the Tropical Highlands of Ethiopia, using Landsat 8 OLI images. The authors found the random forest regressors to be the best performing model for the estimation of TDS, which performed best for the TDS R^2, NSE, MARE, and RMSE of 79%, 0.80, 0.082, and 12.30 mg/L, respectively, for features such as the outcomes of (B4 + B3)/2, (B4 + B2)/2, (B3 + B2)/2, and (B2 + B3 + B4)/3.

Researchers in [149] assessed the water quality of River Beas in India using Landsat 5 TM imagery through multivariate and RS applications for pre- and post-monsoon seasons. They established that TDS correlates positively to the green band and negatively to the red band, using multiple linear regression and β-regression analysis. There was also a highly significant correlation between the predicted and observed values from an ANN for the parameters measured at $p < 0.001$. The study, however, did not report the R^2 values obtained.

Researchers in [107] used band reflectance and a combination of bands termed salinity indices in estimating TDS in the Shatt al-Arab River in Iraq using simple linear regression. Measured TDS were within the range of 800 to over 37,000 mg/L.

Researchers in [150] also used RS spectral indices to estimate TDS in the freshwater Guartinaja and Momil wetlands located in the Wetland Complex of Bajo Sinú, Northern Colombia. The authors utilized Sentinel-2 images in establishing empirical regression models for TDS estimations. Field measured TDS concentration ranged from about 154–218 mg/L. The study used ten spectral bands of the Sentinel-2 image and 11 indices which have been used in literature for the estimation of water, vegetation, or soils, and 2 indices developed by the authors. The model performed with high accuracy with a recorded normalized RMSE of <10%.

Researchers in [151] retrieved TDS concentrations from WQPs such as TSS obtained from drinking, ground, and surface waters for a study performed in a mining community of Tarkwa located in Ghana using models such as Gaussian process regression, principal component regression, and backpropagation neural network models. The findings reveal average R^2, RMSE, and MAE, of 98.7%, 4.090 mg/L, and 7.910 mg/L, respectively.

2.2.6. Strengths and Drawbacks of RS Methods for Measuring TDS and TSS

The concentrations of TDS and TSS in water are some of many environmental phenomena that may be efficiently monitored using cutting-edge, modern, and advanced RS techniques. The use of RS to measure and monitor TDS and TSS has produced promising results in the assessment of water quality [34][58][103][104][107][148][152]. However, some limitations and difficulties must be noted, as with any technology.

Strengths

RS applications allow for the monitoring of WQPs including TDS and TSS on a large spatiotemporal scale. With RS, changes in these WQPs are monitored over time and across large areas and at a great distance ranging from hundreds to thousands of miles compared to grab sampling approaches which are point specific. Additionally, RS can facilitate the study of these WQPs in areas that are hard to access or inaccessible, such as remote, dangerous, or politically sensitive areas. RS also makes it easy to identify sources, routes, and sinks of sediments and other parameters in water bodies in these areas [2][13][36][63][148].

RS images used for monitoring these WQPS range from low, to moderate to high-resolution obtained from Landsat, RapidEye, SPOT, MODIS, MERIS, the Advanced Wide Field Sensor (AWiFS), and Sentinel-2 among many others. A high spatial resolution image captured allows for accurate detection of TDS and TSS comparable with conventional methods [2][34][36][56][65][103][152].

Most RS images are publicly accessible, open-source data that users can obtain for free or at a low cost. Some of these images such as those of Landsat can date back as far as the 1970s and have been used extensively for the estimation of TSS and TDS in several studies possibly due to the fact they are easily accessible and come at little to no cost. RS applications aid in reducing associated cost-intensive laboratory equipment and reagents [96][106][107][148]. By using Landsat image data, users have saved around USD 3.45 billion as of 2017, with users in the United States making up more than half of that total [153]. Landsat imagery has been used in historical as well as contemporary regional assessments of various WQPs to assess water clarity [154].

When used in conjunction with conventional field measurements, RS can be used to develop algorithms and models for accurate estimations of TDS and TSS concentrations even in remote and inaccessible areas and in real-time. Additionally, conventional methods of measurement are susceptible to errors caused by sample storage, transportation, and analysis which can be reduced with the RS application. RS thus offers a non-invasive mechanism that does not require physical water sampling, hence cutting errors associated with sample storage, transportation, and analysis [2][107][155].

Drawbacks

RS applications in the retrieval of WQPs such as TDS and TSS can be quite challenging, particularly in shallow waters where the retrieved parameter levels could be greatly influenced by the contribution of the benthic signal to the overall reflectance signal, requiring the need for specific correction algorithms which consider the influence of the bottom reflectance to improve the accuracy of the WQP estimations. Other factors of the shallow water bodies which could also impact the accuracy of retrieval of the TDS and TSS include the varied bottom depths, types, and substrates which have the potential to impact the scattering and absorptive characteristics of light signals [156][157]. The accuracy of these retrieved WQPs in transitional waters such as estuaries could also be less successful owing to the high optical complexities of these waters coupled with their closeness to the land [158]. Additionally, the accuracy of data acquired might be affected by atmospheric factors such as cloud cover and haze, which are serious drawbacks of using RS for monitoring WQPs such as TDS and TSS. It is much more difficult to obtain accurate data with RS technologies in regions that have regular cloud cover or significant levels of air pollution [2][63][159].

RS may not always produce the level of detail needed for precise TDS and TSS measurements since the resolution of the imagery and data collected can be limited by the altitude of the platform used for the data collection which can present challenges to monitoring and measuring parameters such as TDS and TSS in water bodies with intricate shorelines or highly localized areas [160].

Another drawback with the use of RS in the measurement of TDS and TSS is the difficulty in making distinctions between these components of total solids. TSS is an optically active parameter that can be easily detected with optical sensors, TDS on the hand is difficult to accurately obtain from RS platforms. They are estimated from RS images because of their relationships with colored WQPs with which they may co-vary [2][36][161].

Although most RS images are available at no cost there are some images particularly hyperspectral images that require payment for the use of images. The associated cost of airborne sensors mounted on aircraft to acquire RS images may be significantly high and can deter other people from having access to such technologies. The initial cost of equipment and training for RS technology can be high. This may make them inaccessible to smaller organizations or underfunded researchers particularly those in developing countries [63][160].

RS applications in WQPs measurement require specialized training to analyze the images and data gathered. Individuals using RS in monitoring and measuring WQPs such as TDS and TSS require expertise in the use of software such as ArcGIS and Google Earth Engine among others, which can limit the number of people who can utilize these applications [46][61][160].

Another limitation of RS applications is the spatial, temporal, and spectral resolutions of the sensor used in the data collection. It may be challenging to rely on a certain RS sensor with a longer repeat cycle to detect temporal variations in the TDS and TSS. RS sensors offer a variety of spatial, spectral, and temporal resolutions. One example is contrasting the temporal resolutions of Landsat 8 OLI and Sentinel-2 A/B MSI, both of which have revisit times of 16 days and 5 days, respectively [2][162].

The last but not the least limitation of RS techniques in estimating WQPs such as TDS and TSS, is the lack of field data for the calibration and validation of the models developed with RS data due to the high cost of on-site sampling and the required expertise in analyzing and making inferences from the samples collected. These issues are more prevalent in Sub-Saharan Africa which has less expertise and technology. The lack of proper calibration and validation of remote sensed models exposes the accuracy of these models to questioning [2][7][10][36].

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