Monitoring water quality in two dammed reservoirs from multispectral satellite data

Mariano Bresciani, Claudia Giardino, Daniela Stroppiana, Maria Antonietta Dessena, Paola Buscarinu, Loretta Cabras, Karin Schenk, Thomas Heege, Hendrik Bernet, Giorgos Bazdanis, and Apostolos Tzimas

ABSTRACT

Providing relatively fine spatial resolution multispectral data, Landsat-8, Landsat-7 (L8 and L7, respectively) and Sentinel-2 (S2) from 2013 to 2018 have been used in this study for enabling high-frequency monitoring of water quality of two small (the smaller with an area of 1.6 km²) freshwater dammed reservoirs. Located in Sardinia (Italy) and Crete (Greek), respectively, Mulargia and Aposelemis represent vital resources to supply drinking water in downstream valleys. A total of 400 cloud-free satellite images were turned into information on water quality by using an image processing chain implementing physically based methods for retrieving chlorophyll-a concentration (Chl-a), turbidity, Secchi disk depth (SDD) and surface water temperature. These estimates have been successfully validated (the lower Pearson correlation r was 0.88 for Chl-a) with 23 match-ups of in situ and satellite data. Results of the multi-temporal analyses showed a decrease of SDD due to the increase of Chl-a in Aposelemis or an increase of turbidity in Mulargia. For both freshwater reservoirs, the satellite-derived trophic state index assigned both lakes to mesotrophic conditions. The results finally suggested the effectiveness of S2 and Landsat in increasing, for the latest investigated years, the frequency of observations.

Introduction

Water resources are limited and are facing issues that are caused by over-exploitation, continuous human pressure and also climate changing, which could have serious consequences on water quality (Shevah, 2015), an essential resource for human health, ecosystems and the economy. Degradation of water quality can result in human exposure to harmful diseases and chemicals (Hu & Cheng, 2013), reduced productivity and diversity of ecosystems and damage to aquaculture, agriculture and other water-related industries (Kaiblinger et al., 2009).

With environmental pollution and decrease in water availability becoming an increasingly serious problem, the issue of water quality and quantity has attracted serious attention from the public and the government (Xin, Li, Finlayson, & Yin, 2015). Therefore, the number of artificial reservoirs is rapidly increasing owing to the growth of the world’s economy and related energy and water needs (Zhang et al., 2019) such as domestic, agriculture, and energy, despite the costs to build a dam are getting higher every year (Ahmad, El-Shafie, Razali, & Mohamad, 2014). A primary concern of water authorities is to have information on current status of water quality, so different water quality evaluation methods have been developed and extensively applied (e.g. Gao, Birkett, & Lettenmaier, 2012; Gopal, Goel, Sharma, & Trivedy, 1981; Olsen, Chappell, & Loftis, 2012). Some of these studies (e.g. Robert et al., 2016) showed that a successful approach for water quality monitoring might be carried out through measures which include in situ, laboratory, and satellite measurements. While in situ sampling allows the analysis of a wide range of parameters at various depths to be performed, remote sensing technologies support frequent synoptic measurements and extend the ability to study remote waterbodies that cannot be visited regularly in a cost-effective way (e.g. Bresciani, Stroppiana, Odermatt, Morabito, & Giardino, 2011; MacKay et al., 2009). In situ and remote detection techniques are complementary and overall support a wide range of possibilities for monitoring water quality, including integration into regional and local models for water quality prediction (CEOS, 2017).

Data retrieved through remote sensing techniques have easy access (many moderate spatial resolution images are free; e.g. Landsat, MODIS, Sentinel), yet necessitate some processing for turning measured satellite radiances into water quality information. In particular, the correction for atmospheric interference (e.g. Richter, 2009; Vermote, Tanré, Deuzé, Herman, &...
Morcrette, 1997), for irradiance reflection from adjacent land targets (Kiselev, Bulgarelli, & Heege, 2015) and for air/water effects (Hedley, Harborne, & Mumby, 2005; Zhang & Wang, 2010), is firstly needed for retrieving the water leaving reflectance. Subsequent or simultaneously, the water reflectance is analysed in order to estimate water quality parameters such as chlorophyll-a (Chl-a), coloured dissolved organic matter (CDOM), suspended particulate matter (SPM) or turbidity. Their estimates might be achieved with spectral band algorithms (e.g. Eleveld, Pasterkamp, van der Woerd, & Pietrzak, 2008; Gitelson, Schalles, & Hladik, 2007; Knaeps, Dogliotti, Raymaekers, Rudyck, & Stercxh, 2012; Kutser, 2009) or spectral inversion procedures by which concentrations of water quality parameters are retrieved from water reflectance via spectral inherent optical properties of water constituents (e.g. Doerffer & Schiller, 2008; Gege, 2014; Heege, Kiselev, Wettle, & Hung, 2014; Van Der Woerd & Pasterkamp, 2008).

Moreover, satellite sensors operating in the thermal infrared (TIR) bands are providing measurements on lake surface water temperatures (LSWT) that, apart to indicate the status of water, is of great importance to monitor the consequences of the climate change and to study climatological cycles (Layden, Merchant, & MacCallum, 2015; Song et al., 2016). Overall, the use of thermal data in inland water has been presented for multiple scale applications, ranging from local to regional, up to the global (O’Reilly et al., 2015; Oesch, Jaquet, Hauser, & Wunderle, 2005; Reinart & Reinhold, 2008; Steissberg, Hook, & Schladow, 2005).

The aim of this study is to investigate the use of Sentinel-2 (S2) and Landsat-7 (L7) and Landsat-8 (L8) for monitoring water quality in two freshwater reservoirs. Both satellites have sensors contain overlapping visible, near-infrared (NIR) and shortwave-infrared (SWIR) bands making both instruments capable of monitoring a range of water quality constituents in freshwater ecosystems (Bresciani et al., 2018; De Keukelaere et al., 2018; Lehmann, Nguyen, Allan, & van der Woerd, 2018; Pinardi et al., 2018; Toming et al., 2016). In addition, a synergic use of VIS-NIR and TIR bands of L8 has been proved to be crucial in hydrodynamic modelling of mesoscale phenomena (e.g. Brando et al., 2015). Integration of L7, L8 and S2 satellite-based datasets then enables high-frequency revisit times of about 3 days at medium latitudes, where this study focuses on. The study area is in fact represented by two dammed reservoirs, of two islands of the Mediterranean Sea, which are providing drinkable waters to downstream valleys. By observing water quality parameters from 2013 to 2018, the study also aims to evaluate if significant variation of water quality in the study area occurred in recent years.

**Materials and methods**

**Study area**

Two freshwater dammed reservoirs have been investigated in this study (Figure 1 and Table 1). Both located in the Mediterranean region, they are Mulargia (Italy) and Aposelemis (Greece).

The Mulargia is a dammed reservoir build on Flumendosa river located in south Sardinia, the second-largest Italian island. With a surface area of 12 km$^2$ and a capacity of 347 hm$^3$ (Table 1), Mulargia serves as a drinking water source for the town of Cagliari with hinterland and for about 20 villages around in the greater area, summing up to a population of 700.000 inhabitants. The total annual abstraction for drinking water purposes is estimated to be 100 hm$^3$. The Mulargia waters are in mesoeutrophic state as a consequence of loads of phosphorus mostly due to agriculture and zootechnic, with low transparency and high conductivity representing the most important issues.

The Aposelemis reservoir is also artificial; it is located in the north-eastern part of Crete island.

![Figure 1. Study area. On the left the Mulargia dam (bottom) and from satellite. On the right: Aposelemis dam (bottom) and from satellite (top).](image-url)
Table 1. Main features of Mulargia and Aposelemis reservoirs.

| Season       | Mulargia (Italy) | Aposelemis (Greece) |
|--------------|------------------|---------------------|
| Dam height   | 99 m             | 50 m                |
| Reservoir area | 12 km²          | 1.6 km²             |
| Capacity     | 347 hm³          | 27 hm³              |
| Catchment area | 178 km²         | 62 km²              |
| Rainfall     | 600 mm/year      | 800 mm/year         |

With surface area of 166 km² and a capacity of 27 hm³ (Table 1), Aposelemis reservoir serves as a drinking water source for the towns of Heraklion and Agios Nikolaos, as well as local communities in the greater area, summing up to a population of 300,000 inhabitants. The total annual abstraction for drinking water purposes is estimated to 17 hm³.

**Satellite and field data**

For assessing water quality in the study area, imagery acquired from multispectral optical sensors onboard of the polar orbiting satellites L7, L8 and S2 was used. The two S2 twin satellites A and B (S2A/B) carry the MSI (Multispectral Instrument) optical sensor, which acquires in 13 bands, in the spectral region between 442 and 2201 nm, with a spatial resolution of 10-20-60 m depending on bands. The L7 satellite carries onboard the ETM+ sensor (Enhanced Thematic Mapper Plus), with seven spectral bands in the spectral region between 435 and 2345 nm with a spatial resolution of 30 m, and a TIR band with a spatial resolution of 60 m. Finally, L8 equipped with OLI (Operational Land Imager), which acquires in 9 bands in the spectral region between 435 and 2294 nm with a spatial resolution of 30 m. L8 also carries onboard the Thermal Infrared Radiometer Sensor (TIRS) with a spatial resolution of 100 m. Table 2 shows the main characteristics of different satellite sensors used in this work.

Table 2. Main characteristics of satellite sensors used in this study.

| Satellite | Sentinel-2A; 2B | Landsat-8 | Landsat-8 | Landsat-7 |
|-----------|-----------------|-----------|-----------|-----------|
| Sensor    | MSI             | OLI       | TIRS      | ETM+      |
| Wavelength range (μm) | 0.443–2.190 | 0.435–2.924 | 10.60–12.51 | 0.45–2.35 |
| Number of bands | 13             | 9         | 2         | 8         |
| Spatial resolution (m) | 10-20-60 (depending on spectral bands) | 30        | 100       | 30        |
| Swath width (km) | 290            | 185       | 185       | 185       |
| Repetitivity (days) with constant viewing angles | 10 (1 satellite) | 16       | 16        | 16        |
| Year of launch | 2015 (2A) 2017 (2B) | 2013 | 2013 | 1999 |

For the period 2013–2018, 400 cloud-free satellite images have been processed to obtain water quality products, in particular maps of Chlorophyll-a concentration (Chl-a), turbidity, transparency and trophic status index (based on Carlson, 1977). In particular, the trophic status index has been also implemented by the Copernicus Global Land Service Lake Water Quality (Simis, Stelzer, & Müller, 2018). Furthermore, water surface temperature maps have been produced on TIR measurements.

Table 3 shows the frequency of satellite acquisitions available for estimating LSWT and SDD, TUR and Chl-a over the multi-annual study period and for the four seasons. Since TIR measurements are only available on L7 and L8, it is clear that the improved revisiting for observing water quality parameters by using also S2 is not applicable to LSWT.

The physical methods implemented in the Modular Inversion and Processing System (MIP) (Heege & Fischer, 2004; Heege, Hausknecht, & Kobryn, 2007; Heege et al., 2014) were used for retrieval of water constituents from S2 and Landsat. MIP is a sensor independent image processing chain based on radiative transfer-based which couples atmospheric-adjacency-sunlight correction images. It solves the Radiative Transfer Equation (RTE) using a Finite Element Model (FEM) in a multi-layer system, including atmosphere, water surface, waterbody and, in case of optically shallow waters, the bottom reflectance (Bulgarelli, Kisselev, & Roberti, 1999; Kisselev & Bulgarelli, 2004). All bidirectional dependencies of scattering and absorption properties in the atmosphere and the waterbody, as well as bidirectional reflectance and transmission of the water surface, are accounted for within one consistent RTE model. The model also considers the full range of possible geometrical conditions between sensor, sun and target.

Table 3. Frequency of satellite data available for estimating LSWT (with L7 and L8) and SDD/TUR/Chl-a (with L7, L8 and S2) over the multi-temporal period 2013–2018.

| Season       | Mulargia | Aposelemis |
|--------------|----------|------------|
| Winter       | 105      | 40         |
| Spring       | 22       | 53         |
| Summer       | 53       | 42         |
| Autumn       | 147      | 51         |

| Season       | Tot      |
|--------------|---------|
| Winter       | 105     |
| Spring       | 22      |
| Summer       | 53      |
| Autumn       | 42      |
| Tot          | 147     |
Results of the statistical analysis for evaluation of satellite-derived products.

Av. in situ Av. Sat
0.94 with the lower 2018 time span. Maps of and Physics-based work in the range 0.87
fi
r
implemented in MIP to 4 hr). In fact, unlike SDD and
μ
Schott (2003), Barsi et al. (2014). The model runs with input data on atmospheric profile on air temperature, pressure and relative humidity, preselected according to the latitudes of the target and the season. The method has been extensively adopted in multiple applications, including the retrieval of sea-surface temperature (Brando et al., 2015).

The image-derived products were compared to in situ measurements available for both reservoirs. In particular, a series of field campaigns were organised in coincidence to satellites overpasses in both reservoirs: on 10/11/2016, 05/06/2018 and 22/07/2018 for Mulargia, and 02-03/07/2018 for Aposelemis. Water was collected by sampling in the photic layers including the retrieval of sea-surface temperature (Brando et al., 2015).

Validation
The comparisons of satellite-derived water quality parameters and field data showed a good global agreement as presented in Table 4 with a Pearson correlation coefficient $r$ in the range 0.87–0.94 with the lower value observed for Chl-a. This is likely due to the difference between the time of satellite overpass (instantaneous acquisition) and in situ sampling (typically performed in 3–4 hr). In fact, unlike SDD and turbidity, Chl-a is the parameter showing greater short-term variations due to intra-daily dynamics of phytoplankton. These diurnal periodic changes are particularly evident in summer when solar irradiation

![Figure 2. Physics-based workflow implemented in MIP to derive satellite-based water quality.](image)

| Parameter | N. sample | RMSE | $r$  | Av. in situ | Av. Sat |
|-----------|-----------|------|-----|-------------|---------|
| SPM (g/m$^3$)/TUR | 19 | 1.05 | 0.94 | 6.90 | 6.62 |
| SDD (m) | 23 | 0.41 | 0.93 | 2.27 | 2.23 |
| Chl-a (mg/m$^3$) | 23 | 5.11 | 0.87 | 17.66 | 12.54 |
and air temperature change quickly. Even if satellite remote sensing significantly improves the frequency of observation compared to in situ sampling, in highly dynamic water systems, overpass frequency of satellite observations from polar orbiting systems is still limited to capture diurnal or semi-diurnal cycles (Li et al., 2013).

**Multi-temporal analysis for Mulargia reservoir**

Satellite-based products provided long-term information on LSWT, SDD and Turbidity for the entire dataset of Mulargia reservoir, as shown in the three panels of Figure 3. For each panel, the marker represents lake’s surface average ± one standard deviation values and filling colour shows the source satellite mission (L7, L8 and S2). Since early 2016 (after the closing of the commission phase), the frequency of observation of water quality has been greatly improved by the availability of S2A data (yellow circles) further enhanced by the launch of S2B in spring 2017. For the year 2017 (full availability of S2 data) a total of 55 images were available for deriving maps of SDD and Turbidity. A separate issue is the estimation of LSWT, which relies on the availability of spectral bands in the thermal-infrared wavelengths, so far available only for Landsat (by considering that a moderate to high spatial resolution is needed in this study).

The results clearly show the influence of turbidity levels on Secchi disk values with opposite trends (i.e. highest SDD peaks coincides with lowest turbidity values and vice versa); data shown in Figure 3 highlight maximum SDD and minimum turbidity values occurring in summer with transparent waters. On the contrary, spring and autumn seasons are generally characterized by greater turbidity as a consequence of meteorological extreme rainfall events (Caloiero & Veltri, 2018). Multi-temporal data show that significant events of SDD maximum peaks occurred in 2018: in fact, out of a total of 12 dates with SDD > 3 m, six occurred in the first half of 2018. Anomalous values for summer 2018 are confirmed by the analysis of temporal trends by season, as shown in Figure 4.

Time series for turbidity (NTU values) show a tendency to increase with annual average values equal to 9.9, 12.1 and 8.96 for 2016, 2017 and 2018, respectively; these values are almost twice average values for the preceding years. In particular, highest turbidity values were estimated for January to March 2017: 53.01, 44.54 and 22.31, respectively. Trends are also confirmed by Figure 3 where high turbidity conditions started in winter 2017 carried on to spring months although average conditions for spring 2017 are well comparable to average values for the year 2018. With respect to 2017 and 2018, average spring turbidity for the preceding years was much lower.

For LSWT, as expected, seasonal trends are evident through the years with highest (lowest) values in summer (winter) season (Figure 3 top panel). In particular, highest summer values were observed in July and August 2017 (average monthly LWST ~ 26°C); for the same months and other years, average LWST was in the range 24–25°C.

Average estimated Chl-a over the study period was 10.8 mg/m³, with minima in winter seasons of about 0.8 mg/m³ and maxima occurring in autumn 2017 (~30 mg/m³). In the same period, a cyanobacteria

---

**Figure 3.** The temporal variation of LSWT (top panel), SDD (middle panel) and TUR (bottom panel) parameters in Mulargia reservoir. Each point shows the parameter’s mean value ± one standard deviation (black vertical bars). Filling colour of each marker highlights the source satellite mission and grey vertical dash line the years spanned by the time series.
bloom occurring over the lake surface and observed during in situ surveys (*Planktothrix rubescens*) determined high Chl-a values that reached local absolute maxima of 77.2 mg/m$^3$ close to the central area of the lake. *Planktothrix* is one of the most genus of cyanobacteria presents in the Mulargia (Buscarinu et al., 2003), the depth at which *Planktothrix* stratifies is therefore explained by buoyancy regulation in relation to the irradiance; in autumn 2017, the high cloudiness has driven migration of *Planktothrix* to the surface (Walsby, Ng, Dunn, & Davis, 2004). Highest average annual values for Chl-a were observed in 2016 and 2017 (16.7 and 17.6 mg/m$^3$, respectively) compared to previous years when average annual Chl-a was in the range 10.8–13.7 mg/m$^3$.

The spatial analysis of Chl-a average distribution and variation (Coefficient of Variation, CV) over the lake’s surface (Figure 5) shows higher values in the northern regions, where Flumendosa river transports nutrient-rich waters into the reservoir. In this region, besides the river water inflow, low bathymetry facilitates resuspension of nutrients that are present in the sediments. Lowest Chl-a values can be observed in the southern areas, close to the Mulargia dam, where a water caption point is located.

The conversion of Chl-a concentration maps into trophic state index highlighted that the highest frequency of the pixels (about 5 × 10$^6$) was found to be of class 6 and the second class of frequency was class 7 with about 1 × 10$^6$ pixels.

**Multi-temporal analysis for Aposelemis reservoir**

Figures 6 and 7 show the same trend analysis for the Aposelemis reservoir. By inspecting SDD and turbidity panels in Figure 6, it is noticeable how standard deviation (black bars) is much greater than Mulargia’s...
Standard deviation decrease with the onset of S2 time series, which is characterized by a greater spatial resolution with respect to Landsat sensors, thus reducing adjacency effects. In Aposelemis, two major significant events of turbidity peak occurred in January 2015 and 2017, with average values of 26 and 15 NTU, respectively. These values are in correspondence with minima in SDD observations, since high turbidity, as excepted, leads to loss of transparency.

Since the end of 2017, the reservoir witnessed a significant increase in turbidity levels with monthly average values above 8 NTU and a maximum of 13.8 NTU in June 2018. This positive trend is likely due to a decrease of water levels; reduced water levels also enhance the effect of wind on the resuspension of fine sediments from the bottom of the lake in the shallower areas of the lake. Lowering of water level is a factor that affects turbidity in many lakes (Giardino, Bresciani, Villa, & Martinelli, 2010; Lisi & Hein, 2019) by making wind one of the dominant factors in determining the variability of water transparency (Jalil et al., 2019; Meyer, Leonhardt, & Blindow, 2019). Over the six-year study...
period, the temporal trend of SDD and Turbidity shows a slight tendency to loss of transparency.

Looking at seasonal trends shown in Figure 7, the increase through years for turbidity is clearly visible for spring and autumn whereas a more variable behaviour can be observed for the other two seasons. This trend is confirmed for SDD (decreasing trend over spring values) while, as discussed above, more variable and less consistent behaviour is observed for the other seasons.

For what concerns LWST, maximum summer values were observed in 2017; notice that higher values of 2018 represent estimations only for the month of July hence they are not representative of the entire summer period. In 2014 and 2016, winter statistics show greater variability with respect to the other years of the investigated time series.

Finally, Figure 8 shows average Chl-a and coefficient of variation, CV, as computed over the study period. For Lake Aposelemis, 160 cloud free images show that average Chl-a was 16 mg/m³ (min 1.7 and max 45.2) with reduced spatial variability within the reservoir (Figure 8). In the central regions, slightly higher average Chl-a values are combined with a high coefficient of variation (CV > 75%). The lowest values were found at the northernmost border close to Aposelemis dam, where the water caption point is located.

The conversion of Chl-a concentration maps into trophic state index highlighted that the highest frequency of the pixels (about $4.4 \times 10^4$) was found to be of class 6 and the second class of frequency was class 7 with about $3.4 \times 10^4$ pixels.

Conclusions

Landsat-7 & 8 and Sentinel-2A & B have been used to observe a set of key parameters for monitoring water quality. Satellite-derived products, obtained with physically based image processing chains have been providing multi-temporal and multi-scale data over two small freshwater reservoirs from 2013 to the present. The investigated temporal range also clearly showed how, since early 2016, the frequency of observation of water quality (apart for LSWT) has been greatly improved by the availability of S2A data further enhanced by the launch of S2B in spring 2017.

Despite challenges (due to e.g. adjacency effects) for retrieving water quality parameters over small to medium size lakes (i.e. 1.6 km² for Aposelemis, which is approximately 10 times smaller than Mulargia), the adopted physics-based models produced accurate results. In particular, satellite and field data show a good correlation. Results of the multi-temporal analyses showed a worsening in water quality due to the combination of increasing Chl-a and turbidity for a decreasing of Secchi disk depth. This was mostly occurring in concomitance with low water levels and intense precipitation events, the latter that foster a high run-off of particulate matter from the basin. For both freshwater reservoirs, the trophic state index evaluated from satellite data assigned both lakes to mesotrophic conditions.

Satellite products described in this study were distributed to water managers of Mulargia and Aposelemis basins via web map server for supporting lake water management plans of both freshwater reservoirs.

Acknowledgments

This study was supported by the H2020 SPACE-O project (Space Assisted Water Quality Forecasting Platform for Optimized Decision Making in Water Supply Services) Grant Agreement n. 730005. Many thanks to all ENAS and OAK peoples for the support in the fieldwork activities. Thanks to Giulia Luciani and Rossano Bolpagni for their support during the preparation of the paper. We are grateful to Editor and reviewer for their useful comments on the manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Mariano Bresciani http://orcid.org/0000-0002-7185-8464
References

Ahmad, A., El-Shafie, A., Razali, S.F.M., & Mohamad, Z.S. (2014). Reservoir optimization in water resources: A review. Water Resources Management, 28(11), 3391–3405. doi:10.1007/s11269-014-0700-5

Barsi, J.A., Barker, J.L., & Schott, J.R. (2003). An atmospheric correction parameter calculator for a single thermal band earth-sensing instrument. In IGARSS 2003. 2003 IEEE International Geoscience and Remote Sensing Symposium. Proceedings (IEEE Cat. No. 03CH37477) (Vol. 5, pp. 3014–3016). IEEE.

Barsi, J.A., Schott, J.R., Hook, S.J., Raqueno, N.G., Markham, B.L., & Radocinski, R.G. (2014). Landsat-8 Thermal Infrared Sensor (TIRS) vicarious radiometric calibration. Remote Sensing, 6, 11607–11626. doi:10.3390/rs61116072014

Braga, F., Zaggia, L., Bellafiore, D., Bresciani, M., Giardino, C., Lorenzetti, G., … Brando, V.E. (2017). Mapping turbidity patterns in the Po river prodelta using multi-temporal Landsat 8 imagery. Estuarine, Coastal and Shelf Science, 198, 555–567. doi:10.1016/j.ecss.2016.11.003

Brando, V.E., Braga, F., Zaggia, L., Giardino, C., Bresciani, M., Matta, E., … Bonaldo, D. (2015). High-resolution satellite turbidity and sea surface temperature observations of river plume interactions during a significant flood event. Ocean Science, 11(6), 909–920. doi:10.5194/os-11-909-2015

Bresciani, M., Cazzaniga, I., Austoni, M., Sforzi, T., Buzzi, F., Morabito, G., & Giardino, C. (2018). Mapping phytoplankton blooms in deep subalpine lakes from Sentinel-2A and Landsat-8. Hydrobiologia, 824(1), 197–214. doi:10.1007/s10750-017-4362-2

Bresciani, M., Stroppiana, D., Odermatt, D., Morabito, G., & Giardino, C. (2011). Assessing remotely sensed chlorophyll-a for the implementation of the water framework directive in European perialpine lakes. Science of the Total Environment, 409(17), 3083–3091. doi:10.1016/j.scitotenv.2011.05.001

Bulgarelli, B., Kiselev, V., & Roberti, L. (1999). Radiative Transfer in the atmosphere ocean system: The finite-element method. Applied Optics, 38, 1530–1542. doi:10.1364/OA.38.001530

Buscarini, P., Catani, F., Dessena, M.A., Moretti, S., Righini, G., & Rodolfi, G. (2003). Assessing environmental sustainability: Remote sensing and GIS as tools for water resources evaluation. WIT Transactions on Ecology and the Environment, 63, 465–475.

Caloiero, T., & Veltri, S. (2018). Drought assessment in the Sardinia Region (Italy) during 1922–2011 using the standardized precipitation index. Pure and Applied Geophysics, 176(2), 925–935.

Carlson, R.E. (1977). A trophic state index for lakes. Limnology and Oceanography, 22(2), 361–369. doi:10.4319/lo.1977.22.2.0361

CEOS. (2017). Feasibility study for an aquatic ecosystem earth observing sensor. In A.G. Dekker Ed., CEOS report 2017, p. 203. Canberra: CSIRO.

De Keukelaere, L., Sterckx, S., Adriaensen, S., Knaeps, E., Reusen, I., Giardino, C., Bresciani, M., et al. (2018). Atmospheric correction of Landsat-8/OLI and Sentinel-2/MSI data using iCOR algorithm: Validation for coastal and inland waters. European Journal of Remote Sensing, 51(1), pp. 525–542. doi:10.1080/22797254.2018.1457937

Derffer, R., & Schiller, H. (2008). MERIS lake water algorithm for BEAM’ BEAM algorithm technical basis document (pp. 17). Geesthacht, Germany: GKSS Forschungszentrum.

Eleveld, M.A., Pasterkamp, R., van der Woerd, H.J., & Pietrzak, J.D. (2008). Remotely sensed seasonality in the spatial distribution of sea-surface suspended particulate matter in the southern North Sea. Estuarine, Coastal and Shelf Science, 80(1), 103–113. doi:10.1016/j.ecss.2008.07.015

Gao, H., Birkett, C., & Lettenmaier, D.P. (2012). Global monitoring of large reservoir storage from satellite remote sensing. Water Resources Research, 48, 9. doi:10.1029/2012WR012063

Gege, P. (2014). WASI-2D: A software tool for regionally optimized analysis of imaging spectrometer data from deep and shallow waters. Computers & Geosciences, 62, 208–215. doi:10.1016/j.cageo.2013.07.022

Giardino, C., Bresciani, M., Villa, P., & Martinelli, A. (2010). Application of remote sensing in water resource management: The case study of Lake Trasimenno, Italy. Water Resources Management, 24(14), 3885–3899. doi:10.1007/s11269-010-9639-3

Gitelson, A.A., Schalles, J.F., & Hladik, C.M. (2007). Remote chlorophyll-a retrieval in turbid, productive estuaries: Chesapeake Bay case study. Remote Sensing of Environment, 109, 464–472. doi:10.1016/j.rse.2007.01.016

Gopal, B., Goel, P.K., Sharma, K.P., & Trivedy, R.K. (1981). Limnological study of a freshwater reservoir, Janwa Ramgarh (Jaipur). Hydrobiologia, 83(2), 283–294. doi:10.1007/BF00008279

Hedley, J.D., Harborne, A.R., & Mumby, P.J. (2005). Technical note: Simple and robust removal of sun glint for mapping shallow-water benthos. International Journal of Remote Sensing, 26(10), 2107–2112. doi:10.1080/0143116050034086

Heege, T., & Fischer, J. (2004). Mapping of water constituents in Lake Constance using multispectral airborne scanner data and a physically based processing scheme. Canadian Journal of Remote Sensing, 30, 77–86. doi:10.5589/m03-056

Heege, T., Hausknecht, P., & Kobryn, H. (2007). In Hyperspectral seaﬂoor mapping and direct bathymetry calculation using HyMap data from the Ningaloo reef and Rottnest island areas in western Australia. Proceedings of the 5th EARSeL Workshop on Imaging Spectroscopy, Bruges, Belgium. doi:10.1099/PDIS-91-4-0467B

Heege, T., Kiselev, V., Wettle, M., & Hung, N.N. (2014). Operational multi-sensor monitoring of turbidity for the entire Mekong Delta. International Journal of Remote Sensing, 35(8), 2910–2926. doi:10.1080/01431161.2014.890300

Hu, Y.N., & Cheng, H.F. (2013). Water pollution during China’s industrial transition. Environmental Development, 8, 57–73. doi:10.1016/j.envdev.2013.06.001

Jalil, A., Li, Y., Zhang, K., Gao, X., Wang, W., Khan, H.O., … Acharya, K. (2019). Wind-induced hydrodynamic changes impact on sediment resuspension for large, shallow Lake Taihu, China. International Journal of Sediment Research, 34(3), 205–215. doi:10.1002/jisr.201800031

Kaiblinger, C., Annette, O., Tadonleke, R., Rimet, F., Druart, J.C., Guillard, J., & Dokulil, M.T. (2009). Central European water quality indices applied to long-term data from peri-alpine lakes: Test and possible improvements. Hydrobiologia, 633, 67–74. doi:10.1007/s10750-009-9877-7
