
9 Monitoring Water Quality with Remote Sensing Image Data

*Bunkei Matsushita, Wei Yang,
Lalu Muhamad Jaelani, Fajar Setiawan,
and Takehiko Fukushima*

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9.1 INTRODUCTION

Water covers approximately 74% of the Earth's surface, and it plays many important roles in the lives of all human being. Inland and coastal waters in particular have a direct interface with human society by providing value for food supplies, industrial uses, transportation, commerce, and human health (UNEP 2006). However, many water bodies have encountered severe environmental problems (e.g., eutrophication) in recent decades as a result of human interventions and climate change (Ayres et al. 1996; Haddeland et al. 2014). It is thus crucial to monitor and understand the amount and quality of these water bodies as well as their biogeochemical processes in order to achieve the effective management and sustainable use of the water resources (United Nations Open Working Group 2014).

Since conventional water-monitoring methods (e.g., water sampling from a boat) are very time-, labor-, and cost-consuming, the maintenance of steady monitoring is difficult for local and national governments with meager financial resources,

especially in developing countries. For example, even when a lake is monitored by an in situ sampling method, the number of sampling locations and the frequency of water sampling may not accurately represent the actual status of the entire lake, because the water quality can dramatically change both spatially and temporally (Kiefer et al. 2015). However, with the progress of satellite sensors and water quality estimation algorithms, remote sensing is regarded as a quite useful technique for studying bodies of water, as it can provide synoptic observations at very frequent intervals for water bodies, at relatively low cost (Dekker and Hestir 2012).

In this chapter, we focus on how to obtain water quality data from remote sensing techniques that can be used toward achieving the Sustainable Development Goal 6.3 (Monitoring Ambient Water Quality; United Nations Open Working Group 2014). As noted above, we will describe major satellite sensors and the advances needed to enable further progress in optical water-quality retrieval, several representative algorithms for water area delineation, atmospheric correction, and water quality estimations, plus a hybrid approach for the universal application of these algorithms.

9.2 MAJOR SATELLITE SENSORS FOR MONITORING WATER QUALITY

Since the late 1970s, many attempts have been made to observe water quality from space. The first ocean-color sensor, Coastal Zone Color Scanner (CZCS), was launched in October 1978 aboard the Nimbus-7 satellite (Hovis et al. 1980). With four spectral bands in visible range (443, 520, 550, and 670 nm), and one spectral band in the thermal infrared spectrum (10.5–12.5 μm), the CZCS was the only spaceborne sensor that observed global ocean colors during the period 1978–1986 (Table 9.1 and Figure 9.1). However, since the CZCS was just a proof-of-concept sensor for the first generation of ocean-color observation at that time, there were many limitations in its instrument design such as a lack of a sufficient number of spectral bands in the visible and near-infrared (NIR) range as well as relatively low radiometric sensitivity (Gordon and Wang 1994; Hu et al. 2012a). In light of these limitations, the data provided by the CZCS should be used with caution. For example, Tassan (1988) reported that when CZCS data were used, high concentrations of gelbstoff and suspended minerals reduced the accuracy of both chlorophyll-*a* estimations and atmospheric corrections.

The second generation of ocean-color sensor, Sea-viewing Wide Field-of-View Sensor (SeaWiFS), was launched in 1997 and ended its mission in 2010 (Table 9.1 and Figure 9.1). The SeaWiFS has four additional bands for ocean observations: two in the visible range (412 and 490 nm) and two in the NIR region (765 and 865 nm). The band around 412 nm is useful for separating the detrital and viable phytoplankton signals (Ciotti and Bricaud 2006), and the band centered on 490 nm can assist in the detection of accessory pigments (Pan et al. 2010). The two NIR bands centered on 765 and 865 nm contribute to atmospheric correction (Gordon and Wang 1994). Compared to the CZCS, the radiometric sensitivity of the SeaWiFS was also largely improved (the mean signal-to-noise ratio [SNR] is between 424 and 790 for six visible bands; Hu et al. 2012a). However, the spatial and temporal resolutions of the SeaWiFS are still similar to those of the CZCS.

TABLE 9.1
Summary of Indicative Satellite Sensors Used for Studying Waters

Satellite Sensors	Orbit	Active Period	No. of Bands Used for Water Quality Monitoring	Resolution (m)	Revisit Time	Mean SNR
CZCS	Sun-synchronous	1978–1986	VIS 4	800	1–2 days	193–220
SeaWiFS	Sun-synchronous	1997–2010	VIS 6, NIR 2	1100	1–2 days	424–790 for VIS and 183–219 for NIR
MODISA	Sun-synchronous	2002 to present	VIS 7, NIR 2	1000	1–2 days	1366–2401 for VIS and 806–995 for NIR
MERIS	Sun-synchronous	2002–2012	VIS 8, NIR 7	300	3 days	513–1088 for VIS and 218–667 for NIR (excluding band 11 of 54)
GOCI	Geostationary	2010 to present	VIS 6, NIR 2	500	1 hour	579–833 for VIS and 596–587 for NIR
TM	Sun-synchronous	1984–2011	VIS 3, NIR 1, SWIR 2	30	16 days	29–72 for VIS, 17 for NIR, and 6–10 for SWIR
ETM+	Sun-synchronous	1999 to present	VIS 3, NIR 1, SWIR 2	30	16 days	41–78 for VIS, 13 for NIR, and 6–10 for SWIR
OLI	Sun-synchronous	2013 to present	VIS 4, NIR 1, SWIR 2	30	16 days	144–478 for VIS, 67 for NIR, and 14–30 for SWIR

Note: Mean SNR values are obtained from Hu et al. (2012a) except for SNR of OLI (obtained from Franz et al. 2015).

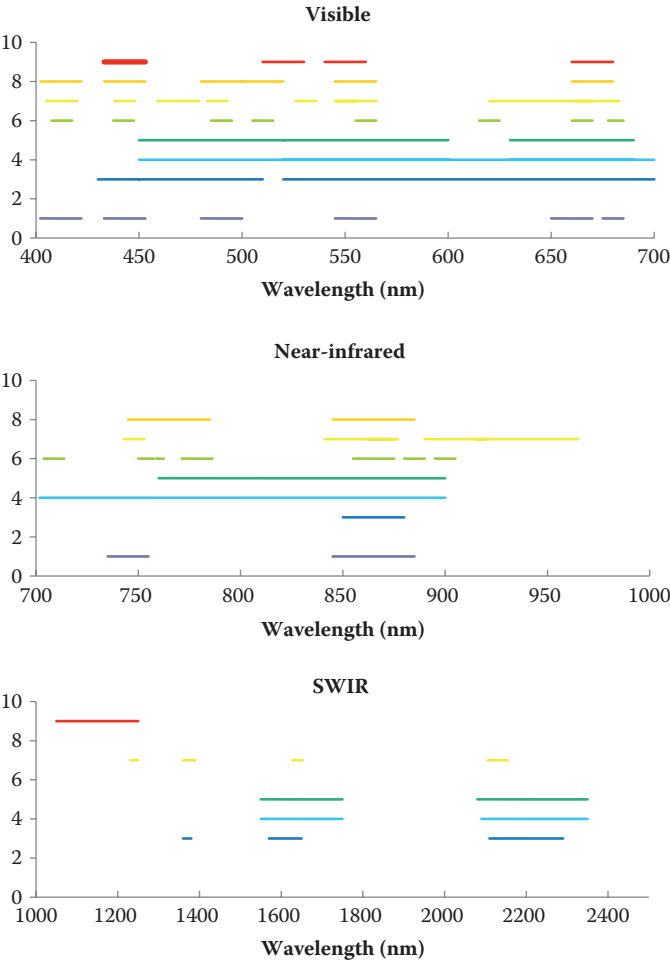


FIGURE 9.1 Location of the spectral bands of several satellite sensors that have been used for studying waters. 1: GOCI, 3: OLI, 4: ETM+, 5: TM, 6: MERIS, 7: MODIS, 8: SeaWiFS, 9: CZCS.

The Moderate Resolution Imaging Spectroradiometer (MODIS), launched in December 1999 (aboard the Terra satellite MODIST) and May 2002 (aboard the Aqua satellite MODISA), is a sensor for both land and water observations. However, the water-leaving radiance obtained from MODIST is almost unusable for ocean-color applications owing to the uncertainties and instabilities of the sensor observed since the start of the mission (Franz et al. 2008). The MODISA has 36 spectral bands in total, of which 9 bands are used for ocean-color remote sensing (Table 9.1 and Figure 9.1). Generally, the MODISA ocean-color bands are similar to those of the SeaWiFS, with three bands in blue and two bands in green, but two bands in red wavelengths are different from those of the SeaWiFS (which has only one red band). The additional red band of the MODISA (around 678 nm) contributes to the

detection of chlorophyll fluorescence. The radiometric sensitivity of the MODISA ocean-color bands were further improved with the mean SNR values of 1366–2401 in the visible range and 806–995 in the NIR region (Hu et al. 2012a). The seven MODISA land bands are often applied to high-turbidity inland and coastal waters because of their higher spatial resolutions (250–500 m) and longer-wavelength bands in the short-wave infrared region (SWIR; Hu 2009; Hu et al. 2010; Wang and Shi 2007).

During a similar active period of the MODIS, the European Space Agency launched another ocean-color sensor (the Medium Resolution Imaging Spectroradiometer [MERIS]) in March 2002. This mission was ended in 2012. Compared to the three ocean-color sensors described above, the MERIS provided higher spectral and spatial resolutions, but slightly lower temporal resolution and radiometric sensitivity (Table 9.1 and Figure 9.1). The new visible band around 620 nm made the MERIS a unique sensor that is able to distinguish cyanobacterial blooms from other algal blooms (Kutser et al. 2006). Another unique band of the MERIS is around 709 nm. This band has been demonstrated to be very useful for estimating chlorophyll-*a* concentrations and detecting algal blooms in turbid inland and coastal waters (Dall’Omo et al. 2003; Gilerson et al. 2010; Gitelson et al. 2008; Gower et al. 2005).

Although the spectral characteristics, temporal resolutions, and radiometric sensitivities of the current ocean-color sensors are adequate to monitor water quality, the relatively coarse spatial resolutions of these data sets (300–1000 m) often limit many applications in inland waters with small size. Therefore, several land sensors with relatively fine spatial resolution (30 m) such as the TM (Thematic Mapper), the ETM+ (Enhanced Thematic Mapper Plus), and the OLI (Operational Land Imager) aboard Landsat satellites (Table 9.1 and Figure 9.1) have also been used for assessing water quality parameters (e.g., Dekker et al. 2002; Oyama et al. 2009; Tyler et al. 2006; Wu et al. 2015). In addition to the relatively fine spatial resolution of the sensors aboard Landsat, another advantage of the use of Landsat data is the longevity of its successive missions (1972 to present; Lobo et al. 2015). However, the wide bandwidth, infrequent revisit time, and lower radiometric sensitivity of Landsat are substantial limitations for applying Landsat data to water quality monitoring.

Unlike all of the abovementioned sensors, the Geostationary Ocean Color Imager (GOCI), launched in June 2010 by the Korea Aerospace Research Institute (KARI), is the first and so far the only sensor in geostationary orbit for monitoring ocean color from space (Ryu et al. 2012). As a benefit owing to its geostationary orbit, GOCI can provide eight images during daylight with 500 m spatial resolution and higher radiometric sensitivity (>579 , Table 9.1). The bands of GOCI are similar to those of MODIS ocean bands, but it uses less one green band than MODIS, centered at 531 nm (Figure 9.1). However, its lack of bands around SWIR wavelengths is a significant limitation for atmospheric correction in turbid inland and coastal waters (Wang et al. 2012). In addition, the lack of bands around 620 nm makes the GOCI unable to distinguish cyanobacterial blooms from other algal blooms (Kutser et al. 2006), and its lack of bands around 709 nm makes it difficult to accurately retrieve the chlorophyll-*a* concentrations in waters with higher concentrations of colored dissolved organic matter (CDOM) and tripton (Gitelson et al. 2008). Another limitation of GOCI is its spatial coverage. GOCI covers only the regions covering Korea,

China, and Japan, and it cannot provide a global data set because it is designed to monitor the ocean color around the Korean Peninsula (130°E, 36°N at the center) on a geostationary orbit (Ryu et al. 2012).

Thus, all past and present ocean-color or land sensors have limitations for monitoring water quality. The following four aspects of future satellite sensors for remotely retrieving water quality parameters should be improved: temporal resolution, spatial resolution, spectral resolution, and radiometric sensitivity (Mouw et al. 2015). First, higher temporal resolution such as acquiring one or more satellite image per hour during daylight would allow not only observations of fast processes of water bodies (e.g., the tidal and diurnal variability of water quality) but also the accumulation of more available satellite data without cloud contaminations (Ruddick et al. 2014). This high temporal resolution could be achieved by a geostationary platform.

Second, finer spatial resolution is required for monitoring water quality in inland and coastal waters and for detecting algal blooms in open oceans. Bissett et al. (2004) showed that the optimal spatial resolution for monitoring near-shore waters (within 200 m of shore) is 100 m. This spatial resolution may also meet the requirement of some inland waters larger than 0.09 km²—corresponding to 9 pixels (i.e., 100 m × 100 m × 9 pixels)—as Verpoorter et al. (2012) reported that it is difficult to verify water bodies smaller than 9 pixels relative to image noise. However, there are numerous water bodies smaller than 0.09 km² (Verpoorter et al. 2014) and water bodies with spatially heterogeneous water quality parameters (Kutser 2004). Further improvements in spatial resolution are thus necessary for these water bodies.

Third, good spectral resolution is highly desirable for many water-quality remote sensing studies such as those concerning the retrieval of water quality parameters, the detection of cyanobacterial blooms or *Trichodesmium* distribution, and the removal of bottom-reflectance effects (Mouw et al. 2015). However, satellite-based measurements with too small spectral intervals often face the problems of how to accurately remove gas absorption effects, how to select appropriate band for efficient data processing, and how to store a large volume of data (Lee et al. 2014). Lee et al. (2014) found that the remote sensing reflectance of the neighboring bands is highly correlated when the spectral distance between two neighboring spectral bands is less than 10 nm, and even when this distance is increased to 20 nm, the spectral information loss is still very limited. Accordingly, they suggested that future ocean-color satellite sensors should have 15 bands space almost evenly between 400 and 700 nm at 10-nm bandwidth intervals. For the wavelength beyond 700 nm, at least two NIR bands and two SWIR bands are necessary for atmospheric correction in clear and turbid waters, respectively (Gordon and Wang 1994; Wang and Shi 2007). In addition, a band around 709 nm is also necessary for estimating chlorophyll-a concentrations and detecting algal blooms in turbid inland and coastal waters (Dall’Omo et al. 2003; Gilerson et al. 2010; Gitelson et al. 2008; Gower et al. 2005).

Finally, previous studies have stated that the radiometric sensitivity of future ocean-color sensors should have SNRs larger than 1000 for wavelengths between 350 and 720 nm, larger than 600 for wavelengths between 720 and 900 nm, and

between 100 and 200 nm for SWIR bands (Hu et al. 2012a; Wang 2007). Since the SNR is in proportion to the pixel size, the bandwidth for a specific band, and the integration time, a longer integration time is necessary if we want to ensure high SNRs as well as fine spatial and spectral resolutions. A sensor on a geostationary satellite would probably achieve this goal because “the sensor can stare at the desired pixels” (Lee et al. 2014). A detailed review of the opportunities and challenges presented by geostationary sensors was provided by Ruddick et al. (2014). Summaries of past, present, and planned ocean-color sensors such as the Pre-Aerosol, Clouds, and ocean Ecosystem (PACE) and the Ocean and Land Color Imager (OLCI) can be found in an appendix of a report published by the International Ocean Colour Coordinating Group (IOCCG 2012).

9.3 WATER DELINEATION FROM SATELLITE IMAGERY

To monitor water quality from satellite data, the first step is the extraction of the water body from the data. This step can also serve to detect cloud-contaminated pixels in water bodies. Many algorithms and techniques have been developed for delineating water bodies from optical remote sensing data. These methods can be summarized as belonging to three categories: (1) digitizing water bodies via a visual assessment of satellite images; (2) using image classification techniques such as supervised or unsupervised classification procedures, spectral transformation, and texture analysis; and (3) using a single or multiple algebraically operated bands such as the band ratio and spectral water index, combined with appropriate threshold values (Verpoorter et al. 2012). Methods based on the spectral water index have been widely used to delineate water bodies from satellite imagery, because not only can this approach efficiently enhance water features while suppressing or even eliminating non-water features, it is also easy to use and less computationally time-consuming than other methods.

The first spectral water index devised for delineating water from land is the normalized difference water index (NDWI), which was proposed by McFeeters (1996) and can be expressed as follows:

$$NDWI = (d_{\text{green}} - d_{\text{NIR}}) / (d_{\text{green}} + d_{\text{NIR}}), \quad (9.1)$$

where d_{green} and d_{NIR} are the digital number (DN) at green and NIR bands, respectively. The NDWI values can range from -1 to 1 . The selection of the green band is done to maximize the typical reflectance of water features. The use of NIR band in the NDWI can not only minimize the water reflectance (strong absorption by water), but also take advantage of the high reflectance at the NIR band by terrestrial vegetation and soil features (even higher than the reflectance of the green band). Accordingly, water features will have positive NDWI values, and land features will have zero or negative values (McFeeters 1996). Zero was thus set as the threshold to distinguish water bodies from land by McFeeters (1996) (i.e., if $NDWI > 0$, then = water; otherwise, non-water).

Xu (2006) found that the NDWI cannot efficiently suppress the signal from built-up land, and thus extracted water bodies were still mixed with built-up land

noise. For example, Figure 9.2a through c show a Landsat5/TM sub-scene for a part of Wuhan City (China), an NDWI image of the same place, and extracted water bodies from the NDWI image, respectively, showing that many built-up lands near Lake Dong (surrounded by a circle in Figure 9.2a) show positive NDWI values in Figure 9.2b and thus were misclassified as water bodies (white color in Figure 9.2c).

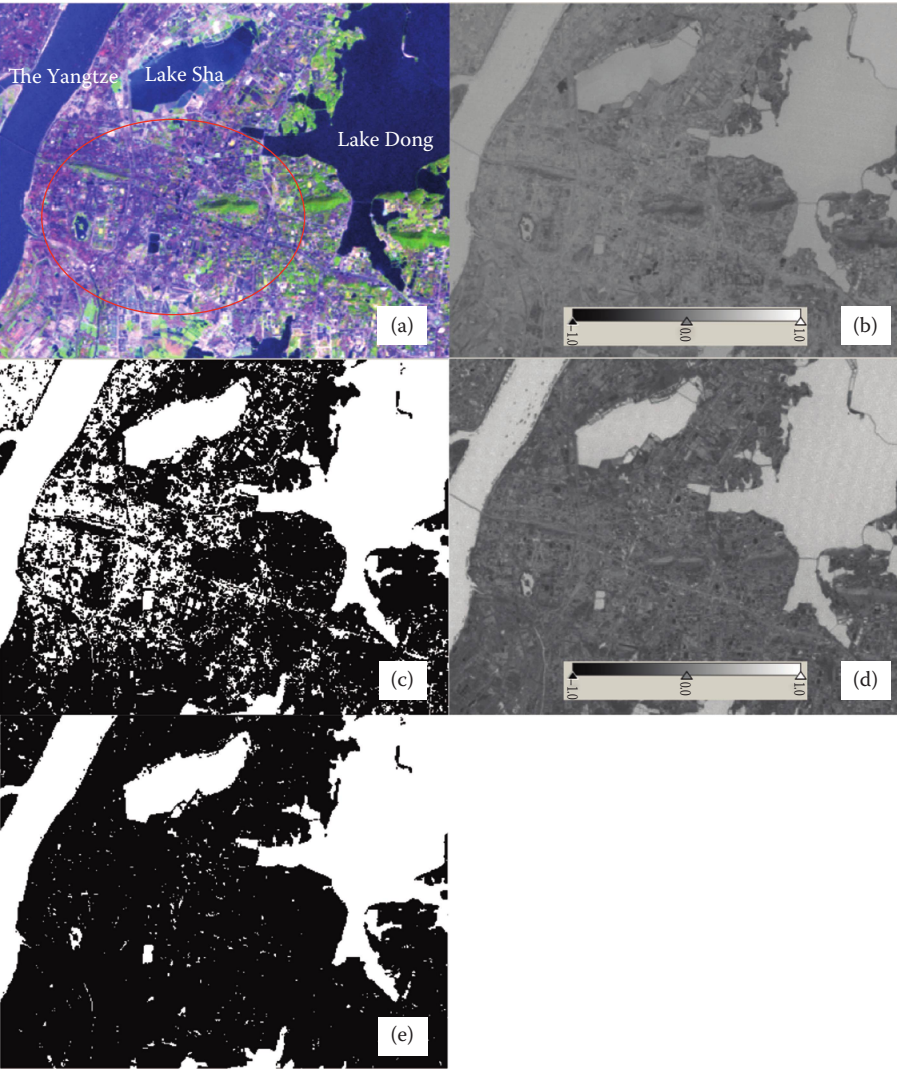


FIGURE 9.2 NDWI and MNDWI images for part of Wuhan City, China. (a) Landsat5/TM image of part of Wuhan City (RGB: 541), acquired on October 24, 2003. (b) NDWI image of the same area. (c) Extracted water bodies from the NDWI image. (d) MNDWI image of the same area. (e) Extracted water bodies from the MNDWI image.

To further suppress these built-up land noises, Xu (2006) proposed a modified NDWI (MNDWI), which uses a SWIR band instead of the NIR band in the NDWI. The MNDWI can be expressed as follows:

$$\text{MNDWI} = (d_{\text{green}} - d_{\text{SWIR}}) / (d_{\text{green}} + d_{\text{SWIR}}), \quad (9.2)$$

where d_{SWIR} is the DN value at a SWIR band such as Landsat5/TM band 5. Figure 9.2d and e show the MNDWI image for the same Landsat5/TM sub-scene and extracted water bodies from the MNDWI image, respectively. Compared to the NDWI image (Figure 9.2b), most of the MNDWI values of the built-up lands became zero or negative values and thus were removed from the water bodies (Figure 9.2e). This is because both built-up land and water reflect green light more than they reflect NIR light, but built-up land also reflects much greater light at the SWIR band than that at the green band, which is different from water features (Xu 2006). In addition, since the soil and vegetation still reflect more SWIR light than green light, the MNDWI can keep negative values for them like the NDWI does.

Although the MNDWI has taken the normalization form, which can reduce shadow noise (Xu 2006), the MNDWI still suffers from mountain and cloud shadows when a satellite image includes these types of surfaces. Figure 9.3a through c show a Landsat5/TM sub-scene of Lake Maninjau (Indonesia), an MNDWI image of the lake and its surrounding area, and the extracted water bodies from the MNDWI image, respectively, showing that many cloud and mountain shadows are misclassified as water bodies. This is because spectral features of cloud and mountain shadows at green and SWIR bands are similar to those of water bodies and thus show positive MNDWI values (Figure 9.4).

Verpoorter et al. (2012) suggested the use of digital elevation model data with the hillshade algorithm and ArcGIS hydrology tools in ArcMap program to reduce the noise attributed to cloud and mountain shadows. It was also found that these cloud and mountain shadowed pixels still show negative NDWI values, indicating that the NDWI also has the potential to suppress these shadow noises (Figure 9.3d and e). This is because the background of these shadowed pixels is vegetation (Figure 9.3a), which reflects more NIR light than SWIR light (Figure 9.4). Table 9.2 shows value ranges of NDWI and MNDWI for several different land cover types; only water features have positive values for both NDWI and MNDWI.

These findings suggest that the combined use of the MNDWI and NDWI can efficiently suppress not only built-up noise but also vegetation shadow noise attributed to clouds and mountains. Figure 9.3f shows the extracted water bodies by combining the MNDWI image with the NDWI image (i.e., if the MNDWI > 0 and the NDWI > 0, then = waters; otherwise, non-waters). The results demonstrate that most of the cloud and mountain noises were markedly suppressed. However, a misclassification owing to a different type of cloud remained (white pixels surrounded by a circle in Figure 9.3f).

An example spectrum of this type of cloud is also shown in Figure 9.4 (i.e., cloud 2 in the figure). Similar to the water features, this cloud type showed NDWI and MNDWI values that were both larger than zero. However, the spectral brightness of both cloud types is greater than those of other land cover types, and thus it is easy to differentiate the cloud from other land cover types using a brightness index such as the Modified Brightness Index proposed by Verpoorter et al. (2012).

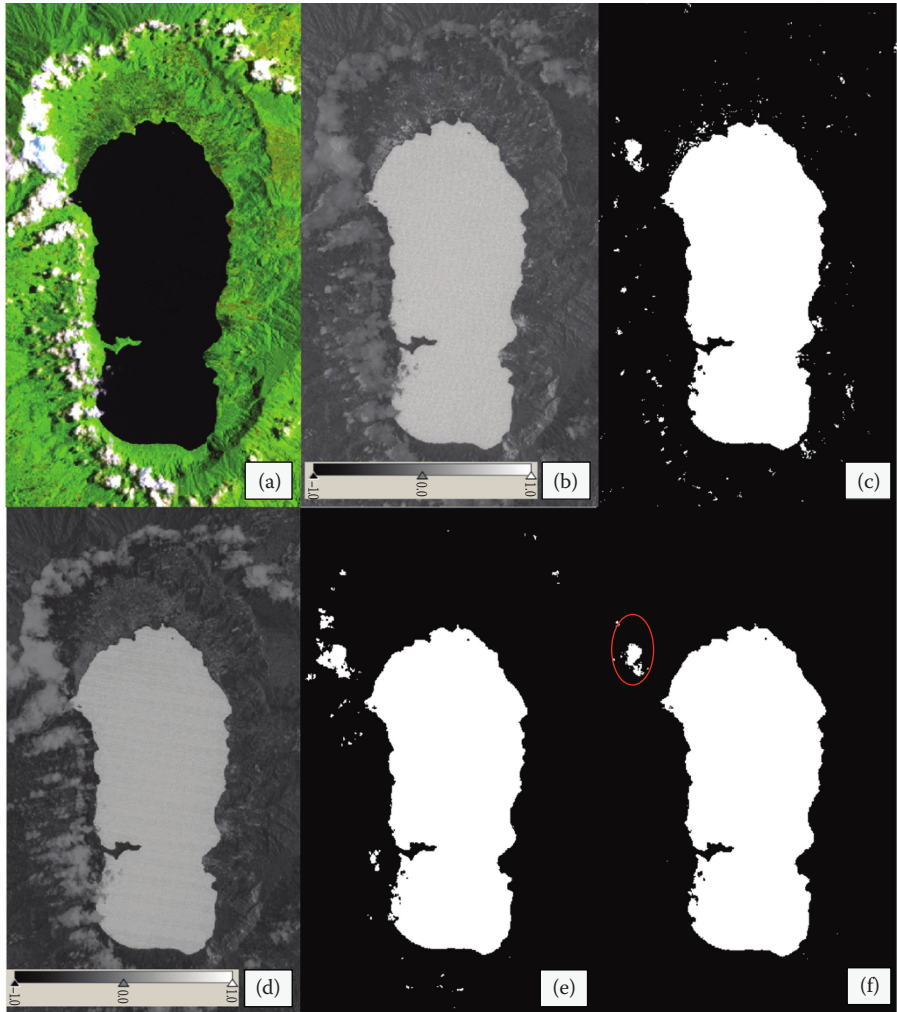


FIGURE 9.3 MNDWI and NDWI images for Lake Maninjau, Indonesia. (a) Landsat5/TM image of Lake Maninjau (RGB 541), acquired on September 11, 1989. (b) MNDWI image of the area. (c) Extracted water bodies from the MNDWI image. (d) NDWI image of the same area. (e) Extracted water bodies from the NDWI image. (f) Extracted water bodies from the combination of MNDWI and NDWI images.

Setting an appropriate threshold for the spectral water index is a challenge for accurately delineating water bodies from other land cover features. McFeeters (1996) and Xu (2006) set zero as the default threshold value for water delineation. However, Xu (2006) also found that a more accurate water body extraction could be achieved if the zero threshold value was adjusted slightly. The variation of threshold value is mainly attributed to the mixed pixel problem, in which a pixel is considered to contain both water and land features.

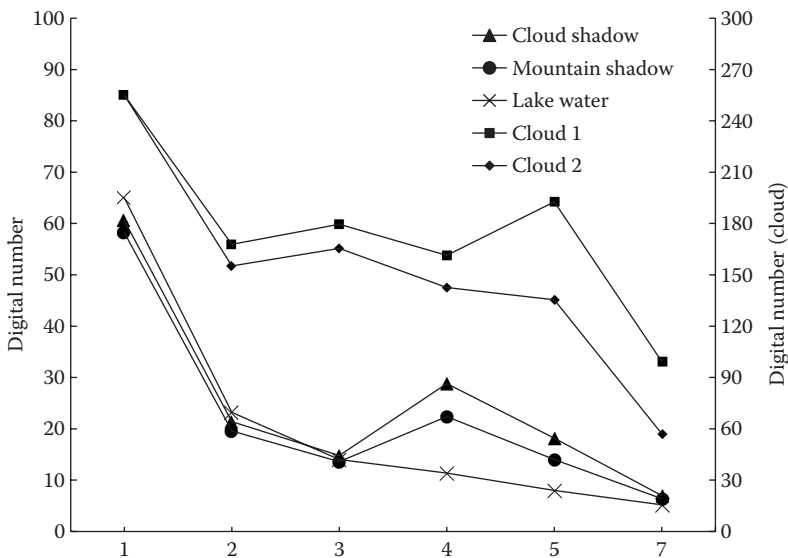


FIGURE 9.4 Spectral reflectance patterns of cloud shadow, mountain shadow, lake water, and clouds (the right y axis) obtained from Landsat5/TM image of Lake Maninjau, Indonesia, acquired on September 11, 1989.

TABLE 9.2
NDWI and MNDWI Value Ranges for Different Land Cover Types

	Water	Vegetation	Soil	Built-Up	Cloud Shadow	Mountain Shadow
NDWI	+	0 or –	0 or –	+	0 or –	0 or –
MNDWI	+	0 or –	0 or –	0 or –	+	+

Using simulation data, Ji et al. (2009) extensively investigated how the threshold values of several spectral water indices (including McFeeters’ NDWI and Xu’s MNDWI) were influenced by the fractions of soil and vegetation at a given water fraction. They found that the MNDWI shows the most stable threshold at a given water fraction, and a zero threshold value was suitable only for extracting pixels with a water fraction close to 100% for both the NDWI and MNDWI. It can thus be considered that the zero threshold value of the MNDWI or NDWI probably provides an underestimated water area compared to the true water body, because the shoreline of a water body is probably a mix of water and land features owing to the image’s spatial resolution, especially for the coarse spatial resolution satellite images (e.g., those provided by SeaWiFS, MODIS, and MERIS). It should also be noted that optical shallow water areas, water areas covered by aquatic vegetation, and water areas with high turbidity caused by strong algal blooms and mineral particles can also provide negative values of spectral water indices and thus influence accurate water body delineations (Verpoorter et al. 2012).

9.4 ATMOSPHERIC CORRECTION FOR USING SATELLITE DATA

For a water pixel, the optical signal received by a satellite sensor (i.e., the top of atmosphere [TOA] reflectance, ρ_{toa}) at wavelength λ can generally be obtained by the following equation (Gordon and Wang 1994):

$$\rho_{\text{toa}}(\lambda) = \rho_r(\lambda) + [\rho_a(\lambda) + \rho_{\text{ra}}(\lambda)] + t(\lambda)\rho_w(\lambda), \tag{9.3}$$

where $\rho_r(\lambda)$ is the reflectance from Rayleigh scattering, $[\rho_a(\lambda) + \rho_{\text{ra}}(\lambda)]$ is the reflectance from the sum of aerosol scattering and the interaction between Rayleigh and aerosol scattering (i.e., the aerosol multiple-scattering reflectance), $t(\lambda)$ is the diffuse transmittances of the atmospheric column, and $\rho_w(\lambda)$ is the water-leaving reflectance.

Figure 9.5 shows two examples of in situ-measured water-leaving reflectance and the corresponding TOA reflectance measured by MERIS in Deadman Bay, Florida (clear water) and Lake Kasumigaura, Japan (turbid water), respectively. It is clear

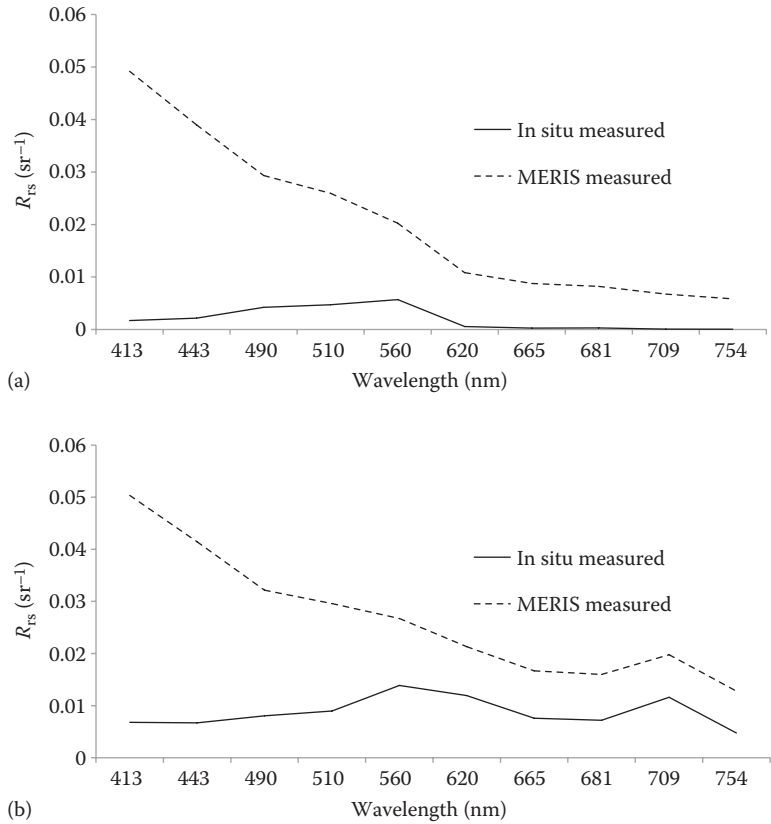


FIGURE 9.5 Examples of in situ-measured water-leaving reflectance and corresponding TOA reflectance measured by MERIS in Deadman Bay, Florida (a) and Lake Kasumigaura, Japan (b).

in these examples that the atmosphere contributes much more signal than the water body itself. According to the IOCCG (2000, 2010), in most water areas, only 10% of the signals recorded by the satellite sensors originate from water bodies in the visible wavelengths (e.g., Figure 9.5a). It is therefore essential to carry out atmospheric correction before applying the satellite data to quantitative estimations of water quality parameters.

The key point for atmospheric correction is to estimate the aerosol type and amount for a given pixel because the Rayleigh-scattering component (ρ_r) can be predicted a priori. The most general approach for estimating the aerosol contribution is to use two specific bands (or reference bands) for which the water-leaving reflectance (ρ_w) can be assumed to be zero. The aerosol contribution at these two specific bands can be estimated as follows:

$$[\rho_a(\lambda_1) + \rho_{ra}(\lambda_1)] = \rho_{toa}(\lambda_1) - \rho_r(\lambda_1) \quad (9.4)$$

$$[\rho_a(\lambda_2) + \rho_{ra}(\lambda_2)] = \rho_{toa}(\lambda_2) - \rho_r(\lambda_2). \quad (9.5)$$

Two specific bands are required because we need to estimate not only the magnitude of the aerosol's contribution but also its dependence on wavelength for extrapolating (or interpolating) the aerosol contribution to the other shorter bands. For this, the estimated aerosol multiple scatterings must first be converted to aerosol single scatterings (ρ_{as}) at the same bands through a look-up table (LUT) as follows (Gordon and Wang 1994):

$$[\rho_a(\lambda_1) + \rho_{ra}(\lambda_1)] \rightarrow \rho_{as}(\lambda_1) \quad (9.6)$$

$$[\rho_a(\lambda_2) + \rho_{ra}(\lambda_2)] \rightarrow \rho_{as}(\lambda_2). \quad (9.7)$$

The atmospheric correction parameter epsilon (i.e., $\epsilon(\lambda_1, \lambda_2)$) is then calculated as follows:

$$\epsilon(\lambda_1, \lambda_2) = \rho_{as}(\lambda_1)/\rho_{as}(\lambda_2). \quad (9.8)$$

The values of $\epsilon(\lambda_1, \lambda_2)$ correspond to different aerosol models. For a given aerosol model, epsilon values for other bands can be extrapolated using the following equation:

$$\epsilon(\lambda, \lambda_2) = \exp[\ln(\epsilon(\lambda_1, \lambda_2))/(\lambda_2 - \lambda_1) * (\lambda_2 - \lambda)]. \quad (9.9)$$

Aerosol single scatterings for all wavelengths ($\rho_{as}(\lambda)$) can then be estimated using the following equation:

$$\rho_{as}(\lambda) = \rho_{as}(\lambda_2) * \epsilon(\lambda, \lambda_2). \quad (9.10)$$

The obtained aerosol single scatterings can be reconverted to the corresponding aerosol multiple scatterings for all wavelengths through the LUT prepared in advance:

$$\rho_{as}(\lambda) \rightarrow [\rho_a(\lambda) + \rho_{ra}(\lambda)]. \quad (9.11)$$

Finally, the water-leaving reflectance ($\rho_w(\lambda)$) at all wavelengths can be derived as follows:

$$\rho_w(\lambda) = (\rho_{toa}(\lambda) - \{\rho_r(\lambda) + [\rho_a(\lambda) + \rho_{ra}(\lambda)]\})/t(\lambda). \quad (9.12)$$

For clear waters (e.g., open oceans, or Figure 9.5a), the water-leaving reflectance at NIR bands can be assumed to be zero owing to the very high absorption of pure water and little or no contribution from suspended particles in these bands. Generally, SeaWiFS bands 7 and 8, MODIS bands 15 and 16, MERIS bands 12 and 13, and GOCI bands 7 and 8 can be used as two specific bands (i.e., λ_1 and λ_2) for the purpose of atmospheric correction. However, for turbid waters (e.g., some inland and coastal water, or Figure 9.5b), these two specific NIR bands should be shifted to longer wavelengths such as SWIR bands because high concentrations of particulate matters make the water-leaving reflectance in the NIR bands nonnegligible (Wang and Shi 2005). At the SWIR bands, even for turbid water, water-leaving reflectance can still be assumed to be zero because the absorption of pure water at these wavelengths is much higher than that at NIR bands (Shi and Wang 2009).

Unfortunately, there is no existing satellite sensor with SWIR bands for ocean-color remote sensing. Although the MODIS land bands at SWIR wavelengths (e.g., bands 5 and 7) have shown potential for atmospheric correction over highly turbid water (Wang and Shi 2007), SNR values of the two SWIR bands that are too low make atmospherically corrected water-leaving reflectance at visible bands quite noisy (Hu et al. 2012a; Wang and Shi 2012).

Another approach for solving the atmospheric correction problem over turbid waters is to estimate the water-leaving reflectance at two NIR reference bands by a bio-optical model instead of assuming them to be zero (e.g., Bailey et al. 2010; Hu et al. 2000; Jaelani et al. 2015; Stumpf et al. 2003; Wang et al. 2012). The estimated water-leaving reflectance values at the two NIR reference bands are then removed from the corresponding TOA reflectance to meet Equations 9.4 and 9.5. This approach is available for the satellite sensors without SWIR bands (e.g., SeaWiFS, MERIS, and GOCI).

A summary of existing atmospheric correction algorithms for turbid waters can be found in papers by the IOCCG (2010) and Jaelani et al. (2013). Most of these algorithms have been integrated into widely used software packages such as SeaDAS (SeaWiFS Data Analysis System; <http://seadas.gsfc.nasa.gov/>) and BEAM (Basic ERS & ENVISAT AATSR and MERIS; <http://www.brockmann-consult.de/cms/web/beam/>), which are easily available and well-supported platforms.