Sains Malaysiana 51(4)(2022): 959-976
http://doi.org/10.17576/jsm-2022-5104-02

Review on RS Technologies for Seagrass Mapping in Tropical Region

(Ulasan bagi Teknologi Penderiaan Jauh untuk Pemetaan Rumput Laut di Wilayah Tropika)

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Received: 6 July 2021/Accepted: 12 September 2021

ABSTRACT

Seagrass ecosystems can be mapped using RS because this technique is versatile and accurate. The availability of seagrass information is very important for the sustainable management of seagrass ecosystems. The use of RS technology to map seagrass has become the focus of many researches worldwide by using various types of platforms, sensors and various algorithms for satellite imagery processing. In literature, there have been many review papers related to seagrass, however, a comprehensive review on various aspects of seagrass is limited. The objective of this review paper was to fill the gap by highlighting the existing RS technology, seagrass biophysical property and image processing analysis. Review results indicated that RS technology is a powerful tool for accelerating seagrass mapping and for monitoring the condition of seagrass ecosystems at regional scale due to the availability of long-archived RS data and their free-access. In literature, the empirical approaches still dominated seagrass mapping methodology compared to the semi-analytic and analytic approaches. A clear conclusion from this review is that the development in sensor technology and data processing algorithm is still ongoing and has driven RS capabilities to map seagrass more rapidly, accurately and less expensive. Future research on seagrass mapping could be focused on a more automated classification by applying machine-learning to handle a large amount of data to improve accuracy and to discover robust methods for image pre-processing that is suitable for tropical shallow waters such as those in Indonesia.

Keywords: RS; seagrass; shallow water; tropical region

ABSTRAK

Ekosistem rumput laut dapat dipetakan menggunakan penginderaan jauh kerana teknik ini serba boleh dan tepat. Ketersediaan maklumat rumput laut sangat penting untuk pengurusan ekosistem rumpai laut yang lestari. Penggunaan teknologi penginderaan jauh untuk memetakan rumput laut telah menjadi tumpuan banyak penyelidikan di seluruh dunia dengan menggunakan pelbagai jenis pentas, sensor dan pelbagai algoritma untuk pemprosesan citra satelit. Dalam kepustakaan, terdapat banyak makalah kajian yang berkaitan dengan rumput laut, namun, tinjauan komprehensif mengenai pelbagai aspek rumput laut adalah terbatas. Objektif kertas ini adalah untuk mengisi jurang dengan mengetengahkan teknologi penginderaan jauh yang ada, harta biofisik rumput laut dan analisis pemprosesan gambar. Hasil tinjauan menunjukkan bahawa teknologi penginderaan jauh adalah alat yang ampuh untuk mempercepat pemetaan rumput laut dan untuk memantau keadaan ekosistem rumput laut pada skala wilayah kerana ketersediaan data penginderaan jauh yang diarkibkan lama dan akses bebasnya. Dalam kepustakaan, pendekatan empirik masih mendominasi kaedah pemetaan rumput laut berbanding dengan pendekatan separa-analitik dan analitik. Kesimpulan yang jelas daripada tinjauan ini adalah bahawa pengembangan teknologi sensor dan algoritma pemprosesan data masih berterusan dan mendorong keupayaan penginderaan jauh untuk memetakan rumput laut dengan lebih cepat, tepat dan lebih murah. Penyelidikan masa depan mengenai pemetaan rumput laut dapat difokuskan pada pengelasan yang lebih automatik dengan menerapkan pembelajaran mesin untuk menangani sejumlah besar data untuk meningkatkan ketepatan dan untuk menemukan kaedah yang kuat untuk pemprosesan gambar yang sesuai untuk perairan dangkal tropika.

Kata kunci: Kawasan tropika; penginderaan jauh; perairan cetek; rumput laut

INTRODUCTION

Coastal environment is a vulnerable ecosystem because of its location between terrestrial and marine ecosystems. Activities that occur in the upstream watershed such as mining and deforestation as well as processes that occur in the coastal area cause damage to coastal ecosystems. Seagrass, coral reefs and mangroves play an important role in a shallow-water coastal ecosystem (Veettil et al. 2020). One of such importance is indicated by the fact that seagrass provides 24 different ecosystem services (Nordlund et al. 2016). There are several important functions of seagrass for coastal ecosystems, such as a place to live for fish (Criales et al. 2015) and the provision of food for dugong and green turtle (Hashim et al. 2017; Scott et al. 2018). Seagrasses contributes to climate change mitigation through carbon sequestration and storage (Stankovic et al. 2021). Seagrass also provide important ecosystem services for protection of coastline from storm surges and coastal erosions (Potouroglou et al. 2017). These important roles of seagrass need to be supported by the availability of data and information, especially seagrass distribution and health. Updated seagrass status information helps decision makers in developing pragmatic action plan since seagrass distribution and abundance are indicators of the coastal ecosystem health.

Green and Short (2003) stated that the world's seagrass area was about 177,000 km^2 and was divided into six bioregions. One of these bioregions is the Tropical Indo-Pacific (TIP), which has the richest seagrass biodiversity in the world (Waycott et al. 2009). McKenzie et al. (2020) estimated seagrass cover worldwide between 160,387 km^2 and 266,562 km^2 and nearly half occurring in the Indo-Pacific region. Fortes et al. (2018) reported that the extent of seagrass in Southeast Asia was about 36,762.6 km^2, consisting of 21 seagrass species, nine genera and four families making up 29% of the world's seagrass species. Human activity and climate change have caused a decline in seagrass areas worldwide (Duarte et al. 2018). On a global scale, the world's seagrass area has decreased by about 3,000 km^2 in 20 years, or by about 7% of the total world seagrass area (Waycott et al. 2009). Sudo et al. (2021) reported that more than 60% of seagrass meadows in Southeast Asia are declining at an average of 4.7% per year.

Several methods are available to obtain information considering the distribution of seagrass. Traditional seagrass mapping has generally focused on onsite field observations by snorkeling, diving and using a boat. Such a method is time-consuming and expensive and causes physical damage to seagrass during sample collections (Misbari & Hashim 2016). Remote sensing (RS) technology has been widely used for seagrass mapping because it has several advantages compared to *in-situ* observations including its capability to observe large areas. RS method is more efficient in terms of time and cost as a repetitive observation can easily be made (Hossain et al. 2015a). In recent years, unmanned aerial vehicles have become a popular way to observe seagrass beds (Yamakita et al. 2019). This study examined papers discussing RS applications for seagrass mapping.

Seagrass has attracted the attention of researchers in many countries from various aspects for instance data acquisition and processing including RS technique, ecological aspect, and economic valuation aspect. Rapid development of research related to RS technology for seagrass has inspired many researchers to review existing papers with various focuses. This study examined more than 160 research papers discussing RS applications for seagrass mapping including satellite image processing needed, seagrass distribution, and key seagrass parameters. Part of the review papers were focused on evaluating the status and potential of using RS technologies in seagrass mapping as well as identifying benefits and limitations of each technique (Ferwerda et al. 2007; Gumusay et al. 2019; Huong et al. 2017; Veettil et al. 2020). In addition, seagrass distribution, seagrass extent, species diversity, temporal change and conservation have also become the focus of some researchers (Fortes et al. 2018; Ooi et al. 2011; Pham et al. 2019; Sudo et al. 2021).

Based on such background, the objective of this paper is to highlight four main aspects, namely: seagrass distribution and condition, especially in the TIP bioregion; RS technology for seagrass mapping; key parameter of seagrass properties; and image processing methods for seagrass mapping. The results of this review can be used by researchers to determine an appropriate seagrass research development strategy and to indicate further exploration. Meanwhile, for coastal managers the existing results may be used to select a suitable method that likely can be implemented for the national mapping program.

SEAGRASS DISTRIBUTION STATUS

Seagrass grows in shallow waters such as bays, estuaries and capes and usually can be found at a depth of less than 90 m. In general, it is located in shallow-water, tidal area and close to coral reef. Seagrass ecosystems are globally distributed covering the world oceans except for Antartica

(McKenzie et al. 2020; Short et al. 2007). Southeast Asia is the center for tropical seagrasses (Short et al. 2001) which has the greatest seagrass diversity in the TIP bioregion, with 17 of the 24 species. Short et al. (2007) reported the TIP has 24 tropical seagrass species, where 13 species are found in Papua New Guinea, 16 species in the Philippines and 16 species in Australia. Fortes et al. (2018) reported that the Southeast Asian region has 21 species. According to Lamit et al. (2017), the highest seagrass species diversity was found in the Philippines (19 species) followed by Malaysia and Indonesia with 16 species each, and the lowest seagrass species diversity is in Brunei (7 species). The most widespread species in the Southeast Asia is *Thalassia hemprichii* having distribution records in all ecoregions (Fortes et al. 2018). Based on Sjafrie et al. (2018), Indonesia has 15 of the 60-seagrass species seen around the world, such as *Cymodocea rotundata, C. serrulata, Enhalus acoroides, Halophila decipiens, H. ovalis, H. minor, H. spinulosa, Halodule uninervis, Haludole pinifolia, Syringodium isoetifolium, Halophila becarii,* and *Ruppia maritima*, including *Halophila sulawesii* found by Kuo (2007).

From the point of view of the seagrass extent, Indonesia has the largest seagrass area among those Southeast Asian countries with the total extent approximately 3,000,000 ha (Ogawa et al. 2011), followed by Cambodia, Thailand, and Vietnam (Sudo et al. 2021). According to Sjafrie et al. (2018), the area of seagrass in Indonesia in 2017 was 150,693.16 ha, while in 2018 the area was 293,464 ha; so, there has been an increase in seagrass area of about 142,771 ha. It is estimated that seagrass area in 2018 were only 16-35% of the whole seagrass area in Indonesia.

TYPE OF RS TECHNIQUES FOR MAPPING SEAGRASS

Seagrass resources can be mapped using approaches that vary from *in situ* field-observation methods to RS. Winters et al. (2017) studied field-survey methods for mapping seagrasses in Gulf of Aqaba, Red Sea such as the snorkeling-based mapping method and down-looking towed video camera. The snorkeling-based method is effective at depths of up to 15 m in relatively turbid water and up to 25 m in clearer water (Mejia et al. 2016). In a deeper water and at large area, seagrass can be mapped using underwater videos or hyper-spectral photography (Vandermeulen 2014), side-scan and multi-beam sonar data, scuba divers or boats as working platforms (Hill et al. 2014). Meanwhile, the selection of an appropriate scale is critical for mapping seagrass. McKenzie (2003) stated that the selected mapping approach depends on the size of survey area and generally divided into regional scales (tens of km), local scales (tens of m to km) and specific scales (m to tens of m). Currently, there are two seagrass citizen science (SCS) programs, namely Seagrass-Watch and Seagrass-Spotter which cover a wide spatial scale, from local to global (Jones et al. 2018). The SCS program is a field-observation method that provide a significant opportunity to assist with filling the gaps of seagrass ecology data, particularly their spatial extent and condition. Seagrass-Watch is a participatory science program (Haklay 2013) developed to integrate scientists and civil to accurately monitor status and trend of seagrass conditions. Meanwhile, Seagrass-Spotter was developed in 2016 by using a smartphone app and website database as its platform and facilitates participants' ability to find something interesting about seagrass and upload geo-tagged photos.

Use of RS technology for seagrass mapping has been made since the Landsat image was released in 1972 (Wulder et al. 2008). A rapid development of RS technology was obvious after the launch of several types of sensor placed on an aircraft such as LiDAR and those mounted-on satellites, including Sentinel, Quick Bird and Pleiades. In general, RS imagery for seagrass can vary from simple to very complex approaches, namely empirical, semi-analytical and analytical methods (Dekker et al. 2007). Currently, the empirical approach is the most widely used method with various satellite images and *in-situ* observations. Ideally, the *in-situ* observation coincides with satellite overpass, however, natural and weather conditions including cost and time needed to mobilize people and equipment may become constraints in achieving this ideal situation. According to Hossain et al. (2015a), drawbacks of the empirical method are: it is statistically extrapolation thus the accuracy of the classification is questionable; classification images are not transferable to other locations or other images; and there is inability to quantify multitemporal cover change detection. The semi-analytical approach provides seagrass maps of better accuracy than the empirical approach (Roelfsema et al. 2014), but this approach requires the spectral library of various components as an input to the model and requires more intensive field surveys (Duffy et al. 2017). The analytical approach uses forward and inverse models based on radiative transfer (RT). It has several advantages over other approaches, such as repeatability, transferability, sensitivity and error analysis and can process archival data by using currently developed methodology (Dekker et al. 2007).

RS is differentiated based on types of system, namely passive and active sensors; both have been used for mapping seagrass (Duffy et al. 2017; Ferwerda et al. 2007). Platforms can be divided into spaceborne, airborne and those placed underwater or on boats (Hossain et al. 2015a). Based on spatial resolutions, satellite RS data can be divided into three groups, namely medium spatial resolution (MSR) with pixel size of 1 km to 30 m, high spatial resolution (HSR) with pixel size of <30 m, and very high spatial resolution (VHSR) with pixel size of <1 m (Huong et al. 2017). Veettil et al. (2020) stated that key factors in determining the type of RS image to be used are spatial resolution, spectral resolution, sensor system, and type of platform.

MSR uses multispectral spaceborne images and is most widely used for seagrass mapping by researchers in Southeast Asia because it is freely available (Huong et al. 2017) and has a short return period of between 10 and 16 days. It has a long-term continuity, for i.e. Landsat and ASTER provided a continuous record of earth observation for 35 and 22 years (ERSDAC 2003; Wulder et al. 2008), respectively. Hence, both are very useful for environmental monitoring. MSR images are used for seagrass study include Landsat (Vidyan 2018; Vo et al. 2020), ASTER (Wicaksono et al. 2017); ALOS AVNIR-2 (Carlson et al. 2018), SeaWiFS (Dierssen et al. 2010) and MODIS (Perez et al. 2018). HSR images have been widely used for seagrass mapping including SPOT (Barillé et al. 2010), Sentinel-2A (Ha et al. 2020; Traganos et al. 2017), RapidEye (Li 2018; Traganos et al. 2018) and PlanetScope (Wicaksono & Lazuardi 2018). In a complex environment with various species, Sentinel-2A has been able to map the distribution of seagrass in Indonesia waters with an overall accuracy of 61.9% (Fauzan et al. 2017). From this research it was likely that Sentinel-2A provides good results for mapping and monitoring coastal resources and shallow-water environments. Furthermore, other advantages of RS data include large coverage, long time series data, and freely available.

VHSR includes a group of sensors that have a spatial resolution of <1 m in the panchromatic band and approximately <4 m for the multispectral bands. It has been widely used for seagrass mapping including GeoEye (Chayhard et al. 2018), WorldView-2 (León-Pérez et al. 2020; Su & Huang 2019), WorldView-3 (Collin et al. 2017; Niroumand-Jadidi & Vitti 2016), IKONOS (Pu & Bell 2017) and QuickBird (Urbanski et al. 2009).

MSR imagery is used for coarse-scale mapping of seagrass distribution. Meanwhile, VHSR and HSR are used to map seagrass in a detailed level to identify seagrass cover, species, and biomass (Valle et al. 2015). Phinn et al. (2008) mapped seagrass species, cover and biomass in shallow water by using Landsat TM, QuickBird-2 and hyperspectral airborne CASI-2. The results showed that the highest overall accuracy was obtained from CASI-2 (>80%) followed by QuickBird-2 and Landsat TM. Benfield et al. (2007) used IKONOS, QuickBird-2 and Landsat ETM+ and the results also showed that Landsat ETM+ provided the lowest accuracy. Pu and Bell (2017) examined the ability of IKONOS to map seagrass cover and compared it with maps from Landsat. In their study, it was found that IKONOS images provided higher accuracy than Landsat TM for submerged aquatic vegetation (SAV).

According to Hedley et al. (2012) seagrass mapping requires RS images with HSR, high radiometric resolution and several bands that can penetrate water. However, HSR and VHSR images have limitations, as stated by Chen et al. (2016) for e.g. narrow coverage, limited temporal resolution, high photographic distortion, low radiometric resolution, and high cloud cover (i.e. in optical RS). In addition, they are difficult to interpret in deep and turbid water due to high variability of sun glint reflectance. Furthermore, they are high priced.

Active sensors such as LiDAR have been used to map seagrass in turbid coastal waters. Pan et al. (2015) applied an image fusion technique between active LiDAR and passive hyperspectral sensors to map seagrass in relatively highly turbid waters. Acoustic technology to map seagrass has been used for tropical waters such as Bintan Island, Indonesia with an overall accuracy of 87% (Manik & Apdillah 2020). Collings et al. (2019) have combined LiDAR data with World View-2 for seagrass mapping. Meanwhile, Luo (2018) assessed seagrass by combining Sentinel-1 SAR and Sentinel-2A and obtained an overall accuracy of 77.7% and a kappa coefficient of 0.75. According to Hossain et al. (2015c), the acoustic method is relatively more effective compared to the use of optical sensors in mapping seagrass species in relatively turbid waters.

KEY PARAMETERS OF SEAGRASS PROPERTIES

BIOPHYSICAL PARAMETERS OF SEAGRASS PROPERTIES

RS is used to map main items of information, namely the biophysical properties of seagrass. The biophysical properties of seagrass include spatial cover, seagrass species, leaf area index (LAI), biomass and carbon stock. In addition, there are also secondary information that affects seagrass life called as aquatic environmental parameters for instance sea surface temperature, salinity, CDOM (colored dissolved organic matter), turbidity, sea-level rise, and pollution (Ferwerda et al. 2007; Hossain et al. 2019). RS has succeeded in analysing the biophysical properties of seagrass parameters, including the distribution of seagrass areas (Hossain et al. 2015a; Kaewsrikhaw et al. 2016), species composition (Dierssen et al. 2015), and carbon stocks (Barillé et al. 2010; Stankovic et al. 2021). The percentage seagrass cover is defined as the substrate area covered by seagrass that can be observed from above (Phinn et al. 2008; Roelfsema et al. 2014). McKenzie et al. (2001) stated that the percentage seagrass cover is a key factor in seagrass monitoring. Phinn et al. (2008) identified seagrass cover by using Landsat TM, CASI and QuickBird imagery in Moreton Bay, Australia; the classification accuracy was no higher than 45%. In literature, empirical model was often used for mapping percentage seagrass cover by correlating pixel value of corrected satellite images with *in-situ* data (Phinn et al. 2008). Zoffoli et al. (2020) studied seagrass percent cover and seagrass leaf biomass using Sentinel-2A in European Atlantic coast. The results obtained quite good accuracy for seagrass biomass prediction (RMSD = 5.31 g DW m−2, $R^2 = 0.88$) as well as for seagrass percent cover (RMSD < 5%, $R^2 \geq 0.98$). Furthermore, when assessing seagrass percentage cover by using variation of images at 2-30 m spatial resolutions, Wicaksono et al. (2019) obtained little RMSE difference (3.4%) from the results. It was represented by relatively similar overall seagrass percentage cover pattern. However, the level of information precision is reduced at lower spatial resolution. The study concluded that the aforementioned situation was strongly affected by seagrass bed configuration; a continuous seagrass bed can be mapped with higher accuracy than a patchy seagrass bed.

LAI describes a total area of photosynthesis per unit area of the substrate and can be used as an indicator of the crop growth rate, radiation intensity and the above-ground height (Solana-Arellano et al. 2004). There are several LAI seagrasses studied by using various RS data (Hedley et al. 2017, 2016). Wicaksono and Muhammad Hafizt (2013) mapped LAI seagrass using ASTER VNIR and ALOS AVNIR-2 in Indonesia. The two resulting images showed similar distribution patterns; the main difference was in the level of precision of the LAI map, where AVNIR-2 was better than ASTER VNIR.

Seagrass biomass can be used as a barometer to assess the effect of changes in seagrass dynamics, composition and water brightness. Several studies of seagrass biomass used various RS data such as WorldView-2, IKONOS and QuickBird-2 (Roelfsema et al. 2014), Landsat TM and OLI/TIRS (Misbari & Hashim 2016), QuickBird, CASI-2 and Landsat TM (Phinn et al. 2008), Landsat ETM+ (Schweizer et al. 2005) and Sentinel-2A imageries (Erzad et al. 2020). Landsat TM/ETM+/OLI/TIRS imageries have been used to observe the dynamics of changes in seagrass in Cam Ranh Bay, Vietnam from 1996 to 2015, and discovered that seagrass had decreased by about 25% (Chen et al. 2016). Hossain et al. (2019) have used Landsat imagery for mapping seagrass distribution changes and assessed environmental impacts on coastal reclamation activities. León-Pérez et al. (2020) studied the changes in seagrass extent from 1950 to 2010 using WorldView-2 data and aerial photos based on object-based image analysis method. The study showed that seagrass had increased by 64%.

Considering advantages and limitations mentioned above, a trade-off between cost, effort and the level of information exist. Landsat imagery is favorable due to its open data policy, large coverage and its long series of images that enable long-term monitoring of seagrass. However, limitations exist since low spatial resolution of Landsat limits its ability to observe seagrass species. The level of seagrass information provided by Landsat is low and can only be used at a regional scale. On the other hand, VHRS images such as QuickBird are able to detect seagrass species with satisfactory detail (Lyons et al. 2011); however, it certainly requires higher costs. Generally speaking, deciding on the selection of satellite imagery must be adjusted to the objectives of mapping activities, and level of detail to be achieved, so that it is not based solely on low cost of acquisition. To the best of our knowledge, up till now, the available satellite images are not able to provide complete information about all seagrass parameters (presence/absence, cover, species, and biomass). Therefore, the integration of field-observation, imagery and mapping approaches is required (Hossain et al. 2015c).

AQUATIC PHYSICAL ENVIRONMENT PARAMETERS AFFECTING SEAGRASS

The aquatic environmental factors that determine the conditions of seagrass growth can be derived from RS data. In this case, sea surface temperature and salinity are two parameters that influence the distribution of seagrass (Chefaoui et al. 2016). In addition, Glasby et al. (2014)

and McMahon et al. (2014) suggested other factors that determine the distribution of seagrass namely turbidity, solar radiation, nutrient and water current. Other studies (Foden et al. 2013; Marbà et al. 2013) stated that seagrass is a good bio-indicator for detecting climate change and ecosystem health. It is because the influence of various physical factors of the aquatic environment on the distribution of seagrass.

The main cause of seagrass loss is a decrease in water transparency caused by increased turbidity and nutrient concentration (Duarte 2002). As has been mentioned by Carruthers and Walker (1999), seagrass growth in tropical waters in Australia was also influenced by water turbidity because turbidity reduced light availability. Moreover, increased sediment has a direct effect on seagrass productivity because sediment inhibits and reduces the light intensity required for photosynthesis (Ferwerda et al. 2007). As the depth of the water column increases, the light intensity decreases. In this situation, light is a limiting factor for the distribution of seagrass (Hemminga & Duarte 2000). Related to suspended sediment, RS images have been used widely to derive suspended sediment in shallow water, for instance by using Landsat (Veettil & Quang 2018), MODIS (Kumar et al. 2016) and MERIS (Ambarwulan et al. 2012, 2011).

Water surface temperature plays an important role in seagrass life. Water temperature can be extracted from RS data for example by using AVHRR and MODIS (Carlson et al. 2018). Several publications have discussed seagrass mortality associated with water temperature conditions, including in the Mediterranean Sea (Jordà et al. 2012). Other environmental factors that also have an impact on seagrass life are salinity (Durako & Howarth 2017) and water depth (Collier & Waycott 2014).

Mapping of seagrass biophysical parameters using RS data is very challenging and uneasy because it is also strongly influenced by aquatic physical environment parameters around seagrass meadows such as water temperature and turbidity. Turbidity caused by the presence of CDOM and sediment make it difficult to map the biophysical properties of seagrass since solar energy that can reach the water column is limited and is blocked by sediment particles. The accuracy of results depends on approaches that are used for deriving biophysical parameters. A semi-analytical/analytical model that considers TSM, CDOM and chlorophyll parameters increases mapping accuracy compared to the empirical model. In addition, spatial and spectral resolutions also determine the accuracy of the results.

RS METHODS FOR MAPPING SEAGRASS

The utilization of RS techniques for seagrass mapping in shallow and complex water environments faces some obstacles due to the presence of atmospheric components, variation in water depth, the presence of bottom albedo and water column attenuation (Cho et al. 2012). The treatment for water column attenuation is the most challenging and important stage because many components, such as scattering and absorption, increase with changes of depth, sediment particle concentration, chlorophyll and CDOM (Yang et al. 2010).

Another challenge for the RS of aquatic environments is the spectral separation of disturbed seagrass in the presence of spectra from other objects (Krause-Jensen et al. 2004). Reflectance values recorded by sensors do not come solely from seagrass but also from other sources such as atmosphere, sun glint and water column. Signals from seabed are difficult to distinguish because signals received by sensors also arise from objects other than seagrass. Hence, these affect beams captured by sensors. In this case, seagrass living in a shallow and sandy water can easily be distinguished, but those that live in dark or muddy environments or mixed with other objects are difficult to detect by using RS images; it requires a wide dynamic range of colors to distinguish.

Several image processing steps are required for seagrass mapping. Image pre-processing consists of systematic error correction and image calibration to produce consistent and uniform data. In general, there are five types of image correction, namely: geometric correction (GC), radiometric correction (RC), atmospheric correction (AC), and water column correction (WCC). According to Giardino et al. (2019) and Pham et al. (2019), the AC and WCC are the most important steps in image pre-processing. The pre-processing steps may differ slightly between studies depending on the purpose of mapping, the condition of input image and spatial resolution of image used (Schroeder et al. 2019). Different types of image processing approach will determine the accuracy of obtained results. Pu et al. (2014) showed that the results of seagrass mapping studies from Landsat TM using corrections such as for atmosphere, sun glint and water column showed increased accuracy (74-80%).

IMAGE PRE-PROCESSING

Radiometric correction is the initial stage of data processing before classification analysis is carried out. Koedsin et al. (2016) stated that the purpose of RC is to normalize satellite images because of sensor drop factor, variations in the sun-to-earth distance, incidence angle, view angle, and data recording time. The RC process includes the conversion of digital number (DN) to the radiance value (in μW/cm^{2}nmsr) using calibration coefficients presented in the image metadata, such as gain and offset of each band.

Atmospheric correction is carried out to clarify the appearance of objects in the image to make it easier in recognizing objects during image interpretation. AC techniques include dark pixel subtraction (DOS) from Chavez (1988) and Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH). DOS is carried out to eliminate atmospheric scattering by fog and aerosols, and waves in the spectral signal (Stumpf et al. 2003).

Sun glint is a signal that is emitted from the water surface toward the sensor which can cause misinterpretation. Kay et al. (2009) differentiated sun glint correction (SGC) into two categories: sun glint in satellite imagery with a resolution of 100-1000 m, used for deep-sea waters; and sun glint in satellite image with a resolution of about 10 m for coastal areas. In their study, near infrared (NIR) wavelengths were used for sun glint correction in coastal water based on the assumption that any NIR signals that exist after atmospheric correction must arise from sun glint (Hedley et al. 2005; Lyzenga et al. 2006). Some examples of SGC applied for high-resolution satellite images are methods proposed by Hedley et al. (2005), Kutser et al. (2009), and Lyzenga et al. (2006). Further discussion of sun glint can be found in Kay et al. (2009). Anggoro et al. (2016) applied SGC to improve the accuracy of benthic maps in the Thousand Islands from WorldView-2 imagery. The resulting benthic maps with and without SGC showed differences in accuracy values of 60 and 53%, respectively. Several publications related to seagrass mapping by using RS technology including SGC are presented in Table 1.

WCC is carried out to improve image quality by reducing the influence of water column (Lyzenga 1981). In principle, passive optical sensors record surface reflectance of the atmosphere. Various processes have influenced to the Top of Atmosphere (TOA) reflectance such as absorption and scattering by atmospheric components, Fresnel reflection, water body backscattering, and bottom reflection (Zoffoli et al. 2014). Lyzenga (1978) outlined two basic approaches used for WCC, namely empirical RT and analytical RT. The empirical approach is a simple method using information contained in the image, while analytical method is a sophisticated and more complex method because it requires a detailed information about bathymetry, water attenuation and spectral library of objects. There are many algorithms for WCC that differ in how they estimate the partial contribution to the surface signal. They are divided into three approaches: the band combination algorithm, model-based algebraic algorithms and optimization/matching algorithms (Zoffoli et al. 2014). Lyzenga's method (Lyzenga 1981, 1978) is one of the most popular band combination algorithms (Benfield et al. 2007) and in most cases show an increase accuracy (Mumby et al. 1998). The algorithm of Sagawa et al. (2010) was based on bottom reflectance index (BRI), while Conger et al. (2006) proposes principal component analysis (PCA). Model-based algebraic algorithms include those of Lee et al. (2005), Maritorena et al. (1994), and Mumby et al. (1998), which require spectral measurement of different water body parameters (e.g. absorption and scattering coefficients) to determine the behavior of light in water column. Further discussion of water column can be found in Zoffoli et al. (2014). Many research on seagrass uses various sensors for WCC resulting in different levels of accuracy. Corrections based on RT models have been used by Tamondong et al. (2013) on WorldView-2 to produce a seagrass map with an overall accuracy of 88.3%. The PCA correction of WorldView-2 was carried out by Wicaksono (2016). Hafizt et al. (2017) mapped benthic habitats on Lintea Island, Indonesia using Sentinel-2 using two different WCC methods. In this case, benthic habitat distribution was produced by using a Relative Water Depth Index (RWDI) and obtained an overall accuracy of 83%. Meanwhile, when using Depth Invariant Index (DII) based on Lyzenga (1981), the overall accuracy was 23%. Manessa et al. (2014) compared two WCC method from Lyzenga for benthic habitat mapping in Lombok, Indonesia using WorldView-2 and found that modified Lyzenga method (Lyzenga et al. 2006) performed better than the original Lyzenga method (Lyzenga 1981).

IMAGE CLASSIFICATION

Image classification is generally performed on corrected images and divided into two categories: pixel-based and object-based image classification (OBIA). Pham et al. (2019) stated that image classification for seagrass can be divided into five types: unsupervised learning, supervised learning, advanced learning, OBIA and sub-pixels. The unsupervised and supervised methods are type of pixel-based classification techniques. In this case, pixels are put into classes that show similarities between them. The unsupervised method consists of iterative self-organizing data analysis (ISODATA) and methods based on spectral indices, such as the normalized difference vegetation index (NDVI) from Barillé et al. (2010). Meanwhile, the supervised classifications for e.g. maximum likelihood classifier/MLC (Koedsin et al. 2016), decision trees (Benfield et al. 2007), use data provided by the user to train the algorithm to classify the data into the defined classes. This method performed better when there are good-quality field data (Schroeder et al. 2019). Furthermore, other available methods include PCA (Pasqualini et al. 2005), on-screen digitizing, and linear spectral unmixing (Uhrin & Townsend 2016).

Seagrass classification techniques from RS data range from fully manual skill-based approach to supervised and unsupervised machine learning. Some of the well-known machine-learning (advance learning) approaches are support vector machine (SVM), convolutional neural network (Islam et al. 2019; Perez et al. 2018), k-nearest neighbors and random forest. Li and Xiao (2011) studied the classification method for seagrass using SVM, naïve Bayesian, and decision tree. The results showed that the overall accuracy of the Bayesian method was the highest (86.11%), and the lowest used SVM (85.90%). SVM is a very powerful machine-learning technique for image classification, which creates a boundary called a hyperplane to separate and classify each pixel into a class (Huang et al. 2002). Marcello et al. (2015) studied MLC, SVM, Mahalanobis distance (MH) and spectral angle mapping (SAM) for mapping seagrass on Gran Canari Island from WorldView-2 and found that SVM provided the best accuracy.

OBIA is a digital classification technique that classifies objects by combining a homogeneous set of pixels into object-based sets through a segmentation process. OBIA is superior to traditional pixel models based on HSR data classification (Qian et al. 2015). Its advantage compared to pixel-based methods is that it can overcome the problem of salt-and-pepper effects caused by high local spatial heterogeneity between pixels (Lillesand et al. 2015). Baumstark et al. (2016) mapped seagrass distribution from WorldView-2 using OBIA and obtained an overall accuracy of 78%. Roelfsema et al. (2014) discussed OBIA and pixel-based classification methods in mapping seagrass species, percentage cover and above-ground biomass from field data, WorldView-2, IKONOS-2, and QuickBird-2. The OBIA method obtained an overall accuracy of 77% and the pixel-based method 35% in seagrass species mapping. In percentage cover mapping, the OBIA accuracy was 57% and the pixel-based was 31%. The application of RS in seagrass mapping and the related image processing techniques used are presented in Table 1.

TABLE 1. List of publications on RS technology for seagrass

Reference	Data sources	Location	Scale	Pre-Processing	Class. Method	Output
Adi (2015)	WorldView-2	Australia	Specific	AC, WCC	Regression analysis	LAI, biomass
Lyons et al. (2011)	QuickBird-2		Specific	AC, WCC	MLC	percentage cover. seagrass species seagrass changes
Lyons et al. (2012)	Landsat MSS, TM, ETM+		Local	RC, AC	OBIA	seagrass cover
Phinn et al. (2008)	QuickBird Landsat TM5 CASI-2		Specific	RC, AC	Supervised	seagrass cover, composition and biomass
Topouzelis et al. (2018)	Landsat 8 OLI/ TIRS	Greece	Local	RC, AC	OBIA	seagrass distribution
Traganos et al. (2017)	PlanetScope		Specific	WCC	SVM	seagrass distribution
Agus et al. (2018)	SPOT-7		Local	AC, WCC	MLH	seagrass distribution
Amran (2010)	QuickBird		Specific	AC, SGC, WCC	MLC	seagrass coverage
Amri at al. (2010)	QuickBird		Specific	RC, WCC	MLC	substrate type
Amri at al. (2010)	WorldView-2		Specific	RC, AC	OBIA	substrate type
Anggraeni et al. (2019)	Landsat 8 OLI/ TIRS		Local	RC, AC, WCC	MLC	seagrass beds distribution
Astuty & Wicaksono (2019)	PlanetScope		Specific	WCC	MLC, RF, & SVM	species composition, biomass carbon stock

Ayustina et al. (2018)	Landsat 8 OLI/ TIRS		Local	RC, WCC	MLC	shallow water depth
Aziizah et al. (2016)	WorldView-2	Indonesia	Specific	RC, AC, WCC	SAM, SVM	seagrass species
Daud et al. (2019)	Sentinel-2 Landsat 8 OLI/ TIRS		Local	RC, AC, WCC	MLC	seagrass distribution oceanographic condition
Fauzan et al. (2017)	Sentinel-2		Local	RC, AC, WCC	MLC	percent cover
Giofandi at al. (2020)	Sentinel-2		Local	RC, AC, WCC	Supervised	seagrass beds, blue carbons
Hamsah et al. (2019)	SPOT-6		Local	RC, AC, WCC	Supervised	percentage coverage
Ilyas et al. (2020)	SPOT-7		Local	AC, WCC	OBIA, SVM, Bayes, DT, and K-NN	benthic habitat
Kurniawan et al. (2014)	GeoEye-1		Specific	RC, WCC	Visual interpretation	seagrass distribution
Lubis et al. (2017)	Landsat 8 OLI/ TIRS		Local	RC, WCC	Supervised	seagrass distribution, temperature and DO
Manuputty et al. (2017)	WorldView-2		Specific	RC, AC, WCC	SVM	seagrass cover
Nurdin et al. (2014)	Landsat MSS, Landsat TM5, Landsat 7 ETM+, Landsat 8 OLI/ TIRS		Local	RC	ISOCLASS	seagrass changes
Patty (2016)	Landsat 8 OLI/ TIRS		Local	RC	Visual interpretation	seagrass condition. percent cover seagrass species
Purnawan et al. (2016)	Landsat 8 OLI/ TIRS		Local	WCC	Unsupervised	seagrass distribution
Semedi et al. (2019)	Sentinel-2		Local	RC, AC,	Supervised	seagrass cover, oceanography parameters
Setiawan et al. (2012)	ALOS AVNIR-2		Regional	RC, AC, WCC	Unsupervised	seagrass changes
Setyawan et al. (2014)	WorldView-2		Specific	RC, SGC	Unsupervised	benthic habitat
Sari and Lubis (2017)	Landsat 8 OLI/ TIRS		Local	RC, WCC	Supervised	seagrass cover
Taufikurrahman et al. (2017)	Landsat 8 OLI/ TIRS		Local	RC, AC	Unsupervised	seagrass cover
Thalib et al. (2019)	Sentinel-2		Local	RC, AC, SGC	MLC	seagrass distribution
Wicaksono (2015)	Worldview-2		Specific	SGC, WCC	Empirical model, Regression	LAI, carbon stock, standing crop above ground
Wicaksono and Lazuardi (2018)	PlanetScope		Specific	AC, SGC	MLC, SVM, and CTA	benthic habitat & seagrass species
Yusuf and Indrawan (2019)	QuickBird		Specific	RC	Unsupervised	seagrass cover
Misbari and Hashim (2016)	Landsat TM5 Landsat 8 OLI/ TIRS		Local	RC, ACC< SGC, WCC	MLC Linear regression	seagrass distribution biomas changes
Hossain et al. (2015)	Landsat 8 OLI/ TIRS Landsat 7 ETM+ Landsat TM5		Local	RC, AC,	NDVI	seagrass changes
Hashim et al. (2014)	Landsat 8 OLI/ TIRS	Malaysia	Local	GC, AC, SGC	BRI method	seagrass distribution biomass changes

Sani and Hashim (2020)	Landsat 8 OLI/ TIRS		Local	GC, AC, RC, SGC	BRI, MLC	seagrass distribution, seagrass biomass
Hossain et al. (2015)	Landsat TM5 Landsat 7 ETM+ Landsat 8 OLI/ TIRS		Local	-	Manual Digitizing	seagrass detection and distribution
Redondo et al. (2017)	Landsat		Local	RC, AC	Supervised	seagrass distribution, seagrass species
Tamondong et al. (2013)	PlanetScope Sentinel 2A	Philippine	Local	RC, AC, WCC	MLC SVM	seagrass percent cover and LAI
Koedsin et al. (2016)	WorldView-2		Specific	RC, AC, WCC	MLC	seagrass species, seagrass cover, and biomass
Chayhard et al. (2018)	WorldView-2 GeoEye-1 Aerial photo by UAV		Specific	RC, WCC	MLC	Seagrass distribution, seagrass species
Kakuta et al., (2016)	Landsat 8 OLI/ TIRS	Thailand	Local	WCC	ISODATA, decision tree decision tree	seagrass species
Komatsu et al. (2012)	ALOS-AVNIR		Local	RC, AC, WCC	OBIA, Pixel base	seagrass species
Yamakita et al. (2019)	QuickBird Aerialphoto		Local	WCC	Supervised	seagrass species
Duffy et al. (2017)	Drone		Specific		Unsupervised, OBIA	seagrass distribution
Baumstark et al. (2016)	WorldView-2		Specific	RC, AC, SGC, WCC	OBIA	benthic cover type
Carlson et al. (2018)	MODIS AVHRR, Landsat 8 OLI/ TIRS	USA	Regional		Empirical	SST, salinity and seagrass cover
Dierssen et al. (2015)	PRISM		Regional	AC, SGC	NDVI	seagrass species
Oguslu et al. (2018)	WorldView-2		Specific	AC	k-Nearest Neighbors	seagrass distribution
Pu et al.	Landsat TM5 EO-1 ALI Hyperion (HYP)		Local	RC, AC, WCC	ISODATA, Multiple regression models	percent cover, percent SAV and LAI
Pu & Bell (2017)	IKONOS Landsat TM5		Specific	RC, AC, WCC	MLC & SVM	seagrass classification
Chen et al. (2016)	Landsat TM, ETM+, OLI/TIRS					
Luong et al. (2012)	ALOS-AVNIR Landsat TM SPOT 5					
Thu et al. (2012)	Landsat, SPOT and ALOS AVNIR-2.	Vietnam	Local	RC, AC, Bio-optic model	Supervised Unsupervised	
Khanh Ni et al. (2020)	Sentinel-2 Landsat 8 OLI/ TIRS V1 imagery		Local	RC, AC, WCC	MLC	
Nguyen et al. (2021)	Landsat 8 OLI/ TIRS Sentinel-2B		Local	RC, AC, WCC	Supervised	

CONCLUDING REMARKS

The Tropical Indo-Pacific is the richest seagrass biodiversity in the world having 24 species out of 60-seagrass species seen around the world. The seagrass areas worldwide decrease due to human activity and climate change. Seagrass mapping and monitoring are essential for the management and conservation of seagrass ecosystems. From literature review that has been conducted, we concluded that RS application is likely more effective and efficient for seagrass mapping than field measurement. Because RS imagery offers a multipurpose and accurate technique for mapping seagrass with varying degrees of detail. Seagrass ecosystem information can be detected by RS through biophysical properties of the seagrass, including distribution area, species composition, biomass, LAI, and changes in the seagrass ecosystem. Large number of environmental parameters that affect the ecological health of seagrass can be monitored using RS data including suspended sediment, sea temperature, salinity, and light penetration. Of the biophysical properties of the seagrass, there are not many publications concerning LAI, biomass or carbon stock. Likewise, only a few studies are related to the physical parameters of the marine environment of seagrass. There are opportunities for researchers to examine these topics concerning the tropical equatorial ecosystem by using various types of sensors and various image processing methods.

A variety of passive and active sensing data are used to analyze seagrass parameters, including underwater and aerial photography, multispectral and hyperspectral techniques, LiDAR, radar, sonar and data from UAVs. Passive sensor satellite imagery is more widely used because active sensors are relatively more expensive, but they can be used in turbid and deep waters. Image fusion techniques combining passive and active sensors provide the opportunity to map seagrass more accurately. Based on the sensor type, MSR imagery such as Landsat is used for global seagrass mapping. Sentinel-2, with spatial resolution of 10 m is able to map seagrass distribution. Both images are easy to obtain, free of charge, large area coverage and are multi-temporal. The advantage of Landsat is that it has a long archive data, so it can provide changes in seagrass over a long period. These two imaging techniques are very suitable to be used to map the distribution of seagrass in a systematic manner. VHSRs such as IKONOS, GeoEye, WorldView-2 and QuickBird are suitable for a more detailed mapping, such as of seagrass species. Each image has advantages and disadvantages depending on the objective and the level of the mapping activities. The disadvantages of VHSR technique are high price, narrow coverage and limited temporal resolution.

Several image pre-processing techniques to improve the accuracy of seagrass classification have been discussed in this paper. In some cases, the classification accuracy can be improved by using AC, WCC, and SGC approaches. Dark pixel subtraction and Lyzenga's DII algorithm are techniques of AC and WCC that are widely used by many researchers. Atmospheric correction is important for multi-temporal analysis to take into account variations in the atmosphere. There are many WCC methods available, however, only a few have been tested for research in the tropical region which generally use the band combination algorithm model. Meanwhile, model-based algebraic algorithms such as those of Lee et al. (2005), Maritorena et al. (1994), and Mumby et al. (1998) still need to be explored. The model is challenging because it requires spectral measurements of various water components. SGC needs to be performed on HSR and VHSR images for seagrass mapping in order to obtain good accuracy, because these images are generally designed for the detection of objects on land, so they do not anticipate the effect of sun glint. There are several SGC methods that have been used by researcher, such as those of Hedley et al. (2005) and Lyzenga et al. (2006), however method from Kutser et al. (2009) is rarely used. Furthermore, various image classification methods have been used for seagrass mapping, but the current trend requires a classification method that is fast, automatic, that can include a large amount of data and that is highly accurate. Machine-learning techniques such as neural networks are likely able to meet these needs.

Future research for underwater seagrass mapping may adopt more automatic data collection, detection and classification. The research can be focused on: Using HSR and VHSR RS images to map the biophysical properties of seagrass using various pre-processing and image classification models (machine learning, linear spectral unmixing, OBIA); using semi-analytical and analytical approaches to map seagrass using optical physical data of seagrass and water parameters; mapping the physical environmental parameters of the water that affect seagrass using satellite imagery and in-situ observation by using empirical and semi-analytical approaches; and mapping and monitoring the seagrass dynamic from Landsat, Sentinel-2A and SPOT6/7 to obtain more complete data on seagrass in Indonesia.

ACKNOWLEDGEMENTS

The authors would like to acknowledge colleagues in the Geospatial Information Agency of Indonesia for providing their supports in writing this manuscript.

This work was funded by the Geospatial Information Agency, grant number SP DIPA- 083.01.1.017216/2020 DIPA Geospatial Information Agency Fiscal Year 2020. The contents are solely the responsibility of the authors and do not necessarily represent the official view of the Geospatial Information Agency of Indonesia.

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