Remote sensing of submerged aquatic vegetation: an introduction and best practices review

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Abstract

Submerged aquatic vegetation (SAV) is a critical component of aquatic ecosystems. It is however understudied and rapidly changing due to global climate change and anthropogenic disturbances. Remote sensing can provide the efficient, accurate and large-scale monitoring needed to ensure proper SAV management. Our objective is to introduce remote sensing to researchers in the field of aquatic ecology. Applying remote sensing to the underwater environment is more complex in comparison to terrestrial studies due to the water column. A wide range of sensors and platforms from remotely operated vehicles to satellites are available for use in the underwater environment, a sample of which being presented herein. The utility of any sensor/platform combination varies depending on the aquatic conditions being observed. An overview of the required corrections, processing, and analysis methods for passive optical imagery is presented and discussed. Previous applications of remote sensing to identify and detecting SAV are briefly presented and notable results and lessons are discussed.

Keywords: Remote sensing; Submerged aquatic vegetation; hyperspectral imaging; species discrimination; extent mapping.

1. Introduction

Submerged aquatic vegetation (SAV) is a key component of shallow aquatic ecosystems as it creates habitat for fauna, regulates water flow, stabilizes sediments, and contributes to biogeochemical cycling (Jia et al. 2017; O'Neill and Costa 2013; Wolf et al. 2013). Further, SAV growth has been shown to limit phytoplankton concentrations and reduce turbidity, improving water quality (Wolter et al. 2005). SAV is therefore a vital ecosystem indicator of both biotic and abiotic processes (Duffy et al. 2019; Malthus 2017; Silva et al. 2008). Despite the numerous physical, ecological, and economic services SAV provides, it is in a state of global decline (Zhang et al. 2017). Several federal and international water quality frameworks, such as those in the European Union, the United States, and Australia and New Zealand, include SAV extent or health as assessment indicators (Bostater et al. 2004; Malthus 2017). Other policies consider the conservation and protection of SAV as its own goal (Duffy et al. 2019). There is therefore a need for accurate, representative, and timely knowledge of SAV extent and community composition (Zhang et al. 2017). The economic value of areas with SAV and the services they provide further increases the importance of proper monitoring (Ackleson and Klemas 1987; Bostater et al. 2004).

Conventional SAV research involves *in situ* visual assessment of extent, species distribution, or plant health using quadrats or transects (Ackleson and Klemas 1987; Malthus 2017). This manual monitoring is costly, time consuming, can be dangerous (e.g. wildlife, parasites, traffic, etc) and often has a high error rate (Ackleson and Klemas 1987; O'Neill and Costa 2013; Vis et al. 2003). These errors stem from observer misidentification, poor estimation, and location accessibility biases that may not represent the full ecosystem heterogeneity (He et al. 2015; Malthus 2017). Other traditional methods include comprehensive sampling and the use of grabs or grappling hooks to collect specimens, which are destructive to the organisms being studied (Saravia et al. 1999; Visser et al. 2013).

Remote sensing (RS) is increasingly being used as a tool in aquatic studies, often in conjunction with conventional techniques, to address some of the limitations of *in situ* methods (Duffy et al. 2019; Visser et al. 2013). RS is time efficient and increasingly affordable for researchers working at local, regional, and global scales. Accessibility issues are reduced as data are gathered at a distance, allowing the survey of fragile or dangerous sites while the operator remains at a single point of safety (Kalacska et al. 2017; Rhee et al. 2018). RS products can be used in quantitative analysis and can be compared over space and time when collected and processed correctly (Jia et al. 2017; Klemas 2016). The precise, quantitative data acquired by RS can also be used to monitor the slow, progressive changes in various ecosystems. As shown in Figure 1, the Landsat series of satellite-based sensors, for example, has an over

40-year historic catalogue of inter-comparable imagery (Jia et al. 2017). Finally, RS may be the only realistic way to efficiently monitor SAV in remote and under-funded regions (Duffy et al. 2019).

Figure 1. Operation chronology of remote sensors used in SAV research by platform and sensor type

The first RS applications in macrophyte research relied on visual inspection of aerial photographs to extract SAV cover and distribution (Ackleson and Klemas 1987; Nelson et al. 2006a). Innovations in aerospace technologies have allowed the evolution of aircraft-mounted (hereafter called “airborne”) sensors and satellite platforms; each increasing the spatial scale of the data available to users. Satellite RS has largely dominated the discipline, as can be seen through the substantial volume of work exploiting this data source (Palmer et al. 2015). Technological advances, though, particularly in terms of unmanned aerial vehicles (UAV), are continuously providing new opportunities. The recent commercialization of

UAVs, and innovations leading to their increased affordability, has made UAVs appealing for RS (Anderson and Gaston 2013; Linchant et al. 2015; Rhee et al. 2018).

Remote sensing has thus far been less extensively applied in aquatic studies than in terrestrial botany and ecology. This can be attributed to the historic lack of technologies specifically designed for use in water, as well as to the aquatic environment and SAV themselves (Brando and Phinn 2007; Visser et al. 2018). The size of SAV features necessitates very high spatial resolution data which is expensive and may be unavailable to researchers working with a small budget (Nelson et al. 2006b). The water column complicates analysis by attenuating the strength of benthic reflectance signals and introducing heterogeneity within a scene through water colour differences (Nelson et al. 2006b). The inconsistent application of calibration and correction methods to account for the atmospheric and water column effects makes sharing and comparing imagery and data across studies difficult (Malthus 2017).

Remote sensing is rapidly evolving. As such, users unfamiliar with the discipline may not be aware of the applications, technological opportunities, and products available to them. Additionally, no single RS method can be effectively employed across all conditions for all research questions (Stocks et al. 2019). It is therefore important to be informed of the options available, their strengths and limitations, and how they may be combined. This paper is thus intended as a preliminary guide for those considering applying RS in aquatic botany, with a focus on optical approaches.

We present the following five aspects of RS application to SAV that any practitioner new to the discipline should be aware of and consider: 1) a technical background on the use of RS in the aquatic medium; 2) an overview of the relevant RS platforms and their operational level; 3) a description of the types of sensors and data produced; 4) an overview of how optical RS data is processed and analyzed; 5) examples of RS applications in SAV research.

2. Technical Background

2.1. What is Remote Sensing?

Earth observation RS measures the energy reflected or emitted by an object or surface, hereafter referred to as a target, to infer information about that target. This is done without having any direct physical contact with the target, hence being “remote”. The information obtained can be qualitative, such as presence/absence or cover classes, or quantitative, such as a reflectance profile or temperature. The data from RS is also positional, meaning that each piece of information obtained represents a discrete known location.

Remote sensors are either passive or active; passive sensors collect ambient incoming energy whereas active sensors emit a signal which is then reflected and recorded (Lillesand et al. 2008). Not all sensors use the same kind of energy; acoustic sensors register sound wave energy while optical sensors recognize

electromagnetic energy. Figure 2 presents the types of remote sensors that have been employed in aquatic research and each is discussed in more detail in Section 3.

Figure 2. Overview of the different types of RS sensors that have been applied to any type of aquatic research

In passive optical RS, each material interacts with electromagnetic radiation according to its molecular composition and physical structure. These interactions cause the radiation at a given wavelength to be absorbed, transmitted, or reflected in different proportions by various materials. Measuring the reflectance of a material across many wavelengths produces a curve called the “spectral profile” or “spectral signature” of that material, examples of which can be seen in Figure 3. If the spectral profiles of all materials potentially in an image are known, a pixel representing an unknown material can be identified by matching its spectrum to one in a “library” of profiles. This is the basis of spectroscopy. Active RS, whether optical or acoustic, emits and records one frequency of energy and determines a target’s distance by measuring how long it takes for that emitted energy to be returned to the device. (Stocks et al. 2019). This means that the information concerning material composition is limited but accurate positional and structural data can be collected. This can be applied, for example, to measure and model coral reef structure (e.g. Collin et al. 2018) or vegetation presence and absence (e.g. Stocks et al. 2019).

Figure 3. A digital image is considered to have three dimensions of data, the number of across track pixels (spans across the field of view), the number of along track pixels (in direction of travel), and the number of bands (n). The values for each band plotted graphically in order of increasing wavelength form a spectral profile where the x-axis is the wavelength of the band and the y-axis is the reflectance value given on a scale from 0 to 100% or if in units of reflectance, values of 0 –1.

SAV extent mapping in clear waters may be done through visual inspection, so only imagery and user judgment and experience are required. More involved research objectives, such as species discrimination or health analysis, may also require reference spectra from the macrophytes of interest, validation data, and specialized analytic tools and software. It is therefore important to define what information is desired from any RS project and which data inputs are required before beginning a data collection campaign.

2.2. Resolutions

Four types of resolution define RS imagery: spatial, spectral (optical RS), radiometric, and temporal. Spatial resolution refers to the fineness of the data, the smallest resolvable detail in the photograph or image. Pixel size refers to the area on the ground represented by one pixel after an image has been geometrically corrected (see Section 5.1) (Abdullah et al. 2015). While pixel size may be resampled during post processing to any desired value, spatial resolution depends on the sensor and imagery collection parameters and cannot be improved post-collection. In SAV research, spatial resolution is vital because of the often-linear distribution of SAV along coastal and bathymetric contours and the general patchiness of SAV growth. The spatial resolution must therefore be fine enough to capture a thin, linear feature using (usually) square pixels. Imagery collected at a high spatial resolution can thus be used to identify far smaller features than coarser images, as shown in Figure 4. The spectral resolution comprises the number of spectral bands, the range over which the bands are located, and the width of the bands

(Lillesand et al. 2008). The large similarity between SAV species' spectral profiles demands very high spectral resolution data to allow discrimination. Additionally, a sensor's spectral range is crucial given that water absorbs most energy in the infrared (IR) region and signals in the ultraviolet (UV) region are often unreliably weak (Wolf et al. 2013). Radiometric resolution describes how fine the differences in energy the system can discern. This is typically given in the form of bits used to encode the pixel values in binary format where each bit corresponds to an exponent of 2 (e.g. an 8 bit file has 256 possible digital numbers) (Klemas 2011). For example, Landsat 5 acquires 8-bit data while Landsat 8 acquires 12-bit data, resulting in 256 and 4096 possible digital numbers per pixel respectively (Markham et al. 2018). Higher radiometric resolution is important when analyzing surfaces with very similar reflectance values. The temporal resolution describes how often a scene is imaged as determined by the platform and its operation. The temporal resolution of satellite imagery is determined by the satellite's revisit time. Landsat missions have a 16-day temporal resolution while the commercial PlanetScope satellite constellation achieves daily revisits (Markham et al. 2018; Planet 2020b). The temporal resolutions of other platforms (e.g. UAV) are determined according to the research project planning (Klemas 2011). For SAV monitoring, a relatively short revisit time is often desired because of the rapid growth and maturation of underwater vegetation. Additionally, identification may be most successful when considering the effect of seasonality. In temperate climatic zones, spring measurements tend to be brightest because of exposed light sediments below still-developing leaves. Dense summer canopies with full cover cause the benthic reflectance to be exclusively from the plants. Fall measurements capture the heterogeneous changes due to senescence (Malthus 2017). A study using multitemporal data would therefore capture the highest amount of spectral variation for each species and may produce the best identification results (Malthus 2017; Wolf et al. 2013; Wolter et al. 2005).

2.3. Underwater light environment

The water column complicates optical RS. Water molecules scatter and absorb electromagnetic energy, adding complexity to the path of light travelling between the sun, the target and a sensor (Kirk 1994), as depicted in Figure 5. The water column decreasingly scatters light with increasing wavelength, resulting in very strongly scattered UV energy and negligible scattering of wavelengths longer than blue. While water absorbs some energy across the spectrum, it attenuates light most strongly for wavelengths greater than 680 nm. Together, this means that optical RS of aquatic environments is largely limited to the visible region (VIS) of the spectrum (Kirk 1994), though some information can often be garnered from the near infrared (NIR) region if the water column is very thin (less than ~ 1 m) (Visser et al. 2013). Water's very strong absorption of radiation in the IR can facilitate the distinction between above and below water targets (Seyhan and Dekker 1986). Increasing water depth increases scattering and absorption, thus reduces signal strength across all wavelengths (Davie et al. 2008).

Figure 4. Comparison of spatial resolutions in representing natural and man-made features (most notably a flooded road) in the Saint-Lawrence River, Ontario. a) 3 cm resampled pixel size image acquired from a UAV platform with the μ CASI sensor (288 spectral bands). Subset is shown as a true color composite R:648 nm/G:548 nm/B:449 nm. b) 1 m resampled pixel size image acquired from an airborne HSI platform (CASI-1500, 288 spectral bands) Subset is shown as a true color composite R:641 nm/G:550 nm/B:471 nm. The red box indicates the spatial extent of frame a. c) Panchromatic film photograph from a KH-9 satellite taken in 1980 at a spatial resolution of 2 to 4 feet. d) 3 m resampled pixel size image from the commercial PlanetScope satellite constellation (Dove-PS CubeSat). e) 10 m resampled pixel size Sentinel-2 satellite image. f) 30 m resampled pixel size Landsat image. For d-f, the respective RGB bands are displayed as true color composites.

Figure 5. A simplified illustration of the interactions of light as they originate from the sun and are recorded by an optical sensor. The labels are as follows: LT= Radiance reflected by the target; LTS= Radiance reflected by the target then scattered out of the path to the sensor; LS= Radiance reflected by the non-target substrate; LA= Radiance reflected by the atmosphere to the sensor (also referred to as path radiance); LAS= Radiance scattered by the atmosphere; LW= Radiance reflected by the water column into the sensor; LWS = Scattered by the water column; LWA= Radiance absorbed by the water column; LI = Radiance reflected by the air-water interface; LE= Radiance that is scattered into the scene by the ambient environment

Natural waters are not however pure; they also carry dissolved organic and inorganic materials, and plankton. Defining the effect of the underwater light environment is therefore complex as these substances change the reflectance properties of a water column and can vary wildly across small temporal and spatial scales (Kirk 1994). For example, the reflectance profiles of sediments suspended in the water column have been shown to depend on the size of those sediments. The reflectance profile of the water column will thus be altered by a disturbance that resuspends sediments, and by how long has passed since the disturbance to allow re- sedimentation (Bale et al. 1994). Some work has found a direct, definable relationship between the concentration of such water column components and their contribution to a measured spectral signal (Byfield 2017). Others have noted that the relationship between particulate and dissolved matter in the water column and their contributions to a spectral signal are complex, for example being depth and wavelength dependent (Kirk 1994; Seyhan and Dekker 1986). It is therefore important to characterize the effect of the water column if the target reflectance is to be calculated; methods to do so are discussed Section 5. Research projects such as the “Spectral Library of Dutch Waters” have

endeavoured to gather spectral information and samples of a wide variety of water types and qualities to clarify the relationship between water column constituents and spectral response (Rijkeboer et al. 1997).

When waves curve the water's surface, light is concentrated by convex wave crests and dispersed by concave wave troughs, resulting in the familiar web pattern of bright lines that one sees in a swimming pool (Kirk 1994). Concentrating and dispersing light does not alter the wavelengths of light reflected by a target but does create disparities in the intensity of light available to be reflected over space and time (Kirk 1994). Waves can therefore produce variation in the *magnitude* of the spectral reflectance profile of a material without affecting the *shape* of the profile. Furthermore, the differences in refraction caused by wave crests and troughs produces unequal magnification of benthic features which can distort the perceived shape of underwater targets (Chirayath and Earle 2016).

The measured spectrum of a target therefore depends on the thickness of the water column, its constituents, and its behaviour. Areas that are sufficiently clear and shallow to see the benthos are called “optically shallow waters” and it is to these areas that optical RS can be applied; waters that are either too deep or turbid to do so are called “optically deep.”

2.4. Spectral properties of SAV

When radiation reaches a leaf, it is either absorbed or scattered by the leaf components (primarily the pigments and cellular structure), with light scattered out of the leaf appearing to be reflected (Gates et al. 1965). Green vegetation thus has an easily identifiable spectral profile because of the consistent absorbance properties of pigments. Chlorophyll, lutein, and a-carotene all absorb blue light (around 445 nm) very strongly and do not absorb green light much at all. Chlorophylls a and b also absorb red light (around 645 nm) (Gates et al. 1965; Malthus 2017). This produces the characteristic “green peak” in the VIS. Accessory pigments, like carotenoids and xanthophylls, create additional absorption features in the VIS that can be used for distinguishing groups or species (Gates et al. 1965). Increasing the concentration of any pigment will reduce reflectance across the spectrum but will do so inconsistently to reinforce and widen any associated spectral features. High concentrations of accessory pigments can therefore attenuate the overall reflectance magnitude and the relative prominence of features indicative of the major pigments (Fyfe 2003). Vegetation also displays a distinct and drastic increase in energy reflection in the IR called the “red edge” and the “IR plateau” due to multiple scattering of IR energy in leaf tissues (Gates et al. 1965). Figure 6 presents a classic example of the spectrum of green vegetation and variations due to water cover or accessory pigments.

The measured reflectance of a species has been shown to vary across seasons, depth, light intensity, and habitat type. Epibionts and sediments on the plants can also confound the reflectance signal registered *in situ*. Therefore, if a spectral library is to be used in image analysis across many scenes or conditions,

sufficient variation must be included in the library to account for the changes in each of these factors (Fyfe 2003).

Figure 6. Examples of vegetation spectra. Note the prominent green peak in the spectrum of *N. odorata* near 550 nm (shown in green) and the red-edge around 670-680 nm (shown in red). From the surface or from the air, the spectra of the submerged plants are seen to be less reflective across the spectrum, especially so in the NIR region. *V. americana* does not display as prominent a green peak due to its higher relative concentration of accessory pigments making the leaves appear reddish-brown.

2.5. Remote sensing application to SAV

Remote sensing has been applied to determine SAV distribution, cover classes, canopy density, health, and species. Assessing the biophysical properties of SAV through RS has yet to be extensively explored, and those studies that did, examined superficial characteristics such as biomass or plant height (Malthus 2017; Rotta et al. 2018). Measurements from aquatic RS have also been used as inputs for modelling fish habitat distributions (Haghi Vayghan et al. 2013). Regardless of the RS technique employed to which end, most research involving benthic macrophytes also includes ground-truth data collection besides capturing the imagery used for analysis (Duffy et al. 2019). Whether this is done through traditional SAV sampling methods, on-the-ground spectral measurements, or geolocated observations from ships, ground truth data allows for proper data calibration, and development and validation of analysis models. A thorough example of ground truth sampling is presented in (Hall et al. 2006).

3. Sensors

3.1. Active

LiDAR and radar are the two types of active RS that employ electromagnetic energy. Terrestrial LiDAR, such as that used in topographical surveys, generally uses IR while radar emits microwaves (NOAA 2020). While terrestrial LiDAR has been successfully applied to map emergent vegetation, it is ineffective underwater due to the absorption of IR radiation (Klemas 2013b). Bathymetric LiDAR that exploits green light (~530 nm) is an effective alternative for underwater research as it balances the strong absorption and scattering effects of the water column (Quadros 2016). The Scanning Hydrographic Operational Airborne Lidar Survey (SHOALS) system operated by the U.S Army Corps of Engineers, for example, uses blue-green light to measure bathymetric features up to 40 m in depth. SHOALS' typical 4-m spatial resolution may however be too coarse to reliably capture small SAV patches and provides only structural and positional data (Wedding et al. 2008). Radar is a useful tool for detecting water features, surface characteristics, and canopy structure of emergent vegetation (e.g. Costa et al. 2002; Idzanovic et al. 2016; Wilson and Rashid 2005), but is not recommended for SAV studies because of liquid water's almost complete reflection of microwave energy (Dwivedi et al. 1999; Klemas 2013b; Silva et al. 2008).

Active acoustic sensors have shown to be advantageous in aquatic settings because of the high transmission of sound waves through water. They perform well in turbid or optically deep waters where optical methods fail (Stocks et al. 2019). The differences in density between the water column and the air spaces contained within macrophyte leaves or the substrate causes sound-wave reflections which allow the distance between the material and the sensor to be calculated (Klemas 2013b). Plant canopies reflect only a part of the acoustic energy, the remainder passing through to be absorbed or reflected by the substrate. Acoustic sensors for underwater research can be either side scanners or vertically oriented. A vertical scanner detects a macrophyte canopy as two echo-return signals aligned vertically in the water column whereas bare substrate returns only one, as illustrated in Figure 7 (Stocks et al. 2019). Side scanners are lowered into the water column to the depth of interest then emit sound energy horizontally; they are thus especially effective in macrophyte studies as their horizontal plane intersects vertically growing plants (Klemas 2013b; Stocks et al. 2019). Continuous innovations in hydroacoustic RS—such as the Dual-frequency Identification Sonar, which produces video footage from acoustic signals—are expected to make acoustic RS more appealing and accessible for work in turbid waters (Stocks et al. 2019).

The exclusively positional data provided by acoustic sensors cannot provide any information about the species, health or maturity of the vegetation. As shown in Figure 8, the applications of acoustic sensors are limited to structural information. The accuracy of hydroacoustic methods has also been inconsistent. For instance, Ford et al (2019) found that hydroacoustic methods produced much higher

SAV height and percent cover measurements than those of divers. Hydroacoustic methods may therefore not capture modest changes in SAV conditions and are not suited to direct comparison with data gathered manually (Ford et al. 2019).

Figure 7. Output from a vertical acoustic sensor at 200 kHz (upper panel) and 800 kHz (lower panel) wave frequency. Macrophyte presence is identified by the areas of signal reflections (in the upper right-hand corner of each panel) above the lake bottom. From Stocks et al. (2019) used according to CC-BY-ND <http://creativecommons.org/licenses/by-nd/4.0/>

Figure 8. An illustration of the extent and success of previous aquatic remote sensing work regarding SAV. The maximum overall accuracy found through a literature review of 368 sources (reported in percent or R2) is depicted

for each sensor-application pairing. White squares indicate that the sensor-application pair was encountered but no overall accuracy measure was provided. Grey squares indicate that no source employed that sensor-application pairing. The large number of white and grey squares respectively demonstrate the need for consistent accuracy reporting and the huge research gaps to date in aquatic remote sensing

3.2. Passive

3.2.1 Panchromatic and Red-Green-Blue (RGB)

RS was first carried out with panchromatic film that is sensitive to a broad range of wavelengths of visible light as one band and produced black and white photographs (e.g. Figure 4c). Red-Green-Blue (RGB) cameras record incoming light in the three colour channels for which they are named and produce colour images. Film and digital aerial RGB photography have been used in mapping SAV, with panchromatic film and physical photographs providing records of macrophyte conditions as far back as the late 1920s in some areas (Madden 2004). These aerial images can be used as raw inputs for maps or supporting information for interpreting satellite imagery (Klemas 2013b). RGB cameras have limited spectral information but produce imagery viewable on a wide range of software that is amenable to manual, visual interpretation. Although it previously seemed that users were moving away from RGB sensors towards multispectral and hyperspectral alternatives, their lower relative cost and flexible deployment options have led to a resurgence in their popularity (Malthus 2017).

3.2.2 Multispectral

Multispectral imagers record information in more wavelengths than traditional RGB cameras. Multispectral imagers generally have 4 to 7 bands in the visible, NIR and shortwave IR (SWIR) regions and may have additional thermal bands (Klemas 2011). The Multispectral Electro optical Imaging Scanner, built in 1983, was one of the first digital, airborne multispectral imager available for academic research and has been succeeded by a plethora of other airborne sensors (see Figure 1). There is a multitude of multispectral sensors on orbiting satellites, each strategically designed with different spectral, spatial and radiometric parameters dependent on their intended targets and use (Tatem et al. 2008). Bands across the VIS to SWIR range may be placed to detect specific features such as the green peak, red edge, or reflectance features of valuable minerals (or other materials of interest). Short-wave IR bands can also be positioned to detect atmospheric greenhouse gas concentrations such as water vapour and carbon dioxide (Jallad et al. 2019). Thermal bands may be chosen to record sea-surface temperatures (Byfield 2017). While multispectral imagery (MSI) contains less spectral information than hyperspectral imagery (HSI), it is well suited to aquatic applications such as ocean colour investigations or detecting SAV cover, and tends to be less expensive than HSI of the same spatial resolution (O'Neill and Costa 2013). As seen in Figure 8, multispectral imagers have been used in a variety of applications, and generally produce moderately accurate results.

3.2.3 Hyperspectral

Hyperspectral imagers have between a dozen and hundreds of spectral bands that can range across the UV to thermal IR regions (Lillesand et al. 2008). They are especially useful for species identification studies because information about accessory pigments (e.g. beta carotene) can be estimated besides the chlorophyll pigments that are typically targeted by multispectral sensors (Palmer et al. 2015). As the signals recorded in SAV research are often weak in comparison to terrestrial applications, discrimination and analysis rely on subtle features detectable using HSI but potentially not with MSI (Silva et al. 2008). Some hyperspectral imagers, such as the Compact Airborne Spectrographic Imager (CASI), allow the user to define the band placement and width according to the expected spectral features (Fyfe 2003; McIlwaine et al. 2019). This flexibility makes them especially well-suited to macrophyte studies compared to other fixed-band sensors whose bands may be too wide or inappropriately placed. While most current sensors are whiskbroom or pushbroom sensors, meaning they respectively collect data one pixel and one row of pixels at a time, there are also full frame options that capture a full 2D frame instantaneously. The hyperspectral snapshot cameras from Cubert, for example, collect all the spectra for 160,000 pixels at once and can be used to collect video footage as well as stills (Cubert GmbH 2017). The available waterproof housing makes such sensors an attractive option for underwater research.

Several portable spectroradiometers are available that collect single spectra of a target (i.e. non-imaging). These are often used for ground-truth spectral collection or spectral sample measurement under laboratory conditions. Close-range measurements from these spectroradiometers produce accurate classification, identification and detection results, as shown in Figure 8. Common examples of such portable, hand-held hyperspectral sensors include the ASD Fieldspec series (Panalytical 2020), the SVC HR-640i (Spectra Vista Corporation 2005), the Flame series (Insight 2019), and Spectral Evolutions' SR series (Spectral Evolution 2020). Each hand-held sensor has different features which provide various advantages; for example, the ASD Fieldspec's obligate use of a fibre-optic cable for spectral sampling allows for underwater measurements without the need for a housing while SVC sensors can be equipped with an underwater housing.

3.3. Advancing technologies

Water's absorption of electromagnetic radiation often produces weak signals from aquatic targets, a high signal-to-noise ratio (SNR) allows the low magnitude target signal to be discriminated from atmospheric and sensor noise. Muller-Karger et al. (2018) suggest an SNR of 800 or more to be ideal for sensors designated for coastal RS, though few current sensors comply with such a high SNR requirement. Macrophytes often grow individually or in small patches and, as with terrestrial vegetation, may have very similar spectral profiles across different species. SAV monitoring therefore necessitates high spatial and spectral resolution data that can resolve subtle features. As the near UV and blue regions are not

strongly absorbed by water, these regions could provide essential information about aquatic targets. Furthermore, when successfully captured, blue wavelengths are suggested to be useful for discriminating between seagrass species (Fyfe 2003). Short wavelengths are, however, highly susceptible to atmospheric scattering, so the blue region signal is often especially weak. A sensor well suited to aquatic research would therefore have a high SNR across its spectral range; high radiometric, spatial and spectral resolutions; and would be sensitive to the near UV and blue regions. Such sensors are being actively designed and developed.

The Portable Remote Imaging Spectrometer (PRISM) airborne sensor operated by the American National Aeronautics and Space Administration (NASA), for example, was designed to address aquatic research needs. Its spectral range is from 350 nm to 1053.5 nm with bands 2.83 nm wide. The 14-bit radiometric resolution allows for 16,384 discrete radiance values and the SNR of 500 in the blue region is an improvement over most other sensors. Depending on the flight parameters of its deployment, pixels of less than 1 m can be achieved (Mouroulis et al. 2014).

The Canadian Space Agency (CSA) and NASA agree on the need to improve satellite RS capabilities for underwater environments (Qian et al. 2017). There are therefore several sensors being developed to address that need. The CSA has planned the WaterSat microsatellite mission to improve its RS capabilities in inland waters (particularly rivers and lakes below 10 km in width) and in near-shore coastal areas. The proposed specifications for the WaterSat optical imager are aligned with the previously identified aquatic needs: 100 m spatial resolution over a 300 km swath width and 10 nm spectral resolution from 400 nm to 1000 nm (Qian et al. 2017). A prototype for this optical sensor, the Water Imaging Spectrometer Experiment (WISE), was developed by ITRES in 2018 (Achal et al. 2018) and is currently being tested. NASA is also planning improvements to its satellite constellation to include better aquatic capabilities. The Pre-Aerosol, Clouds and ocean Ecosystems (PACE) sensor, planned to be launched in 2022/2023, will provide ocean colour information and data relating to phytoplankton and atmospheric conditions at a 1 km spatial resolution (Del Castillo and Platnick 2012; Qian et al. 2017). If the WaterSat and WISE prove successful, a similar sensor called the Coastal Ocean Colour Imager will be added to the PACE mission, thus providing large spatial scale multispectral, and finer spatial scale hyperspectral, imagery. NASA is additionally developing two new active sensors for aquatic observation purposes: the MiDAR, designed to help correct for the effects of waves, and the Surface Water & Ocean Topography (SWOT) sensor which will allow improved measurements of in-land and marine surface height to better understand hydrological dynamics (Chirayath and Earle 2016; Fu 2016). The completion and deployment of these sensors is expected to drastically improve satellite RS observation of ocean colour and distinct targets like macrophytes (Qian et al. 2017).

4. Platforms

4.1. Basic set-up

RS systems include all components required to collect, store, process, and analyze RS data. On a satellite platform, the user bypasses the majority of the components, interacting solely with imagery. For user operated platforms (e.g. manned aircraft, UAV, ROV) however, not only is the choice of sensor important but also the platform upon which it is mounted and any additional hardware. While the operational levels and set-ups of platforms vary, all systems that provide spatially explicit information incorporate a device for doing so. This is especially important for aquatic research as landmarks that may later help situate imagery are rare.

Most RS systems include one or both of a Global Navigation Satellite System (GNSS) receiver and an inertial navigation system (INS). A GNSS receiver records its positional coordinates at a set interval, by calculating its position relative to satellites transmitting their known locations. The best results are produced when many well-spaced satellite signals are intercepted (Grewal et al. 2006). Time-stamped positional information collected in this way allows contemporaneous measurements to be registered with the associated coordinates. While a conventional GNSS receiver can achieve geolocational accuracy on the scale of a few metres (Daakir et al. 2017), realizing better geographic accuracy necessitates more involved positioning systems and corrections. Real-time kinematics (RTK) and post-processing kinematics (PPK) can improve this accuracy by incorporating correction transmissions from base stations at known locations (Zhang et al. 2019). RTK receives the base station corrections and applies them concurrently to data collection while PPK incorporates the corrections after data collection is complete in post-processing (Kalacska et al. 2020). By measuring how many signal cycles occurred between the base station and receiver, the distance between the two is known with accuracy equal to the wavelength of the signal (Koenig and Wong 2010). While GNSS uses only the coded signal, RTK and PPK use both the coded and carrier signal types and can thus obtain positional accuracy on the centimetre scale (Koenig and Wong 2010). As RTK and PPK are dependent on base station corrections, their accuracy is limited by the accuracy of the base station position (Kalacska et al. 2020). Any error or uncertainty in the base station position will translate into equal error and uncertainty in the position of the receiver. INSs collect information on the acceleration and attitude of the platform. Considering the acceleration and rotational changes during the data acquisition allow the user to calculate the position and look direction of the sensor throughout acquisition (Grewal et al. 2006). Attitude information provided by the INS can be used to trace the direction of the sensor lens and indicates how the area imaged differs from one instance to the next. If the positional accuracy of the image registration through such methods is inadequate, or the equipment is unavailable, placing or finding easily visible ground control points (GCPs) with precisely known locations within the image and registering the image to those points can also be effective (Bostater

et al. 2004). In aquatic settings however, placing GCPs may be difficult due to accessibility or currents. As very high accuracy GPS receivers do not function underwater, using GCPs to position an image with high accuracy is limited to shallow and intertidal sites (Joyce et al. 2019).

4.2. Operational level

Remote Sensing platforms for aquatic applications can be situated within the water column, at or near the surface, in the near atmosphere, or in orbit. As such, they are inconsistently influenced by atmospheric and water column effects, and produce imagery of vastly different quality, spatial resolution, and spectral resolution. The platforms employed in aquatic RS (Figure 1) can be categorized as on-water or off-water platforms, and as moving or fixed (Stocks et al. 2019). Sensors mounted on on-water platforms are negligibly – if at all – affected by the atmosphere and so do not require atmospheric correction. Fixed platforms collect information about a single point over a given period of time. Moving platforms collect a snapshot of data across multiple locations (Bostater and Bassetti 2004). On-water moving platforms comprise submerged vehicles, hand-held equipment, and vessels; on-water fixed platforms include buoy- and pier-mounted systems. Unmanned aerial vehicles (UAVs), aircraft, and satellites are all off-water moving platforms.

4.2.1 ROVs and AUVs

Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs) are used to overcome accessibility issues in aquatic environments. ROVs and AUVs are motorized instruments that can collect data underwater replacing a person in snorkel, scuba or submersible equipment. ROVs are tethered to the point of operation and receive power and instruction from this tether. The tether also allows data to be transmitted in real time to the operator. ROVs are therefore valuable tools in complex sites, where water conditions are unpredictable or unideal, and for bottom sampling (Chadwick 2010). AUVs are entirely unattached, with their own navigation, power, and data storage equipment onboard. This allows their missions to be pre-programmed and leaves the user free to address other tasks during the AUVs' operation (Chadwick 2010).

ROVs and AUVs range greatly in ability and price point, both of which should be considered when choosing a vehicle. The wide range of available ROVs and AUVs is a direct reflection of the variability of aquatic conditions. While small, relatively fragile ROVs may be suitable for conducting research in shallow waters with weak flow regimes such as a coral reef, much larger and sturdier instruments are required to collect data near deep-sea hydrothermal vents (Chadwick 2010). These more advanced units are more expensive to acquire and operate, and are thus often developed and managed by governmental agencies or large research facilities (Chadwick 2010; Odetti et al. 2017). Table 1 presents a small sample of the sizable variety of ROVs and AUVs used in research and their functions.

Table 1. Small sample of ROVs and AUVs employed in aquatic research, their operators, and select uses

Type	Name	Operated by	Uses	Source(s)
ROV	ROPOS	Canadian Scientific Submersible Facility	Deep-sea benthic collection, hydrothermal fluid sampling, videography, etc.	Chadwick 2010
	KIEL 6000	German GEOMAR	Various research applications in shallow or deep-sea including video and HSI	GEOMAR 2020
	PHOCA	German GEOMAR	Various research applications in shallow or deep-sea including video and sampling	GEOMAR 2020
	OpenROV	Consumers	Leisure, videography, photography, exploration	Thaler et al. 2015
AUV	Autonomous Benthic Explorer (ABE)	Woods Hole Oceanographic Institution	Deep-sea videography, temperature and salinity mapping, chemical analysis (Reported Lost)	Chadwick 2010; Lippsett 2010
	REMUS series	Research institutes	Various research applications including acoustic mapping	Hydroid 2020
	Starbug	Australian CSIRO	Videography, photography, water quality measurements	Dunbabin et al. 2005
Hybrid	e-URoPe	Italian CNR-ISSIA	Variable depending on user needs	Odetti et al. 2017

While open sourced or low-cost ROVs and AUVs may not be suited to specialized sampling or extreme environments, they do offer the advantage of customization. Davie et al. (2019) showed that simple additions to the Starbug AUV greatly facilitated and improved depth correction during post-processing. These aquatic vehicles can otherwise be easily upgraded by changing or adding to their stock sensors (Davie et al. 2008).

There are certain risks associated with the use of ROVs and AUVs. In the case of imperfect waterproofing or sealing, data on the device or the device itself may be compromised. In benthic surveys, the vehicle may become entangled in debris or vegetation which could lead to complications in the mission or complete loss of the vehicle. Malfunctions due to temperature or pressure extremes can additionally cause vehicular damage or loss (Lippsett 2010). Apart from potential risks to the research operation, ROV and AUV use can be damaging to the environments in which they are employed, particularly through the spread of invasive species (Thaler et al. 2015).

4.2.2 Hand-held, vessels and fixed platforms

Sensors mounted on vessels, piers, or buoys, and hand-held devices can be used to collect data above or below the water's surface. For spectral data collection, however, it is suggested that only in

collecting measurements both above and below the surface can a researcher account for all factors contributing to the measured signal (Malthus 2017). In the case of a sensor being mounted on a large platform—such as a boat, pier, or researcher—the influence of the platform should be considered in planning the collection geometry and procedure. A boat or pier may shadow the target if the sensor is poorly placed. A researcher may stir up sediments or disrupt epibionts—or the SAV itself—during collection (Fyfe 2003; Malthus 2017). If the field observations are taken to be used as ground truth or validation data for airborne or satellite imagery, scale discrepancies must also be accounted for through sampling designed to be representative of the whole scene being validated.

4.2.3 UAVs

UAVs range dramatically in size and flight capabilities (Anderson and Gaston 2013; Watts et al. 2012); those referred to here are ones that are available to civilian researchers and are thus relatively small (<25 kg) and operate at low-altitudes. Most regulatory bodies also limit this kind of drone operation to the pilot's visual line of sight (Kalacska et al. 2020). The units are lightweight and can be deployed by a small team of users with limited available space. UAVs range in complexity from balloons to gliders to motorized vehicles (Klema 2016). There are two groups of motorized UAVs: fixed-wing and rotary-wing. Fixed-wing UAVs operate similarly to traditional aircraft in that they require an open area to take off and land in. Rotary-wing UAVs can ascend vertically (therefore sometimes referred to as Vertical Takeoff and Landing UAVs) and are thus not constrained in this way (Watts et al. 2012).

The expansion of UAV employment in RS provides many advantages. UAV-mounted sensors are preferred in situations when very high spatial resolution optical data over a small physical area is needed (Anderson and Gaston 2013; Visser et al. 2013). These systems can be deployed quickly with varying sensor configurations, thus making them well suited to environmental monitoring missions (McIlwaine et al. 2019; Rhee et al. 2018). Their proximity to the target lessens the atmospheric contribution in the registered signal. The expansion of UAVs is pushing sensor development towards lightweight, financially accessible sensors of similar quality to those traditionally flown on aircraft or satellites (Rhee et al. 2018). The application of UAVs in RS is constrained by their flight duration and their limited payload tolerance. As small UAVs tend to be battery powered, they can only fly so long as the charge lasts. Rotary-winged UAVs are especially affected as vertical ascent and hovering are energy-intensive operations (Watts et al. 2012). Joyce et al. (2019) provide an extensive look into the logistical, practical, and regulatory considerations of implementing UAVs in aquatic research.

4.2.4 Airborne

Airborne imagery is especially useful when high spatial resolution information is required over a larger spatial extent than can be achieved with a UAV, or when the desired sensor cannot be accommodated by a UAV due to size or weight restrictions. It provides a link between very high-

resolution ground or UAV data and satellite data and can aid in the interpretation of the latter (Arroyo-Mora et al. 2018).

Airborne campaigns can be planned to acquire imagery suited to various purposes as the imagery properties are largely dependent on the flight parameters. The altitude, flight speed and sensor characteristics determine the across-track and along-track pixel dimensions respectively (Inamdar et al. 2020; Soffer et al. 2019). The altitude will also affect the swath width imaged during the mission, with lower flights covering smaller geographic locations for the same sensor configuration (Klemas 2013a). The stability of the aircraft during flight will contribute to how well positional and attitude distortions can be corrected. An experienced pilot is thus essential for a successful mission.

Airborne imagery is expensive to procure either directly or from a data provider which may be financially restrictive (Rhee et al. 2018). It is therefore sometimes useful to use less costly products such as satellite imagery to identify priority areas to be analyzed with airborne imagery instead of procuring imagery for an entire region (Klemas 2013b).

4.2.5 Satellite

Satellite platforms and the sensors they carry tend to be referred to collectively, a convention that is followed in this text. Data collected from orbiting platforms generally have near-global coverage and can have temporal resolutions of less than a day (e.g. AVHRR, PlanetScope), though most satellites or constellations have revisit times of a day up to two weeks. Open access satellite data products, such as those provided by the United States Geological Survey from the Landsat missions, are, however, limited in their spatial, spectral and temporal resolutions. Moderate (e.g. 10 – 30 m) (Figure 4 e,f) and low spatial resolution satellite products (e.g. 500 m – 1 km) are often too coarse to capture the natural variation in aquatic vegetation distribution that is of interest to researchers (Klemas 2013b; Lehmann and Lachavanne 1997). For example, patches must have a diameter of 85 m to be reliably identified by the 30 m moderate resolution products from Landsat (Figure 4f) and SPOT satellites (Heblinski et al. 2011). Large pixels also increase the chance of multiple materials or species contributing to the single signature registered for that pixel. Satellites thus have limited applicability in identifying SAV to the species level but have often been used to map broad SAV community extent (Silva et al. 2008). Newer satellite systems are addressing this spatial limitation; the commercial multispectral satellite products from Maxar's WorldView series and Planet's SkySat for example can achieve multispectral spatial resolutions of 1.24 m and 50 cm, respectively (Maxar 2020; Planet 2020a). The small number of spectral bands on multispectral satellites further restricts the information contained within each pixel.

Figure 8 presents a non-exhaustive list of currently operating satellite sensors or constellations, their previous applications in aquatic research, and the accuracy achieved for each sensor and application pairing. As can be seen from Figure 8, the open-access products appropriate to, and available for, use in

SAV research are limited to moderate spatial resolution satellite imagers such as Sentinel-2 (10-60 m), Landsat (30 m), and Hyperion (30 m). These are only accurate if studying large features such as extensive seagrass meadows. Commercial systems like WorldView-3 have very high spatial (0.31 m panchromatic and 1.24 m multispectral) and moderately high spectral resolutions (29 bands through the VIS and IR regions) and can be used to accurately answer a wider range of SAV research questions. However, they are commercial products and their acquisition can be financially unrealistic (Klemas 2011). Furthermore, imagery that is considered of sufficient quality to vendors may not be well suited to certain research applications or locations due to cloud cover, positional accuracy, glint, etc. (Bostater et al. 2004; Wolter et al. 2005).

5. Corrections and analysis

5.1. Correction of passive optical RS imagery

While photographs and RGB imagery can sometimes be visually interpreted as-is, imagery being used in quantitative analysis, or to compare between different dates or locations, must first undergo a range of corrections. The three corrections applied to RS optical imagery are radiometric, atmospheric compensation, and geometric. Water column and air-water interface corrections are additionally commonly applied to imagery of aquatic environments.

Sensors record reflected radiance from the surface (and in-scattered from nearby objects) in the form of digital numbers (DN), with the range of possible DN values corresponding to the radiometric resolution. Radiometric correction converts the raw DN data to radiance for the user, which is the amount of energy reaching the sensor, given in Spectral Radiance Units ($1 \text{ SRU} = 1 \mu\text{Wcm}^{-1}\text{sr}^{-1}\text{nm}^{-1}$) (Ripley et al. 2009). This correction accounts for the sensor-specific detection and sensitivity variations and is often done using calibration files provided by the sensor manufacturer or another calibration provider (Lekki et al. 2017). Satellite imagery is provided to the user having already undergone radiometric correction (although a scaling factor or simple function may need to be applied to the data as delivered); RGB (or black and white) photographs do not require this correction.

Next, for imaging sensors, the scattering and absorption effects of the gases and aerosols in the atmosphere must be compensated for to isolate the target's signal. The magnitude of atmospheric contribution to a signal is directly related to the thickness of the atmosphere between the target and the sensor and the composition of the atmosphere (Schläpfer and Richter 2002; Seidel et al. 2008; Wendel and Underwood 2017). While reflectance profiles collected through contact measurements are not affected by the atmosphere, for spaceborne sensors, the atmospheric contribution can be the predominant contributor to the signal received in certain wavelengths (e.g. absorption of the signal at $1.4 \mu\text{m}$ and $1.9 \mu\text{m}$ by atmospheric water vapor) and a less significant contributor in others. The scattering and attenuation by the atmospheric constituents are wavelength dependent. While always required for

quantitative analysis of MSI and HSI, atmospheric compensation is especially important when comparing scenes from different regions or collection dates as the effect of the atmosphere is inconsistent in space and time (Vincent et al. 2019). Atmospheric compensation can be accomplished using a scene-specific calibration called the empirical line method (ELM) (Smith and Milton 1999) or through radiative transfer models (RTMs) (see Manolakis et al. 2016 for a comprehensive description). In the ELM, materials such as calibration panels, calibration tarpaulins, concrete, bright sand, or deep water are often used as calibration pixels. The reflectance spectra of both bright and a dark calibration pixels, ideally characterized on the ground as close in time to the imagery collection as possible, are used to define the relationship between the at-sensor radiance value and the target's actual reflectance (Brook and Dor 2011; O'Neill and Costa 2013; Ripley et al. 2009). The ELM is considered to be reliable, including for aquatic scenes, and is most accurate when the conditions are constant between the ground and sensor measurement collections (Lekki et al. 2017). Such calibration is only effective if appropriate and well-characterized materials are present in the scene; deep-water pixels may not be suitable calibration pixels when the target is also underwater or there are effects such as glare contaminating the pixels (Silva et al. 2008).

Radiation transfer models use parameters such as sensor altitude, ground elevation, visibility, and atmospheric composition to model the interaction of the radiation through the atmosphere and estimate what portion of the recorded radiation was reflected by the target (Silva et al. 2008). A variety of RTMs are available for atmospheric correction—such as MODTRAN (Berk et al. 1989), LibRadTran (Mayer and Kylling 2005), and 6SV (Vermote et al. 1997)—each with its own strengths and limitations. Such RTMs are often applied with specialized software tools or dedicated user interfaces (Vincent et al. 2019). Lyzenga's RTM and subsequent modification by Sagawa et al. (2010) were designed for the analysis of shallow coastal waters and uses a ratio of bands with similar attenuation coefficients called the “depth-invariant index” and “reflectance index” respectively, to account for both the atmosphere and the water column (Lyzenga 1978; Sagawa et al. 2010). Appropriate atmospheric correction procedures should therefore be considered while planning the acquisition of the imagery.

Imagery is geometrically corrected to assign coordinates to every pixel in the image and remove attitude induced positional distortions. This is done by accounting for distortions produced by changes in sensor altitude or attitude, differences in terrain elevation, and sensor optics (Lillesand et al. 2008). Systems equipped with both a GNSS and INS produce the most geographically accurate and precise imagery. By combining the inputs of where the sensor is, how it is directed, and the scene elevation, a ray can be traced onto the ground to the location being imaged (Lekki et al. 2017).

5.1.1 Corrections specific to aquatic applications

Compared to terrestrial RS, aquatic applications have the additional processing requirements of accounting for the effect of the water column (Klemas 2013b). In shallow waters, the reflectance signal is most dependent on the vegetation density and the bottom reflectance. As depth increases, the water column contributes more significantly to the measured profile. This can result in sparse crown cover in deep waters spectrally resembling dense canopies in shallower areas (Ackleson and Klemas 1987; O'Neill and Costa 2013). Bathymetric data can therefore be helpful as an additional variable to perform water column correction. Even the simplest method of accounting for depth, masking out deep-water pixels, has been shown to improve the accuracy of classifications (Ackleson and Klemas 1987; Gagnon et al. 2008; Klemas 2013b). Specialized algorithms can also correct for the effect of the water column as a function of depth. For example, Lyzenga's RTM can be used to account for the effect of the water column, and can be inverted to estimate water depth instead of bottom reflectance (Lyzenga 1978). Water column correction algorithms can also be developed for a specific situation. To do so, Cho and Lu (2010) measured the reflectance of white (100% reflectance) and black (<5% reflectance) targets at various depths to calculate absorption and reflectance parameters which could then be applied to imagery with known bathymetry. Algorithmic correction methods that rely on the spectral information as input parameters, however, are limited by the quality of the data and therefore by optical depth (O'Neill and Costa 2013). The interested reader is directed to the methodology of (O'Neill and Costa 2013) for a sample application of pre-existing algorithms.

As for atmospheric correction, planning for depth correction should begin before data collection to facilitate later processing. Davie et al. (2008) incorporated a colour correction key into the field of view of their camera during imagery collection using a customized system of mirrors installed on their low-cost AUV. Knowing the above-water reflectance of each colour in the key as measured by the camera, they were able to calculate the attenuation of each RGB band for every image. They were then able to distinguish between algae, sand, and rock reliably (Davie et al. 2008).

Evaluating the results of water-column corrections has not yet been a prominent area of research, though some ad hoc methods have been developed. For example, O'Neill and Costa (2013) compared the water-column corrected spectra achieved through algorithmic manipulation to the "true" measurements of the substrates laid out on a dry, black background. It was found that the water column correction's success was dependent on depth and wavelength considered.

The air-water interface complicates the analysis of RS imagery because of white caps, sun glint, wave action, reflection, and refraction. White caps and sun glint increase the radiation reflected towards the sensor (Bostater et al. 2004). The best way to minimize the impact of sun glint and wave action is to collect imagery during calm surface conditions, and by gathering data along a path perpendicular to the

incident sunlight (Bostater et al. 2004; Kirk 1994; O'Neill and Costa 2013). Post-processing of sun glint in imagery can include masking out the affected pixels or algorithmic corrections such as the ones presented by Hedley et al. (2005) and Kutser et al. (2012), though no single algorithmic correction is effective under all conditions (Kutser et al. 2012; Visser et al. 2018). Applying these algorithmic glint corrections can also be time-consuming (Hedley et al. 2005). To the best of our knowledge, there are no analogous algorithms to correct pixels affected by white caps; these are instead masked out or not used in the analyses.

When imagery is collected with the sensor nadir to the water's surface—and the radiance reaching the sensor is therefore largely perpendicular to the water's surface—refraction and reflection have very minor effects on the radiation's path. However, as the angle of incidence increases (away from the nadir) a higher percentage of the light is reflected and the path of light is altered through refraction (Kirk 1994). When waves disrupt the water's surface, the angle of incidence of light is altered and becomes inconsistent across the image, thus producing inconsistent reflection and refraction between pixels and across time. Though these distortions can be small in magnitude, they add uncertainty to the locations, shapes, and reflectance of objects. Fluid lensing (Chirayath and Earle 2016) is a new analytical method to account for such wave distortions. Fluid lensing uses very high frequency videography to track the movement of waves and identify where the wave crests are in each frame. By reconstructing a scene using only image segments affected by wave crests, fluid lensing homogenizes the effect of waves across the composite scene, effectively removing distortion. It also exploits the magnification caused by convex wave crests to increase the spatial resolution of the imagery without changing the system configuration (Chirayath and Earle 2016).

Finally, refraction diffuses upwelling radiance as it re-enters air, resulting in the above-water radiance intensity being only roughly 55% of the below-water radiance per unit area (Kirk 1994). This produces a weaker at-sensor signal than would have been measured just below the water's surface. Researchers primarily account for the effects of reflection and refraction by avoiding data collection on windy days, and by using a nadir sensor configuration to reduce the angles of incidence and refraction.

5.2. Analysis of passive optical RS imagery

Computer-aided image interpretation allows more imagery to be analyzed more rapidly than ever before. This has expanded the use of quantitative analysis as compared to the previous largely qualitative, manual, visual interpretation of SAV cover and canopy density. However, while digital analysis is faster, it is limited by the information available for the model being implemented (Malthus 2017). For computer-aided analysis of MSI or HSI to be accurate, sufficient spectral information must be inputted to represent the total variation of a scene. SAV research often requires a common set of analyses; some of which are described below.

5.2.1 Hyperspectral Dimension Reduction

Hyperspectral imagers produce highly complex data, meaning there is an exceptionally large set of possible spectral signatures. The large number of bands (e.g. > 200) requires unfeasibly large training sample sets for pixels to be accurately recognized in classification or target detection processes (discussed below) if all bands are used (Landgrebe 2002). High dimensional data can, however, be projected onto a lower dimension without losing much useful information. This is the foundational theory of dimension reduction (Landgrebe 2002). Dimension reduction not only improves the accuracy of target detection and scene classification but also reduces the size of the data being worked with, also reducing processing time and storage requirements (Landgrebe 2002). This data dimension reduction can be performed in a variety of ways. The most common methods include band/feature selection and the transformation methods of principal component analysis (PCA) and minimum noise fraction (MNF).

Band selection, also referred to as feature selection, entails subsetting the available spectral bands to the optimal set for analysis (Bolón-Canedo et al. 2015; Fyfe 2003; Mathur et al. 2005; Niroumand-Jadidi et al. 2019). Importantly, band selection retains the original units and physical meaning of the data as opposed to transformations. Bands are selected if they are both relevant and not redundant by maximizing the accuracy of the analysis (e.g. classification) (Bolón-Canedo et al. 2015; van der Heijden et al. 2004). A band is considered relevant if its inclusion improves the prediction accuracy of the chosen model, i.e. if it contains useful discriminatory information about the target. A band is not redundant if it is not completely correlated with another band or set of bands included in the subset (Bolón-Canedo et al. 2015). Feature selection can be performed with a variety of algorithms (see van der Heijden et al. 2005 for a review). Some biological and ecological researchers have successfully used statistical methods such as ANOVA or SIMPER to perform band selection (e.g. Fyfe 2003, McIlwaine et al. 2019), however these methods are not recommended for high dimension data as they do not consider band redundancy or classification accuracy.

Transformations change the units of the features being considered by combining multiple features into one or through rotation to produce orthogonal features (e.g. PCA). Though this can produce more compact feature sets with stronger discriminating ability, it also produces features that may not be easily interpretable (Bolón-Canedo et al. 2015). The PCA and MNF transformations follow the same principle of producing orthogonal component vectors; PCA orders the vectors according to which explains the greatest variance while MNF orders the transformed components according to the signal to noise ratio (SNR) (Keshava and Mustard 2002).

5.2.2 Indices

Spectral Vegetation Indices (SVIs), such as the most commonly used in the literature Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), can be used to distill single values from all the

bands in the imagery, simplifying analysis and comparison across different locations or times. Different types of materials can be defined as having different SVI value ranges. Although originally developed for broadband satellite imagery, NDVI remains as one of the most commonly used SVIs for vegetation-related RS research, and is calculated as follows in equation 1:

$$NDVI = \frac{(NIR\ band - red\ band)}{(NIR\ band + red\ band)} \quad [1]$$

Red and NIR are used because of the strong chlorophyll absorption feature and high scattering due to spongy mesophyll in each of those regions, respectively (Klemas 2013b). Some work contests the utility of NDVI in underwater studies because of the high absorption of red and NIR radiation by the water column (Klemas 2016; Peñuelas et al. 1993). Hyun et al. (2008) found that while NDVI alone was not suitable for detecting SAV in raw imagery, it can be effective if the attenuation according to depth is accounted for. The obstacle of IR attenuation has also been addressed by modifying the NDVI index to use the red edge region instead of NIR (Brooks et al. 2019). Indices such as the normalized difference aquatic vegetation index (NDAVI) (Equation 2) and the water adjusted vegetation index (WAVI) (Equation 3) have been developed with the aquatic medium in mind (Villa et al. 2014):

$$NDAVI = \frac{(NIR\ band - blue\ band)}{(NIR\ band + blue\ band)} \quad [2]$$

$$WAVI = (1 + L) * \frac{(NIR\ band - red\ band)}{(NIR\ band + red\ band)} \quad [3]$$

where L is a correction factor to account for the effect of the background water valued between 0 and 1 (Villa et al. 2014). As expected, each index may perform best for different conditions and retrieves different vegetation characteristics (Zhou et al. 2018). The normalized total pigment to chlorophyll- a ratio index (NPCI) (Equation 4) can provide an indication of vegetation health by analysing the ratio of total pigments to chlorophyll a (Peñuelas et al. 1993):

$$NPCI = \frac{(red\ band - blue\ band)}{(red\ band + blue\ band)} \quad [4]$$

where the blue band (around 445 nm) reflectance represents the total pigments as all major leaf pigments (chlorophylls, xanthophylls, and carotenes) reflect radiation in this region. The red band (around 645 nm) represents chlorophyll content as it is the only pigment to be strongly reflective in this region (Gates et al. 1965). As chlorophyll a strongly absorbs red light and healthy plants contain higher chlorophyll concentrations than stressed ones of the same species, the spectra of healthy plants will produce higher NPCI values (Peñuelas et al. 1993). Combining indices can also provide additional information, such as estimates of ecological diversity (He et al. 2015). In addition to being used as primary tools of analysis, index values can be used as variables in more advanced analysis like decision trees (Chen et al. 2018).

It is vital to remember that indices are developed with a specific sensor and application in mind. They do not therefore necessarily translate well when applied to different sensors, environments, or questions, thus their function and structure should be thoroughly examined before adopting an index from one project to another. Additionally, indices are all designed to be applied to the reflectance values of imagery, not the radiance or DN. They can therefore only be properly applied to radiometrically and atmospherically corrected imagery.

5.2.3 Classification and target detection

Many SAV research questions in RS studies are answered with classification and target detection analyses. Classifications assign an identity (label) to every pixel in an image using either a spectral library provided by the researcher, training pixels from the image itself or statistical measures of separability (i.e. unsupervised clustering). The results of classifications illustrate how multiple materials known to be present are distributed throughout a scene. Target detection locates pixels in an image that resemble a reference spectrum and is usually employed to verify if and where a material of interest occurs in a scene (Shaw and Manolakis 2002). Classification and target detection can be used to determine SAV extent, canopy density, stressors (such as disease and salinity), the taxonomic composition of a canopy, and where a SAV species occurs (Ackleson and Klemas 1987; Chen et al. 2018; Peñuelas et al. 1993; Thamaga and Dube 2019; Tian et al. 2010; Tilley et al. 2007).

Supervised classification requires the user to identify materials of interest in a scene according to previous knowledge or other data sources. The pixels identified are then used to create training data of each known material in the image (Klemas 2011). The training data are then used to find other pixels with similar profiles. One such method, called the Spectral Angle Mapper (SAM), interprets each spectrum as a vector in n-dimensional space, where n equals the number of bands. The angle between a reference spectrum and the pixel spectrum is calculated, and should the angle fall within a defined threshold, the pixel is labelled as that reference material (Kruse et al. 1993). SAM therefore evaluates the shape of the spectra but not the magnitude which is beneficial when examining data affected by uneven illumination conditions (Ripley et al. 2009).

Unsupervised classification is an iterative statistical clustering process that progressively groups pixels by spectral similarities to minimize within-cluster variation and maximize between-cluster variation. In the CLUSTER classification algorithm for example, pixels are mapped in n-dimensional space and the maximum cluster radius and minimum cluster distance are determined manually, defining the maximum intra-group and minimum intergroup variation (Ackleson and Klemas 1987). Pixels are grouped, and the centre of the cluster is iteratively redefined until pixels no longer move between clusters. Other schemes may be entirely automated, estimating the parameters from the data without any user input

or employing nonparametric clustering methods. Results vary significantly amongst methods, materials, and algorithms chosen (Eismann 2012).

Species discrimination through classification is possible, but spectral differences are sometimes subtle and there are often relatively high intraspecific variation and low interspecific variation (Malthus 2017; Silva et al. 2008). In such cases, additional information such as training samples, spatial information, or researcher judgment may be needed to properly classify species (Malthus 2017; Silva et al. 2008; Visser et al. 2013). Object-based image analysis, for example, groups contiguous sets of similar pixels into objects to be analyzed together, either spectrally, geometrically or both (Visser et al. 2018).

Target detection (e.g. Adaptive Coherence Estimator, Mixture Tuned Matched Filter, etc.) identifies if and where a target material exists in a scene and is typically employed for rare or scarce materials (Shaw and Manolakis 2002). If the target material is abundant, the classification methods described above usually suffice. Statistical target detection relies on probabilistic tests, such as the likelihood ratio test or the generalized likelihood ratio test (Manolakis and Shaw 2002). In these statistical approaches, the null hypothesis of the target material not being present in a pixel is tested against the alternative hypothesis that the pixel contains the target material. This process produces a map in which each pixel is either target or background. In all such tests, the probability threshold is inversely related to the odds of recording a false positive (Manolakis and Shaw 2002). If, for example, it is vital that every instance of target presence is flagged, the user can set a low probability threshold. This will improve the chance that all pixels containing the target are found, though there may be more false alarms. If the target material is unknown, anomaly detection algorithms may be used to identify cells that are significantly different from a background material (Stein et al. 2002). This is useful in cases where the anomalous pixels may contain several different materials or could have been weathered or degraded in unknown ways.

Considering that pixels may be larger than the ground features they represent, and the manner in which optical images are generated (e.g. see Inamdar et al. 2020), several materials often contribute to the measured signal of a pixel. Unmixing estimates how much of a pixel's signal originates from each of the possible materials, and thus relatively how much of each material there is in the pixel. Unmixing methods follow one of two general assumptions: the contributions are either linear or non-linear. Linear mixing infers that a material's contribution is directly proportional to its relative surface coverage of the pixel (Keshava and Mustard 2002; Zhu and Zhang 2017). Non-linear mixing occurs when the materials within a pixel are mixed homogeneously or when there are multiple reflections of light between the different materials (Keshava and Mustard 2002). Non-linear mixing may also arise when materials partially transmit light, such as in the case of thin leaves, allowing the underlying materials to contribute to the

signal without being considered as “cover.” In these situations, the spectral contribution is indirectly related to the material’s cover and the relative abundance is more difficult to calculate.

Due to the reduced growing season in temperate latitudes, SAV matures and senesces rapidly relative to terrestrial plants. This means that the pigment concentrations and leaf structures in macrophytes that are the primary determinants of their reflectance spectra can vary widely depending on the date of observation (Gates et al. 1965). Seasonality thus influences the separability of different species of SAV and thereby can affect how successful classification and target detection analysis is. Some research has shown that the end of the growing cycle is best suited for discrimination between species (Klemas 2013b).

5.2.4 Time-series and time sequence analyses

Time series and time sequence analyses presents a special problem in image analysis because of the variable nature of the atmosphere. Time series refers to multiple measurement acquired equally spaced in time, whereas time sequence refers to multiple measures with varying sampling intervals. Imagery collected at the same time on successive days will have similar, but not identical, solar geometry and may have vastly different atmospheric conditions (water vapour concentration, particulate matter, etc.). Imagery collected over a series of years may have a wide variety of atmospheric conditions that need to be accounted for. Time series and time sequence analyses to flag condition changes can be done in a variety of ways, common examples of which are described below.

Post-classification comparison (PPC) detects changes in environmental variables by classifying two images of the same scene from different times and identifying the differences between the classification results. This, though, means that an error in the first image that did not occur in the second image, and vice versa, would be falsely marked as a change, thus compounding the likelihood of misclassifications over time (Klemas 2013b). Such compounding errors can be reduced using the alternate method of temporal image differencing (TID). In TID, one image is classified, then the values of a single band in both images are used to identify a change if the difference in band values between two corresponding pixels is above a defined threshold. TID’s success is, however, dependent on a reliable classification of the original image and appropriate selection of the band to be compared (Klemas 2011).

If the analysis is being performed on reflectance images or transformed data with many bands (e.g. stack of SVIs from different dates), Change Vector Analysis (CVA) is recommended as it can consider all bands at once. In CVA, an n-dimensional vector is created to represent the change between the spectra of two co-registered pixels from different images in a time series. The vector is then assessed against a user-defined magnitude threshold. This analysis technique allows for intra-group variation to be classified as static depending on the threshold and is therefore valuable when classifying complex materials, such as vegetation (Klemas 2013b).

5.3. Structure-from-Motion photogrammetry

Analysis of optical MSI or HSI imagery is largely focused on the reflectance values that provides information on the composition of the scene. An image is, however, a two-dimensional representation of a three-dimensional surface; structural information is not captured.

Structure-from-Motion Multiview Stereo photogrammetry (SfM-MVS) analysis on a set of 2-D photographs recreates the 3-D surface of a landscape for structural applications. Photographs should be collected in a grid pattern with high overlap between neighbouring images. Common points, seen from different angles in different photographs, can be used to infer the relative external orientation and internal camera parameters (e.g. focal length) of the photographs – and thus the position of the points therein – to create a 3-D point cloud (see Kalacska et al. 2017 and Kalacska et al. 2018 for a detailed description). The surfaces between the points in the cloud can then be connected to produce a 3-D mesh or interpolated to create a Digital Elevation Model (DEM). Figure 9 provides a simplified illustration of the theory behind SfM-MVS.

Figure 9. Illustration of the general principle of Structure-from-Motion. Common points at the corners of the rectangular prism seen from A the side, B the top, and C the front can be used to reconstruct the surface from the matched common points observed from multiple photographs into a three-dimensional representation of the object/surface such as that depicted in d. In reality, hundreds to thousands of key points (uniquely identified points) points per photograph are needed with hundreds to thousands of matches between photographs to reconstruct a surface in 3D.

3-D meshes produced through SfM-MVS can be used as visualization products, VR simulations, or as data inputs for qualitative or quantitative analysis. Rugosity, grain size, and fractal dimension are important physical traits in classifying aquatic habitats and can all be computed through quantitative analysis of DEMs or 3-D mesh surfaces (Kalacska et al. 2018; Reichert et al. 2017). Measures from an SfM-MVS model are often more accurate and precise than traditional methods, and can be applied to an entire scene as opposed to the few transects that can reasonably be conducted *in situ* (Storlazzi et al. 2016). Canopy volume and plant biomass information can also be reliably estimated using DEMs produced through SfM-MVS of terrestrial and emergent vegetation (Jing et al. 2017), though it has yet to

be demonstrated for SAV. SfM-MVS can create very high-resolution digital elevation models when LiDAR are unavailable (Fonstad et al. 2013; Kalacska et al. 2017), such as in the case of underwater SAV research. SfM-MVS has been a popular tool for studying highly structured marine environments such as coral reefs (e.g. Bryson et al. 2017; Leon et al. 2015) but has yet to see the same level of adoption in freshwater. Recent work by Kalacska et al. (2018) demonstrates the viability of applying SfM-MVS to freshwater fluvial environments and provides a preliminary set of recommendations on employing the method in such ecosystems. An example of an SfM-MVS 3D point cloud of a tropical freshwater river with emergent, floating, and submerged macrophytes is shown in Figure 10.

6. Applications

Previous applications of RS to the aquatic environment have included work in freshwater, brackish, and marine ecosystems, and have answered a variety of spatially explicit questions. In the case of SAV studies, these can be largely broken down into: “What SAV is here?” and, “where is this SAV found?” The first is an identification problem, either of the species, growth type, or another biophysical state, while the second is a question of detecting extent or presence and absence. This section presents a selection of previous work to provide insights when considering implementing RS for SAV research.

6.1. Identification

Determining if a group of species are distinct from one another is often the first step in studies aiming to map vegetation at the species level. McIlwaine et al. (2019) extensively examined the spectral separability of eight macroalgal species. These analyses identified which bands were most valuable in discriminating species and higher-level groups. While not all species could be differentiated, the three groups were spectrally distinct as were pairs of species from separate groups. Everitt et al. (2011) similarly evaluated the spectral separability of 9 freshwater SAV species using multiple comparison analysis and stepwise discriminant analysis to select the best bands for spectral discrimination. The consequent species classification using the identified bands was between 96.3% and 100% accurate (Everitt et al. 2011).

Besides examining species, Fyfe (2003) investigated the effect of habitat type, season, and fouling on spectral response. She conducted statistical analyses on the profiles of leaves collected across three sites and two years to determine if three species of seagrasses, *Zostera capricorni*, *Posidonia australis*, and *Halophila ovalis*, are spectrally distinct. The seagrasses were separable when considering the VIS-NIR region and the VIS alone, suggesting that these spectral differences should be perceivable through a water column. Additionally, there were consistent patterns of intraspecific variation between samples of *Z. capricorni* grown in brackish and marine habitats (Fyfe 2003). This suggests that some intraspecific variation could be both a product, and indication, of SAV habitat.

Figure 10. Dense 3D point cloud from the Salobra river, Mato Grosso do Sul, Brazil generated through a Structure-from-Motion Multiview Stereo workflow from 768 UAV photographs. Photographs were acquired with a DJI Mavic 2 Pro UAV with an integrated Hasselblad L1D-2C camera. The camera has a 1" sensor (77° field of view) producing an image size of 5472 x 3648 pixels. A median of 67,753 keypoints were found per photograph with a median of 13,416 matches per photograph. Final ground sampling distance of the model is 1.2 cm. Extensive floating water hyacinth (*Eichhornia crassipes*) can be seen. The interactive point cloud can be accessed at <https://bit.ly/waterhyacinth3D> Panel A (yellow) illustrates a shallow (< 30 cm) area with several species of SAV which produce a habitat utilized by small characins. Panel B (blue) illustrates floating *E. crassipes* in deep (> 2 m) water

frequented by giant otters (*Pteronura brasiliensis*) and caimans (*Caiman yacare*). Panel C (purple) is a mid-range depth (1-2 m) with large patches of algae on the substrate. This open water habitat is frequented by larger fish species such as *Prochilodus lineatus*. Panel D (red) shows a bed of *Camboba* sp. in deep water (> 2m). The dense stems provide habitat for species such as *Pygocentrus nattereri* and *Serrasalmus maculatus*.

At the canopy-level, Dierssen et al. (2015) used PRISM airborne imagery to investigate differentiating between species of seagrass and macroalgae that form wracks off the coast of Florida. During analysis, the researchers employed indices such as NDVI and the floating algal index to identify vegetation at or near the surface. The fine spectral (2.83 nm sampling from 349.9 to 1053.5 nm) and spatial resolutions (1 m) afforded by the PRISM sensor allowed them to discern between the types of vegetation and age the debris in the wracks (Dierssen et al. 2015).

Visser et al. (2013) used sub-centimetre resolution data from hand-held and UAV-mounted sensors to perform object-based image analysis (OBIA) when spectral analysis alone was unable to discriminate between species. By combining the texture, shape and spectral information of the targets, they successfully distinguished three species of SAV. Later, Visser et al. (2018) expanded on the OBIA method to discriminate between five species of SAV, areas of species mixing, general vegetation and background materials. They used spectral thresholds in multiple bands and geometric analysis to identify plants' properties such as stem length or leaf shape. Although the classification accuracy was modest (61% overall accuracy), they believe that OBIA shows promise in SAV research (Visser et al. 2018).

Brooks et al. (2019) gathered data using hand-held, vessel-mounted, and UAV-mounted sensors to determine if the invasive *Myriophyllum spicatum* could be discriminated from amongst the other SAV species present. Analysis using the untransformed multispectral measurements could not successfully distinguish *M. spicatum* from the background vegetation. Hyperspectral data, and multispectral data transformed into modified NDVI values, however, did show *M. spicatum* to be distinct from native vegetation.

When taxonomy is unimportant, SAV can be identified by growth type or physiological characteristics. To do so, Chen et al. (2018) used GF-1 satellite imagery, field measurements and a decision tree analysis using band ratios to classify emergent vegetation, submerged vegetation and alga with over 90% accuracy. Seasonality, spatial resolution, and canopy density were critical determinants of separability. Further, the band ratios chosen for identification were not effective in all depths and turbidity levels (Chen et al. 2018). Similarly, Nelson et al. (2006) used Landsat 5 TM imagery of a set of Michigan lakes to test how well macrophyte growth types could be predicted through modelling. While the model they produced performed well (61–98% classification accuracy) for the calibration lakes, it did poorly when applied to a set of validation lakes. This inconsistent model success is potentially due to the lack of variation captured by their set of calibration lakes which thereby limits the conditions that the model is suited to. This work highlights both the strong potential of RS as a monitoring tool, and the need for

extensive input data in developing robust classification models. Finally, Rotta et al. (2018) calculated bottom-reflectance index values from Spot-6 imagery and related those index values to field observations to infer SAV height. Though the model produced only moderate accuracy ($R^2 = 0.54$) and was limited to depths of less than roughly 5 m, further calibration could improve the model's performance (Rotta et al. 2018).

6.2. Detection

Detection studies seek to locate targets, such as community extent, a certain SAV species, or a growth type. In mapping community extent and density with Landsat imagery, Ackleson and Klemas (1987) found that the unsupervised classification algorithm produced more accurate results when pixels over deep water were masked out. The deep water pixels were confused with dense canopy cover, and vice versa (Ackleson and Klemas 1987). Wolter et al. (2005) found that incorporating a multitemporal differencing technique improved classification accuracy. By subtracting the red reflectance at the start from the end of the growing season and using this difference as a band along with the visible green and red, the effect of the water column was reduced and SAV was more reliably detected. Work by Giardino et al. (2015) combined mapping community extent and species identification. Water column constituent concentrations, water column depth and SAV community extent were modelled using field measurements and airborne MSI as input data. They were also able to probabilistically classify the bottom cover as *Chara* spp., other SAV, or substrate.

Locating a species of SAV instead of a community may require different data and analyses. Williams et al. (2003) conducted a preliminary exercise of species mapping using hyperspectral airborne imagery to match the spectral features of two species to those present in pixels' spectra. The contributions of active water column constituents, such as chlorophyll, were minimized through band selection. Although the results seemed align with reality, the lack of appropriate validation data meant that no measure of accuracy could be calculated. O'Neill and Costa (2013) mapped the extent of *Zostera marina* using both airborne and high-resolution satellite imagery. They found that performing dimension reduction on the airborne imagery produced the most accurate results and that the products of different classification algorithms varied widely. Notably, the map accuracy decreased after water column correction because of the additional error introduced, highlighting the importance of appropriate and verified water column corrections. Such species-specific mapping is especially valuable considering invasive species. Kumar et al. (2019) used Landsat 8 imagery as input data to a model of the invasive *Hydrilla verticillata*'s presence. The model effectively predicted *H. verticillata*'s presence/absence as validated by a concurrent field campaign. Such models allow managers to better and more frequently monitor plant growth and the effects of their control efforts.

In a study comparing current macrophyte monitoring techniques, Stocks et al. (2019) had two teams of researchers use hydroacoustic sensors, satellite imagery and hand-held geolocation devices to create maps of macrophyte cover in two lentic environments with different turbidity levels. In comparing the resulting maps between teams and amongst techniques, they found that vertical hydroacoustic and optical RS methods were consistent between operators while acoustic side-scanning and manual delineation of polygons were subject to user error. In turbid waters, the vertically oriented acoustic data far outperformed the optical footage taken from an RGB camera. Vis et al. (2003) similarly conducted a cross validation experiment to compare the utility of various SAV extent mapping methods. In comparing optical RS, hydroacoustic data and three environmental models, they found that optical RS was the least accurate. However, the optical imagery was collected 10 years before the ground data, and had been spatially resampled to a coarser size. Given the significant temporal and spatial variability in macrophyte communities, this procedure was not well suited to SAV studies and could explain why optical RS was shown to be inaccurate. Echo sounding RS was shown to be the most accurate method of detecting macrophyte type, supporting the use of this technology for SAV studies in turbid waters. As inland waters are often turbid and this turbidity varies over space and time, the ability to operate both optical and acoustic sensors (and combine them if necessary) is an asset for lentic or fluvial RS researchers.

7. Discussion and conclusions

7.1. Regulatory challenges

As with most new technologies, the regulatory environment surrounding RS is still in development and may differ amongst governments. It can however be largely broken down into two categories: policies regulating the platforms and those regulating imagery collection. Regulations regarding the use of platforms such as aircraft, UAVs, or vessels are primarily concerned with safe operation and respecting territorial boundaries. Aircraft and vessels must follow all relevant operational and navigational regulations in the study's administrative district(s). Most localities also have regulations relating to unmanned flight. In Canada for example, all UAVs over 250 g must be federally registered and flown by a licensed pilot. They cannot be flown near airports or in military airspace without permission and permission is also required for operations within a national park (National Research Council Canada 2019). Operations may also be restricted near private property such as homes or businesses to minimize the risk of personal injury should an issue arise during flight. The American Federal Aviation Association has implemented similar regulations for all UAVs in their airspace (Watts et al. 2012).

7.2. Future directions

While there has been tremendous progress in aquatic RS, this has focused primarily on post-processing methodologies and analytical tools. Data collection procedures are not yet standardized, making comparing data from different studies difficult or impossible. Spectroradiometric measurements

depend heavily on context, may not be reproducible, and contain many uncertainties and sources of error that are not well defined (Hueni et al. 2017). Without common methods to normalize data and quantify the uncertainty throughout data collection, processing and analysis, users can be left with little idea of how representative the data actually are.

Remote sensing, when used appropriately, is a novel tool for policymakers and ecosystem managers across the globe. However, the current lead time and expertise needed for a beginner to implement a new RS system is an obstacle. Automation is therefore a primary goal for aquatic RS (O'Neill and Costa 2013). Being able to produce reliable, rapid, and accurate information without extensive user input would allow the proliferation of RS into environmental management. Complete automation is unlikely, but advances such as creating more complete spectral libraries and tailoring atmospheric correction to specific locations will make RS more user-friendly and widely applied (O'Neill and Costa 2013; Wolf et al. 2013).

Besides applying RS to the identification and detection of SAV, there has been progress in harnessing it to collect data as environmental variables for modelling. The Bio-ORACLE (Ocean Rasters for Analysis of CLimate and Environment) database, for example, contains 23 global rasters incorporating satellite and in situ measurements that can be used for modelling shallow water species distributions (He et al. 2015). The Ocean Biogeographical Information System (OBIS) database for marine biodiversity research illustrates regional disparities in marine RS research. While regions like the Florida Keys and the South American upwelling area are heavily researched, Southeast Asia, eastern Africa, eastern South America, and other poorly resourced regions are not (Muller-Karger et al. 2018). Creating a global network of aquatic RS infrastructure and researchers could efficiently fill these data gaps. Developing such databases will allow more accurate modelling and predictions considering the changing climate.

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