ISPRS Journal of Photogrammetry and Remote Sensing 130 (2017) 217–230

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

The impacts of environmental variables on water reflectance measured using a lightweight unmanned aerial vehicle (UAV)-based spectrometer system

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ARTICLE INFO

Article history:
Received 13 April 2017
Received in revised form 17 May 2017
Accepted 8 June 2017

Keywords:
Water reflectance
Environmental variables
Hyperspectral data
Water quality
Chlorophyll-a
Turbidity
CDOM
Unmanned Aerial Vehicle (UAV)

ABSTRACT

Remote sensing methods to study spatial and temporal changes in water quality using satellite or aerial imagery are limited by the inherently low reflectance signal of water across the visible and near infrared spectrum, as well as environmental variables such as surface scattering effects (sun glint), substrate and aquatic vegetation reflectance, and atmospheric effects. This study exploits the low altitude, high-resolution remote sensing capabilities of unmanned aerial vehicle (UAV) platforms to examine the major environmental variables that affect water reflectance acquisition, without the confounding influence of atmospheric effects typical of higher-altitude platforms. After observation and analysis, we found: (1) multiple water spectra measured at the same location had a standard deviation of 10.4%; (2) water spectra changes associated with increasing altitude from 20 m to 100 m were negligible; (3) the difference between mean reflectance at three off-shore locations in an urban water body reached 29.9%; (4) water bottom visibility increased water reflectance by 20.1% in near shore areas compared to deep water spectra in a clear water lake; (5) emergent plants caused the water spectra to shift towards a shape that is characteristic of vegetation, whereas submerged vegetation showed limited effect on water spectra in the studied lake; (6) cloud and sun glint had major effects and caused water spectra to change abruptly; while glint and shadow effects on spectra may balance each other under certain conditions, the water reflectance can also be unpredictable at times due to wave effects and their effects on lines-of-site to calm water; (7) water spectra collected under a variety of different conditions (e.g. multiple locations, waves) resulted in weaker regression models compared to spectra collected under ideal conditions (e.g. single location, no wave), although the resulting model coefficients were relatively stable. The methods and results from this study contribute to better understanding of water reflectance acquisition using remote sensing, and can be applied in UAV-based water quality assessment or to aid in validation of higher altitude imagery.

1. Introduction

Water-quality indicators of inland waterbodies such as lakes and rivers are widely used to guide resource management, ensure drinking water safety, protect public health, and control pollution and diseases (Moore et al., 2014). There are, however, limitations on current abilities to characterize spatial and temporal variability of water quality conditions over water bodies, using *in situ* measurement (Dörnhöfer and Oppelt, 2016). Increasingly, researchers are turning towards satellite and airborne remote sensing technology (e.g., Olmanson et al., 2013; Brezonik et al., 2015; Matsushita et al., 2015; Mouw et al., 2015) as a complementary tool for generating detailed, spatially and temporally distributed water quality information.

Remote sensing approaches have most commonly been applied to the retrieval of optical water quality parameters of inland water such as Chlorophyll-*a* (Chl-a), turbidity, and coloured dissolved organic matter (CDOM) (Odermatt et al., 2012; Matsushita et al., 2015; Watanabe et al., 2016), and others (Chen et al., 2014; Knudby et al., 2016; Song et al., 2017). Most studies have used empirical regression models between water reflectance in different spectral bands and water quality parameters; such models are often valid only in the studied water bodies. A detailed summary

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http://dx.doi.org/10.1016/j.isprsjprs.2017.06.004
0924-2716/

and comparison of different empirical methods was given in Matthews (2011) and Dörnhöfer and Oppelt (2016). In contrast to empirical models, bio-optical models utilize bio-geophysical attributes of water based on radiative transfer equations. These physically-based approaches are potentially more effective for modelling water quality, particularly since they are, theoretically, more generalizable and therefore transferable in space and time. Detailed reviews of physics-based inversion methods can be found, such as Odermatt et al. (2012), Palmer et al. (2015), and Dörnhöfer and Oppelt (2016)

To better understand water spectral characteristics, hyperspectral imagery has been used to investigate water-light interactions and retrieval of water-quality parameters for more than two decades (e.g., Vasilkov and Kopelevich, 1982; Vertucci and Likens, 1989; Lee et al., 1999; Zarco-Tejada et al., 2012). Hyperspectral data are comprised of tens to hundreds of spectral bands usually with 1–10 nm spectral resolution. This high spectral resolution can enhance capabilities to distinguish water reflectance changes caused by inherent optical properties of water. For example, Wang et al. (2016) estimated Chl-a concentrations in fresh water outdoor ponds in south China based on surface reflectance derived from laboratory spectra, using an empirical model. Satellite sensors, however, remain limited in their ability to collect imagery with high spatial, spectral, and temporal resolution. Airborne sensors (e.g., Bergamino et al., 2010; Olmanson et al., 2013) are currently the major source of hyperspectral imagery suitable for inland water-quality research, but they can be prohibitively expensive and time-consuming with respect to flight planning and implementation.

Apart from hyperspectral data scarcity, water is unique from other ground features for its low reflectance in visible and near-infrared wavelengths. Less than 10% of the radiation of water pixels received at the satellite sensor originates directly from the water column (Giardino and Kondratyev, 1991), while over 90% of the remaining signal is from water surface, the atmosphere (Moore et al., 1999), and adjacent pixels (Santer and Schmechtig, 2000). Therefore, decomposing satellite image radiation to retrieve actual reflectance from inland water is challenging yet critical for water constituent concentration modelling. Furthermore interactions between light and water include scattering, absorption, and attenuation, and these are affected by environmental variables such as waves on the water surface, particles or vegetation in the water and, in the case of shallow waters, the bottom substrate (Mobley, 1999). It is therefore difficult to separately analyze these environmental variables and their effects on water quality parameter estimation. The light-water interaction is usually studied via simulating water quality parameters (Gallegos, 2001; Lee et al., 2005; McKee et al., 2007) or laboratory experiments (Zhang et al., 2009; Wang et al., 2016), but natural light and natural environmental conditions differ from simulations and lab experiments. Hence a platform without atmosphere effects and that offers more control over environmental variables during data acquisition is valuable for studying water-light interactions and further water constituent modelling.

Unmanned aerial vehicles (UAV) are a rapidly evolving, affordable, and flexible remote sensing platform that provide exceptional control over the flight location, time, altitude, path, and angle. With hyperspectral sensors mounted on low-altitude UAV platforms, data can be collected with negligible atmospheric effect and high spatial resolution. The improvement of UAV platforms and the miniaturization of sensors have stimulated much remote sensing research and development of new systems (Colomina and Molina, 2014; Pajares, 2015). Specifically in the hyperspectral domain, there are new sensor system developments (Uto et al., 2016), data calibration using field or lab spectrometry (Liu et al., 2014; Aasen et al., 2015), and inversion models for the study of water quality parameters (Ampe et al., 2015). Currently, two dimensional (2D) hyperspectral imaging systems are generally too heavy and/or complex to operate on small low cost UAVs. Moreover, most hyperspectral imagers rely on accurate GPS/IMU instrumentation and an on-board computer for effective data collection. Finally, hyperspectral cameras are expensive, adding an additional financial liability, particularly for UAV applications over water where aircraft failure would almost certainly result in complete loss of the imaging system. The objectives of this study, therefore, were threefold: (1) to develop a system to acquire 1D spectra for small water bodies using a light-weight, low-cost spectrometer mounted on a consumer-grade UAV platform; (2) to study the impact of internal (i.e., sensor stability, noise floor) and environmental (i.e., location, altitude, illumination conditions) variables on water spectra, and (3) to build preliminary water quality regression models using acquired spectra, and analyze the impact of environmental variables on such models.

2. Materials and Methods: UAV system design and data processing

2.1. UAV spectrometer system components and reflectance measurement

The data collection system is designed for consumer-level UAVs in order to minimize cost and to promote flexibility and ease-of-use. Fig. 1 shows the air and ground units of the system. The air unit is comprised of a UAV platform and associated components, including the navigation and flight control systems, a standard color (RGB) camera and a compact spectrometer. The micro-computer in the air unit communicates with the sensor control system via wireless network to start, stop, and view the spectrometer data during UAV flights within the range of the wireless signal. The color camera collects videos and images to help with interpretation of spectral data, in particular the assessment of water surface conditions associated with wind and sun. The spectrometer and the color camera are mounted under the UAV and visually aligned to nadir view. Data collected by these two sensors are matched over time by their time stamp with 1 s resolution.

In this study we used two UAV platforms, a quad-copter (DJI Phantom 2 Vision Plus) and a hexa-copter (DJI Spreading Wings S800). The quad-copter and the hex-copter have take-off weights (including the sensors) of 1.4 kg and 6 kg, respectively. Since small multi-rotor aircraft are now widely available, a detailed description of these specific models is not presented. The spectrometer (Ocean Optics STS-VIS) is 4.0 cm × 4.2 cm × 2.4 cm and weighs 60 g. It has a spectral range from 350 nm to 800 nm with 1.5 nm optical spectral resolution, and 1024 spectral bands in this wavelength range. The field of view (FOV) is 25°, which produces a footprint of approximate 44.3 m diameter at an altitude of 100 m. The integration time is manually set between 100 ms and 1000 ms, depending on illumination conditions. The spectrometer is controlled by a Raspberry PI 3 Model B microcomputer (dimensions with case: 22.9 cm × 17.5 cm × 4.8 cm), which is remotely operated through a 2.4 GHz wireless network. A 3000 mAh lithium ion battery is used, which lasts about 3.0 h in operation. In total, the air unit spectrometer components weigh approximately 190 g. Spectrometer dark noise sensitivity to temperature and the comparison of spectrometer reflectance over reference targets were discussed in Appendix A.

The ground unit includes the flight control system, the sensor control system, and a second STS-VIS spectrometer pointed vertically upward to record downwelling sun and sky radiance. The flight control system has a transmitter and a mobile device such as a tablet, a smartphone, or a laptop to design flight paths and