AIRBORNE ACTIVE OPTICAL SENSORS (AOS) FOR PHOTOSYNTHETICALLY-ACTIVE BIOMASS SENSING: CURRENT STATUS AND FUTURE OPPORTUNITIES

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ABSTRACT

The first published deployment of an active optical reflectance sensor (AOS) in a low-flying aircraft in 2009 catalyzed numerous developments in both sensor development and sensor platform integration. Integral to these sensors is a modulated light source composed of high power LED technology that emits high radiance polychromatic light. The sensor easily mounts to agricultural aircraft and can sense agricultural landscapes at altitudes from a few meters to altitudes exceeding 40 meters while traveling at velocities of more than 270 km/h. The rather large sensor-to-canopy measurement range allows the sensor to accurately measure ratio-based spectral reflectance indices such as the NDVI over fields with rolling terrain. Two versions of the sensor have since been developed and tested. A key advantage of airborne AOS is that they provide ratio-based index values unaffected by path radiance. This alone offers a viable, large scale sensing technique for researchers interested in plant and soil moisture investigations using the 'reflectance index-temperature' space concept or for the large scale, yet location specific conversion of 'top-of-atmosphere' vegetation indices, as derived from satellite imagery to the 'top- of-canopy' values.

Key Words: Active optical sensing, Thermal infrared, NDVI, Normalized difference vegetation index, SR, Simple ratio index, Red-edge, Plant and soil moisture status, Plant growth models

INTRODUCTION

Airborne and satellite remote sensing is a viable and cost-effective means of measuring and mapping photosynthetically-active biomass in crops and pastures (Moran et al. 1997; Pohl and van Genderen 1998; Lamb 2000; Pinter *et al.* 2003; Liaghat and Balasundram 2010). However, commercial remote sensing systems available to agricultural land managers for general management activities are generally passive, meaning that they rely on incident sunlight for target illumination. Unless individual wavebands are calibrated to at-canopy reflectance values, the datasets are restricted to mapping relative plant 'vigor' (Lamb 2000) or for discriminating between plant types e.g. crops versus weeds (Lamb and Brown 2001). Moreover, the use of these systems for multi-temporal assessment such as crop growth or land cover change requires images be calibrated to one another either by span normalization or through the use of spectrally invariant targets in the field of view (Pohl and van Genderen 1998). Last, these sensors cannot be deployed during times of non-optimal target irradiance, that is, when the illumination of the target is non-uniform (for example patchy clouds), it changes over the data acquisition window or data is collected at night.

Active, optical plant canopy sensors (AOS) are devices that, by virtue of integrated light sources, irradiate a target and record the reflected portion returning to similarly integrated detectors. Generally the sources are modulated LED's or laser diodes (LD's), with synchronous detection electronics that renders the recorded information impervious to changes in ambient light conditions. Such sensors can even be operated even at night. These sensors, with source wavelengths ranging from blue through to near infrared wavelengths (≈450 – 850 nm) are finding increasing use in agriculture, with applications ranging from quantifying the nutritional requirements of crops (Inman et al. 2005; Solari et al. 2008; Holland and Schepers 2010; 2013; Barker and Sawyer 2012), as a basis for applying agrochemicals in real-time (Holland et al., 2013; Falzon et al., 2012) and as an objective biomass assessment tool in pastures (Künnemeyer et al., 2001; Trotter et al., 2010).

The radiometric principles behind the use of AOS have been discussed by Holland et al. (2012). The irradiance at the photo-detector of the AOS, as generated by the target radiance resulting from illumination by the sensor's internal light source is governed by the inverse square law which will cause a significant change in detected signal magnitude when the relative distance between sensor and target varies. However, Holland et al. (2012) also demonstrate that using more than one wavelength in the source (as produced by a polychromatic light source described in Holland et al., 2004) and then combining the two radiance values in a ratio-based index allows for a measurement that is insensitive to sensor-target distance, the maximum of which is limited only by the signal to noise ratio of the detection electronics.

The use of airborne, active, optical sensors over crops provides a number of potential benefits compared to passive airborne (or satellite) remote sensing. First, land managers can acquire data under conditions where passive satellite or airborne imaging is impossible, such as under low cloud, or cloud cover that produces spatially-variable illumination conditions, or at night. Moreover, the use of ratio-based reflectance indices such as the normalized difference vegetation index (NDVI) renders the sensor invariant to changing sensor-target distances (for example when flying over undulating ground) and measured irradiance at the sensor, emanating from the target radiance, is not affected by path radiance components (Holland et al., 2012). Secondly, as on-ground, Red/NIR-based and Red-edge/NIR active optical sensors are being extensively investigated (and calibrated) for quantifying the nutritional requirements of crops (Inman et al.

2005; Solari et al. 2008) and as an objective biomass assessment tools in pastures (Künnemeyer et al. 2001; Trotter et al. 2010), it would therefore be possible to extend the application of derived algorithms over very large fields where on-ground surveys may otherwise be time-consuming, or in situations that preclude on-ground vehicle access such as when the field is impassable due to wet conditions or the crops are sufficiently well advanced in growth that on-ground vehicle surveys would cause considerable damage. Finally, these sensors are relatively inexpensive, can be easily retrofitted to existing aircraft (Lamb *et al.* 2009) and can be deployed on low-level aircraft already committed undertaking other operations such as top-dressing.

THE STATUS OF AIRBORNE AOS

The bat can be credited as one of creation's oldest known variations of active airborne sensing (SONAR- SOund Navigation And Ranging; Simons and Stein, 1980). Active airborne sensing involving humans evolved over the last century, tracking closely behind the developments and navigation or combat requirements of aircraft. Airborne RAdio Detection and Ranging (RADAR) kicked off during the Second World War (Brown 1999) with aircraft-aircraft interception while airborne SONAR was, and still is largely confined to remote interaction with SONAR devices on the surface of water using SONAR for detecting underwater objects. A notable 'fully-air' example of SONAR however is human echolocation (Schenkman and Nilsson, 2010) although no known application of this in the context of airborne deployment is known. The concept of active optical sensing, that is using optical wavelengths to detect objects is not new, dating back to the early Greek philosophers (5^{th} – 2^{nd} century BC). This was, of course, one of the early theories of human vision, alas since disproved by science. However this so-called 'extramission theory' is, incredibly, still a misconception held by some even in this present century (Winer et al., 2002). Practical (and real) airborne active optical sensing dates back to the 1950's with the introduction of LIDAR (LIght Detection and Ranging), initially used for atmospheric research (primarily 'D for detection') but then, following the introduction of the GPS, enabled airborne surveying of ground targets (primarily 'R for ranging') (Carson et al., 2004).

Lamb *et al.* (2009) reported the first trial of an aircraft-mounted, active, optical reflectance sensor, involving red (R) and near infrared (NIR) wavelengths, over the canopy of a 270 ha field of sorghum. This LED-based, 'profiling' sensor was simply a Crop Circle ACS-210 (Holland Scientific, Lincoln NE USA) initially designed for on-ground use, and it proved capable of recording and mapping spectral reflectance indices (in this case the simple ratio; SR= NIR/R and NDVI = (NIR-R)/(NIR-R)) at an altitude of 3-5 m above the ground (AGL) (Figure 1(a)). Maps generated from the sensor transects showed excellent agreement with a digital multispectral image (involving the same wavebands) taken by an overflying aircraft at an altitude of 1800 m AGL. A second trial, this time using more powerful LEDs and sensitive detection electronics, demonstrated the ability to collect band-ratio index data (NDVI) from altitudes up to 45 m above crop canopies (Lamb et al., 2011(b)). Using this Raptor™ ACS-225LR

(a) (b)

Figure 1. Low-level airborne data acquisition trials using (a) Crop Circle™ ACS-210 at 4 m AGL over a field of sorghum and (b) Raptor™ ACS-225LR at 50 m AGL over a field of wheat.

Figure 3. A RapidSCAN CS-45U deployed on an Octocopter. Sensing range is 0.5 m to 4+ meters above canopy.

(Holland Scientific, Lincoln NE USA), comparisons with a detailed on-ground NDVI survey indicated the aerial sensor values were highly correlated to the on-ground sensor ($0.79<R^2<0.85$), with close to unity slope and zero offset. Moreover, the maximum average deviation between aerial and on-ground NDVI values was only 0.04.

Figure 4. A 3D printed prototype ACS-225LR-U UAV-ready AOS sensor.

Holland and colleagues (personal Communications, 2013) recently demonstrated the opportunities for deploying this class of sensor on unmanned aerial vehicles (UAV) (Figure 3).

Since this early trial, one of the authors (KH) has ported the sensing electronics from the Raptor ACS-225LR into a UAV ready sensing platform. The Raptor enclosure was redesigned and fabricated using 3-D printing. The new sensor casing (Figure 4), has resulted in a reduction in mass of almost 60% (1100gm to 450gm). Similarly, the electronics have been modified to reduce the overall power consumption from ~10W to ~2.4W in order to facilitate longer flights and use of lighter weight batteries. It should be noted that these technical merits were achieved without diminishing the sensor's sensing range or signal-to-noise performance. Additionally, the number of spectral channels have been increased from 2 bands to 5 bands plus the addition of IRT and ambient air temperature sensors. An integral data logger and GPS will make the sensor completely self-contained and independent from the UAV's electrical system. Plans for flight test are scheduled to begin in the last quarter of 2014.

OPPORTUNITIES FOR INTEGRATING AOS WITH OTHER SENSORS

The physical integration of AOS sensor with other passive sensors on the same aerial platform was most recently demonstrated by Lamb et al. (2014) using a purpose-built Raptor ACS-225LR-IRT (Holland Scientific, Lincoln NE USA). This integrated active optical (Red/NIR) and passive thermal sensor was tested on a low-level aircraft for recording and mapping both the optical reflectance and surface temperature characteristics of a cotton crop from an altitude of 50 m above the canopy (Figure 5). The passive thermal sensor integrated into the Raptor ACS-225-IRT sensor appeared to provide a realistic map of canopy

Figure 5. (a) Low-level airborne data acquisition trials using the Raptor^{TM} ACS-225LR-IRT at 50 m AGL over a field of cotton. (b) Close-up view of the Raptor^{TM} ACS-225LR-IRT.

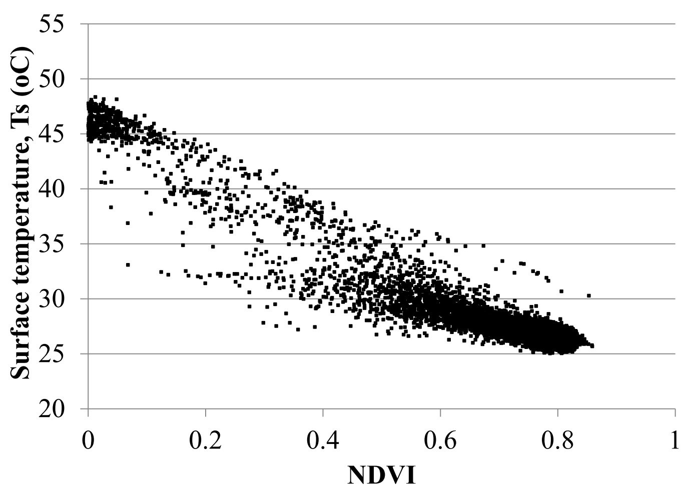

Figure 6. Scatter plot of target surface area (both soil and cotton crop) as a function of NDVI, generated using the coincident measures from the Raptor^{TM} ACS-225LR-IRT.

temperature. Given the measurements of target temperature were coincident with the active optical reflectance measurements, the integrated sensor is capable of generating reflectance index-surface temperature (eg NDVI-T_s) curves for these targets, along the lines of those generated by others using more complex and expensive imaging systems (for example, Moran et al. 1994; Sandholt et al., 2002; Patel et al. 2009) (Figure 6).

Following the earlier discussion regarding the effects of path radiance on passive sensor-derived imagery, AOS's offer the means of collecting large geographic scale path radiance correction data, as discussed in Lamb et al. (2014). A convenient 'in-scene' technique for quantifying path radiance in satellite imagery, is the 'raster correlation' method (for example as presented in Cheng et al. (2012)). In many cases, the path radiance components in the NIR bands are largely ignored; assumed to be zero and a raster correlation plot between shorter-wavelength bands including the Red band and an NIR band is a convenient means of estimating the path radiance component of the shorter-wavelength band from the Red band axis intercept. To illustrate this point, Figure 7(a-c) depicts scatterplots of Red versus NIR radiance values (here the respective axes are

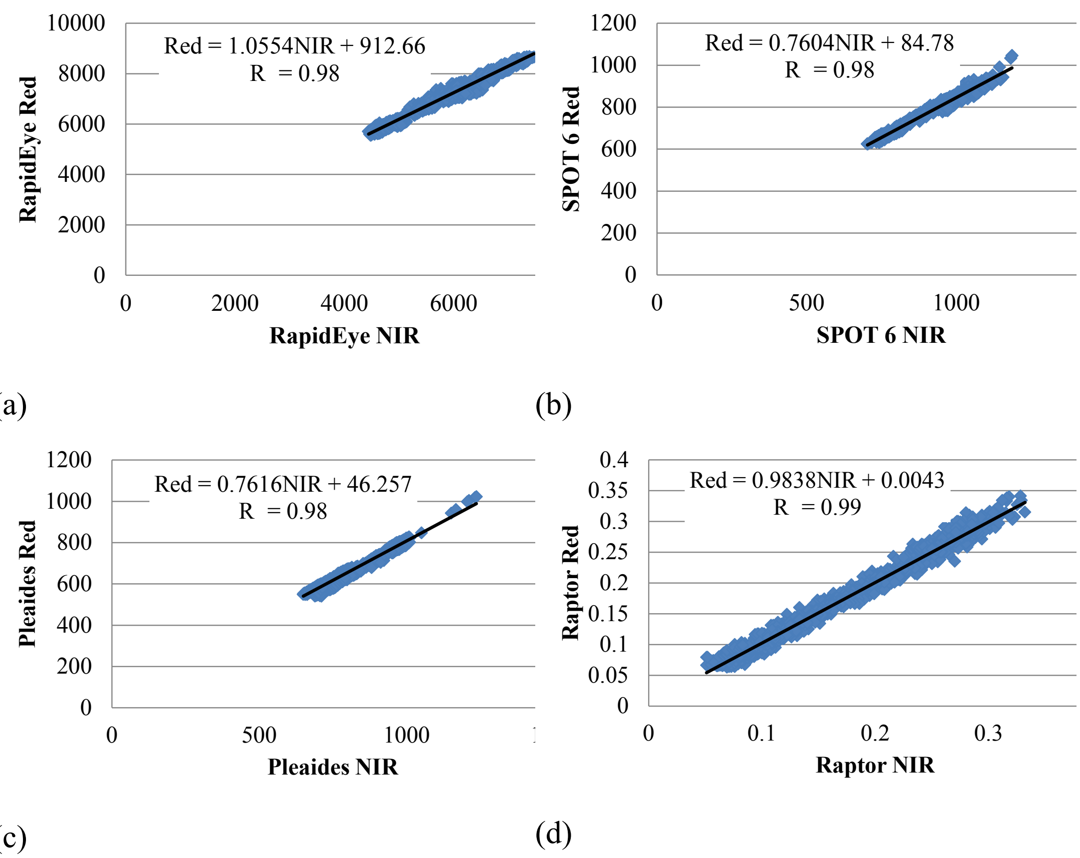

Figure 7. Scatterplots of channel brightness; Red versus NIR for (a) RapidEye, (b) SPOT 6 and (c) Pleiades satellite images, and (d) aircraft-mounted Raptor^{TM} ACS-225LR-IRT for the same transect of land (approximately 20 km long) over bare soil cotton fields.

quantified in raw ‘digital numbers’) extracted along a ~20 km transect from satellite imagery of a cotton region in eastern Australia. The transects data for each of the three satellite systems; RapidEye (Figure 7a), SPOT 6 (Figure 7b) and Pleiades (Figure 7c) are all coincident, as is the data collected by the aircraft-mounted Raptor™ ACS-225LR-IRT (Figure 7d). The satellite systems all exhibit ~ 5- 10% of path radiance component (percentage of maximum y-axis value). Only the Raptor data exhibits a significantly smaller path radiance contribution, as evidenced by the near zero y-intercept value (~ 1% of the maximum y-axis value) given in the regression equation. The Raptor data serves as a means of removing the path radiance component of the Red channel in each satellite sensor, effectively from its top-of-atmosphere brightness value to the equivalent top-of-canopy brightness value and is useful for correcting ratio-based indices such as NDVI.

INTEGRATING AOS WITH ON-AIRCRAFT ACTUATION AND CONTROL

The ability to actively measure a vegetation index such as NDVI ‘on-the-go’ offers the opportunity to use the ‘live’ data to feed directly into some form of actuation mechanism, onboard the aircraft, to dispense fertilizer or herbicide. However the raw data stream is likely to be very noisy, and also the actuation mechanism may not be able to physically keep up with the control inputs. Falzon et al. (2012) have discussed the practical problems encountered in this scenario and have developed a statistical method specifically designed for real-time airborne prescription fertilizer applications. The ‘Dynamic Aerial Algorithm’ (DAS) is designed to batch process a dynamically updated dataset, for example after the aircraft completes each successive pass over the field, to forecast ahead of the aircraft basic high, medium or low zone in the upcoming pass. A key aspect of the DAS algorithm is that it allows a variety of different regression and segmentation modules to be added or deleted to suit user requirements.

FUTURE OF AIRBORNE AOS

Moreover, on-board sensors that detect the degree of an aircraft's pitch, roll and yaw will improve sensor measurement by pinpointing the location of the projected beam on the landscape relative to the sensor's recorded position. The addition of beam 'time-of flight' (eg LIDAR) sensing could be useful in determining crop height or stand quality while helping augment the accuracy of crop biomass measurements. Clearly the rapid developments in UAV platforms, albeit followed by a more ponderous legislative process for facilitating commercial deployment, will see this new class of sensor conducting field surveys 'on demand'.

The potential applications for airborne AOS technology in agriculture are many, and in many cases mimic those advances in 'on ground' sensing . We haven't even started on areas such as tactical environmental sensing and monitoring, for example mapping the extent of an algal bloom on a water body, or using such data to control the aerial application of some mitigating chemical, or rangeland sensing, given the increasing demands on farmers to report on land condition to state management agencies. It is fair to say that the authors consider the future of airborne AOS as only just beginning.

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