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Prospective HypsIRI global observations of tidal wetlands

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ABSTRACT

Tidal wetlands are highly productive and act as critical habitat for a wide variety of plants, fish, shellfish, and other wildlife. These ecotones between aquatic and terrestrial environments also provide protection from storm damage, run-off filtering, and recharge of aquifers. Many wetlands along coasts have been exposed to stress-inducing alterations globally, including dredge and fill operations, hydrologic modifications, pollutants, impoundments, fragmentation by roads/ditches, and sea level rise. For wetland protection and sensible coastal development, there is a need to monitor these ecosystems at global and regional scales. Recent advances in satellite sensor design and data analysis are providing practical methods for monitoring natural and man-made changes in wetlands. However, available satellite remote sensors have been limited to mapping primarily wetland location and extent. This paper describes how the HypsIRI hyperspectral and thermal infrared sensors can be used to study and map key ecological properties, such as species composition, biomass, hydrology, and evapotranspiration of tidal salt and brackish marshes and mangroves, and perhaps other major wetland types, including freshwater marshes and wooded/shrub wetlands.

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1. Introduction

The Hyperspectral Infrared Imager (HypsIRI) will likely offer unique opportunities to globally study ecosystems where land meets sea. These environments play a critical role in global biogeochemical cycles and in shaping and sustaining marine and terrestrial ecosystems. They are highly complex, interconnected, and are important to human habitats and economy. They are changing with climate and increasing human activities. Remote sensing is a critical tool for the study of inland and coastal waters and their watersheds and the advent of hyperspectral imaging is expected to be transformational to that capability. However, HypsIRI will not only provide global 30-meter resolution hyperspectral imagery, it will also provide contemporaneous thermal data at 60-meter resolution. This is an unprecedented opportunity and offered by no other planned space mission, domestic or international. In this paper, we discuss the benefits and challenges of HypsIRI observations to the global study of coastal tidal wetlands.

Tidal wetlands and estuaries are highly productive and provide important habitat for a wide variety of plants, fish, shellfish, and other wildlife (Batzer & Baldwin, 2012). Tidal wetlands also provide flood protection, a buffer from storm and wave damage, water quality

improvement through filtering of agricultural and industrial waste, and recharge of aquifers (Barbier et al., 2011, 2008; Odum, 1993). These ecosystems have been impacted by a wide range of stress-inducing alterations, including dredge and fill operations, hydrologic modifications, pollutant run-off, eutrophication, impoundments, invasion by non-native plant species, and fragmentation by roads and ditches (Zedler & Kercher, 2005). There is also considerable concern regarding the impact of climate change on coastal wetlands, especially due to relative sea level rise, increasing temperatures and changes in precipitation (Church & White, 2006; McInnes, Walsh, Hubbert, & Beer, 2003; Watson et al., 2014). Increased CO₂ levels and temperature changes may change the current distribution of C3 and C4 plants (Bromberg-Gedan, Silliman, & Bertness, 2009). Most marshland grass species are C4 plants and are not expected to increase productivity under higher CO₂ levels, but that is probably not the case for C3 plants (Erickson, Megonigal, Peresta, & Drake, 2007), which include many of the marsh sedges and rushes. Rising temperatures from global warming may bring invasion of warmer water species into colder zones (Zomer, Trabucco, & Ustin, 2009). At the same time, tidal ecosystems (including marshes, mangroves, and seagrasses) represent a significant standing carbon pool in soils and vegetation. The carbon stocks and future cumulative carbon storage in these systems are referred to as “Blue Carbon,” and play an important role in managing atmospheric carbon (Pendleton et al., 2012). In an extensive study by Cebrian (2002), tidal

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marshes and mangroves were also shown to have the greatest carbon production and flux per area compared to other types of terrestrial and aquatic coastal ecosystems. Thus changes in these systems could also influence the role of coasts in biogeochemical cycles or affect the status of coastal carbon reservoirs.

To plan for protection and responsible development of these wetlands, there is a need to map and monitor changes in tidal wetlands at local, regional and global scales (Ozesmi & Bauer, 2002). Much has been done since the early 1980s to map wetlands nationally with remote sensing particularly through the U.S. Fish and Wildlife Service (USFWS) National Wetlands Inventory (NWI) (Dahl & Stedman, 2013) and the NOAA Coastal Change Analysis Program (NOAA, 2015) and mapping wetlands continues to be a national priority in the USA, and global efforts to monitor wetlands are increasing (USFWS, 2015). Early work with multispectral imagery has been based predominantly on Landsat Thematic Mapper data (Klemas, 2011, 2013a,b). This legacy continues with the recently launched Landsat 8 Operational Land Imager (OLI), which was used to derive the color-infrared (CIR) image in Fig. 1, an example of a tidal wetland system on the eastern shore of Chesapeake Bay.

More recently, wetland mapping has been augmented with the use of hyperspectral imagery (Adam, Mutanga, & Rugege, 2010). Hyperspectral remote sensing data have been shown to improve efforts to map wetland location and extent, classify wetlands according to vegetation functional types or species, and derive critical functional properties of wetlands across types and scales (Brando & Dekker, 2003; Christian & Krishnayya, 2009; Hirano, Madden, & Welch, 2003; Jensen et al., 2007; Papes, Tupayachi, Martínez, Peterson, & Powell,

2010; Pengra, Johnston, & Loveland, 2007; Schmidt et al., 2004; Ustin, Roberts, Gamon, Asner, & Green, 2004; Yang, Everitt, Fletcher, Jensen, & Mausel, 2009; Zomer et al., 2009). In addition with hyperspectral, narrow-band vegetation indices, researchers have made progress on estimating biochemical and biophysical parameters of wetland vegetation, such as water content, biomass and leaf area index, and leaf constituents such as nitrogen, as demonstrated in the literature (see Adam et al., 2010; Artigas & Yang, 2006; Filippi & Jensen, 2006; Gilmore et al., 2008; O'Connell, Byrd, & Kelly, 2014; Ozesmi & Bauer, 2002; Pengra et al., 2007; Tian et al., 2011; Wang, 2010).

Hyperspectral classification is an important analysis tool for studying salt and brackish marsh systems. Tidal salt and brackish marshes tend to form monospecific canopies, with certain species favoring different salinity and drainage conditions that change geographically. As a result, the landscape becomes partitioned into zones of plant species that can deal with different levels of salinity, a process called *zonation* (Adam, 1990; Day et al., 2012). Observing changes in zonation can provide information about how a marsh system is responding to changes in hydrologic processes or sea level. Change in distribution can also be caused by invasive species. Hyperspectral classification techniques have been applied to map the distribution of marsh species (Adam & Mutanga, 2009; Adam et al., 2010; Andrew & Ustin, 2008; Artigas & Yang, 2005; Barducci, Guzzi, Marcoianni, & Pippi, 2009; Judd, Steinberg, Shaughnessy, & Crawford, 2007; Zomer et al., 2009). Unlike multi-band sensors, hyperspectral imagers can detect fine differences in spectral features, enhancing wetland species discrimination (Brando & Dekker, 2003; Christian & Krishnayya, 2009; Papes et al., 2010; Pengra et al., 2007).

Fig. 1. Satellite imagery of coastal wetlands. Shown is part of a Landsat 8 Operational Land Imager (OLI) Color-Near IR (CIR) scene over the western coast of the Delmarva peninsula, south of Cambridge, Maryland USA on 2 February 2014. The region corresponds to the map depicted in Fig. 2. Melting remnants of recent snowfall can be seen as small light blue or white spots, which suggests increased flow rates and sediment fluxes. In this region, residential and agricultural land use at higher elevations of the watershed feed nutrients and soil into the wetlands below. What the wetlands do not filter into the adjacent estuaries. In the east is the Chesapeake Bay and to the right are Fishing Bay, Nanticoke River, and Money Bay. The confluence of the last three connects with the Chesapeake via Hooper's Strait between Bishops Head and Bloodworth Island. Fresher, more soil and CDOM rich waters mix with the "greener" Chesapeake waters just east of the strait. The waters in the northern end of Fishing Bay, and in Blackwater Lake further northwest, are dark with heavy concentrations of chromophoric dissolved organic matter (CDOM), a product of decaying vegetation. The red–green–blue (RGB) imagery inset also shows the appearance in these estuaries of heavy concentrations of suspended sediment, which only observable by including the red channel. High-resolution spectroscopy and thermal measurements from HypSIIRI provide further information regarding the biological and environmental responses to these processes. Credits: USGS.

In the following sections, we focus our discussion on coastal tidal marshes and mangrove vegetation and processes involving hydrology and hydrometeorology. The paper highlights areas in which the hyperspectral capability, spatial resolution, swath-width and signal-to-noise (SNR) ratio of HypSIIRI meet most of the requirements for mapping wetland types and processes at regional to global scales. This summary is then followed with a review of specific HypSIIRI data applications for these various wetland types and processes. Finally the paper describes expected challenges associated with coastal wetland remote sensing.

2. Hyperspectral sensors

Hyperspectral sensors have been primarily available on aircraft (Fearn, Klonowski, Babcock, England, & Phillips, 2011; Lesser & Mobley, 2007; Li, Ustin, & Lay, 2005; Ozesmi & Bauer, 2002; Rosso, Ustin, & Hastings, 2005). However, to map and monitor wetlands globally, spaceborne platforms are required, and it is ideal if the data are available to public at no cost. To date, only three hyperspectral imagers have been placed in orbit. All three were intended to be low cost, prototype sensors that were developed as a proof-of-concept with on-demand image acquisition of selected sites on the globe. None were designed to provide global wetland coverage on a regular basis.

In 2000, the National Aeronautics and Space Agency (NASA) of the USA launched the first spaceborne hyperspectral sensor, Hyperion aboard the Earth Observatory 1 (EO-1), with 220 contiguous spectral bands. Images over selected sites covered a narrow strip (7.5 km by 200 km) with 34 m spatial resolution. At the time of writing this paper, NASA extended the mission one more year. However, it is highly unlikely that Hyperion will be in orbit during any date chosen for a HypSIIRI launch. In 2001, the European Space Agency (ESA) launched the Compact High Resolution Imaging Spectrometer (CHRIS), aboard the Project for On-Board Autonomy 1 (Proba-1). CHRIS/Proba is a programmable sensor that can acquire 13 km × 13 km images of specified locations at five viewing angles. The sensor has built-in modes for acquiring these images with 17 m to 34 m spatial resolution, for 18 to 62 bands over a spectral range from 400 nm to 1050 nm (Barnsley, Settle, Cutter, Lobb, & Teston, 2004). The USA Naval Research Laboratory later built the Hyperspectral Imager for the Coastal Ocean (HICO), which was situated on the International Space Station (ISS) in 2009. HICO image dimensions were 42 km × 192 km, at about 90 m spatial resolution, for 128 bands from 352 nm to 1080 nm. Because HICO was designed to observe coastal waters, its radiometric performance was superior to Hyperion and CHRIS/Proba in sensitivity and SNR. Unlike Hyperion and CHRIS/Proba, HICO could not acquire imagery above 45° latitude because of the ISS orbital characteristics. Unfortunately, HICO operations ended due to an X-class solar storm in September 2014 (see <http://hico.coas.oregonstate.edu/>).

In the next few years, Italy plans to launch the PRecursive IperSpettrale della Missione Applicativa (PRISMA), which is a push broom imager with 30 m spatial resolution and a 30 km swath width. PRISMA has over two hundred bands spanning 400 nm to 2500 nm. Germany plans to launch its Environmental Mapping and Analysis Program (EnMap), which is designed to acquire a 30 km × 30 km image at 30 m spatial resolution, with 245 bands going from 420 nm to 2450 nm.

After Hyperion and HICO, the only hyperspectral missions planned by the USA include the Hyperspectral Infrared Imager (HypSIIRI), the Pre-Aerosol, Clouds and Ecosystems (PACE) mission, and the Geostationary Coastal and Air Pollution Events (GeoCAPE) mission. HypSIIRI will include an imaging spectrometer measuring from the visible to shortwave infrared wavelengths in 10 nm contiguous bands, as well as a multispectral imager measuring from 3 µm to 12 µm in the mid-wave and thermal infrared wavelengths. Details regarding the mission and sensor characteristics are given in Table 1 and a comparison of the

Table 1

Key characteristics of the Hyperspectral Infrared Imager (HypSIIRI) mission.

	VSWIR	TIR
Spectral range	380 to 2500 nm	3.98, 7.35, 8.28, 9.07, 10.53, 11.33, and 12.05 µm
Spectral bandwidth	10 nm, uniform over range	0.084, 0.32, 0.34, 0.35, 0.36, 0.54, 0.54, and 0.52 µm
Radiometric resolution	14 bit	14 bit
Angular field of view	12°	51°
Altitude	700 km	700 km
Swath width	185 km	600 km
Cross track samples	>2400	10,000
Spatial resolution	30 m (depth < 50 m) 1 km (depth > 50 m)	60 m (depth < 50 m) 1 km (depth > 50 m)
Orbit	Polar ascending	Polar ascending
Equatorial crossing	11:00 a.m.	11:00 a.m.
Equatorial revisit	16 days	5 days
Rapid response	3 days	3 days
Tilt	4° West	4° West

HypSIIRI instrument to other existing and future sensors can be found in Table 2.

Both PRISMA and EnMap have capabilities that would be useful to study specific marsh systems, but neither are intended to produce global or synoptic maps and neither have thermal bands. Thus, unlike HypSIIRI, these missions cannot be expected to support global observations of tidal wetlands (e.g., to understand the effects of global climate change), nor can they provide as extensive suite of contemporaneous data products that HypSIIRI offers, such as soil moisture or evapotranspiration, as discussed later in this paper. Also, the greater temporal resolution of PACE and GeoCAPE could certainly complement HypSIIRI observations. However, the respective spatial resolutions for PACE and GeoCAPE of 1000 and 250 m are far less capable of observing wetland structure. Also, only HypSIIRI offers thermal bands, which can be useful in coastal wetlands studies.

To illustrate the importance of spatial resolution in observing tidal wetlands, a pixelization simulation was applied to a wetland mask to derive the percentage of pixel mixing as a function of resolution for a large marsh system. Fig. 2 shows a map of wetland cover types from the United States Fish and Wildlife Service (USFWS) National Wetlands Inventory (NWI). The area shown includes a large marsh system along the eastern shore of the Chesapeake Bay (USFWS, 2014). Polygons from a NWI shape file were used to create a layer in GIS software called QGIS and rasterized to approximate one-meter resolution. This captured much of the small-scale features seen in the NWI polygon data, including variation along the marsh boundaries and within its interior, including small ponds and channels. The resulting image, with about 10⁴ pixels on a side, was loaded into IDL, which is software designed for image analysis. An array of the same dimensions as the NWI image was created. Elements of this array were set to unity where image pixels were designated as being the Estuarine and Marine Wetland cover type (see Fig. 2) and the rest of the array was left as zero. Then the array was subsequently aggregated to increasingly coarser pixel sizes. The resulting average of ones and zeros in each aggregated pixel thus indicated the fraction of the selected wetland type that it contained. Fig. 3 uses a gray scale to illustrate the spatial distribution of this fraction within a magnified rectangular inset (identified by the small red box in Fig. 2), which includes an area of marsh between the Blackwater Lake in its northwestern corner and Fishing Bay in its southeastern corner. The meandering river running between these two bodies is the Blackwater River, which becomes noticeably gray at as fine as 60 m resolution. The top row of simulated images represents the effects of moderate-resolution sensors (30–90 m) and the bottom low-resolution sensors (e.g., PACE and GeoCAPE). Fig. 4 shows the fraction of the wetland type that remains unmixed as the pixel size increases. Generally, 30 m (the fourth circle) is where significant degradation

Table 2

Feature comparison with existing and upcoming remote sensing resources.

	Sensor	Status	Resolution			Swath dims (km)	Global?	Source
			Spatial (m)	No. of bands	Rep cycle (days)			
Moderate spatial resolution	HyspIRI — VSWIR	Under development	30	212	16	185	Y	USA
	HyspIRI — TIR	Under development	60	8	5	600	Y	USA
	Hyperion	Termination planned	34	220	16	7.5	N	USA
	Landsat OLI — VSWIR	Operational	30	8	16	185	Y	USA
	Landsat OLI — TIR	Operational	100	2	16	185	Y	USA
	EnMap	Launch 2017	30	245	27	30	N	Germany
	PRISMA	Launch 2017	30	237	29	30	N	Italy
	Sentinel 2	Launch 2015 (1st Sat)	10–60	13	5	290	Y	ESA
	CHRIS/Proba ^b	Operational	17	18	7	13.5	N	ESA
	ASTER — VSWIR	Operational	15	9	16	60	N	USA/Japan
	ASTER — Thermal	Operational	90	5	16	60	N	USA/Japan
	HISUI	Launch 2018	30	185	60	30	Y	Japan
	HICO ^a	Terminated	90	87	3	42	N	USA
	PACE — VisNIR	Under development	500–1000	110	2	2300	Y	USA
	PACE — SWIR	Under development	500–1000	3	2	2300	Y	USA
Low spatial resolution	GeoCAPE — VisNIR	Under development	250–375	>1000	>0.04	300–500	N	USA
	GeoCAPE — SWIR	Under development	250–375	3	0.1	300–500	N	USA
	GOCI	Operational	500	8	0.04	2500	N	Korea
	MODIS — VSWIR	Operational	250–1000	21	2	2300	Y	USA
	MODIS — Thermal	Operational	1000	15	2	2300	Y	USA
	VIIRS — VSWIR	Operational	250–750	14	<2	3000	Y	USA
	VIIRS — Thermal	Operational	250–750	7	<2	3000	Y	USA
	MISR	Operational	275–1100	4	9	360	Y	USA
	OLCI/Sentinel 3	Launch 2016	300	21	2	1270	Y	ESA
	SPOT-5 — VSWIR	Operational	10–20	3	5	120	N	Commercial
	SPOT-6 — VisNIR	Operational	6	4	5	60	N	Commercial
	SPOT-7 — VisNIR	Operational	6	4	5	60	N	Commercial
	QuickBird II ^a	Terminated	2.6	4	4	18	N	Commercial
	IKONOS	Operational	4	4	14	13–70	N	Commercial
	Pleiades	Operational	0.5	4	1	20	N	Commercial
High spatial resolution	GeoEYE 1	Operational	2	4	2	50	N	Commercial
	RapidEye	Operational	1.8	4	1	100	N	Commercial
	Worldview 2	Operational	2	8	4	16	N	Commercial
	Worldview 3 — VSWIR	Operational	1.2	28	<1	13	N	Commercial

VisNIR = 400–1000 nm; VSWIR = 400–2500 nm; TIR = 3–12 μ m.^a Terminated mission.^b Set to mode (3b) for dark targets and highest spatial resolution.

begins to occur and beyond 60 m the loss is substantial. Therefore, low-resolution sensors are less appropriate for mapping, assessing, or monitoring marshes, or similar wetland systems.

It should be noted that HyspIRI was originally planned to provide imagery with global coverage at 60 m resolution, a swath width of 145 km, and equatorial revisit period of 19 days. However, in response to a congressional mandate in 2014 that the USA federal government should support Sustainable Land Imaging (SLI) for the next twenty-five years, NASA instructed the HyspIRI mission management to conduct a study that would determine whether the HyspIRI mission could supplement the existing Landsat imaging capability. A review of available technology led by the Jet Propulsion Laboratory (JPL) concluded that replacing the originally proposed Offner spectrometer with a Dyson spectrometer for HyspIRI would support Landsat spatial resolution, while keeping the original spectral and radiometric characteristics. Therefore, as of this writing, HyspIRI mission will employ a VSWIR spectrometer that provides a 30 m spatial resolution equal to Landsat legacy instruments. In addition, the new spectrometer design will have Landsat's 185 km swath width, which should also decrease the equatorial revisit period to 16 days (Green, 2015).

With SNR comparable or better than the now defunct HICO instrument, HyspIRI should be more suited than Landsat to observe water optical characteristics (Devred et al., 2013), especially along shallow coastal waters. This is useful because wetlands tend to be darker than typical terrestrial targets and it would also be useful to study the characteristics of adjacent water ecosystems and environments. This also could better support studies of interaction between coastal wetlands and estuarine and marine waters. HyspIRI's greater spectral resolution and coverage should afford it superior capabilities in discriminating

species and vegetation functional types and provide a better chance at observing the spectral signatures of plant stress and changes in production. With its spectral range extending into the SWIR, the HyspIRI mission should provide broader use than HICO could in covering both aquatic and terrestrial features.

HyspIRI's eight thermal bands will be more than adequate to observe subtle variations in water surface temperature, which would be ideal for tracing fresh or melt water fluxes along water body margins with land and ice, respectively. Its VSWIR spectral capabilities could then observe aquatic biospheric response to contemporaneously observe coastal fluxes. The combined use of 30 m resolution satellite data from HyspIRI's optical and thermal infrared radiometers is promising for multiple applications, including the retrieval of latent and sensible heat fluxes, and soil surface moisture variations (Petropoulos, Carlson, Wooster, & Islam, 2009; Sandholt, Rasmussen, & Andersen, 2002). This information will also be contemporaneous to the water and vegetation attributes derived from the hyperspectral measurements.

3. HyspIRI and tidal wetland vegetation observations

3.1. Tidal marsh vegetation

Coastal tidal marshes are the dominant coastal ecosystem in the United States and all temperate latitudes. They cover approximately 22,000 km² of North America (Bridgman, Megonigal, Keller, Bliss, & Trettin, 2006). Tidal marshes are typically characterized by emergent vegetation, and may have mineral or peat substrate. Tidal marshes are highly productive (Rocha & Goulden, 2009), and emergent plant growth leads to peat formation in some of the most significant coastal areas of

Fig. 2. Major wetland types classified in the US Fish and Wildlife Service National (USFWS) Wetland Inventory (NWI) mapped over a portion of the eastern shore of the Chesapeake Bay in Maryland, USA. The area shown contains large a brackish marsh system that were used in a pixelization simulations.

the United States, including South Florida, the Mississippi River Delta, and the Sacramento–San Joaquin River Delta (Miller & Fujii, 2010; Nungesser, 2011; Tornqvist et al., 2008).

Salt marshes are widely distributed along many of the world's coasts and are often dominated by specifically adapted species of grasses, sedges and rushes that tend to form monospecific canopies across regions with a high salinity gradient (Chapman, 1960). For instance, smooth cordgrass (*Spartina alterniflora*) tends to dominate the eastern North American seaboard and the Gulf of Mexico. The relative monospecificity and size of some salt marshes and aquatic nature of the substrate make it possible to map them from satellites. Multispectral medium resolution satellite imagers, such as Landsat TM and *Satellite Pour l'Observation de la Terre* (SPOT), and high resolution satellites, such as IKONOS® and QuickBird, have been effective primarily for mapping wetland location and extent, at local or regional scales (Gilmore et al., 2010; Jensen et al., 1998; Klemas, 2011; Lunetta & Balogh, 1999; Lyon & McCarthy, 1995; Wang, 2010), as well as vegetation pattern and condition (Kelly, Tuxen, & Stralberg, 2011; Ramsey & Rangoonwala, 2005; Tuxen, Schile, Kelly, & Siegel, 2008; Tuxen et al., 2011).

Remote sensing efforts have been made to assess and monitor coastal marshes in order to improve our understanding of their essential services, as described above, and to aid in their management (Dahl & Stedman, 2013; Kelly & Tuxen, 2009; UNEP, 2006). Part of the process of managing degradation of coastal marsh services includes identifying changes in marsh systems that would affect these services (Barbier

et al., 2011). Studies of changes in ecological function and response are often limited to a small number of plots, and scientists must extrapolate findings to regional scales. Although monitoring widespread changes to these landscapes could assist researchers and policymakers in assessing and monitoring marsh deterioration or restoration, limited accessibility makes large-scale, in situ, evaluation challenging (Seher & Tueller, 1973). Remote sensing techniques offer an efficient approach to quantify changes in marsh vegetation (Klemas, 2013a,b). The utility of remote sensing techniques has been explored for measuring quantities over large regions of wetlands, such as species and cover type (Artigas & Yang, 2005; Jensen et al., 1986; Jollineau & Howarth, 2008; Judd et al., 2007; Schmidt & Skidmore, 2003; Silvestri, Marani, & Marani, 2003; Underwood et al., 2006; Zomer et al., 2009), canopy density or Leaf Area Index (LAI) (Sone, Saito, & Futakuchi, 2009; Wang, Huang, Tang, & Wang, 2007; Xavier & Vettorazzi, 2004; Xiao et al., 2002), biomass (Byrd, O'Connell, Di Tommaso, & Kelly, 2014; Klemas, 2013a; Mishra et al., 2012; Mutanga, Adam, & Cho, 2012), or quantities related to plant production and stress (Klemas, 2013a; Mendelssohn, McKee, & Kong, 2001; O'Connell et al., 2014; Ramsey & Rangoonwala, 2006; Tilley, Ahmed, Son, & Badrinarayanan, 2003; Vaesen, Gilliams, Nackaerts, & Coppin, 2001; Zhao et al., 2009).

Hyperspectral imagery, in its broad spectral range and radiometric sensitivity could assist in improving applications in wetlands. Recent analysis of full spectrum field spectrometer data indicates that hyperspectral first derivative reflectance spectra improve predictions of wetland vegetation biomass over simulated broadband spectra

Fig. 3. Effects of increasingly coarser resolution on spatial representation of an example wetland. Shown is an inset of a rasterized layer from polygon data mapped in Fig. 2 for the Estuarine and Marine Wetland type (see the double-line box in Fig. 2).

under low inundations conditions (Byrd et al., 2014) or wetland canopy structure (Fan, Xu, Liu, & Cui, 2010). Furthermore, biomass studies of grasslands demonstrate the greater capacity of hyperspectral imagery to reduce the saturation problems in biomass estimation compared to multispectral sensors (Mutanga & Skidmore, 2004), suggesting that hyperspectral data will improve biophysical models in marshes as well, which are typically dominated by grass species like *S. alterniflora*.

Hyperspectral resolution over a broad spectral range is necessary to discriminate and unmix cover types in these spectrally complex regions,

and also address atmospheric correction along coastal boundaries (Li et al., 2005; Ozesmi & Bauer, 2002; Rosso et al., 2005; Schmidt et al., 2004). Detailed mapping of species composition, dynamics and plant vigor in complex salt marshes will require additional spectral data beyond what is found in multispectral imagery alone (Kelly & Tuxen, 2009). For example, AVIRIS (Airborne Visible and Infrared Imaging Spectrometer) has been successfully used to map estuarine wetland extent and type in the San Francisco Bay Area, California, USA (Li et al., 2005; Rosso et al., 2005), and Everglades National Park, Florida, USA (Hirano et al., 2003), as well as other study areas. These earlier proof-of-concept studies using airborne hyperspectral imagers demonstrate good potential utility for data generated by HypsIRI.

3.2. Mangroves

Mangroves help reduce the erosional impact of storms, serve as breeding and feeding grounds for juvenile fish and shellfish, trap silt that could smother offshore coral reefs and cleanse water by the uptake of nutrients and pollutants (Barbier, 2011; Ewel, Twilley, & Ong, 1998). Mangroves, which once occupied 75% of tropical and subtropical coastlines, are now seriously threatened by coastal development and climate change, including sea level rise (Friess & Webb, 2014). In many countries, mangrove swamps are being cut to provide firewood or building material and are being destroyed by development of shrimp ponds (Alongi, 2002; Heumann, 2011; Pinet, 2009; Tomlinson, 1995; Vaiphasa, Ongsomwang, Vaiphasa, & Skidmore, 2005; Wang & Sousa, 2009).

Rapid losses of mangroves make it crucial to inventory and monitor the remaining mangroves to protect them from harmful development (Blasco, Aizpuru, & Gers, 2001; Gunawardena & Rowan, 2005; Terchunian et al., 1986). Mapping and quantifying the structure and biomass of mangrove ecosystems on a large scale is also important for studies of carbon storage, biodiversity, forest quality, and habitat suitability. Remote sensing has had a crucial role in monitoring mangroves,

Fig. 4. Effects of increasingly coarser resolution on pixel mixing over an example wetland. Shown fraction of the Estuarine and Marine Wetland (simulated at one-meter resolution) that remains unmixed as a function of pixel size.

but the majority of applications have been limited to mapping areal extent and patterns of change (Alongi, 2002; Blasco, Aizpuru, & Din Ndongo, 2005; Heumann, 2011).

Mangrove forests are patchy and can have gaps in the canopy that expose moist soil or water. Therefore, high spatial resolution (<10 m) is required for mapping them in detail. Large-scale mangrove mapping has been performed in the past using medium-resolution satellites, such as Landsat-TM and SPOT (Gao, 1998; Kovacs, Wang, & Blanco-Correa, 2001; Saito, Bellan, Al-Habshi, Aizpuru, & Blasco, 2003). SPOT multispectral data was shown to be suitable for mapping dense mangroves. On the other hand, sparse mangroves were less accurately mapped, due to the spectral interference of their mudflat background (Gao, 1998).

The advantages and problems associated with hyperspectral mapping have been clearly demonstrated by Hirano et al. (2003), who used hyperspectral data to map vegetation for a portion of the Everglades National Park in Florida. The hyperspectral imagers offered some operational challenges, including large data volumes and more complex image processing procedures. However, the hyperspectral data proved effective in discriminating spectral differences among major Everglades species, such as red, black and white mangrove communities and enabled the detection of exotic invasive species. Furthermore, techniques for optimizing hyperspectral band selection for mangrove mapping have been developed (Koedsin & Vaiphasa, 2013). Laboratory experiments have also shown that discrimination between multiple species is possible (Heumann, 2011; Vaiphasa et al., 2005). Satellite-borne hyperspectral imagers, such as Hyperion, have been able to detect fine differences in spectral reflectance. (Blasco et al., 2005; Heumann, 2011). With its high signal-to-noise ratio and good spatial resolution, the HypsIRI hyperspectral imager should be able to map mangrove extent and provide major species discrimination on a global scale.

3.3. Invasive species in wetlands

Wetlands can be invaded by plant species that displace native plants and degrade habitat. Mapping tools are needed to document the location and extent of such invasive species. Pengra et al. (2007) were able to map *Phragmites australis*, a tall grass that invades coastal marshes throughout North America, with Hyperion hyperspectral satellite imagery in wetlands of Green Bay in Wisconsin, USA. Artigas and Yang (2005) used hyperspectral imagery from Airborne Imaging Spectroradiometer for Applications (AISA) in New Jersey, USA to classify marsh condition based on field-captured reflectance spectra of dominant marsh species and seasonal spectra of *P. australis*. Hestir et al. (2008) developed a regional-scale monitoring framework to map wetland weeds in the Sacramento–San Joaquin Delta, California USA. They focused on the terrestrial riparian weed, perennial pepperweed (*Lepidium latifolium*) using an airborne hyperspectral imager (HyMAP) that collects 128 bands in the visible and near-infrared (VNIR; 0.45–1.50 μm) through the shortwave infrared (SWIR; 1.50–2.5 μm), at bandwidths from 10 nm in the VNIR to 15–20 nm in the SWIR. The spatial resolution of the data was 3 m, with a swath width of 1.5 km. At a field scale Sonnentag et al. (2011) used multispectral webcam imagery to track perennial pepperweed in the Sacramento Delta in California. The success of these studies indicates that HypsIRI has the potential to be useful at mapping some invasive species. HypsIRI's repeat visits should afford the opportunity to monitor spread of those species over time.

4. HypsIRI and wetland hydrology and hydro-meteorology

Evapotranspiration is an important variable in water and energy balances of the earth's surface. Understanding the distribution of evapotranspiration is a key factor in hydrology, climatology, agronomy, and ecological studies. On a global scale, about 64% of precipitation on the continents is evapotranspired. Of this amount, about 97% is

evapotranspired from land surfaces and 3% evaporated from open water (Rivas & Caselles, 2004). In some zones of the world, about 90% of the precipitation can be evapotranspired (Varni, Usunoff, Weinzettel, & Rivas, 1999). Thus the greatest amount of water from the hydrologic system is transpired and evaporated, showing the importance evapotranspiration.

Knowledge of latent and sensible heat fluxes, as well as soil water content, is important to many environmental applications, including monitoring plant water requirements, plant growth, irrigation, land degradation and desertification. Such data are also significant in the numerical modeling and prediction of atmospheric and hydrologic cycles, and for improving the accuracy of weather forecast models. The combined use of satellite data from optical and thermal infrared radiometers has shown promise for the retrieval of latent and sensible heat fluxes and soil surface moisture variations within the top 5 cm of the soil depth (Ghilain et al., 2011; Marshall et al., 2013; Petropoulos et al., 2009).

HypsIRI's thermal bands would provide additional information regarding wetland hydrology and hydro-meteorology. The evaporation flux from freshwater wetlands has been estimated using thermal infrared sensing data and a parameterization of the surface energy balance (Jackson, 1985; Mohamed, Bastiaanssen, & Savenije, 2004). For instance, in the upper Nile Sudd wetlands of Sudan, the spatially averaged evaporation over three years was found to vary between 1460 and 1935 mm/yr. This is substantially less than open water evaporation, and the wetland appears to be 70% larger than was previously assumed. This new set of spatially distributed evaporation parameters from thermal IR remote sensing forms an important dataset for calibrating a regional climate model enclosing the Nile Basin (Chen, Kan, Tan, & Shih, 2002; Mohamed et al., 2004). Having evaporation flux and spectral types contemporaneous and collocated would better inform studies of ecosystem and canopy dynamics by enabling coordinated mapping of wetland extent and vegetation characteristics such as leaf area with hydrological processes.

Spatial patterns of evapotranspiration in marshes can now be calculated using satellite data with a minimum of ground meteorological data (Meijerink, 2002). Rivas and Caselles (2004) have shown that the evapotranspiration of vegetation in a large river basin can be estimated by combining the surface temperature, as obtained from satellite images, with conventional weather information. Carlson (2007) prepared an overview of the Triangle Method for estimating surface evapotranspiration and soil moisture from satellite imagery. A review of methods using remotely sensed surface temperature data for estimating land surface evaporation is provided by Kalma, McVicar, and McCabe (2008).

Continuous reduction of water levels and other man-made and natural modifications of wetland hydrology are causing wetland stress and losses in many parts of the world. These hydrologic changes influence vegetation species composition, distribution and condition. In worst cases, this can lead to a drying out of the whole wetland (Chopra, Verma, & Sharma, 2001; Xin, 2004). The hydrological conditions of emergent wetland vegetation have been explored with the help of remotely sensed biophysical data, such as surface temperature and vegetation indices (NDVI). Using a digital elevation model and regression models, a relation between surface temperature and water stress has been established (Banks, Paylor, & Hughes, 1996). Results show that surface temperature and NDVI can be used for a better understanding of hydrological conditions of wetlands (Banks et al., 1996; Bendjoudi, Weng, Guérin, & Pastre, 2002; Petropoulos et al., 2009). MODIS daily and 8-day composite products have been used effectively to map floodplain and wetland inundation extent corresponding to peak flows of significant flood events (Chen, Huang, Ticehurst, Merrin, & Thew, 2013). In comparison, HypsIRI's higher spatial resolution should provide even more accurate information.

Satellite data have been used to improve rainfall mapping and to monitor relationships between rainfall and vegetation responses. Vegetation and inundation dynamics and aspects of water quality of wetlands have been monitored in many parts of the tropics and elsewhere

by using multi-spectral, thermal and radar imagery (Meijerink, 2002). To study the dynamics of regional vegetation responses in southern Africa to the dry El Nino years and intervening wetter years, Kogan (1998) used a Vegetation and Temperature condition index (VT) based on NDVI values after radiometric corrections and the brightness temperature of the surface based on the thermal channel of the Advanced Very High Resolution Radiometer (AVHRR). Effects of transpiration of healthy vegetation are included by the temperature component of the index. Kogan (1998) found that it took 5 to 6 weeks for the VT index to decrease to a level that indicates severe stress ($VT = 10\text{--}20$), whereas with adequate moisture, the index is around 60. The numerical value of the VT can be used for multi-temporal studies and for comparing values via the HypsIRI sensors in different parts of the world.

Natural vegetation patterns, as observed on images, can also be related to groundwater occurrences and groundwater flow systems (Meijerink, 2002). Locating ground-water discharge zones in bodies of surface water can provide information about the ground-water flow system in wetlands and about the potential transport of contaminants. This information can aid in the design and emplacement of ground-water monitoring networks and determining remediation techniques. Knowing the areal extent of ground-water discharge to surface water can also be useful for selecting sampling sites and for estimating the environmental effects of contaminant migration (Klemas, 2011, 2013b; Thomson & Nielsen, 1980). Thermal infrared imaging is an effective method for assessing large areas and getting information about specific locations of ground-water discharge since the ground-water usually has a different temperature from the background water (Byers & Chmura, 2014; Thomson & Nielsen, 1980; Xin, 2004). Simulated flooding patterns obtained from coupled surface water-groundwater models have been compared to patterns derived from satellite multispectral, thermal infrared and radar data that provided such model inputs as topography, aquifer thickness, channel positions, evapotranspiration and precipitation (Milzow, Kgotlhang, Kinzelbach, Meier, & Bauer-Gottwein, 2009).

5. Challenges

Although darker than most terrestrial vegetation remote sensing targets, wetlands are more reflective than most non-turbid, open

water targets. However, these environments are still subject to sun glint (Hochberg et al., 2011) when observed, which presents a challenge for most aquatic remote sensing capabilities along coasts. For coastal emergent vegetation, the issue of glint becomes much more complex. For example, in salt marshes, tidal emergent vegetation is typically erectophile, with small ponds and channels interspersed. These features are typically ranged in spatial scale from fractions of a meter to tens of meters. In these systems, glint would undoubtedly contribute to the remotely sensed signal of the HypsIRI instrument with its 30 m nadir pixel size. Naturally, the effect would vary with sun and view angles, being more intense at low latitudes and growing worse with closeness to the summer solstice. Measurement and modeling capabilities for glint in wetlands lag those for shallow and deep oceans. Suitable models or measurement techniques have yet to be developed to quantify this effect because the relationship between surface roughness and various environmental factors are unknown (Turpie, 2012).

It is possible to demonstrate glint effects from multi-angle satellite images acquired by CHRIS/Proba. Fig. 5 illustrates an example of glint in the wetlands on remote sensing reflectance observations. With a nominal view zenith angle of 0° , glint is visually apparent in water bodies among the vegetated areas (Fig. 5a). This glint is likely caused by capillary waves patterned by the local wind field. With a nominal view zenith angle of 55° , glint is much less visually apparent (Fig. 5b). These visual glint patterns are supported by sample spectra. For the same region of wetland, the 0° nominal view angle spectra (Fig. 6a) have higher reflectance values and are more variable than the 55° view angle spectra (Fig. 6b). The bulk of the vegetation signal, seen between the 1st and 3rd quartiles, shows an increase in visible reflectance with increased glint and a slight decrease in the NIR, which is possibly an effect of the canopy bidirectional distribution function of a largely erectophile canopy.

Although using conventional techniques to separate glint from the vegetation spectral signal may appear to be challenging, the effect of glint on the relatively stronger signal from subaerial vegetation is less than the effect on remote sensing retrievals of water column and benthic communities. In addition, wetland vegetation cover tends to reduce surface roughness from wind, thus the range of angles that are influenced by sun glint are reduced in comparison to ocean water (Vanderbilt et al.,

Fig. 5. Multi-angle CHRIS/Proba images over Maryland marsh systems. Images are cropped and co-registered and pertain to the single-line box in Fig. 2. The 872.1, 551.3, and 490.2 nm bands are used for the red, green, and blue channels, respectively. (a) At 0° nominal view zenith angle glint is visually apparent on water bodies interspersed among subaerial vegetation. (b) At 55° nominal view zenith angle glint is much less apparent. Boxes cover same ground area in (a) and (b). This region is extracted for statistics shown in Fig. 6.

Fig. 6. Spectra extracted from regions highlighted by boxes in Fig. 5. (a) At 0° nominal view zenith angle, glint produces very high values across the spectrum, evidenced by the maximum spectral curve. (b) At 55° nominal view zenith angle, the glint effect is greatly reduced.

2002). The 11 AM equatorial crossing of the spacecraft and 4° tilt of the HypSIPI instrument away from the subsolar point should greatly reduce the effect of sun glint in these coastal and inland wetlands.

On the other hand, the consistent satellite acquisition time will not allow for control of tide stage, and differences in tidal inundation when the imagery is captured can influence efforts to map wetland extent and land change (Allen, Couvillion, & Barras, 2012). In addition, the optical properties of an inundated canopy can present new challenges for some of the traditional dry-land remote sensing techniques, such as red edge position (REP) based methods and other such spectral analyses (Turpie, 2012, in press). This is driven by the spectral absorption properties of the aquatic substrate and the fact that the inundated background is much less isotropic than dry soil.

To date, there have been no true hyperspectral instruments with global coverage of coastal regions at 30 m resolution or better. This problem may be remedied as HypSIPI and other advanced satellites are launched. However, wetlands can exhibit considerable temporal variability and spatial complexity, as demonstrated in Figs. 1 and 2. Some key features, such as peak aboveground biomass, are often found along channel edges (Schile, Callaway, Parker, & Vasey, 2011). Thus some finer scale wetland observations are more commensurate with higher spatial and temporal resolution imagery, such as those provided by airborne and high spatial resolution satellite sensors. However, at 30 m resolution, spectral mixture analysis could still be used to accurately map wetland extent and features masked by mixed pixels at the land/water edge (Hestir et al., 2008; Michishita, Jiang, Gong, & Xu, 2012; Rosso et al., 2005).

For instance, some areas covered by coastal wetlands may be too small and patchy to be resolved by HypSIPI or any other medium resolution satellite and may require ancillary data. Furthermore, the floristic diversity of some higher-elevation wetlands can have a more mixed vegetation cover, producing a more complex, composite spectral signature than most saltwater wetlands. Mapping of wetland vegetation with high spectral heterogeneity among plant communities caused by variation in background reflectance from water, submerged aquatic vegetation, mud substrate, and dead vegetation could benefit from the use of linear spectral unmixing techniques, such as Multiple Endmember Spectral Mixture Analysis (MESMA) (Roberts et al., 1998). MESMA models measure spectra as linear combination of pure spectra, called *endmembers*, and allows the types and number of endmembers to vary on a per pixel basis. This method enables vegetation to be characterized by a unique set of endmembers and their fractions. MESMA can improve vegetation mapping even with high-resolution imagery. In a recent application of MESMA in the Sacramento–San Joaquin River Delta, a freshwater marsh, with a higher degree of floristic diversity than typically observed under high saline conditions, was mapped with 2-meter resolution World View-2 imagery. This enabled the accurate classification of green emergent vegetation (*Schoenoplectus acutus* and *Typha* spp.), dead standing vegetation, *Salix* sp., floating aquatic vegetation, and non-vegetated areas (e.g., open water or paved areas) (Byrd et al., 2014), all of which were varying at much finer scales than the sensor's pixel size.

The performance of linear unmixing techniques may be limited, in part, by any nonlinear mixing of spectral signatures along the optical path of the sensor. Unless the canopy is very dense, there will be small gaps exposing moist soil or water, which could “contaminate” the pure spectral reflectance signatures of the vegetation. However, light reflected from the canopy substrate and understory must propagate through the canopy above and are subject absorption and multi-scatter processes. This may necessitate the application of canopy reflectance models or empirical models of vegetation communities, not just plant species endmembers for individual plants or leaves. In addition, the influence of a varying submerged substrate (e.g., water depth changing with tides) to the optical properties of any inundated canopies will present additional challenges for some of these techniques. In such cases, a priori information about canopy and substrate conditions the maybe necessary in spectral signature analysis, thus increasing uncertainty. Further sensitivity analysis is recommended to determine the degree of influence variation in substrate water depth variation has on canopy spectral signatures (Turpie, 2012, in press).

Finally, the hydro-meteorological data for many of the world's freshwater marshes is still quite inadequate (Jackson, 1985; Mohamed et al., 2004). The areal size of these marshes, the evaporation rates and their influence on the micro and meso climate are still unresolved questions of their hydrology (Carlson, 2007; Rivas & Caselles, 2004). The combination of HypSIPI's thermal infrared radiometer and imaging spectrometer will be effective for observing these hydrologic conditions of wetlands, including water levels and other hydro-meteorological properties.

6. Conclusion

According to current plans, HypSIPI will be the only hyperspectral imager supported by the USA with 30 m spatial resolution, which is necessary to observe fine-scale structure in coastal wetlands. It will also be the only mission in world that would regularly map the wetlands globally. HypSIPI will also uniquely provide contemporaneous observation in the thermal infrared. Although orbiting, multi-spectral imagers with moderate and high spatial resolution have been useful in observing wetlands, HypSIPI's combination of hyperspectral imagery with contemporaneous thermal bands would provide greatly enhanced information. Hyperspectral imagery could offer improved classification of wetland vegetation functional types and perhaps discriminate species or produce maps of zonation in salt and brackish marshes or dense

mangroves. Hyperspectral imagery could also offer the estimation of biochemical and biophysical parameters of wetland vegetation. HypsIRI's radiometric performance will also provide opportunities to observe the optical properties of adjacent water bodies, which could help support studies of how wetlands tie to marine ecosystems, biogeochemical cycling, and water quality. HypsIRI's thermal infrared and hyperspectral sensors will be able to contemporaneously observe hydrologic and hydro-meteorological processes, including ground water seepage, nitrogen load, water quality, and evapotranspiration (Banks et al., 1996; Bendjoudi et al., 2002; Byers & Chmura, 2014; Chen et al., 2002; Meijerink, 2002; Moffett, 2010; Mohamed et al., 2004; Xin, 2004). Along with some canopy structure from hyperspectral data (Fan et al., 2010), a more complete model of wetland energy and water exchanges with the atmosphere may be obtained. Contemporaneous observations of water surface temperature could provide some insight into coastal freshwater discharges and hence yield further information tying wetland processes to open water systems.

The HypsIRI mission will operationally generate publicly available data products that cover the entire globe. Other higher level, derived attributes and maps used in wetland research and applications are currently expected to be produced by the research community. Expressed community awareness and subsequent interest in using and developing these specialized observations should guide NASA in allocating funding and resources to higher level data product generation and distribution, as appropriate. To encourage that appropriate support is provided, it is imperative that wetland scientists voice their needs early to the agency as the mission development proceeds. This is likewise important in guiding the NASA and other funding agencies in identifying open questions and understanding the challenges, such as those described in this paper, when allocating research resources and developing funding opportunities.

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