The Sharper Image: Hyperspatial Remote Sensing of Wetlands

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Abstract

Recent advances in remote sensing such as increased availability of high-spatial-resolution data and new processing techniques promise to broaden the applicability of remote sensing to wetland scientists and managers. We aim to introduce wetland practitioners to several cutting-edge remote sensing imagery analysis techniques now available; illustrate new innovative uses of these techniques by highlighting four case studies where high spatial techniques were employed; and finally to identify the unique abilities, challenges, and limitations of these remote sensing tools. We present four case studies of high spatial resolution remote sensing data used in wetland research applications, each using different data sources and processing techniques. These case studies illustrate the use of multispectral and historical aerial photography, aerial LiDAR, and Terrestrial Laser Scanning, to investigate invasive species, land use change, and mapping in wetland systems. We demonstrate how emergent remote sensing technologies offer both unique abilities and unique challenges.

Keywords: Wetlands, Remote Sensing, Hyperspatial, OBIA, LiDAR, TLS

Introduction

Since the early 1970s, scientists have mapped, monitored, and studied wetland ecosystems using remote sensing techniques, which continue to facilitate understanding of wetland ecosystems at multiple spatial scales (Ozesmi and Bauer 2002). Unfortunately, the spatial resolution of many remotely sensed data is too coarse to resolve individual wetlands and is not often useful in wetland science. For example, 88 % of wetlands in the prairie pothole region of North Dakota are smaller than 0.4 hectares (Gilmer et al. 1980),thus, satellite imagery with a 30 meter pixel size (e.g., Landsat) cannot map these wetlands. Recent advancements in computer processing, sensor capability, and analytical techniques, coupled with wider availability of remotely sensed data of finer spatial, temporal, and spectral resolutions promise to broaden the applicability of remote sensing to wetland scientists and managers.

The trend towards hyper-resolution of remote sensing has always been part of the discipline; however, the aforementioned factors have recently accelerated this trend. Thus, Chambers et al. (2007) defined the term 'hyper' in remote sensing, where the spatial dimension is referred to as hyperspatial, spectral dimension as hyperspectral and temporal dimension as hypertemporal. Data that resolve differences in scene properties at a location separated by 1 meter or less, such as: aerial photography, aerial, terrestrial and mobile light detection and ranging (LiDAR), and multispectral satellite imagery (e.g., IKONOS and Quickbird) have been referred to as hyperspatial (Chambers et al. 2007; Greenberg et al. 2005; Turner et al. 2003).

Hyperspatial data can include historical black and white aerial photography, a temporally rich resource allowing for studies of change detection in wetlands. Although the historical frequency of hyperspatial data is not in the hypertemporal realm, the ability to look at landscapes as early as the 1930s is appealing and the data frequency can facilitate multitemporal analysis such as decadal change detection studies. Much of the historical hyperspatial aerial photography data are in the public domain making it an attractive choice to research projects struggling with funding limitations (Moskal et al. 2011). With the advent of hyperspatial data availability, new tools and methodologies for working with these types of data are necessary; moreover, it is important to understand how traditional per-pixel based techniques developed for coarse spatial resolution imagery (e.g., Landsat) can be applied to hyperspatial data. Therefore, we focus on hyperspatial resolution remote sensing application in wetland sciences.

We aim to introduce wetland practitioners to several cutting-edge remote sensing techniques now available; illustrate new innovative uses of these techniques by highlighting four case studies where hyperspatial techniques were employed; and finally to identify the unique abilities, challenges, and limitations of these remote sensing methods.

Specifically we present the following case studies:

- Mapping of an invasive wetland plant using pixel-based classification of hyperspatial-resolution aerial photography.
- Investigating historical changes to wetlands using Object-Based Image Analysis of hyperspatial-resolution aerial photographs with low spectral resolution.
- Mapping montane wetlands using Object-Based Image Analysis and aerial LiDAR.
- Mapping and monitoring intertidal microtopography using Terrestrial Laser Scanning.

Case Study 1: Using remote sensing to map Phragmites australis in Great Salt Lake wetlands

In this case study we used pixel-based classification (PBC) of hyperspatial multispectral aerial imagery to map the distribution of the invasive strain of the wetland grass *Phragmites australis* (herein *Phragmites*). *Phragmites* is a widespread invasive wetland plant across North America, with large populations in the northeast, great lakes region and areas in the west (Bourgeau-Chavez et al. 2012; Kettenring et al. 2012; Kulmatiski et al. 2011; Saltonstall 2002). It is a tall, clonal, perennial grass that creates dense monocultures, displaces beneficial native wetland vegetation, fragments marshes, and can reduce the quality of the habitat and ecosystem services provided by wetlands (Chambers et al. 2008; Silliman and Bertness 2004). *Phragmites* has become a major problem in the wetlands of the Great Salt Lake (GSL), Utah. Despite significant resources spent controlling this plant on public and private lands in Utah, the full extent of Phragmites around the GSL wetlands remains unknown (Kettenring 2012). Previous mapping efforts using field surveys and low-resolution air photos were outdated (2006), limited in extent and at a coarse resolution. *Phragmites*-dominated marshes are dense and difficult to walk through, making field surveys of *Phragmites* challenging. Additionally, these marshes are often hard to access due to deep water, water control structures, and land ownership issues. These reasons underscore the value of using remote sensing techniques to determine current extent of Phragmites around the lake.

Pixel Based Classification

Pixel based classification (PBC) of remote sensing imagery is one of the simplest, best understood, and most commonly used classification techniques for aerial imagery (Jones and Vaughn 2010), and has been used for a variety of wetland research applications. PBC classifies landscape features using their spectral signatures, the intensity of reflected and emitted radiation of different wavelengths. With coarser-resolution imagery, such as satellite imagery, PBC can often only classify vegetation types into broad categories. However, as finer-resolution multispectral aerial imagery becomes more available, PBC can be used to differentiate between wetland plant species.

With PBC, each pixel is assigned a class based on its spectral signature. We used supervised classification techniques, in which the user selects 'training pixels' of a known class type (e.g., *Phragmites* marshes). The computer then assigns each remaining pixel to the class of the training pixel of greatest spectral similarity.

Process

In May and June 2011, we acquired hyperspatial multispectral aerial imagery for all major wetland areas around the GSL. We used the Utah State University Remote Sensing Services lab Cessna TP206 aircraft, which is set up for remote sensing data collection, and collected imagery specifically for this project. Images are one-meter pixel resolution, with imagery in four spectral bands- red, green, blue, and near-infrared. We acquired data in late spring, an ideal time to identify *Phragmites* using remote sensing, because of the differences in growth stages between *Phragmites* and other wetland plants (Maheu-Giroux and Blois 2005; Neale et al. 2007).

Following image acquisition, we pre-processed the aerial images using ERDAS Imagine 2010 software ("Intergraph, Geospatial Operations, Norcross, GA). We identified training pixels from ground-truthed data by visiting major wetland units in the summer and fall of 2011, and again in the spring of 2012. We used PBC to classify vegetation into nine groups based on the dominant species and/or communities to determine the distribution of wetland plant species of interest: *Phragmites australis* (common reed), *Typha* spp. (cattail), *Distichlis spicata* (saltgrass), *Salicornia europeae* (pickleweed), *Schoenoplectus acutus* (hardstem bulrush), playa wetlands, native emergent wetland, upland, and open water. We used ground-truthed points that we had set aside and not used as training pixels to evaluate the accuracy of the classification.

Our vegetation map represents the most extensive and detailed mapping of *Phragmites* around the GSL to date. Our results indicate a substantial *Phragmites* invasion of key federal, state, and private wetland areas around GSL. Management of these wetlands for waterfowl habitat should benefit from our documentation of *Phragmites* distribution. We created an interactive online website that displays the imagery, and allows users to draw an area of interest and return the amount of *Phragmites* or other wetland vegetation in that area (http://maps.gis.usu.edu/gslw/index.html). The resulting vegetation data will also be used for future work to determine correlations between environmental and anthropogenic variables and the presence of *Phragmites*.

Considerations

Pixel-based classification and hyperspatial imagery offered a time and cost effective method for determining the extent of an invasive wetland plant that would have been difficult to survey in the field due to dense vegetation, varying water level and access issues from a patchwork of land ownership around the GSL. However, in our study there were several areas where management actions such as early season mowing, breached dikes, or previous herbicide applications caused classification errors. These areas were generally easily identifiable because of their large size, and were manually recoded based on verification from field visits, land manager information and aerial imagery. Despite these complications, using hyperspatial remote sensing to map wetland vegetation around the GSL proved to be a better solution for determining the current extent of *Phragmites* distribution as opposed to labor intensive comprehensive wetland field surveys. PBC was successful because we were able to acquire multispectral imagery at a high resolution. Hyperspatial multispectral imagery can be somewhat expensive to acquire, but is relatively efficient to process using PBC methods. While our aerial imagery was acquired specifically for this project, there are often publically available hyperspatial image datasets. For example, the state of Utah collects hyperspatial 4-band multispectral imagery every two to three years (Utah AGRC), and other states may have similar programs. More readily available, true-color aerial photographs do not allow for as much spectral differentiation, and would not work as well for differentiating between wetland species.

Case Study 2: Understanding historical ecology using aerial photographs and Object Based Image Analysis

In this study we sought to quantify long-term decadal changes in wetlands in a region of semi-arid sage shrub-steppe in eastern Washington State, and to understand how trends in the surrounding land uses influenced these wetlands. In the study area, conversions of the sage shrub to livestock grazing lands and agricultural uses over the past century have affected water resources, native plant species and wildlife habitats, generally leading to a decline in species populations (Foster Creek Conservation District 2013; Mitsch and Gosselink 2007). We hoped to identify areas where wetlands persisted and to identify the long-term factors that influenced them. However, understanding historical wetland conditions and identifying the drivers of wetland change across a large landscape can be challenging. Evidence of past conditions is often ephemeral, as when a wetland has been plowed over, or non-existent, because field data on wetland conditions were never collected.

Historical aerial photographs offer the unique opportunity to see and measure temporal changes in wetlands and the surrounding land uses. These photographs allow investigations into past wetland conditions before satellite imagery became available. They are available to the public from archives in governmental agencies and university libraries, at hyperspatial resolutions and at modest, if any, cost.

The limited spectral information contained in black and white historical aerial photographs and lack of near-infrared coverage, has limited their use to projects where manual photo interpretation and hand delineations were appropriate, for example, the National Wetland Inventory (NWI). In this case study we used Object-Based Image Analysis (OBIA) methods to develop a new way to use these historical images to quantify changes in wetlands. We combined our

OBIA classifications of wetland ponds and agricultural activities with County precipitation records and WA State Geographic Information System (GIS) geology layers to develop a more complete picture of the historic ecology of these wetlands.

Object-Based Image Analysis

Object-Based Image Analysis (OBIA) is a technique to derive "meaningful objects" from a raster dataset by delineating or classifying areas with similar characteristics (Blaschke 2010). These "objects" can range from features of interest in the landscape to critical medical anomalies in a tissue biopsy. OBIA differs from the traditional PBC technique in that it mimics human pattern recognition. The first step in an OBIA process is image segmentation, which aggregates pixels into objects based on their spectral similarities. After the initial segmentation by the computer, the human analyst begins an iterative and heuristic process to select spectral characteristics such as color as well as spatial characteristics such as shape and texture that will best classify the objects of interest. The analyst builds a unique computer algorithm, called a ruleset, using the characteristics that best separate the classes of interest. The primary differences between OBIA and PBC are the initial segmentation, and OBIA classification of multi-pixel objects as opposed to individual pixels.

Process

In this study, we classified the open water ponds and plowed agricultural fields in a 20,200 hectare study area, known as the channeled scablands. We used five sets of images: historic, black and white aerial photographs from 1955, 1965, 1978, and 1991, and true color National Agriculture Imagery Program (NAIP) imagery (red, green blue) from 2006 obtained through the USDA Farm Service Agency. This study focused on changes to wetland ponds during this time span. The ponds were classified as a central feature anchoring the seasonal wetlands surrounding them. The "plowed fields" classification defined a land use where the native sage and shrub-steppe vegetation had been completely destroyed, and land cover no longer had the surface hydrology and water infiltration characteristics of the native plant coverage (Figure 1).

Our approach mapped and quantified changing water resources and related wetland habitats across the landscape. It indicated influences on the variability of surface and ground water flows around the ponds from the nearby land uses and vegetation conditions. We also spatially correlated locations of ponds and wetlands that persisted and varied less through the decades with areas of intact native sage shrub-steppe vegetation. These persistent ponds and sage shrub habitats were underlain with thin basaltic soils, which are both less porous for ground water penetration, and historically have limited plowed agriculture.

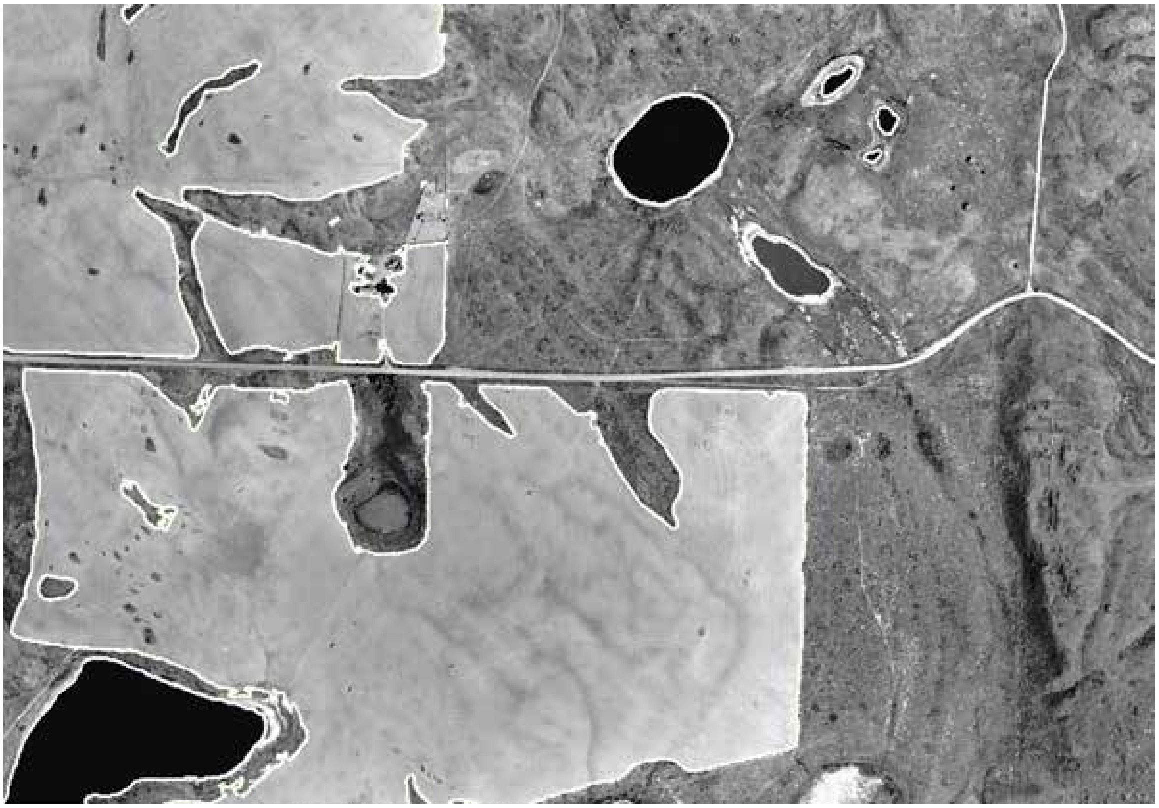

Figure 1: Black and white aerial photograph from 1955 showing high resolution of historical imagery with ponds and agricultural fields classifications.

Considerations

Although the classifications were limited to ponds and plowed fields in part due to the limits of the black and white imagery for this analysis, OBIA allowed historical aerial images to be used in a new way and to quantify wetland changes over a much longer period of time than previous work. Although the historical imagery provides only one band of image information with which to discern critical classification characteristics such as size, shape, texture and pattern, it often offers wetland researchers several additional dates of hyperspatial images for analysis. In contrast, though a full color infrared image will offer the analyst and the software red, green, blue, and infrared bands as well as the ratios between them with which to develop a classification algorithm; it may lack either the resolution or the historical reach needed to answer all research questions.

Challenges with using historical imagery include repurposing imagery that was originally taken for other goals, as well as finding archived imagery. These individual photographs required extensive preprocessing to standardize the gray-scale variability between images and then to mosaic the image tiles into a single raster for the complete study area.

Case Study 3: Mapping montane wetlands using Object-Based Image Analysis and aerial LiDAR.

Comprehensive wetland inventories are a necessary first step in protecting and preserving wetlands. The National Wetland Inventory (NWI), the most comprehensive wetland inventory in the U.S., was created by manual interpretation of hyperspatial aerial photos. In some areas the NWI can be used as a reliable source, while in other areas it is either out-of-date or inaccurate (Morrissey and Sweeney 2006; Tiner 1990). The accuracy of the NWI varies across the U.S., with omitted wetlands being particularly common in forested areas where the forested canopy obstructs the aerial view of the wetlands beneath (Morrissey and Sweeney 2006). This problem is exacerbated in areas that contain high densities of evergreens, as the persistent forest canopy never allows an unobstructed view of the ground. Additionally, tree canopy and complex topography create shadows that can impede the photograph interpreter's view of wetlands.

Previous research mapping wetlands in eastern Washington proved OBIA to be an accurate (overall accuracy was 89 %), yet affordable technique to automate mapping of semi-arid wetlands (Halabisky et al. 2011); however, this project focused on non-forested areas. To adapt this method to map wetlands in forested and mountainous areas with steep topography and tree canopy, we used data products derived from aerial LiDAR and combined them with aerial imagery and thematic data to map wetlands in Mt. Rainier National Park.

Aerial LiDAR

LiDAR is an active remote sensor that emits laser light toward a target and measures its return time to the sensor. Using this information the sensor is able to record a three-dimensional coordinate of the objects that the laser light hits. Scanning a surface with LiDAR produces a cloud of such coordinates, known as a point cloud. LiDAR allows the analyst to identify wetlands that would otherwise be obscured by trees or shadows.

Typically LiDAR is delivered to a researcher as three unique data products; a ground model, a canopy surface model, and an intensity image. Raw data are also delivered, and should be archived as future processing and algorithms can improve the applicability of the data. The ground model provides hyperspatial detail of the topography. In our instance, we were able to detect even the decimeter-scale changes in elevation surrounding small ponds within our study area. A canopy surface model provides a surface of the highest objects in the scene (e.g., tree canopy). Finally, an intensity image provides the intensity of the reflected laser energy, which is typically an infrared wavelength. This intensity varies across a landscape as the laser pulses come in contact with different materials. The patterns evident within intensity images can be used to identify wetlands. Because water absorbs light energy it often has low intensity values or will even contain “no data” if the light is fully absorbed by water. On the other hand, wetlands that do not have standing water during the time of LiDAR acquisition may highly reflect infrared light due to the presence of photosynthetic wetland vegetation.

Process

In addition to the LiDAR data products available to us, we created several data layers to assist with the classification. We used the LiDAR ground model to create a slope index to help us highlight areas of low or no slope and a canopy height model, by subtracting the LiDAR ground model from the canopy surface model, which helped us to detect wetlands with low or no vegetation.

To map wetlands within our study area we analyzed the ground model, canopy surface model, canopy height model, intensity image, aerial imagery, and GIS layers of park roads and trails. We used OBIA to segment an image composed of the aforementioned data, and then created and applied an object classification rule set to delineate and classify wetlands in the study area. Not only could we detect substantially more wetlands than the NWI, we could also produce a finer, more accurate delineation (Figure 2).

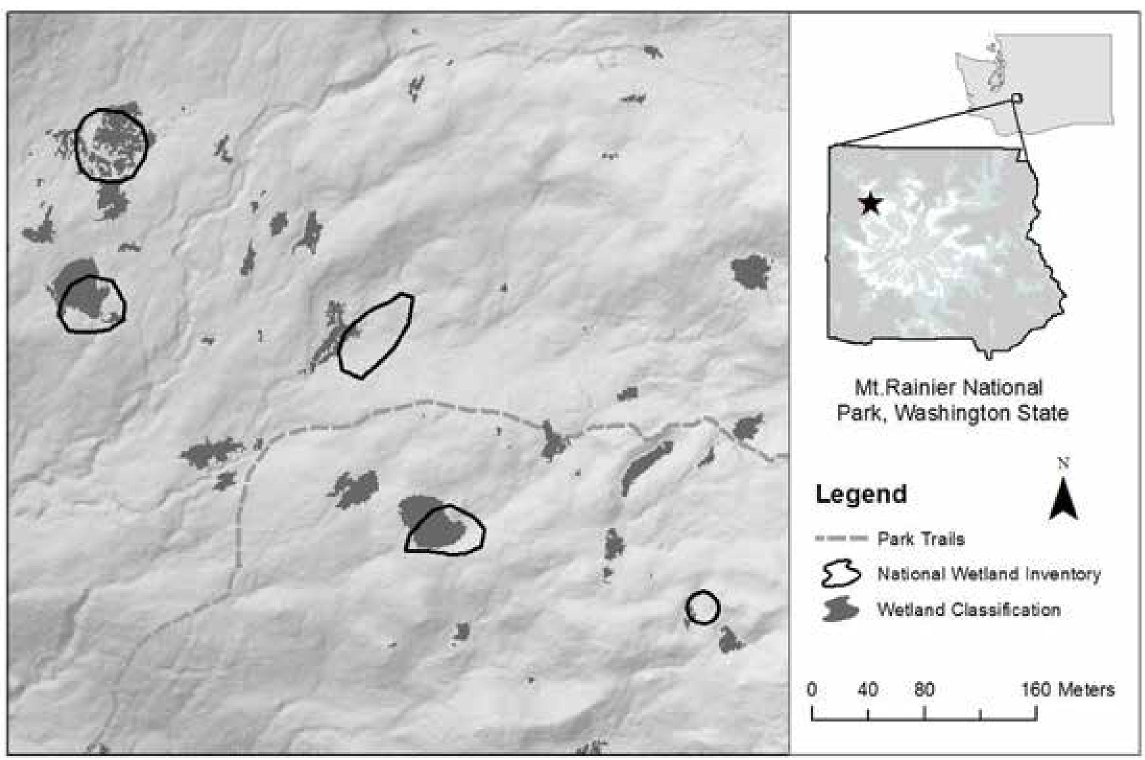

Figure 2: Comparison of the National Wetland Inventory to semi-automated classification of montane wetlands using LiDAR and OBIA.

OBIA software programs, such as eCognition (Trimble Navigation, Ltd, Sunnyvale, CA), allow the user to detect patterns within multiple data inputs. This can improve upon photo interpretation because it allows identification of patterns that might otherwise be hard to detect manually from so many different data layers. This was helpful for our project which incorporated many data input layers describing wetland characteristics such as slope and canopy height.

Some challenges inherent in LiDAR analyses result from the technology's relative youth. LiDAR intensity data commonly fluctuates across a scene due to internal sensor errors, rather than actual target properties. Recent advances allow normalization of LiDAR intensity across a LiDAR acquisition (Vain and Kaasalainen 2011), but such data are not yet commonly available. Intensity values cannot be easily used to detect more subtle patterns such as specific vegetation communities or individual plant species because few datasets are normalized.

When studying forested areas, LiDAR data must be acquired at a high enough density to penetrate the forest canopy. Low-density LiDAR, typically acquired for topographic applications, will be unable to detect forested wetlands as the laser will be unlikely to reach the ground below the canopy. Thus, as with the decadal aerial photography change analysis, one can find challenges using data collected for a different application.

An additional challenge is that the output dataset from an OBIA process delineates the pixel edges, creating highly detailed wetland polygons with many vertices. This differs from manual delineation, which simplifies the wetland border, using significantly fewer vertices. Although the increased detail provided by OBIA is usually more accurate, it creates a large and unwieldy dataset that can be difficult to display in GIS. Finally, although this technique can be more cost effective than manual photo interpretation, the high cost of both LiDAR data acquisition and OBIA software programs, and the computational hardware requirements, limit their availability to many users.

Case Study 4: Terrestrial Laser Scanning of Intertidal Habitats

Intertidal estuarine topography, even at centimeter to decimeter scales, can profoundly affect biological communities by affecting local tidal inundation patterns and temperature (eg., Garrity 1984), but it is particularly difficult to measure. Soft, unconsolidated sediment hinders direct measurement both by limiting travel, and by making it difficult to measure elevations without disturbing or compacting sediments. Unfortunately, remote measurements are also problematic. Conventional aerial LiDAR data must be obtained during a low tide (e.g., Chust et al. 2008), which precludes the use of much readily-available LiDAR data. Even during a low tide exposure, standing water and saturated soils reduce the efficacy of the infrared lasers used in most aerial LiDAR applications. The shallow water depth at such locations inhibits sonar surveys.

Terrestrial Laser Scanning (TLS), also known as ground-based LiDAR, may potentially overcome some of the aforementioned challenges to topographic measurement in estuarine wetlands. These tripod-mounted instruments are capable of mapping surfaces with sub-centimeter precision (Vierling et al. 2008). Just as aerial LiDAR, TLS measures the time of flight of emitted laser pulses to create three dimensional point clouds of a surface (Figure 3). With this technique, sediment disturbance can be limited to the scanner location while remotely measuring undisturbed areas.

Process

An invasive, intertidal seagrass, *Zostera japonica*, appears to be influenced by centimeter-scale topography when growing alongside its native congener, *Zostera marina* (Shafer 2007). To elucidate this relationship, we first sought to quantify the relationship between local microtopographic relief and cover of these two species. Second, we sought to quantify spatiotemporal variability in the patterns of intertidal microtopographic relief at the study site.
We created fine scale topographic maps, digital elevation models (DEMs), of the study site from TLS surveys over three years. From these DEMs, we calculated a Bathymetric Position Index (BPI), a scalable index of topographic

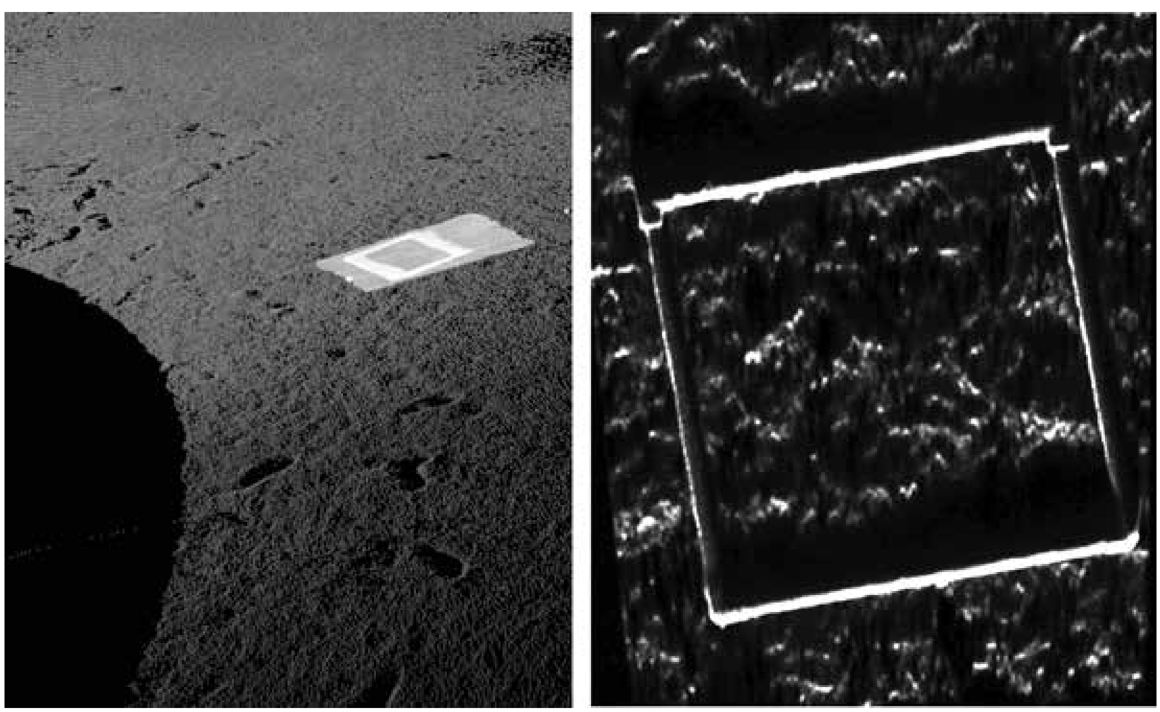

Figure 3: Example of TLS scan data. Note that the scan resolves footprints in left panel. The right panel shows a close up intensity image of a 0.5 meter X 0.5 meter PVC quadrat.

position (Lunblad 2004). With the DEMs and BPI maps, we examined the relationships between microtopographic setting and species cover, and investigated temporal changes in site topography.

During each mapping visit at our study site, we conducted multiple TLS scans from different vantage points to extend the spatial extent of our study area. Multiple stationary, reflective targets placed in the study site provided common spatial landmarks for subsequently combining scan data. We georeferenced scans by taking kinematic Global Positioning System (GPS) measurements at each reflective target during each survey.

Considerations

Despite the logistical challenges of managing the equipment required for TLS surveys in soft sediment intertidal environments, we could relate species cover to centimeter scale topographic relief at the site.

TLS data acquisition may be limited by characteristics of the landscape, and by characteristics of the instrument. Intertidal mudflats are characteristically wet, and periodically submerged. Although saturated sediments did not inhibit data acquisition in this study, standing water did. Pools of standing water greatly reduced TLS return density, and introduced occasional reflection artifacts.

A common instrument-specific limitation of TLS is its stationary tripod mount. Scanner height limits data acquisition because of its fixed vantage point. Data-point spacing increases as target range increases because the vertical and horizontal angle between successive scan lines is fixed within a scan. This limited our useful scan radius to approximately 50 meters. Some researchers have extended the useful range of scans by elevating the scanner to considerable heights above the sediment surface (e.g., Anderson et al. 2009).

Another challenge presented by the TLS vantage point is shadowing created by topography, or erect vegetation. Although shadowing was nonexistent in our application because of the gentle nature of site topography and the lack of erect vegetation, it could pose a serious challenge in densely vegetated sites (Anderson et al. 2009). To overcome this challenge, the researcher may increase the point density of scans to penetrate more vegetation gaps, and scan from multiple vantage points.

Quantification of temporal change in microtopography proved more difficult than relating species to topography. Quantification of temporal change requires the spatial alignment of scans from different dates. This may be done by creating persistent, stable landmarks in the study area that can be referenced at different survey dates, or by georeferencing scans from different dates with GPS, as we did. The dynamic nature of an intertidal environment makes the former approach challenging, although permanent monuments can be created in tidelands (Boumans 1993). GPS was our greatest source of positional error in our workflow. Longer GPS observations should yield some improvement in GPS, error, but the tidal regime and security of a study site will determine the feasibility of this approach.

Perhaps the greatest challenge of many TLS-based studies is determining how to use the acquired data. A "shoot first and ask questions later" approach will likely cause frustration. TLS data are dense and detailed (Figure 3), and a researcher must first plan on how to extract useful summaries or measurements from the data. This can be both a conceptually and practically difficult problem.

Discussion

Hyperspatial remote sensing promises to provide wetland scientists and managers with data at spatial scales that are relevant to wetland issues. Like traditional satellite based remote sensing, hyperspatial remote sensing allows for non-destructive sampling, measurements of great spatial extent, and investigation of locations that are difficult to access in person. Hyperspatial remote sensing and the new analysis techniques that accompany it additionally provide unique opportunities and unique challenges to those who employ them.

By virtue of the finer spatial detail afforded by hyperspatial remote sensing, the size of objects that can be detected and mapped has decreased, sometimes enough to resolve individual study organisms. Improved resolution allows the study of smaller wetlands, which are both numerous, and perhaps more vulnerable than larger wetlands (Tiner 2003). Although the spatial resolution of data has grown finer, the spatial extent remains broad. This wealth of data allows for multi-scale investigations of ecological phenomena.

The fine spatial resolution of hyperspatial remote sensing data is a double-edged sword. Increased information density yields novel insight, but requires greater storage capacity and processing power, and often more complex analyses. For example, an aerial image with a 1 meter pixel resolution is more than 300 times larger than one with the 30 meter per pixel resolution typical of most Landsat satellite imagery (Table 1). These large file sizes result in time-consuming computationally expensive processing. While continuing improvements in computational ability and data storage will ameliorate one aspect of the problem, file size is not the only challenge of too much information

The great detail in hyperspatial data includes information irrelevant to the investigator. Hyperspatial aerial photography resolves shadows that would be averaged in a 30 meter pixel. This kind of detail often necessitates more complex analytical procedures such as OBIA. TLS data may map every limb of

Data Type	File Size/ Hectare	Spatial Resolution/ Spatial Extent	Strengths	Weaknesses
Hyperspatial Data				
Black and white aerial photography	~140 kb	0.25m/varies based on camera type and flight parameters	Inexpensive to acquire, historical coverage as early as the 1930's	Spectrally limited, rarely acquired after year 2000
True color aerial photography	~38 kb	1m or finer	Publicly available imagery	Radial distortion, not radiometrically standardized
Multispectral aerial imagery	~250 kb	1 m/ based on camera and flight parameters; example: 50 km2 at 1:30,000 scale	More spectral bands than true color photographs	Sometimes expensive to acquire
Aerial LiDAR	~5 MB	Variable, but mostly 1 m to sub m, flight swaths cover up to 500 m	Provides 3-D data. Not impacted by shadows	File size, not always available
TLS	~ 200 MB	Variable, can be sub-centimeter and cover areas as large as 20 m radius	Fine spatial resolution	File size, acquisition logistics, issues with occlusion
Multispectral Satellite Imagery				
Example: Landsat	~114 b	30 m/~185 km2	Widely available, free to download, global coverage, historical coverage	Low spatial resolution
Example: IKONOS	~300 kb	1m to 4m/11 km2	Widely available, free to download, global coverage, historical coverage	Availability varies

Table 1: Comparison of file size, spatial resolution and potential value of hyperspatial remotely sensed data. Landsat and IKONOS are included for comparison.

a tree (Moskal and Zheng 2011) or individual blades of a sedge (Moskal and Zheng 2012). Such detail requires data summary, just as plot-based surveys summarize vegetation for a site. It is imperative for a researcher to have a hypothesis and an analytical plan before beginning to collect these data.

PBC can be a time and cost-effective option for classification of high resolution remote sensing imagery. PBC is one of the most well-known and straight-forward ways of classification of hyperspatial imagery. PBC can be an especially good option for institutions and agencies that focus most of their analysis in GIS software, as the method can be implemented in GIS such as ArcGIS 10.0 (ESRI, Redlands, CA) without requiring a separate software package or more expensive programs such as ERDAS Imagine. Furthermore, spatial features implemented in OBIA analysis can, to some extent, be utilized in PBC with the implementation of texture (Franklin et al. 2000). Additionally, there are open source software options for PBC such as GRASS (GRASS Development Team 2012) and MultiSpec (Purdue Research Foundation 2011).

Hyperspatial resolution tends to come at a penalty to the other resolution dimensions applicable in remote sensing: the spectral and temporal. Although many hyperspatial sensors are also multispectral (collecting four or more wide spectral bands), there are only a few hyperspatial sensors capable of collecting hyperspectral data (data collected at 10 nanometer or finer spectral increments). Such data availability is only a recent development and very costly, especially for repetitive (temporal) observations. Although hyperspectral data are often utilized to determine vegetation species composition, and could be a useful indicator related to ecological condition of wetlands; few studies have employed this technology to study wetlands (but see Adam et al. 2009; Hestir et al. 2008).

Finally, some satellite hyperspatial data does not easily allow for repeat coverage at ‘hyper’ frequencies, such as the daily or better coverage defined by Chambers et al. (2007), or long term bi-weekly satellite imagery such as Advanced Very High Resolution Radiometer (AVHRR) or Moderate-Resolution Imaging Spectroradiometer (MODIS) satellites, due to the orbit characteristics of the sensors. However, aerial platforms, including non-traditional platforms such as: kites, blimps, balloons and drones, can provide for such frequencies, at costs much lower to the traditional aerial platforms such as a fixed-wing aircraft and helicopter. For example, open technology and science initiatives such as “The Public Laboratory” (cite: http://publiclaboratory.org) are leading the incorporation of the public remote sensing community by collecting near-infrared remote sensing data with alternative aerial platforms. Although the data collected have pixel sixes of much less than 1 meter, and can be deployed by the user at any time, the technical aspects of processing such data and acquiring it at large spatial extents are a technological challenge, but this is also being tackled by the community.
The temporal resolution of these data make them suitable for understanding wetland function, unfortunately, the coarse spectral and spatial resolution of these data has limited such research. As new remote sensing platforms such as unmanned aircrafts and webcams become cheaper and more common, these could revolutionize wetland observations the way wireless sensor networks and iButtons have changed *in-situ* field data collection.

Conclusion

The advances in high-resolution, and specifically hyperspatial remote sensing, computational power, and analytical techniques promise great improvements in the inventory, monitoring, and study of wetlands and wetland-related species. The applications of these technologies, only a few of which we have outlined here, could be useful to wetland research and management in a variety of ways. However, wetland researchers and managers should be aware of the benefits and limitations of each method. Using hyperspatial remote sensing can be extremely useful in wetland management, given the capacity to monitor large spatial extents with often incredible detail, and ability to monitor areas that are difficult to access, which is commonly an issue with wetlands. However, cost of data acquisition and processing may limit the practicality of these techniques in some cases. Presently, mapping and studying of wetlands through the use of hyperspatial data is typically a secondary use and not the primary reason for hyperspatial data acquisition. Researchers and managers should take into account the spatial extent of the study area, project budget, and resolution needed on a case-by-case basis.

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Author Contributions

Michael Hannam helped conceive of the paper and orchestrate the collaborative effort. Meghan Halabisky, Michael Hannam, and A. Lexine Long contributed to the introduction and conclusion. Meghan Halabisky wrote the case study mapping montane wetlands using LiDAR and OBIA, Michael Hannam wrote the terrestrial laser scanning case study, A. Lexine Long wrote the pixel based classification case, and Chris Vondrasek wrote the historical aerial photography case study. L. Monika Moskal assisted in the writing of the introduction and conclusions as well as advised and supported the authors on three of the four case studies.

Glossary

Classification: To arrange into classes according to shared characteristics; an analyst-defined system or order for describing distinct features (such as wetland types, land uses, location of patches of similar vegetation).

Hyperspatial: Data that resolves differences in scene properties at a location separated by 1 meter or less.

Multispectral: Imagery capturing data at frequencies across the electromagnetic spectrum, including light from frequencies beyond the visible range (red, green, blue).

Pixel based classification: A remote sensing method which classifies objects using their spectral signatures, the intensity of reflected and emitted radiation of different wavelengths. Each pixel is assigned a class by matching the spectral signature that mostly closely matches each class.

Object-based image analysis (OBIA): A technique to classify objects based on shared spectral, spatial, and contextual properties. OBIA differs from the traditional PBC technique in that it mimics human pattern recognition and allows for additional object features, not just spectral information.

LIDAR: "Light Detection and Ranging" or "Laser Imaging Detection and Ranging" is an optical remote sensing technology. It is an active remote sensor that emits laser light toward a target and measures its return time to the sensor. Using this information the sensor is able to record a three-dimensional coordinate of the objects that the laser light hits. As an active remote sensor LIDAR differs from a passive remote sensor (such as aerial photography) because it measures light that is provided directly from the sensor rather than reflected sunlight.

References

Adam, E., O. Mutanga, and D. Rugege. 2009. Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review. Wetlands Ecology and Management 18: 281–296.

Anderson. K., J. Bennie, and A. Wetherelt. 2009. Laser scanning of fine scale pattern along a hydrological gradient in a peatland ecosystem. Landscape Ecology 25: 477–492.

Blaschke, T. 2010. Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing 65: 2–16.

Boumans, R. 1993. High precision measurements of sediment elevation in shallow coastal areas using a sedimentation-erosion table. Estuaries: 375–380.

Bourgeau-Chavez, L. L., K. P. Kowalski, M. L. Carlson, K. A. Scarbrough, R. B. Powell, C. N. Brooks, B. Huberty, L. K. Jenkins, E. C. Banda, D. M. Galbraith, Z. M. Laubach, and K. Riordan. 2012. Mapping invasive Phragmites australis in the coastal Great Lakes with ALOS PALSAR satellite imagery for decision support. Journal of Great Lakes Research, 2012, doi: 10.1016/j.jglr.2012.11.001.

Chambers, J. Q., G. P. Asner, D. C. Morton, L. O. Anderson, S. S. Saatchi, F. D. B. Espírito-Santo, M. Palace, and C. Souza. 2007. Regional ecosystem structure and function: ecological insights from remote sensing of tropical forests. Trends in Ecology & Evolution 22: 414–23.

Chambers, R. M., K. J. Havens, S. Killeen, and M. Berman. 2008. Common reed Phragmites australis occurrence and adjacent land use along estuarine shoreline in Chesapeake Bay. Wetlands 28: 1097–1103.

Chust, G., I. Galparsoro, Á Borja, J. Franco, and A. Uriarte. 2008. Coastal and estuarine habitat mapping, using LIDAR height and intensity and multi-spectral imagery. Estuarine, Coastal and Shelf Science 78: 633–64.3

ERDAS, Inc, Erdas Imagine. 2010. Intergraph, Geospatial Operations, Norcross, GA.

ESRI. 2011. ArcGIS Desktop 10.0. Environmental Systems Research Institute, Redlands, CA.

Foster Creek Conservation District. 2013. Douglas County multi species general conservation plan.

Franklin, S. E., R. J. Hall, L. M. Moskal, A. J. Maudie, and M. B. Lavigne. 2000. Incorporating texture into classification of forest species composition from airborne multispectral images. International Journal of Remote Sensing 21: 61–79.

Garrity, S. D. 1984. Some adaptations of gastropods to physical stress on a tropical rocky shore. Ecology 65: 559–574.

Gilme,r D.S., E. A. Work, J. E. Colwell, and D. L. Rebel. 1980. Enumeration of prairie wetlands with Landsat and aircraft data. Photogrammetric Engineering and Remote Sensing 46: 631–634.

GRASS Development Team. 2012. Geographic Resources Analysis Support System (GRASS GIS) Software. http://grass.osgeo.org.

Greenberg, J. A., S. Z. Dobrowski, and S. L. Ustin. 2005. Shadow allometry: Estimating tree structural parameters using hyperspatial image analysis. Remote Sensing of Environment 97: 15–25.

Halabisky, M., L. M. Moskal, and S. A. Hall. 2011. Object-based classification of semi-arid wetlands. Journal of Applied Remote Sensing 5:13.

Hestir, E. L. , S. Khanna, M. E. Andrew, M. J. Santos, J. H. Viers, J. A. Greenberg, S. S. Rajapakse, and S. L. Ustin. 2008. Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. Remote Sensing of Environment 112: 4034–4047.

Jones, H.G., and R. A. Vaughn. 2010. Remote Sensing of Vegetation: Principles, Techniques, and Applications. Oxford University Press.

Kettenring, K.M. 2012. Management of Phragmites in the Great Salt Lake watershed. Final report to Utah Department of Natural Resources, Division of Forestry, Fire & State Lands.

Kettenring, K. M., S. de Blois, and D. P. Hauber. 2012. Moving from a regional to a continental perspective of Phragmites australis invasion in North America. AoB Plants, 2012.

Kulmatiski. A., K. H. Beard, L. A. Meyerson, J. R. Gibson, and K. E. Mock. 2011. Nonnative Phragmites australis invasion into Utah wetlands. Western North American Naturalist 70: 541–552.

Lunblad, E. R. 2004. The development and application of benthic classifications for coral reef ecosystems below 30 m depth using multibeam bathymetry: Tutuila, American Samoa. Oregon State University.

Maheu-Giroux M., and S. de Blois. 2005. Mapping the invasive species Phragmites australis in linear wetland corridors. Aquatic Botany 83: 310–320.

Mitsch, W. J., and J. G. Gosselink. 2007. Wetlands. John Wiley & Sons, New York.

Morrissey, L. A., and W. R. Sweeney. 2006. Geographic Information Systems and Water Resources IV 2006 AWRA Spring Specialty Conference May 8-10 , 2006. Pp. 1-6 In Assessment of the National Wetlands Inventory: Implications for Wetland Protection.

Moskal, L. M., D. M. Styers, and M. Halabisky. 2011. Monitoring urban tree cover using object-based image analysis and public domain remotely sensed data. Remote Sensing 3: 2243–2262.

Moskal, L. M., and G. Zheng. 2012. Retrieving forest inventory variables with terrestrial laser scanning (TLS) in urban heterogeneous forest. Remote Sensing 4: 1–20.

Neale, C. M. U., D. Wenger, H. Jayanthi, and F. Farag. 2007. Mapping and monitoring wetlands using airborne multispectral imagery. Water Research: 100–109.

Ozesmi, S., and M. Bauer. 2002. Satellite remote sensing of wetlands. Wetlands Ecology and Management 10: 381–402.

Pengra, B., C. Johnston, and T. Loveland. 2007. Mapping an invasive plant, Phragmites australis, in coastal wetlands using the EO-1 Hyperion hyperspectral sensor. Remote Sensing of Environment 108: 74–81.

Purdue Research Foundation. 2011. MultiSpec 9.2.11, Purdue Research Foundation, West Lafayette, Indiana.

Saltonstall, K. 2002. Cryptic invasion by a non-native genotype of the common reed, Phragmites australis, into North America. PNAS 99: 2445–2449.

Shafer, D. J. 2007. Physiological factors influencing the distribution of the non-indigenous seagrass Zostera japonica along the pacific coast of North America. University of South Alabama.

Silliman, B., and M. Bertness. 2004. Shoreline development drives invasion of Phragmites australis and the loss of plant diversity on New England salt marshes. Conservation Biology 18: 1424–1434.

Tiner, R. 1990. Use of high-altitude aerial-photography for inventorying forested wetlands in the United-States. Forest Ecology and Management 33: 593–604.

Tiner, R. W. 2003. Geographically isolated wetlands of the United States. Wetlands 23: 494–516.

Trimble. 2011. eCognition Trimble Navigation, Ltd, Sunnyvale, CA.

Turner, W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling, and M. Steininger. 2003. Remote sensing for biodiversity science and conservation. Trends in Ecology & Evolution 18: 306–314.

Vai,n A., and S. Kaasalainen. 2011. Correcting airborne laser scanning intensity data. In: Laser Scanning, Theory and Applications. InTech.

Vierling, K. T., L. A. Vierling, W. A. Gould, S. Martinuzzi, and R. M. Clawges. 2008. Lidar: shedding new light on habitat characterization and modeling. Frontiers in Ecology and the Environment 6: 90-98.

Zheng, G. and L.M. Moskal. 2012. Leaf orientation retrieval from terrestrial laser scanning data. IEEE Transactions on Geoscience and Remote Sensing 50: 3970-3979.