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PERSPECTIVES AND OPPORTUNITIES OF USING DIFFERENT REMOTE SENSING PRODUCTS IN MONITORING OF ECOLOGICAL INDICATORS IN WETLAND AND RIPARIAN ECOSYSTEMS

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Applications of remote sensing data from satellite, aerial and unoccupied instrument platforms have been rapidly growing in different areas of ecological monitoring. Coverage of large spatial extents and possibility of repeated observations make this technology cost-effective compared to extensive field surveys. Opening access to some of the global satellite archives (such as Landsat [1]) as well as advances in open-access image processing platforms, such as Google Earth Engine [2] have made these opportunities more accessible and computationally efficient for a wide range of users. This potential is of special interest to ecosystems with high biodiversity potential but difficult field access and sensitive, heterogeneous environments, such as wetlands and riparian systems, which have been globally threatened and disappearing at alarming pace [3]. However, wetland monitoring efforts have been somewhat slow to adopt remote sensing-based monitoring and incorporate these novel possibilities on a regular basis [4,5]. The purpose of this paper is to review the key remaining challenges presenting major “bottlenecks” in wetland remote sensing analyses and to discuss how they can be addressed using some of the recent methodological and technological innovations to support monitoring of these complex environments.

Remote sensing applications in wetlands and riparian systems to date have enabled a wide suite of ecological indicators [4,6,7], some of which are based on the “raw” spectral reflectance values as fingerprint of landscape properties and vegetation status, while others are derived by mapping, i.e., computer-based classification of wetland surfaces into landscape cover categories or vegetation types of interest. The latter efforts are of particular interest to this review because they create unique possibilities to not only delineate wetland ecological zones and habitats, but also measure their size, shape, connectivity and various other metrics relevant to ecological modeling, management and planning [5]. However, unique ecological properties of wetland and riparian systems as land-water ecotones pose several challenges to their mapping from remote sensing data, limiting the overall use of this cost-effective technology in wetland planning, management and conservation. The structure of wetland landscape surfaces is often heterogeneous due to vegetation zonation and presence of fine-scale microtopographic and hydrological gradients. Sparseness of vegetation cover and hydrological attenuation due to flooding can make spectral reflectance less representative of the target landscape categories and reduce their mapping accuracies. Finally, wetlands with periodic or seasonal flooding can change dramatically in their landscape properties over the course of a year and exhibit transitional states over vast portions of their extent. This makes it hard to delineate wetland cover types using 'traditional', static definitions and may call for alternative classification schemes, such as dynamic categories representing characteristic change regimes rather than static classes [8].

Historically, these challenges have been also aggravated by limited access to high spatial resolution imagery, while more accessible medium- to coarser-resolution products (such as 30m Landsat data) cannot adequately represent wetland cover type boundaries and patch geometry (Fig.1). Not surprisingly, mapping studies in wetlands have reported fairly low accuracy both for the overall outcome and individual cover types, or "classes" (often falling below the conventional standard of 85% [9]). These mapping challenges translate into operational barriers and limited ability to understand and interpret wetland change as well as to inform management and planning action based on the spatial information provided by the classification results.

Another suite of important difficulties arises for validation of mapping outcomes in wetlands and computing mapping accuracy. Traditional approaches to mapping accuracy assessment ideally require sufficiently large and representative "test" samples of targeted cover type classes, and such samples should be different from "training" samples used by "supervised" classification algorithms [9]. However, wetland areas can be extremely difficult to access and survey in the field due to impenetrable site conditions, dense vegetation, and the need to minimize human disturbance of sensitive species and habitats. This may effectively restrict both the spatial scope of field surveys and representativeness of the field observations for quantitative validation of mapping results. Furthermore, smaller size of test sample sets increase the cost of test sample misclassification for the overall accuracy metrics [9].

a. **b.** **c.**

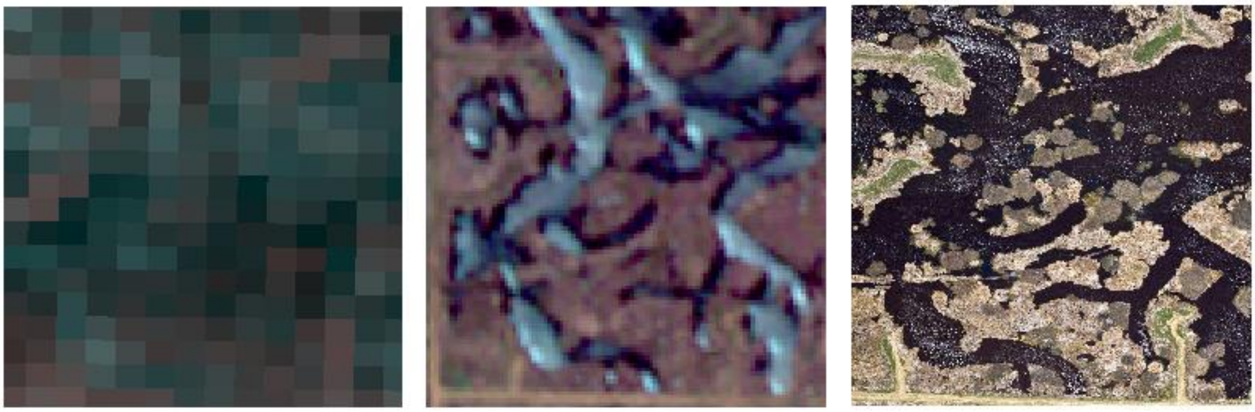

Figure 1. The effect of image spatial resolution on representation of a patchy wetland surface: a) Landsat satellite image (30m), b) RapidEye satellite image (5m), c) aerial photo (0.15m).

Many of these limitations have been somewhat alleviated by advances in higher spatial resolution image products (Fig.1), where smaller dimensions of image pixels provide a closer match to ground entities and their boundaries, such as complex wetland patches. Historically, high-resolution products have been available largely as on-demand aerial photography or commercial satellite imagery with high cost and inconsistent revisiting, making them unfeasible for repeated monitoring. More recently, new opportunities have emerged for higher-resolution satellite-based datasets with high (~3-5 day) revisit frequency, such as open-access Sentinel-2 (part of the Copernicus program by the European Satellite Agency with some products as low as 10m in spatial resolution) and commercial PlanetLabs (based in the USA, products ≤5m spatial resolution). Finally, unoccupied aerial vehicles (UAVs, also broadly referred to as drones) have revolutionized the local-scale imaging applications [10], providing unprecedented levels of spatial detail and customization flexibility for wetland monitoring at the site level [11]. In addition to novel capacity for detailed wetland mapping, high level of visual recognition in UAV data provides an alternative form of ground truth to increase sampling coverage of wetland sites without expanding the field surveys on the ground [11].

However, high spatial resolution brings its own suite of challenges to the mapping workflow, which become especially obvious in the heterogeneous setting of wetland and riparian landscapes. With finer scale of pixels as "minimum mapping units" (particularly at sub-meter resolution of UAV images), their dimensions become much smaller than the landscape entities they are supposed to represent (e.g., water bodies, vegetation patches, and similar). As such, they become much more likely to capture local variability in color, illumination, shadows and spatial detail that may not be of primary interest to mapping and, in fact, might increase the risk of land cover type confusions by mapping algorithms [7] and the infamous "salt and pepper" speckle in image classification outputs. Resolving this problem may be especially difficult when data are limited in spectral information; for example, a number of commercial high-resolution satellite platforms (such as IKONOS, QuickBird, or Pleiades) collect the data largely in broadband visible and near-infrared electromagnetic regions. Similarly, UAV instruments that are more affordable and practical for hazardous wetland setting often use cameras operating in red, green and blue (RGB) regions that have limited sensitivity to nuances among wetland vegetation types and heterogeneous surfaces [11]. As a result, limited spectral richness may present barriers for distinguishing highly nuanced wetland classes such as vegetation community types, particularly with traditional mapping algorithms relying on spectral means and variances of class samples for their discrimination from the images [12].

Overcoming these uncertainties requires updating image classification workflows in a way that take a fuller advantage of the progress in both remote sensing data and image processing tools. Given the wetland-specific mapping challenges discussed above, three areas of intervention are especially important: 1) **informing the choice of input images** to facilitate class discrimination even with spectrally limited products; 2) **modifying minimum mapping units** to increase signal-to-noise ratio and reduce the salt-and-pepper effect; and 3) **revisiting the choice of classification (mapping) algorithms** to enhance class recognition. Most importantly, these measures should be considered together as complementary opportunities that can be integrated in the same workflow.

The choice of input images is critical for classification success because if wetland cover types or vegetation categories are too spectrally similar, they can be hard to distinguish even with the most sophisticated mapping algorithms. However, spectral similarity may change during the course of the year based on vegetation phenology and wetland hydrological cycles. Thus, one of the key ways to improve class discrimination from spectrally limited data is by strategically choosing image dates maximizing contrasts among different classes (Fig.2). This task can be greatly facilitated by using open-access satellite time series computing cloud-based processing tools such as Google Earth Engine [2]. Using satellite time series to determine suitable time windows can be also helpful in planning UAV flights to reduce their logistical burden and optimize the number of flights efficiently [11,12].

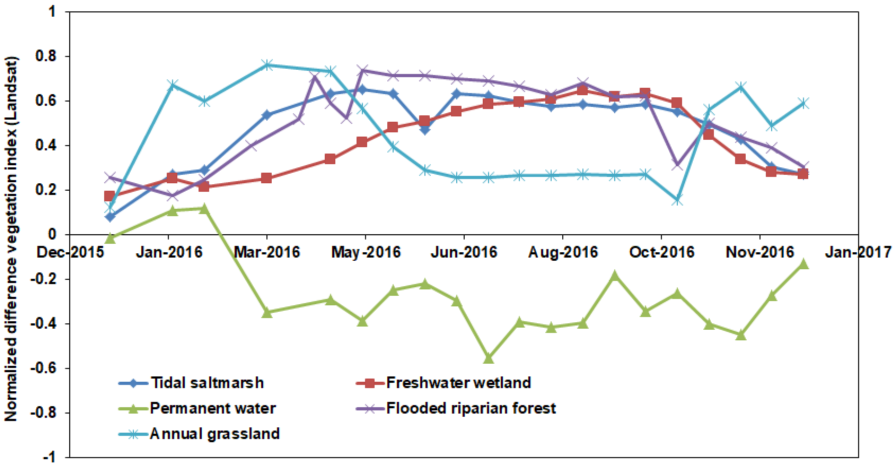

Figure 2. Example of seasonal variation in the indicator of vegetation greenness, Normalized Difference Vegetation Index, computed from Landsat data for pixels representing different landscape types in California, USA's San Francisco Bay-Delta estuary.

The choice of minimum mapping units is another important consideration in wetland mapping, where traditionally used pixels have been criticized for insufficient representation of class contrasts in heterogeneous wetland setting and excessive local spectral variability reducing the quality of mapping [7,8]. An extremely promising methodology to overcome these challenges is the object-based image analysis (OBIA) which instead of pixels uses small multi-pixel image regions, or "objects", as minimum mapping units [7,14]. In OBIA workflows, objects are first delineated from the raw imagery using some of the many available image segmentation methodologies, and then classified into target landscape categories using the same types of algorithms as in pixel-based analyses – from stepwise threshold-based workflows to supervised algorithms utilizing training samples of classes for classification decisions. Two major advantages of OBIA in wetland setting are: 1) the possibility to reduce spectral noise by averaging spectral information at the object (image region) level (Fig.3), and 2) the opportunity to include not only spectral values, but also object shape, internal spectral variability (texture) and contextual attributes (e.g., spatial relationships with other objects or classes) as a basis for distinguishing landscape classes.

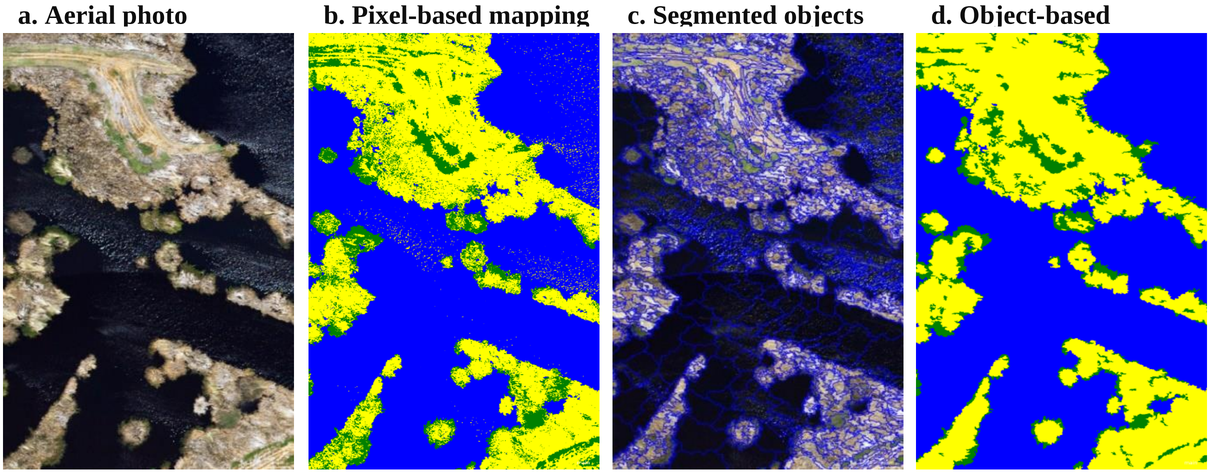

Figure 3. Example of a pixel-based and object-based wetland mapping from high-resolution imagery. Colors in b) and d) represent water (blue), green vegetation (green) and senescent vegetation/bare soil (yellow).

However, although OBIA has been applied in wetlands for almost two decades [7], its use still shows remaining challenges that hinder more widespread applications. Historically, a major barrier has been limited accessibility and high cost of the proprietary OBIA software, which have become easier with the development of image segmentation tools in other popular remote sensing and geospatial software, both commercial packages such as ArcGIS (Esri Inc.) and open-access platforms including QGIS, spatial toolboxes in R Studios and Python-based tools, and more recently Google Earth Engine [15]. Nevertheless, more fundamental practical challenges result from the need to choose and parameterize an appropriate segmentation algorithm, which can be much harder in heterogeneous wetland setting than, e.g., in human-dominated landscapes with distinct object typologies (such as buildings, trees, or land parcels). However, performing segmentation becomes much easier once this step no longer pursues a full capture of landscape entities with object units but rather aims to generate smaller, “primitive” objects that average local noise and provide relevant mapping units for subsequent classification [7,8], where full class boundaries are recovered by merging of classified objects.

This possibility leads to the final key intervention – **choosing the best-performing image classification algorithms** capable of accurate cover type recognition despite high spectral heterogeneity of wetlands and low spectral richness of some data. These issues can be handled by the novel machine-learning classification algorithms which often enhance class recognition capacity, while relaxing some of the limiting assumptions of traditional likelihood-based methods [7,8,16]. Although various algorithm families utilize different principles (e.g., artificial neural networks, decision trees, support vector machines), a common aspect among them is the ability to iteratively “learn” how to distinguish classes based on based on properties of the provided training examples. Such learning is typically accomplished by the repeated, automated adjustment of the algorithm parameters with the goal to minimize the error between predicted and actual class identities. The use of machine-learning algorithms has been greatly facilitated by their inclusion in geospatial software packages as well open-access computational toolkits (e.g., R, Python, Weka, etc.). Wetland studies comparing such methods to traditional classifiers report substantially higher accuracies, often exceeding 90%, especially when combined with OBIA [7,8].

Notably, however, these successes have not been universal, and no clear consensus has been yet established on which methods deliver most superior results in wetlands. The reasons behind such non-uniform performance are also rarely discussed, sometimes attributing this to the “black box” nature and complexity by design. This gap clearly highlights the need for more research to determine how specifically these methods should be chosen and applied, and what steps can ensure greater confidence in conclusions about their performance in a given wetland mapping task. In particular, two important under-discussed aspects of algorithm use call for more attention: 1) *parameterization* of methods, and 2) *cross-validation*, or some other form of *intermediate performance assessment*. Parameterization refers to selection of method parameters that may affect its ability to distinguish landscape classes from training samples. Such parameters are method-specific and typically require some preliminary sensitivity analysis to optimize their values for a given mapping problem. For example, the Random Forest algorithm needs the initial number of decision trees to develop from training data and subsequently average; support vector machines require decisions about the acceptable margin of error, penalty for misclassification and mathematical shape of the decision boundary, among other factors. Simply guessing such parameters or using software defaults is not sufficient and requires a formal sensitivity analysis of their combined effects. Intermediate assessment of accuracy performance provides an initial sense of algorithm performance and, in addition to guiding parameterization, can also elucidate the quality of training information and potential needs for additional samples. In wetland remote sensing applications, these measures are still less common, and more research is needed on how to guide such steps and make them easier to implement in practical mapping and monitoring.

In summary, advances in instruments, image products and computation tools create novel opportunities to enhance multiple aspects of wetland and riparian ecosystem mapping and facilitate assessments of their landscape indicators. Such enhancements can be applied collectively; for example, multi-date images can be used as inputs to OBIA workflows where objects generated by the segmentation of such multi-date imagery are classified with machine-learning algorithms, and automated workflows can be applied with less intensive adjustments to other points in time or space. Importantly, this potential as well as progress in high-resolution customizable UAV imaging cannot completely replace the value of field surveys and ground truthing; however, they can help reduce the scope of the required field surveys and make them more strategic. Finally, although these opportunities are especially relevant to limited-access wetland environments, they are not limited to those and could be tested and further developed in future research for a variety of other ecosystems and monitoring objectives.

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