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RESEARCH

Geospatial Tools for the Large-Scale Monitoring of Wetlands in the San Francisco Estuary: Opportunities and Challenges

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ABSTRACT

Significant wetland losses and continuing threats to remnant habitats have motivated extensive restoration efforts in the San Francisco Bay–Delta estuary of California, the largest in the western United States. Consistent monitoring of ecological outcomes from this restoration effort would help managers learn from past projects to improve the design of future endeavors. However, budget constraints and challenging field conditions can limit the scope of current monitoring programs. Geospatial tools and remote sensing data sets could help complement field efforts for a low-cost, longer, and broader monitoring of wetland resources. To understand where geospatial tools could best complement current field monitoring practices, we reviewed the metrics and monitoring methods used by 42 wetland restoration projects implemented in the estuary. Monitoring strategies within our sample of monitoring plans relied predominantly on field surveys to assess key aspects of vegetation recovery while geospatial data sets were used sparingly. Drawing on recent publications that focus on the estuary and other wetland systems, we propose additional geospatial applications to help monitor the progress made toward site-specific and regional goals. These include the use of ecological niche models to target on-the-ground monitoring efforts, the up-scaling of field measurements into regional estimates using remote sensing data, and the analysis of time-series to detect ecosystem shifts. We discuss challenges and limitations to the broad-scale application of remote sensing data in wetland monitoring. These notably include the need to find a venue to store and share computationally intensive data sets, the often cumbersome pre-processing effort needed for long-term analyses, and multiple confounding factors that can obscure the signal of remote sensing data sets.

KEY WORDS

Geospatial tools, wetland, restoration, monitoring, remote sensing, landscape metrics, ecological niche models, invasive species

INTRODUCTION

Ecological restoration is increasingly used to address the substantial worldwide loss of wetland ecosystems and their ecological benefits (Davidson 2014). In the US, the *No Net Loss of Wetlands* policy mandates that federal agencies offset unavoidable wetland losses through the restoration, creation, or enhancement of a site of equal functional value. As a result, wetland restoration efforts have intensified across the country (Deland 1992; NRC 2001). The policy itself is implemented through different regulatory frameworks, including Section 404 of the Clean Water Act enforced by the US Army Corps of Engineers, which regulates the discharge of dredged and fill material in most wetlands (NRC 2001). The growing societal awareness of wetlands' key role in supporting biodiversity and ecosystem services has further motivated non-profit and governmental organizations to fund restoration efforts throughout the US (Dahl 2011). However, evidence from previous scientific studies shows a substantial variability in post-restoration outcomes, even under similar approaches (Matthews and Spyreas 2010; Matthews 2015). Regional assessments and global meta-analyses have documented projects that fall short of targets, or fail to meet the richness or ecosystem functions of reference sites, sometimes even after more than 50 years (Matthews and Spyreas 2010; Moreno–Mateos et al. 2012). A current lack of consistent long-term monitoring, as reported in previous publications, limits the availability of robust ecological information to help identify the site characteristics, restoration interventions, and landscape planning strategies that promote site recovery (Simenstad et al. 2006; Matthews and Endress 2008; Suding 2011). There is increasing recognition that monitoring is key to detecting ecosystem stressors and promoting adaptive management, particularly in sites exhibiting high spatial and temporal complexity (Perring et al. 2015; Brudvig et al. 2017).

Nearly 80% of wetlands historically present in the San Francisco Bay and 95% of the wetlands in the Sacramento–San Joaquin Delta have been heavily modified or converted into urban and agricultural lands (Goals Project 1999; Whipple et al. 2012). In the Suisun Bay, most tidal wetlands were diked and are now managed as freshwater habitats used by duck clubs (Goals Project 1999; Moyle et al. 2013). Remaining wetlands are subject to increasing ecosystem stress from rapid urbanization, urban and agricultural runoffs, and invasive species (Lund et al. 2010; Luoma et al. 2015). Global climate changes may further affect wetland processes by increasing droughts (Diffenbaugh et al. 2015), salinity, and sea level rise (Holmes 2012), which will affect plant growth and composition (Parker et al. 2011). Furthermore, these ecosystem stressors may increase the habitat extent needed to fulfill ecosystem services (Simenstad et al. 2006) and exacerbate the vulnerability of local human populations to extreme climatic events (Barbier et al. 2013; Jankowski et al. 2017).

In response to this continuing pressure on remaining wetland habitats, several restoration projects have been initiated in the San Francisco Bay–Delta estuary ("the estuary"). The first significant restoration efforts date from the early 1970s with the adoption of the Clean Water Act (Callaway et al. 2011). Wetland restoration intensified in the early 2000s with the formation of CALFED, a multi-agency effort to address both societal and environmental water needs in California. From 2002 to 2015, 6,300 acres were opened to the tides in the San Francisco Bay, and 25,000 acres were restored in the Sacramento–San Joaquin Delta (SFEP 2015). Over the last 2 decades, projects have increased in size and topographic complexity (Callaway et al. 2011; Callaway and Parker 2012). Common restoration goals for the estuary include enhancing species diversity, reducing coastal erosion, and improving water quality, among many other objectives (Table 1).

The current abundance and variety of restoration projects in the estuary present an outstanding opportunity for in-depth analyses of wetland monitoring practices and strategies to make this monitoring more cost-effective. Since the 1970s, over 300 projects have been launched in different parts of the estuary (CWMW 2018), which have been documented by impressive regional data-collection efforts. The EcoAtlas database of restoration projects in California is a notable example that provides information on project scope and goals, and thus significantly facilitates the understanding of project characteristics, time-frames, and geographic representation (CWMW 2018). However, these efforts have not yet extensively addressed the monitoring

Table 1 Conservation documents for the estuary and their main habitat goals

Conservation document	Restoration related-goals										
	Recover endangered species	Enhance species diversity	Control non-native species	Enhance ecosystem resilience	Enhance commercial and recreational harvest	Rehabilitate ecological processes	Enhance adaptability to climate change	Enhance habitat connectivity	Promote adaptive management	Control erosion and floods	Improve water quality
CALFED I (CBDA 2004)	X	X	X		X	X					
Bay–Delta Conservation Plan (CBDA 2004)	X	X	X			X	X	X		X	X
Suisun Marsh Habitat Management, Preservation, and Restoration Plan (USBR et al. 2013)					X						
California Water Fix (ICF 2016)	X			X		X	X		X		X
Delta Plan (DSC 2013)	X		X	X	X	X		X	X		X
California Water Action Plan (CNRA 2014)	X	X				X	X	X		X	
Delta Conservation Framework (Sloop et al. 2017)	X	X	X	X	X	X	X	X	X		
San Francisco Bay Plan (SFBCDC 2015)	X	X	X	X	X	X	X	X	X	X	X
Baylands Ecosystem Habitat Goals (Monroe et al. 1999)	X	X						X			
San Francisco Bay Joint Venture Implementation Strategy (SFBJV 2001)		X									X
Conservation Strategy for Restoration of the Sacramento–San Joaquin Delta, Sacramento Valley, and San Joaquin Valley Regions (CDFW et al. 2014)	X	X	X		X	X	X	X			X

aspect of restoration. Given the recent approval of Measure AA, a California parcel tax that funds wetland restoration projects in the region, there is an emergent need and opportunity to improve monitoring practices in the region. This measure will fund the restoration of 24,000 acres of additional wetland habitats over the next 20 to 30 years.

Robust post-restoration data could inform the planning and design of future projects in the estuary and help measure the progress made toward regional goals (Table 1). Previous papers have called for a broadening of restoration planning (Kimmerer et al. 2005; Simenstad et al. 2006) and monitoring (Kentula 2000; Breaux et al. 2005), recognizing that the combined benefits of multiple restoration projects may be needed to fulfill regional wetland conservation objectives; these objectives include increasing habitat quantity and connectivity, or enhancing regional carbon sequestration potential (Table 1). These goals require data with a large spatial scope and high temporal frequency (Kentula 2000; Matthews and Spyreas 2010). Yet, many field-focused approaches are resource-intensive, and need to be repeated in time and space (Noss 1990; Wilcox et al. 2002; Moorhead 2013). Geospatial tools (i.e., spatial or remote sensing-based analyses of changes in vegetation extent, structure, and composition) have been applied at both local and regional scales to measure the contribution of conservation efforts to ecosystem service provisioning (e.g., Botequilha Leitão and Ahern 2002; McGarigal et al. 2009; Nagendra et al. 2013) but remain somewhat under-utilized in wetland restoration monitoring (Taddeo and Dronova 2018). The increasing availability of low-cost, frequent, and high-resolution remote sensing data sets (e.g., National Agriculture Imagery Program [NAIP], Landsat, RapidEye) provides an opportunity to complement field surveys economically and at a larger scale, to help project managers evaluate compliance with site-specific or region-wide wetland

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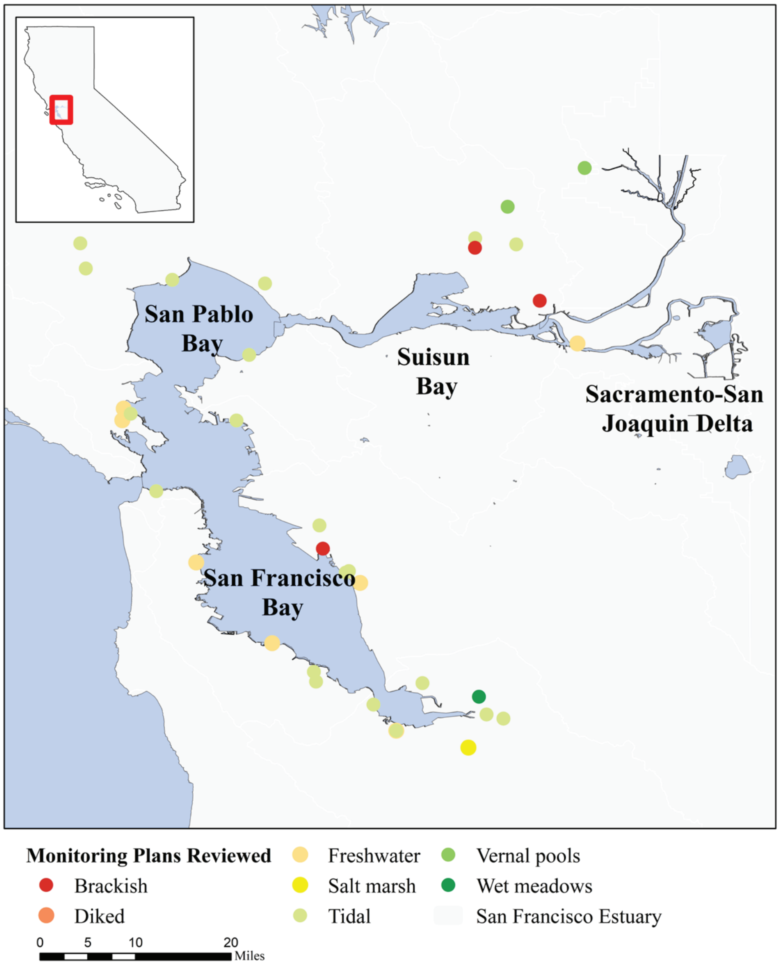

Figure 1 Study area and post-restoration management plans reviewed for this study, by wetland type

objectives. Recent papers focusing on the estuary have leveraged different geospatial time-series to monitor fluctuations in vegetation productivity and composition (e.g., Tuxen et al. 2008; Chapple and Dronova 2017), up-scale field measurements into regional estimates (e.g., Byrd et al. 2018), track invasive species (e.g., Hestir et al. 2008; Khanna et al. 2018), and map critical habitats for species of concern (e.g., Stralberg et al. 2010; Moffett et al. 2014).

To understand the extent to which geospatial tools are currently used in the estuary, we reviewed 42 monitoring plans implemented in the region. Drawing on studies conducted in the estuary and elsewhere, we discuss how geospatial tools and data sets could be leveraged—in conjunction with field monitoring efforts—to track currently monitored vegetation metrics at a larger spatio-temporal scale. We also list indicators of vegetation recovery that remain more accurately monitored on the ground, because of limitations in the resolution and availability of geospatial data sets.

METHODS

Study Area

We focus on restored wetlands of the San Francisco Bay–Delta estuary in California. The estuary is located between the cities of San Francisco at its western border and Stockton and Sacramento at its eastern border (Figure 1). The estuary also includes the cities of Santa Rosa, to the north, and Gilroy, to the south. It is characterized by a salinity gradient from the combined influence of the Pacific Ocean and freshwater from the Sacramento and San Joaquin rivers. The estuary supports a variety of wetland types, including freshwater wetlands dominated by *Schoenoplectus acutus* and salt marshes dominated by

Salicornia pacifica and *Spartina* spp. (Parker et al. 2011; Vasey et al. 2012). Brackish wetlands dominated by *Schoenoplectus americanus* and *Bolboschoenus maritimus* are found at the confluence between salt and freshwater in the Suisun Bay, the largest remaining brackish wetland in the western US (Vasey et al. 2012; Moyle et al. 2013).

Selection of Projects and Data Collection

We used the EcoAtlas database of wetland restoration in California to find projects implemented within the estuary (Figure 1). Among the 332 projects listed for this region, we identified 35 restoration projects that corresponded to our research criteria. Those criteria were: (1) wetland-based projects (or restoration projects including a wetland component); (2) located within the estuary, and for which (3) a monitoring plan or report was available. We also consulted the U.S. Army Corps of Engineers' RIBITS (Regulatory In-lieu fee and Bank Information Tracking System) database to identify an additional seven sites with adequate documentation. Monitoring reports or plans had to include—at a minimum—the list of indicators used to evaluate their restoration progress.

For each monitoring plan and report, we recorded (1) the indicators used to monitor wetland restoration progress, (2) the sampling design used to measure these indicators; (3) the length and frequency of the monitoring effort, and (4) the success criteria used to assess whether restoration objectives had been met. We also noted information on initial restoration treatments and goals, when such information was available. We noted whether spatial data sets, such as remote sensing data, were proposed or used as the basis to map and/or quantify some of the monitored indicators. Finally, we collected information on the "reference data" used to establish restoration targets, including the number of reference sites considered, how these sites had been selected, and the sampling design used in these reference sites.

RESULTS

General Information About Projects

We identified 42 wetland restoration projects with enough information to meet our filtering criteria. These projects were restored between 1976 and 2015, with 24 projects restored after 2000, and 14 restored after 2005. Our project sample included 24 tidal wetlands, three brackish sites, nine non-tidal or

Table 2 Summary of monitoring plans analyzed for this review

Restoration type	Wetland type	Restoration year	Number of projects	Mean project size (acres)	Restoration indicators	Mean monitoring length (years)
Compensatory mitigation	Brackish	1995	1	4	Vegetation cover, species composition, plant survival	5
	Diked	1993	1	94	Vegetation cover, vegetation composition	5
	Freshwater	1976–2009	9	39	Vegetation cover, species composition, plant height and height heterogeneity, stem density	6
	Salt marsh	1993–2007	2	6	Vegetation cover	5
	Tidal	1995–2004	13	83	Vegetation coverage, species composition, plant height, biomass, habitats mapping, community similarity	8
	Vernal pools	2005	2	534	Vegetation cover, species composition, habitat mapping	10
Non-mitigation	Brackish	1996–2003	2	1,077	Vegetation cover, plant height, species composition	10
	Diked	1998	1	72	Vegetation cover	10
	Tidal	1998–2015	10	205	Vegetation cover, species composition, habitat mapping, plant survival, plant height, rate of lateral expansion	10
	Wet meadow	2002	1	492	Vegetation cover, rare species	10

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diked freshwater sites, four vernal pools, and two wet meadows (Table 2). Projects varied in size from 0.1 to 1,800 acres, with a mean area of 210.94 acres and a standard deviation of 366.33 acres.

Over half of the projects served as compensatory mitigation for the damage or destruction of existing wetlands from levee maintenance and construction (e.g., Mare Island Navy Mitigation Marsh), freeway extension (e.g., Caldecott Tunnel), and infrastructure development (e.g., Muzzi Marsh, Madera del Presidio). The overall goals of compensatory mitigation were to replace lost ecosystem functions (e.g., habitat provisioning for wildlife and endangered species) via wetland restoration or enhancement. Success criteria used to measure compliance with these goals varied among projects, but included maintaining a high diversity and coverage of native species and reaching a set acreage of wetland habitat (e.g., 5 acres of estuarine emergent wetlands). Restoration goals for non-compensatory projects included creating wildlife habitats, increasing species diversity, promoting recreational usage, or reversing land subsidence. For tidal wetlands, common restoration actions included breaching to restore flows and tidal prisms, creating a system of channels, excavating and grading to improve topographic heterogeneity, and using dredged material to increase elevation. Common restoration treatments for freshwater wetlands included planting native or desirable species (e.g., *Schoenoplectus acutus* or *Salicornia pacifica*) and removing non-native species.

Length and Frequency of Monitoring

Most of the reviewed projects included a monitoring plan to collect information on post-restoration dynamics. Twenty sites were monitored for 5 years or less; 34 sites were monitored for 10 years or less. Three sites had planned for 15 to 25 years of monitoring; two sites planned to monitor in perpetuity. Finally, three sites established a monitoring protocol but did not specify the intended length of post-restoration monitoring. In terms of monitoring frequency, 34 sites planned to sample wetland conditions every year, and three monitored every other year. Five sites adopted an incremental monitoring schedule, with yearly monitoring during the first 5 years, and every other year after that. Another project planned to monitor every year from years 1 to 8, then every 5 years from years 10 to 20, and then every 10 years in perpetuity. Only one project used seasonal monitoring to account for the effect of plant phenological differences on composition.

Sampling Design and References

Eighteen projects indicated using reference sites as a benchmark to set restoration targets, and two of them used more than one reference site. One project described the statistical approach used to assess whether restored sites became statistically similar to reference sites. Fourteen projects had conducted a prior ecological assessment to establish baseline conditions (i.e., site condition before restoration). The length of baseline data monitoring was typically 1 year, although two sites conducted pre-restoration monitoring for 2 non-consecutive years. Most projects focused their baseline monitoring effort on the year before restoration; three sites used monitoring data collected 2, 7, and 8 years, respectively, before restoration. No project specified the statistical test used to compare baseline and post-restoration conditions.

All projects included field observations to evaluate vegetation-based indicators of recovery; less than half of projects also used geospatial data to monitor progress at a broader site extent. The latter employed either high-resolution satellite aerial imagery or ground-level photography of vegetation coverage, but only two of these specified the sensor or image database used. In both cases, the images were obtained from a commercial satellite data provider (e.g., Ikonos, GeoEye). Remote sensing data were predominantly used to map annual changes in vegetation cover and patch extent. Seven sites used ground-level photography to compare annual changes in vegetation abundance by monitoring the proportion of a focal area covered by vegetation throughout a time-series. Few of the restoration plans specified any methodology for the ground-truthing of ecological data derived from aerial images. However, one site applied the framework developed for the *2009 Vegetation Map Update of the Suisun Marsh*, from which restoration progress can be inferred from true color imagery ortho-rectified that uses ground control points and a manual delineation of vegetation types (CDFG 2012).

All the reviewed projects leveraged vegetation indicators to evaluate restoration progress. All sites included structural indicators (i.e., indicators that characterize the distribution of plant biomass throughout the canopy) as part of their post-restoration assessments. Vegetation cover proxies were the most commonly used among all structural indicators, assessed either as the proportion of the surface covered by all green vegetation (total coverage) or the coverage of one single species or functional group (plant coverage). Fourteen projects specifically targeted the plant coverage of native or non-native species; the remaining projects did not distinguish between species status. Three projects measured vegetation cover by functional types (i.e., classification of plants by their main physical, phylogenetic, or phenological characteristics); four projects targeted a certain plant coverage for specific species (e.g., *Salicornia pacifica*, *Bolboschoenus maritimus*).

Twenty-six projects tracked indicators of plant composition (i.e., taxonomic identity, abundance, and diversity of species within the plant assemblage) to monitor site progress. Fifteen of these conducted a floristic inventory of sites through a visual identification of species presence within permanent monitoring plots. Floristic composition targets focused on the percentage of native species or wetland-specific species. Other projects concentrated on matching the species composition of reference sites. Three sites looked at species richness (i.e., number of species present in a plant community); four sites examined species diversity (i.e., species richness and evenness). Two sites focused on target species: one considered rare species, and the other the coverage of Californian wetland-specific species.

Four project plans included spatial indicators of recovery. Three of them used habitat mapping (i.e., delineation and quantification of vegetated habitats), and the last one focused on the ratio of water to vegetation. Habitat was mapped using both aerial and satellite images from commercial providers or delineation of the field boundary with a GPS. Finally, one site included an assessment of ecological function: in this case, seedling establishment and recruitment.

DISCUSSION

Our analysis reveals a sustained effort in the estuary to track wetland response to restoration treatments. The spatio-temporal scope and performance metrics of this effort vary among projects, likely reflecting a diversity of goals and monitoring requirements as discussed in previous publications that focused on wetland restoration in California (e.g., Kimmerer et al. 2005) and elsewhere (e.g., Matthews and Endress 2008). Monitoring practices in our sample of projects focused on structural indices of vegetation recovery (e.g., plant coverage) and, to a lesser extent, on indicators of species composition. Only a subset of monitoring plans utilized geospatial tools, primarily to measure changes in vegetation cover or map habitats. Although these are important objectives for wetland monitoring and restoration assessments, evidence from recent studies in the region and the growing accessibility of remote sensing data highlight other, still somewhat under-utilized opportunities to cost-effectively expand the spatio-temporal scope at which we evaluate restoration progress (Table 3). With several conservation plans setting landscape-scale goals for the region (Table 1), there is now an opportunity to develop a more consistent monitoring framework to track the combined contribution of multiple projects toward regional objectives. Geospatial tools can also help project managers measure the progress made towards site-specific objectives.

Project managers now have access to a multitude of sensors that provide repeated data (e.g., Ikonos, RapidEye, Landsat; Table 4) enabling vegetation tracking at a constant phenological stage, medium to high spatial resolution, and over large extents. Several of the sensors listed in Table 4 provide multi-spectral data in three to seven broad spectral bands sensitive to plant biomass and coverage (Pettorelli et al. 2005; Jensen 2007). Hyperspectral sensors can provide spectral information in thousands of narrow bands sensitive to plant chemical composition, facilitating the identification of dominant species (Hestir et al. 2008; Andrew and Ustin 2009; Muller–Karger et al. 2018). While free medium- to high-resolution data sets (e.g., Landsat, Satellite Pour

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Table 3 Examples of geospatial applications for measuring the progress made toward restoration goals in the San Francisco Bay–Delta estuary.

Restoration goals	Geospatial applications	Local examples
Recover endangered species	Quantify suitable habitats using aerial and satellite images or 3-D LiDAR products	Stralberg et al. 2010
		Tuxen and Kelly 2008
		Schaffer–Smith et al. 2018
	Use ecological niche models to identify potential suitable habitats and target field monitoring	Zhang and Gorelick 2014
	Use landscape metrics of habitat size, diversity, density, and connectivity	Moffett et al. 2014 Tuxen and Kelly 2008
Control non-native species	Monitoring using repeated satellite images	Hestir et al. 2008 Ta et al. 2017 Khanna et al. 2018 Andrew and Ustin 2008
	Use hyperspectral data to detect changes in extent and coverage of target plant species	
Rehabilitate ecological processes	Up-scaling of field measurements into site or regional estimates of ecosystem functions	Byrd et al. 2014 Byrd et al. 2016 Byrd et al. 2018 Knox et al. 2017 McNicol et al. 2017
Enhance adaptability to climate change	Measure effect of climatic fluctuations on vegetation extent and productivity	Chapple and Dronova 2017
Enhance habitat connectivity	Use landscape metrics to measure connectivity	Zhang and Gorelick 2014
	Conduct connectivity analyses using network analysis or resistance kernel approach	
Promote adaptive management	Use time-series of satellite images to identify thresholds of ecosystem change for intervention	Moffett and Gorelick 2016
	Use repeated aerial survey to detect early signs of ecosystem shifts	
Erosion and flood control	Up-scaling of field measurements into site or regional estimates of ecosystem functions	Schaffer–Smith et al. 2018 Buffington et al. 2016
	Identifying changes in terrain and hydrological properties using 3-D LiDAR products	

l'Observation de la Terre [SPOT]; Table 3) can provide adequate spatial detail to detect general patterns of change in vegetation extent and productivity (e.g., Baker et al. 2007; Wang et al. 2015; Knox et al. 2017), higher-resolution data is needed to track changes in plant composition and dominant species. The NAIP data set provides the finest resolution (0.6 to 1m) of all free data sets (Table 4), but its low acquisition frequency (one image every 2 to 3 years) and variable timing of acquisition (some images captured at the beginning of the summer, others at the end) make change analysis difficult if this dataset alone is relied upon. However, combined with other products, the NAIP data set can increase spatial detail and enhance vegetation mapping for a more robust quantification of wetland processes (e.g., Byrd et al. 2018). Some commercial data sets (Table 3) provide both high resolution and high frequency—but this can be costly for project managers who oversee large sites. Hyperspectral data can best differentiate species that would otherwise be too similar at a lower spectral resolution, but is expensive for large sites or regional assessments.

Opportunities to Complement Field Monitoring Using Geospatial Tools

Habitat Mapping

Increasing the extent and quality of ecological habitats is a key restoration objective in the estuary as reflected in the regional goals (Table 1) and objectives of both compensatory mitigation and non-compensatory projects. Habitat quality and

Table 4 Examples of common high- to moderate-resolution remote sensing data sources and their potential for post-restoration assessments of wetlands

	Sensor / Database	Agency	Temporal scope	Spatial resolution	Bands	Examples of applications
Commercial	RapidEye	PlanetLabs	Every 1-6 days; 2008–present	5 m	5	Habitat mapping (Jung et al. 2015)
	World-View	DigitalGlobe	Every 1–2 days; 2009–present	0.31–1.24 m	8	Land cover mapping, quantify vegetation expansion (Chapple and Dronova 2017)
	IKONOS	DigitalGlobe	Every ~3 days; 1999–2015	0.82–4 m	4	Mapping vegetation, detecting invasive species (Belluco et al. 2006)
	Quickbird	DigitalGlobe	1–3.5 days; 2001–2015	0.65–2.9 m	4	Mapping vegetation (Gilmore et al. 2008; Laba et al. 2008), detecting invasive species
Public	NAIP (National Agriculture Imagery Program)	USDA	Every 2–3 years; 2003–present	0.6–1 m	3–4	Inform sampling design (Lackey and Stein 2014), monitoring invasive species (Xie et al. 2015)
	Landsat	NASA	Every 16 days; 1972–present	30–120 m	4–11	Base data for wetland elevation (Byrd et al. 2016) and carbon flux models (Knox et al. 2017; McNicol et al. 2017), phenological analyses (Knox et al. 2017)
	Sentinel	ESA	Every 5–10 days	10–60 m	13	Estimate plant biomass and coverage (Mo et al. 2018)
	SPOT (Satellite Pour l'Observation de la Terre)	ESA	Every 26 days since 1986	1.5–20 m	4–5	Monitoring wetland vegetation (Davranche et al. 2010)
	Light Detecting and Ranging (LiDAR)	Variable	Variable	Variable		Base data for soil accretion model or carbon budget (Hladik et al. 2013; Kulawardhana et al. 2014), map certain non-native species (Rosso et al. 2006) and habitats (Bradbury et al. 2005)

extent can be characterized by several field-based vegetation metrics (Craft et al. 2003; Bradbury et al. 2005) or mapped from remote sensing data via well established spatial analysis methods (Nagendra et al. 2013; Rocchini et al. 2018) to reduce the high cost associated with wildlife observations and stock assessments. Remote sensing data can be used to map suitable habitats for species of interest based on prior knowledge of their occurrence as well as association with vegetation composition, height, structure, or phenology, which translate into spectral contrasts among different habitat types (Nagendra et al. 2013; Andrew et al. 2014). For example, structural diversity (i.e., heterogeneity in growth forms or canopy height), which can be measured using light detection and ranging (LiDAR) data, promotes avian and macroinvertebrate richness in wetlands (Zedler et al. 1999; St. Pierre and Kovalenko 2014). Pickleweed (*Salicornia pacifica*), a species used by the endangered salt marsh harvest mouse (*Reithrodontomys raviventris*), can be identified by its late phenology and spectrally homogeneous stands (Tuxen and Kelly 2008). Recognition of different vegetation types can be further enhanced using multi-date imagery, which accentuates phenological contrasts (e.g., Wang et al. 2012, Zhong et al. 2012), or narrow-band hyperspectral data sets that are more sensitive to biochemical differences among plant types, based on leaf water or chlorophyll content (Andrew et al. 2014).

Analysts can combine different geospatial data sources or leverage ancillary data to improve habitat quantification. For example, using high-resolution topographic data improved the detection of suitable habitats for shorebirds in the Sacramento National Wildlife Refuge Complex (Schaffer–Smith et al. 2018). Stralberg et al. (2010) used LiDAR-derived elevation data—in addition to a remotely sensed survey of vegetation composition—to map suitable habitats for three endangered bird species in the

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Bay–Delta. Such analyses can also more effectively account for how adjacent land uses and covers affect the likelihood that species will adopt suitable habitats (Nagendra et al. 2013). For instance, Tuxen and Kelly (2008) leveraged high-resolution aerial photography and LiDAR data to map suitable habitats for the salt marsh harvest mouse (i.e., dense covers of pickleweed) and its preferred landscape context (i.e., proximity to elevated patches where it can find refuge during tides).

Landscape metrics (i.e., statistics that describe the spatial structure, heterogeneity, and distribution of habitat patches) can help evaluate the quantity and quality of habitats as they reflect key processes and properties, including species dispersal, water flows, and water quality (Moreno–Mateos et al. 2008; McGarigal et al. 2009; Sloey et al. 2015). As an example, three landscape metrics that described the size and shape of habitat patches effectively predicted the Song Sparrow's (*Melospiza melodia pusillula*) distribution in the estuary (Moffett et al. 2014). Landscape metrics may also reveal patterns of fragmentation (Markle et al. 2018) or landscape homogenization (Costanza et al. 2011), which might reduce the capacity of sites to meet species diversity targets or maintain wildlife populations. Several conservation plans—including the BDCP and Delta Conservation Framework—target an increase in the connectivity of wetland habitat patches. Habitat connectivity can be similarly approximated by a suite of landscape metrics (Turner et al. 1998) but was not explicitly measured in our sample's monitoring plans. Landscape connectivity promotes the movement of resources, genes, seeds, and individuals (Rudnick et al. 2012) critical to ecosystem resilience (Turner et al. 1998; Lindborg and Eriksson 2004). Using a consistent classification nomenclature and methodology to map suitable wetland habitats across the estuary could help measure the contribution of restoration efforts to regional habitat connectivity. To this effect, the Tidal Monitoring Framework for the Upper San Francisco Estuary (IEP TWM PWT 2017) recommends applying the CalVeg habitat classification system upon aerial images to maintain consistency among different monitoring efforts. Once such a consistent mapping of vegetated habitats is completed, different GIS-based methods—including network analyses and resistance kernels—can quantify habitat connectivity throughout the region (Minor and Urban 2008; Fortin et al. 2012; Rudnick et al. 2012).

Finally, applying the aforementioned strategies to spatially contiguous remote sensing data may help detect the presence and coverage of target species—such as undesirable non-native species, or, in contrast, rare species—as indicators of restoration progress. Both the Delta Plan (DSC 2013) and Delta Conservation Framework (Sloop et al. 2017) stress the importance of early detection and timely prevention of biological invasions, which are expected to intensify with climate change (Callaway and Parker 2012; Grewell et al. 2013). Furthermore, eradication is more cost-effective when populations are still small and isolated (Reaser et al. 2008; Kettenring and Adams 2011). Several studies conducted in the Bay–Delta highlight the promise of repeated remote sensing data to track the progression of non-native species (e.g., Hestir et al. 2008; Ta et al. 2017; Khanna et al. 2018), which were predominantly monitored in the field within our sample. Invasive species can be distinguished from co-existing native species when they present distinct spectral or phenological properties (Bradley 2014), such as unique flowering schedules (Andrew and Ustin 2008), or, in the case of aquatic weeds, a contrast to open water (Hestir et al. 2008; Bradley 2014). The characteristic spatial pattern, or "texture," of some invasive species can also facilitate their detection; for instance, Boers and Zedler (2008) identified areas of high *Typha* x *glauca* dominance within aerial images by their dark homogeneous circular patches. Though more expensive, hyperspectral imagery facilitates the detection of invasive plant species based on more subtle spectral contrasts that result from unique biochemical, anatomical, and structural plant properties (Hestir et al. 2008).

Ecological niche models may help target the monitoring of non-natives when sites are too large to use more costly high-resolution or hyperspectral data, or where populations are too small to be detected using remote sensing data alone (Andrew and Ustin 2009). Project managers could leverage existing data sets that document non-native species occurrences to construct their habitat models (e.g., Calflora and CalWeedMapper) and identify suitable habitats where monitoring efforts that use high-resolution, spectral, or field data should be targeted. Such an approach (i.e., using models) could also be applied for more targeted monitoring of rare species or species of particular interest because these models provide habitat benefits and additional ecosystem services (Guisan and Thuiller 2005; Sousa–Silva et al. 2014).

Up-Scale Field Measurements into Site or Regional Estimates

Some of the restoration goals set for the estuary will rely on the combined effect of multiple projects, which creates the need to develop region-wide estimates of the key ecosystem parameters and indicators assessed by individual projects. Well calibrated relationships between ecosystem processes of interest and vegetation properties detectable from satellite images could enable such an up-scaling of field measurements, both within large spatial extents of individual projects and across the region. Using spectral vegetation indices derived from open-access and commercial remote sensing data, several regional studies have demonstrated promise for up-scaling wetland vegetation biomass (e.g., Byrd et al. 2014, 2016, 2018), leaf area index (e.g., Dronova and Taddeo 2016), and primary productivity and greenhouse gas fluxes (e.g., Knox et al. 2017; McNicol et al. 2017). In general, these relationships—similar to previous successes from terrestrial ecosystems—are based on the effects of physiological, biochemical, and structural properties of vegetation on the absorption, transmission, and reflection of solar radiation that shapes plant signatures in remote sensing data (Jensen 2007). Wetland environments, however, pose unique challenges to up-scaling frameworks because of the patchiness of their vegetation and the suppression of plant spectral signals by background effects of dead biomass (Rocha et al. 2008; Schile et al. 2013; Byrd et al. 2014) and water (Kearney et al. 2009; Byrd et al. 2014; Kulawardhana et al. 2014). Correcting for these effects may be possible with specialized image-processing methods, such as determining relative fractions of vegetation, water, and dead biomass inside minimum mapping units (Dronova and Taddeo 2016) or selecting data with spectral regions that show a high sensitivity to target properties (Byrd et al. 2014).

Other studies have tested the potential of LiDAR instruments to monitor vertical accretion in wetlands (e.g., Rosso et al. 2006; Kulawardhana et al. 2015). LiDAR systems are active sensors that emit and receive radiation signals. The time needed for a LiDAR pulse to reach land surfaces and return provides information on the elevation and height of land features (Hudak et al. 2009), and, to some degree, on the vertical structure of plant canopies. Annual changes in the digital elevation model (DEM) derived from LiDAR data can be measured to characterize vertical accretion in wetlands (Rosso et al. 2006; Deverel et al. 2014). However, because of the high cost of LiDAR data acquisition and processing, it has not been used systemically across the Bay–Delta region to survey and compare sites.

Establish Baseline and Reference Conditions for Restoration Targets

The monitoring of baseline and reference conditions in our project sample was typically limited to 1 year (or, in rare cases, 2 years). Current literature emphasizes the importance of tracking baseline and reference conditions for multiple years to account for how climate, salinity, hydrology, and species succession affect wetland conditions (White and Walker 1997; Zedler et al. 1999; Moorhead 2013; Johnson et al. 2017). Ecosystem variability is an important concern in the estuary, where annual fluctuations in precipitation and salinity can affect the vegetation extent (Chapple and Dronova 2017), productivity (Parker et al. 2011), and composition (Chapple et al. 2017) of both restored and reference sites. Expanding the temporal scope and frequency at which reference or baseline data are collected is, therefore, critical in setting realistic restoration targets, and accounting for the effect of landscape context and abiotic conditions on a site's capacity to meet those targets. To account for how environmental fluctuations affect restoration indicators, the dynamic reference concept proposes to set such flexible targets via simultaneously monitoring restored and reference sites, and then adjusting restoration targets (Hiers et al. 2012). Repeatedly acquired remote sensing data can facilitate this task by tracking key environmental and vegetation parameters and comparing them among restored and reference sites. For example,

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Tuxen et al. (2011) used high-resolution aerial photography to track changes in the extent and diversity of plant communities in a series of the estuary's reference and restored tidal wetlands. Their analyses revealed a higher variability and diversity of plant communities in more recently restored sites than in mature ones. Tracking environmental conditions in several reference sites could also help determine a range of acceptable post-restoration targets. Previous studies have even suggested using less successful restoration projects to set a lower limit of expectation and using reference wetlands to set the upper range of acceptable wetland conditions (Kentula 2000; Matthews and Spyreas 2010). Understanding year-to-year fluctuations in wetland vegetation properties could also help identify which specific characteristics should be measured more frequently. For example, Chapple and Dronova (2017) showed that droughts affect vegetation expansion, suggesting that monitoring may need to be intensified under such climatic conditions.

Although there are still few examples of wetland studies that use remote sensing to measure baseline and reference conditions, research conducted in other ecosystems shows interesting approaches that could be applied to wetlands. For example, a study in the Iberian Peninsula used a time-series of vegetation indices that spanned 20 years to describe the typical range of fluctuations in the spectral signature of different plant functional types in response to climatic conditions (Alcaraz–Segura et al. 2009). This allowed authors to identify a range of acceptable conditions that accounted for natural fluctuations, and consequently to set thresholds under which large abnormal changes would require adaptive management. Adopting a similar method for wetlands could help establish a range of expected conditions, and a departure from this expected range of values might indicate an ecosystem stress or a failure to recover.

Resilience and Detection of Ecosystem Stress and Shifts

The ability to cost-effectively monitor wetland change with geospatial data sets is also crucial to assessing the resilience and adaptive capacity of both restored and reference systems. Some of the conservation frameworks for the region (Table 1) included resilience as a primary objective, although none of the reviewed plans explicitly tracked this or identified its specific indicators. Across our sample, monitoring efforts were limited to an average of 1 year before and 6 years after restoration, which may not be long enough to assess region-specific stressors, such as droughts and salinity fluctuations. Repeated effort to map wetland cover or habitat types enables not only general dynamics to be tracked, but also early signals of important shifts. For example, a change analysis conducted on an 85-year data set of manually classified aerial images revealed fluctuations in vegetation composition and habitat connectivity, and their effect on the local herpetofauna of a Canadian wetland (Markle et al. 2018).

Resilience is notoriously hard to measure and predict, and several publications have called for the development of robust tools for its assessment (Carpenter et al. 2001; Standish et al. 2014). Recent publications that leverage long-term time-series of remote sensing data show promising approaches to estimate resilience and detect early signs of ecosystem shifts (e.g., Díaz–Delgado et al. 2002; Sen et al. 2012; Alibakhshi et al. 2017). For example, Alibakhshi et al. (2017) showed that an increased temporal auto-correlation in a composite water–vegetation index could indicate an ecosystem shift triggered by repeated droughts. Similarly, Daz–Delgado et al. (2002) used Landsat time-series after a series of fires to measure the time needed for different forest patches to return to pre-disturbance biomass levels.

Maintaining a multi-metric, site-wide monitoring effort to assess the progress made toward multiple objectives can increase the likelihood of detecting unexpected fluctuations, yet the required field effort may incur a high logistical and financial burden (Moreno–Mateos et al. 2015; Brudvig et al. 2017; Taddeo and Dronova 2018). Remote sensing provides a framework to detect ecosystem stressors that may warrant further on-the-ground monitoring and signal a potential ecosystem shift. Shifts in the spectral properties or phenology of vegetation could expose environmental stress or reveal a decline in the quality of habitat patches (Nagendra et al. 2013). Project managers can detect early signs of ecosystem shifts

(Moffett et al. 2015) by tracking spatial variations in vegetation extent and progression (Chapple and Dronova 2017) and habitat complexity (Moffett and Gorelick 2016). Monitoring programs can also focus on vegetation characteristics known to increase a site's resistance to ecological threats. For example, some monitoring plans already track plant productivity, a key contributor to soil accretion, which increases wetlands' resistance to sea level rise and erosion (Miller et al. 2008; Parker et al. 2011), as well as bird populations' resistance to droughts (Selwood et al. 2017), and both could be measured using both large-scale remote sensing data and site-level phenocams (Shuman and Ambrose 2003; Kulawardhana et al. 2015; Knox et al. 2017). Response diversity (i.e., variability of plant responses to fluctuations in environmental conditions) has been shown in field observations and simulations to help ecosystems maintain key processes during and after disturbances. Response diversity can be measured as the range or degree of divergence within a set of traits (i.e., plant characteristics that respond to resource availability, hydrology, and disturbances) in a community (Mori et al. 2013)—some of which can be measured using hyperspectral data (e.g., foliar nitrogen or chlorophyll content) or long-term time series of multi-spectral data (e.g., phenology) (Andrew et al. 2014).

Limitations and Future Directions

Although different remote-sensing data sets and tools are becoming increasingly available, their limitations in addressing the objectives of wetland restoration monitoring should be recognized and considered carefully. Despite an extended spatial and temporal observation scope compared to traditional ground surveys, most spatial instruments are not sufficiently sensitive to some of the critical characteristics of vegetation that can be assessed in the field, particularly indicators of floristic composition and diversity (Shuman and Ambrose 2003). Furthermore, to calibrate and validate the patterns observed from image data sets, field surveys are very important to "ground-truth" remote-sensing analyses. Thus, future monitoring efforts should seek strategies to combine remote and ground observations in complementary ways. This section discusses some key monitoring needs and opportunities that highlight the importance of such complementary efforts.

Species Composition and Diversity

Increasing species diversity is a key goal of restoration efforts in the estuary (e.g., BDCP, CALFED I, Delta Conservation Framework; Table 1) because of its potential to promote productivity, resistance to biological invasions, and ecosystem stability (Yachi and Loreau 1999; Caldeira et al. 2005; Cardinale et al. 2012). Furthermore, Boyer and Thornton (2012) observed that restored sites in the estuary maintained fewer species than reference sites on average, further emphasizing the importance of monitoring species richness in the region. Incidentally, 26 of the monitoring plans we reviewed included indicators of species composition (e.g., richness, diversity). Monitoring species composition in the field is challenging because it requires frequent sampling to account for seasonal and annual variability in species composition and a large spatial extent to increase the likelihood of observing rare species (Noss 1990). Yet, considering the limitations of remote sensing data sets, species composition might be best assessed using field observations. Remote sensing has been leveraged to map dominant species, but many wetland species can have similar spectral signatures at peak biomass (Schmidt and Skidmore 2003). It is much easier to use remote sensing data to distinguish plant functional types compared to a single species—unless that species presents phenological characteristics or a spectral signature that is clearly distinct from its surroundings (Bradley 2014). Furthermore, to be detectable, this species must cover a significant portion of the pixel (Bradley 2014). LiDAR can help distinguish species by structural differences but has a limited effectiveness in short canopies where species have a similar structure or height (Kulawardhana et al. 2015). Hyperspectral images can help differentiate species by their chemical characteristics (e.g., chlorophyll and water content; Andrew et al. 2014) but remain more effective in ecosystems with a lower overall richness (Andrew and Ustin 2008).

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Early Stages of Recovery

Some restoration plans in our sample included plant survival as a primary component of their monitoring program. It can be difficult to get a reliable signal of plant biomass or survival at the earliest stage of site development, when plant individuals are sparsely distributed, because the spectral signal of bare soil or water might obscure the spectral signature of green vegetation (Bradley 2014). Advances in the use of satellite images to map vegetation growth in arid environments nonetheless suggest potential methodological approaches to facilitate site monitoring at early stage of vegetation development using remote sensing data. For example, Khanna et al. (2007) showed that indices based on the relationship, or angle, between the near- and shortwave-infrared bands could help distinguish green vegetation from background soil in arid environments. Alternatively, project managers could focus their effort on repeated field assessments in the very early stages of wetland recovery, and transition into more remote sensing-based assessments for specific indicators when the vegetation is more established and perceivable using aerial or satellite images.

Tidal Effects

In coastal wetlands, periodic tidal flooding attenuates the spectral reflectance of vegetation as a result of higher water levels and increased soil moisture (Kearney et al. 2009; Adam et al. 2010). This introduces a lot of noise into the data, particularly when wetland changes through a time-series are studied or the phenological cycle of tidal wetlands is being modeled. Correction factors have been used to account for the attenuation of spectral signals by high water levels, but they must be tailored to the structural characteristics of dominant species (Kearney et al. 2009; Byrd et al. 2014) and their phenology (O'Connell et al. 2017), both of which affect the proportion of water visible from aircrafts or sensors. Correction factors are typically established using field observations of plant biomass and structure, including leaf area index and vegetation fraction (Mishra and Ghosh 2015). For example, O'Connell et al. (2016) developed a correction factor for tidal pixels based on plant phenology and spectral reflectance in the green- and shortwave-infrared bands. One of the projects we reviewed circumvented this challenge by restricting analyses to images acquired at low tide, which may be a tedious procedure for analysts who focus on large sites or extended time-series.

Logistical Challenges

As the quality and quantity of satellite data increases, so do data-storage needs. The large-scale and long-term monitoring of restored sites in the estuary, although critical to advancing our understanding of post-restoration dynamics, will generate heavy data sets that organizations with limited resources might have trouble maintaining. As such, there is a crucial need in the estuary to develop a platform that enables different organizations and managers to store and share their geospatial data. Developing such a repository could reduce redundancy in efforts, and also provide large-scale, consistent data sets that enable regional analyses and syntheses.

In the meantime, advances in online application programming interface (API) platforms provide cost-effective opportunities for such analyses by allowing cloud-based access to some large remote sensing data repositories without the need to manually download and pre-process the imagery. For instance, a cloud-based Google Earth Engine (GEE; *https://earthengine.google.com/*) API platform provides access to long-term data sets for several sensors and programs, including Landsat, MODIS (Moderate Resolution Imaging Spectroradiometer), and NAIP (Table 4). Users can leverage the GEE platform to perform a set of spatial analyses, including change detection, land-cover classification, and band arithmetic. A new data API by Planet (*https://www.planet.com/*) facilitates access to and analysis of high-resolution (3–5 m) imagery from Planet satellites. Several other remote sensing data repositories allow raw satellite and aerial imagery, and some of the derived products, to be obtained; for example, the US Geological Survey's Earth Explorer (*https://earthexplorer.usgs.gov/*), NASA's Land Process Distributed Active Archive Center (LPDAAC; *https://lpdaac.usgs.gov/*), NOAA's Data Access Viewer (*https://coast.noaa.gov/dataviewer/#/*), and the NAIP imagery collections at California Department of Fish and Wildlife libraries.

New Tools and Opportunities to Reduce Costs for Multi-Approach Strategic Monitoring

To circumvent the logistical challenges of ground surveys and reduce the risk of site disturbance, several technological advances in remote sensors provide novel opportunities for customized monitoring of vegetation properties and seasonality at individual sites. Unmanned aerial vehicles (UAVs), for example, allow very high-resolution imagery (<10–50 cm) to be collected at a desired frequency (Anderson and Gaston 2013). The data can be mosaicked across the site to map wetland surface and vegetation types, or measure relevant indicators such as plant coverage (e.g., Zweig et al. 2015). Depending on the specifications of imaging instruments, it might be possible to detect individual species with such data; using a scale more easily identifiable to the human eye may enable reference samples of vegetation types to be collected directly from the images, thus reducing the scope of required field work. However, there are challenges with these techniques, including the rigorous pre-processing of data to achieve radiometric calibration and the precise co-registration of images to spatially align them in the time-series. Furthermore, high-resolution imagery may be sensitive to local noise and color variation, which requires specialized processing and mapping methods such as object-based image analysis (OBIA; Blaschke 2010; Dronova 2015).

Another promising cost-effective monitoring strategy involves using in situ phenocams: small, inexpensive digital cameras that can record fixed-view images of specific locations within sites as well as monitor changes in vegetation phenology and status at high temporal frequency. Networks of such strategically placed small cameras have been widely adopted by both wildlife ecologists (to detect occurrences of mobile species; e.g., Steenweg et al. 2017) and by environmental scientists who monitor vegetation greenness as an indicator of productivity and greenhouse gas sequestration (Sonnentag et al. 2012). Some local wetland restoration projects have adopted such networks (Knox et al. 2017). Phenocams offer an important opportunity to detect the precise timing of plant phenological shifts, including periods that fall between cloud-free satellite data acquisitions. Their views can be further equipped with fixed-visual-scale references to measure changes in plant height or water levels. Furthermore, the data from small cameras can be transmitted wirelessly to a receiving computer server station to automatically extract vegetation parameters, such as greenness.

CONCLUSIONS

This synthesis of monitoring efforts across 42 wetland restoration projects from the estuary reveals a comprehensive effort to track wetland responses to restoration treatments. Current monitoring strategies rely primarily on field surveys to assess key aspects of vegetation recovery, habitat properties, and their change. In contrast, spatially comprehensive geospatial data sets, including remote-sensing imagery, are still used sparingly, mainly to track plant cover and the extent of identifiable vegetation types. The nature of indicators commonly targeted by monitoring efforts makes it obvious that remote-sensing and spatial tools can complement field surveys via instantaneous and repeated coverage of wetland sites, but cannot replace the informative value of ground-level assessments, particularly for parameters that remote sensors cannot easily perceive. In particular, the increasing availability of remote-sensing data sets enables the characterization of spatial extent, phenology, and (in some cases) biomass and vertical structure of dominant vegetation types—as well as the detection of signatures of plant invasions at whole-site and regional scales that are unfeasible for comprehensive field surveys—while also reducing site disturbance and trampling. Remote-sensing data alone cannot provide a robust understanding of on-the-ground processes that underlie observed ecological dynamics, and remains limited in its capacity to accurately map individual species or their diversity. To be robust, geospatial tools and analytical methods require training and validation using on-the-ground data. Making monitoring strategies informative, cost-effective, and reproducible thus calls for a complementary use of spatial/remote and field-based strategies to capitalize on their respective unique advantages. Increasing

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monitoring strategies informative, cost-effective, and reproducible thus calls for a complementary use of spatial/remote and field-based strategies to capitalize on their respective unique advantages. Increasing the use of geospatial tools and remote sensing data will also require new data exchange venues to allow managers to compare site progress, share relevant data, and measure the combined progress made toward goals.

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