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SYNTHESIS

Leveraging time series of satellite and aerial images to promote the long-term monitoring of restored plant communities

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Abstract

Aims: Ecological restoration is integral to meeting conservation goals in rapidly changing landscapes, but outcomes vary substantially with some projects failing to meet their targets. To understand the causes of this variability, long-term monitoring of existing projects is critical, but this comes at considerable costs. Current literature counts several studies using time series of satellite images to assess vegetation responses to disturbances and landscape transformations. Yet such methods are seldom used in the restoration literature and in practice. This synthesis seeks to identify how common remote sensing approaches for the assessment of plant recovery could inform the monitoring and management of restored plant communities.

Methods: This paper reviews the methods and metrics used to detect trajectories (i.e., change through time) in plant properties from rich time series of aerial and satellite images following change drivers including fire, extreme climatic events, climate change, and pest outbreaks. Specifically, it reviews the sensors, vegetation properties, modeling approaches, and indicators that can help measure plant stress and response to interventions.

Results and Conclusions: Remote sensing methods commonly used in disturbance ecology and assessments of land-cover changes could inform the monitoring of restoration projects at low cost and over large spatio-temporal scales, thus bridging the gap between field surveys to rapidly identify stressors or unexpected vegetation responses. Potential applications include comparing sites to identify factors impacting their responses to restoration, assessing restoration success, and testing ecological hypotheses to guide future project planning and design.

KEYWORDS
adaptive management, Landsat, MODIS, phenology, plant community, reference, thresholds, time series, trajectory

1 | INTRODUCTION

Recognizing the urgency of restoring natural habitats to halt biodiversity loss and mitigate the impacts of climate change, the United Nations (UN) has proclaimed 2021–2030 the Decade on Ecosystem Restoration. As part of this effort, the UN announced the ambitious goal of restoring a billion hectares of ecosystem. Governmental and conservation organizations are increasingly leveraging ecological restoration to mitigate the impacts of habitat loss on biodiversity and ecosystem services, and to meet conservation targets. Yet the outcomes of restoration interventions vary substantially (Moreno-Mateos et al., 2012). To explain this variability, improve restoration design, and achieve the goals identified by the UN, it is vital to study the role of site and regional factors in shaping habitat responses to interventions (Brudvig et al., 2017). This calls for a more consistent monitoring of restored ecosystems, as stated by the Group on Earth Observations Biodiversity, which is developing a set of essential biodiversity variables that combine field data and remote sensing to facilitate the consistent monitoring of ecosystems.

Restoration practice is influenced by the theory of ecological succession; initial restoration treatments (e.g., stressor removal, abiotic modifications, seeding) are expected to elicit a directional and progressive recovery towards pre-set goals. However, the pathway to restoration success—often called the "trajectory" (i.e., changes in ecosystem properties from the moment of restoration until targets are met)—is rarely perfectly linear. Sites can take years, sometimes decades, to achieve a structural and compositional complexity likely to support targeted ecosystem functions and reminiscent of a pre-set reference point (Moreno-Mateos et al., 2012). Some sites may never meet these targets or rely on active management to maintain habitat properties.

Several factors can influence the response of a site to restoration interventions. Projects frequently observe an initial upward increase in vegetation extent, biomass, and sometimes diversity, as restoration opens up new niches favoring species establishment (Figure 1), sometimes accelerated via reintroduction. The slope of this increase varies with the intervention, site conditions, and landscape context (Matthews et al., 2009c; Matthews, 2015). Passive restoration (i.e., disturbance removal without further intervention) relies on species recovery from the seed bank or colonization from surrounding populations and might consequently see a slower upward trajectory (Hubbell et al., 1999). Even projects using active restoration (e.g., planting, seeding) may take time to meet plant coverage, height, or composition targets because species vary in their germination and growth rates or responses to environmental fluctuations (Kettenring & Tarsa, 2020).

After this initial increase, projects can observe an asymptotic phase (Figure 1a) during which vegetation properties remain stable. The timing of the transition between this upward trajectory and the asymptote depends on the properties of the vegetation (e.g., vegetation coverage targets are generally met earlier than composition or diversity), whether recovery is assisted via active interventions, and the initial degree of site degradation. Sites in which previous land uses have depleted the seed bank can experience a slower recovery and necessitate planting or seeding (Kettenring & Tarsa, 2020a). The capacity of a site to meet targets also depends on well-connected nearby habitats providing propagules to maintain populations (Kettenring & Tarsa, 2020). Sites supporting a greater richness might also be more stable due to a greater biotic resistance and diversity of responses to disturbance (Elmqvist et al., 2003). Other projects may see a temporary decline after the initial upward trend or following an asymptote (Figure 1b) due to nearby landscape transformations modulating nutrients, pollution, or the likelihood of pest and non-native species introduction, all of which can impact plant persistence and composition (Matthews et al., 2009a, 2009b,).

Identifying the factors impacting post-restoration trajectories can inform adaptive management and improve the design of future projects. Comparing the trajectories of sites with similar ecological characteristics or restoration design might reveal factors affecting plant recovery that would not be immediately evident from field observations alone. For example, a global meta-analysis of post-restoration wetland recovery revealed the impacts of climate and project size on the capacity to meet ecosystem function targets (Moreno-Mateos et al., 2012). Site comparisons have also highlighted the role of factors including hydrology, the identity of planted species, and landscape context on restoration success (Matthews et al., 2009b, 2009c; Meyer et al., 2010).

Time series of satellite and aerial images are extensively used to monitor gradual, abrupt, linear, and nonlinear trends in vegetation responses to disturbances. Remote sensors capture spectral information (i.e., patterns of light reflectance and absorption by different land surfaces) in different portions of the electromagnetic spectrum sensitive to vegetation abundance, photosynthetic activity, and moisture. Some programs have been acquiring satellite images at a regular interval for over 20 years (e.g., Landsat, Moderate Resolution Imaging Spectroradiometer [MODIS]; see Table 2), thus enabling long-term monitoring of vegetation responses to different drivers of change. In parallel, rapid technological advancements in unoccupied aerial vehicles (UAVs) promote post-restoration monitoring by facilitating image acquisition at custom time intervals and spatial extents (Anderson & Gaston, 2013). Comparing temporal changes in the light reflectance and absorption of vegetation has enabled previous studies to assess how natural disturbances and landscape transformations have impacted biomass, photosynthetic activity, or

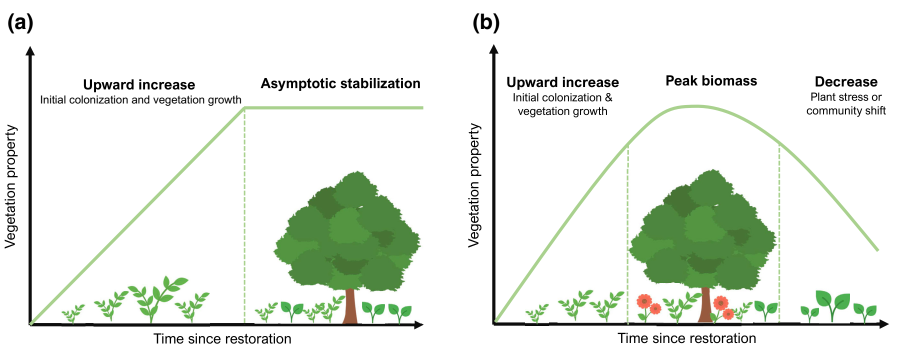

FIGURE 1 Hypothetical vegetation response to restoration and environmental change where (a) is an asymptotic response and (b) a unimodal response

composition. This synthesis focuses on vegetation properties as a central component of post-restoration monitoring and an indicator of the ecosystem's response to management, site conditions, and stressors. Although times series of satellite and aerial images have been frequently used to monitor vegetation recovery following disturbances, fewer studies have used them to monitor restorations. Restoration interventions, whether they involve stressor removal, topographic transformation, or seeding, are likely to trigger a plant response akin to that observed after a sudden disturbance (e.g., fire, flood) or a gradual change in environmental conditions (e.g., climate change). Here, I review how time series of satellite and aerial images have been used to characterize plant trajectories following disturbances and landscape transformations. I then discuss how these approaches could inform the long-term monitoring and adaptive management of restored sites at low cost. This study focuses on remote sensing instruments that can capture larger swaths (i.e., can capture larger study sites or regions), including spaceborne (i.e., data acquired via satellites) and airborne sensors (i.e., data acquired by cameras mounted on aircrafts and UAVs). The review excludes ground-based sensors such as phenocams, spectrometers, and flux towers, which can nonetheless provide valuable information for post-recovery assessments (Knox et al., 2017).

2 | METHODS

I used the Web of Science database and different combinations of the keywords restor*, traject*, remote sensing, time series, recovery, drone, UAV, radar, hyperspectral, and vegetation, to identify peer-reviewed papers using time series of satellite or aerial images to describe the vegetation response following disturbances or landscape transformations. After reviewing the abstracts, I excluded papers that were not peer-reviewed, did not focus on the trajectory of plant communities, included less than two years of data, or did not use satellite, aerial, or UAV-acquired images (Appendix S1). When reading selected papers, I noted their target ecosystem(s), the sensor(s) used to generate trajectories, their time span and scale (e.g., site, regional, national, continental, global), and location. I then assessed the methods and spectral vegetation indices used to generate site trajectories. I remarked whether/which thresholds were used to detect the impact of disturbances on plant communities and characterize their recovery, or whether/which similarity indices were used to compare the trajectories of several sites. Lastly, I recorded the factors that each study considered to be drivers of plant community trajectories (e.g., fire, climate, succession; Figure 2).

3 | RESULTS

This keyword research identified 120 papers published between 1996 and 2022 (Appendix S1). These papers all used time series of aerial or satellite images to identify vegetation response (section 4.1) to change drivers (Figure 2). Several papers (67%) used a remote sensing-based trajectory approach to assess plant community response to pulse disturbances (i.e., short-term, well delineated disturbances to ecosystems) including wildfire, pest outbreaks, and droughts (Figure 2). One-third of papers focused on press disturbances (i.e., long-term ecosystem perturbations; Figure 2) including land-cover or land-use change (Kariyeva & van Leeuwen, 2012; Qiu et al., 2018) and climate change. Fewer papers (8%) assessed site response to restoration interventions. The scale of the assessment varied from site level, to regional, continental, or even global level. Studies covered a time span of 3 to 76 years, with an average of 17 years.

Most studies (52%; $n = 62$) were conducted in forests, with fewer studies focused on other ecosystems including wetlands (i.e., areas permanently or temporarily flooded, and supporting species adapted to these conditions; $n = 16$), drylands (i.e., ecosystems in arid and semi-arid climates; $n = 7$), chaparrals (i.e., shrub-dominated ecosystems found in Mediterranean climates; $n = 4$), crops ($n = 7$), and grasslands (i.e., ecosystem dominated by grasses, $n = 3$). Some papers, particularly those assessing the impact of changes in land use/land cover on vegetation dynamics, simultaneously monitored various ecosystems ($n = 12$). Several studies focused on fire-prone regions including Brazil, the United States, Europe, and China. Long-term assessments of land-cover changes were conducted in China, Africa, and Latin America (Figure 3). Studies focusing on restoration and management interventions were equally distributed among the Americas, Europe, Africa, and Asia. Finally, studies conducted at a global scale ($n = 10$) predominantly analyzed the impact of climate change, land-cover changes, or local dynamics among a globally distributed ecosystem.

4 | DISCUSSION

This sample of peer-reviewed papers includes various approaches to monitoring plant dynamics over time and space. These studies generated trajectories from time series of satellite and aerial images to characterize plant community responses to both pulse (e.g., fire, pests) and press (e.g., climate or land-cover changes) disturbances over a short (<5 years) to long (>20 years) time span. Although few studies focused on restored ecosystems, their methods can nonetheless support post-restoration monitoring because it elicits a similar vegetation response (i.e., initial disturbance decreasing vegetation biomass followed by its recovery). The methods and indicators described in this review could thus help answer key management questions including: how are plant communities responding to restoration treatments (Figure 4, Q1); is the project meeting restoration targets (Figure 4, Q2); are post-restoration vegetation dynamics changing through time (Figure 4, Q3); and which factors are impacting the post-restoration responses of plant communities? (Figure 4, Q4). To answer these questions, project managers and researchers must first identify the remote sensing indicators (section 4.1; Figure 4) and sensors (section 4.2; Figure 4) best suited to their projects to then model plant community response through time (section

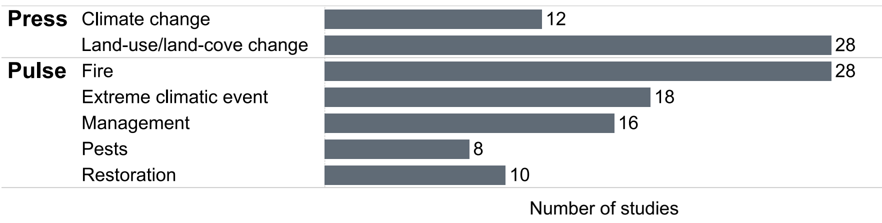

FIGURE 2 Publications reviewed for this study by drivers of change. Press disturbances are long-term disturbances on ecosystems, whereas pulse disturbances tend to be more temporary

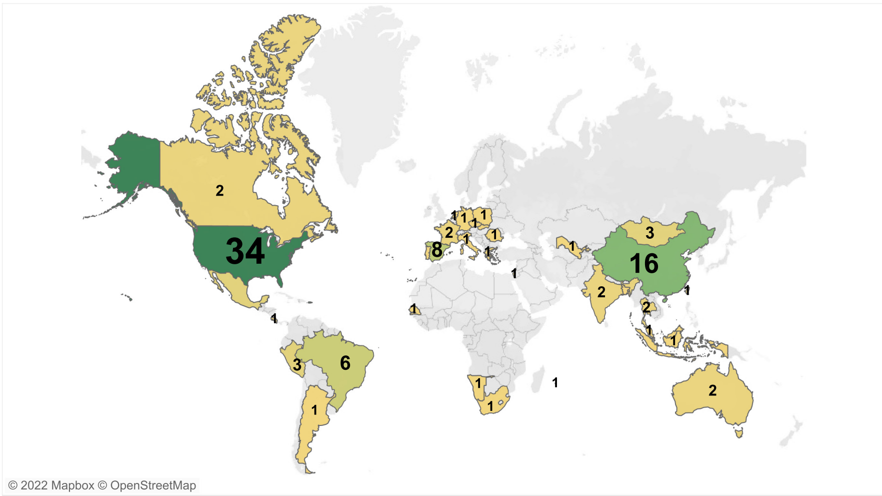

FIGURE 3 Publications reviewed in this paper, by study area. Excludes 10 studies with a global scope

4.3; Figure 4). From the resulting model of plant responses, project managers and researchers can detect thresholds and benchmarks to assess if restoration targets have been met (section 4.4; Figure 4) or breakpoints signaling changes in vegetation dynamics (section 4.4.2; Figure 4). Finally, models of vegetation responses can be compared across several sites to identify factors modulating responses to restoration (section 4.5.1; Figure 4) or test ecological hypotheses (section 4.5.3; Figure 4).

4.1 | Indicators of vegetation condition

In assessing long-term plant responses, managers must first identify the vegetation properties of interest and their spectral indicators (Figure 4, Q1, Step A) to model their trajectory (Figure 1). Managers can focus on the structural attributes (e.g., above-ground biomass, photosynthetic activity; section 4.1.1) of plant communities, their composition (section 4.1.2), or the ecosystem functions they provide (section 4.1.3), which all affect their spectral reflectance through time, season, and within different portions of the electromagnetic spectrum sensitive to plant characteristics. These dynamics can be monitored at the pixel, community, or site scale. Some studies choose a pixel approach to capture spatial heterogeneity in plant response and its drivers or establish the spatial extent of a phenomenon (e.g., extent of fire damage). Others focus on the plant community, patch, or site level to reduce the influence of noise or serve as a basis for site comparison and assessment of restoration effectiveness. These studies use different statistics (e.g., mean, median, maximum) to summarize values across all the pixels included in a unit.

4.1.1 | Structure

Structural indicators describe the three-dimensional distribution of plant biomass in a canopy (Noss, 1990) and include canopy height, cover, and biomass. They are commonly used in ecological restoration as an early metric of success because of their rapid response compared with composition or diversity (Craft et al., 2003). Structural indicators signal the capacity of restoration projects to provide key ecosystem services including habitat provisioning, carbon sequestration, and erosion control. Spectral vegetation indices (e.g., Normalized Difference Vegetation Index [NDVI], Enhanced Vegetation Index) sensitive to variations in plant biomass, coverage, and photosynthetic activity (Huete et al., 1997) are commonly used to estimate changes in vegetation coverage and biomass following disturbances. Spectral information from active sensors (section 4.2.2) such as light detection and ranging (LiDAR) and radio detection and ranging (radar) can detect three-dimensional changes in plant biomass, height, and density across different canopy layers (e.g., understory, upper canopy) (Bergen et al., 2009). After a disturbance, germination from the seed bank, leaf regrowth from remaining trees and shrubs, and plant colonization in open niches all modulate light absorption in different spectral bands; thereby increasing spectral vegetation index (SVI) values (Cai et al., 2018,) until vegetation growth and colonization have stabilized or led to the saturation of SVIs (Huete et al., 1997). Increases in canopy height, density, and patch expansion can also be perceived by active sensors (Räpple et al., 2017). These can also detect successional changes following disturbances, thanks to their sensitivity to canopy layers and their height and density

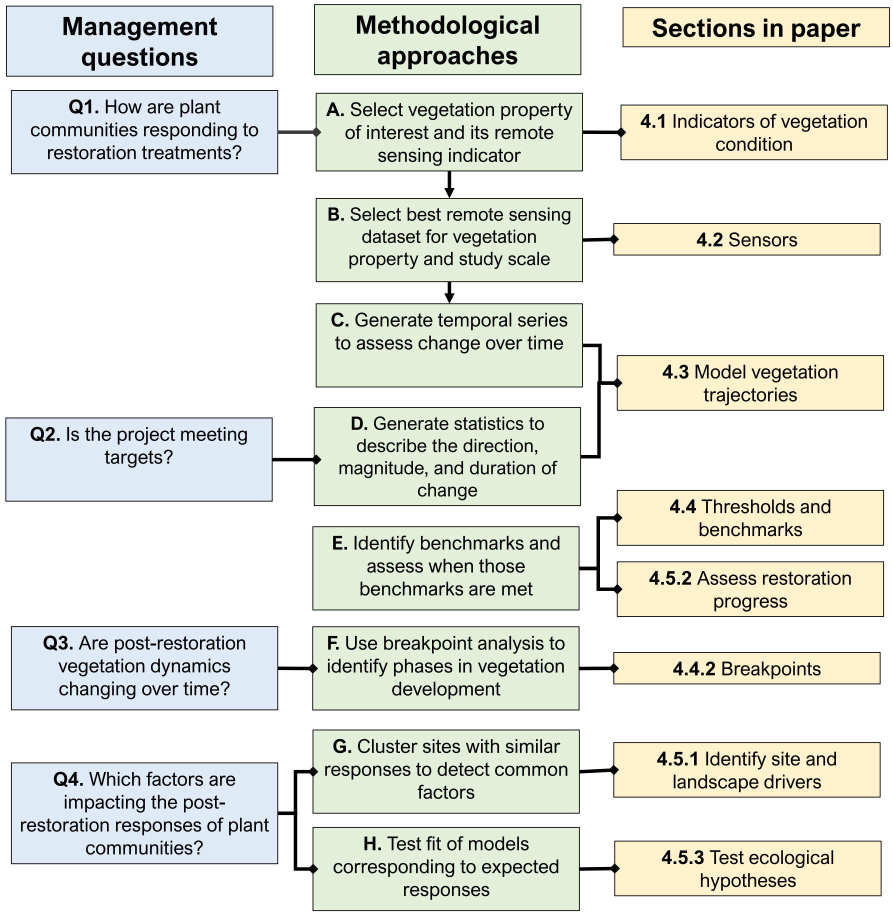

FIGURE 4 Common management questions and potential methodological approaches to answer them

TABLE 1 Examples of remote sensing indicators used to estimate vegetation properties and condition and their applications in studies reviwed in this synthesis

Indicators of vegetation condition	Remote sensing indicators	Site properties	Data requirements
Structure	Spectral vegetation indices	Vegetation coverage, biomass, photosynthetic activity (Cai et al. (2018a,); rate of vegetation recovery (Storey et al., 2016)	At least one satellite or aerial image captured at low cloud coverage
	Digital elevation model and digital surface model	Canopy height (Reis et al., 2019); patch expansion (Räpple et al., 2017)	Data from LiDAR sensor
Composition	Spectral signature of individual species; phenological metrics	Species composition; species turnover (Kariyeva & Van Leeuwen, 2012)	Hyperspectral or high-resolution data for some species, dense time series for species with distinct phenology
	Maximum annual greenness, texture metrics	Species diversity (Hernández-Stefanoni et al., 2012)	Several images throughout the growing season
Function	Spectral vegetation indices	Evapotranspiration (Mexicano et al., 2013); Gross Primary Productivity (Khare et al. 2017); Net Primary Productivity (Villa et al., 2012)	Several images throughout the growing season; models or field data to convert spectral vegetation index into estimates of function
	Phenological metrics	Phenology (Chen et al., 2019)	Several images throughout the growing season

differences (Ramsey et al., 1999). Structural indicators (Table 1) are also sometimes sensitive to changes in composition, particularly where species turnover impacts canopy characteristics (Sato et al., 2016).

Prior to generating trajectories, several studies conducted field measurements of structural properties (e.g., vegetation coverage, biomass) to establish their relation to SVIs or to validate digital elevation and surface models derived from LiDAR data (Chasmer

TABLE 2 Remote sensing data sets used within reviewed studies, their properties, and applications included in this review. Information on additional sensors of interest not covered by this synthesis is available in Transon et al. (2018) and Toth and Jóźków (2016)

Data sets	Spatial resolution	Frequency	Time span	Bands	Scale of analysis
Open-access					
AVHRR	1 km	Daily	1979–2019	4–6	Regional, global
AVIRIS	2–20 m	Variable	1998–Present	224	Site, regional
ASTER	15–90 m	16 days	1999–Present	14	Site, regional
CORONA	2–8 m	Variable	1960–1972	1	Site, regional
EnMAP	30 m	4–27 days	2022–…	242	Site, regional, state, country, global
ERS	26–30 m	35 days	1991–2011		Site, regional, state, country, global
Hyperion	30 m	16–30 days	2001–2017	220	Site, regional, state, country, global
Landsat	30–60 m	16 days	1972–Present	4–11	Site, regional, state, country, global
MODIS	250–1000 m	Daily	2002–Present	36	Regional, state, country, global
PRISMA	30 m	7–14 days	2015–Present	249	Site, regional, state, country, global
Sentinel-1	5–40 m	6–12 days	2014–Present	4	Regional, state, country, global
Sentinel-2	10–20 m	2–10 days	2015–Present	13	Regional, state, country, global
Commercial					
GeoEye	0.5–1.84 m	2–8 days	2008–Present	5	Site
IKONOS	0.82–3.2 m	1–14 days	1999–2015	4	Site
SPOT	10–20 m	1–3 days	1986–Present	4–5	Site
WorldView	0.31–1.24 m	1–2 days	2009–Present	8	Site

et al., 2018; Cai et al., 2018). Studies should conduct these measurements along a gradient of vegetation coverage or disturbance to establish robust relationships between field-measured vegetation properties and their remote sensing indicators. Once these relationships are established, projects can derive trajectories from daily interpolated SVI values (i.e., interpolation to create a complete time series from periodic observations) to account for seasonal and annual fluctuations. Other studies use annual values estimated either by aggregating observations (e.g., based on maximum, mean, or the sum of positive values over the growing season) or using one image per year captured at peak biomass (Meigs et al., 2011).

Lastly, some studies opt to derive recovery indices from spectral vegetation indices. Recovery indices can be computed from both active and passive sensors and measure the time needed for a pixel to reach its pre-disturbance greenness (João et al., 2018) or biomass (Freund et al., 2021; Nicolau et al., 2021), or the greenness or biomass of reference sites (Storey et al., 2016) following a disturbance. Because they integrate a baseline value (e.g., 5-year median, average during normal years), recovery indices can account for spatio-temporal variability in abiotic characteristics, plant composition, and their spectral properties. Local variation in resources—with topography, management, land use, or microclimate—can all impact plant coverage and productivity and their spectral signature. Even after full recovery, mixed pixels may remain below the site or regional average, because they encompass different land covers (e.g., forest, water, grassland) or growth forms (e.g., trees, shrubs, herbs) with contrasted spectral values. Climatic fluctuations and landscape transformations can further impact the capacity of a pixel to reach a certain level of greenness or biomass. Using nearby, undisturbed pixels as a reference (Storey et al., 2016) might provide more realistic targets for restoration projects and a flexible approach to goal-setting where landscape transformations and climate change result in shifting baselines (Fule et al., 2017).

4.1.2 | Composition

Compositional indicators describe the identity, richness, and diversity of the species in a plant community (Noss, 1990). Restorations commonly seek to reach the composition and/or diversity of reference sites and historical assemblages. However, compositional indicators are perhaps the most challenging to track using airborne and spaceborne sensors. When the spatial resolution of the sensor is coarser, it can be particularly difficult to detect individual species in mixed pixels in which their spectral signature becomes blended. Furthermore, several species can seem to have similar spectral reflectance when using broadband data sets. Hyperspectral data sets (section 4.2.4), which summarize spectral information within hundreds of narrow bands, can best differentiate species based on their chemical differences. For example, Meng et al. (2018) mapped variations in species composition along a burn gradient by deriving crown characteristics from LiDAR data (e.g., height, crown vigor) and spectral indices sensitive to different pigments from hyperspectral data (e.g., chlorophyll, carotenoid), which enabled them to detect individual species and their response to fire.

Some of the studies reviewed here also used indicators sensitive to changes in plant dominance, composition, and diversity instead of identifying individual species. For example, fluctuations in phenological metrics (e.g., start and end of flowering season) can signal plant community shifts including changes in diversity or dominance by a non-native species with a different phenology. Kariyeva and van Leeuwen (2012) used phenological metrics to detect crop changes and transitions from natural to anthropogenic plant communities. Using phenological metrics, Steinaker et al. (2016) revealed that woodland deforestation in Argentina reduced the growing season by up to 100 days because the loss of tree coverage favored the proliferation of shrubs. Recent research also shows the potential of remote sensing data sets to help estimate plant diversity. For example, maximum greenness (e.g., the highest SVI value observed each year) can help estimate plant richness due to the positive relationships between ecosystem productivity and diversity, which promote the efficient use of resources in time and space (Castillo-Riffart et al., 2017; Madonsela et al., 2017; Taddeo et al., 2019). Similarly, some studies have shown that indicators of spectral heterogeneity can be sensitive to plant diversity and variations in plant composition (Hernández-Stefanoni et al., 2012; Taddeo et al., 2021).

4.1.3 | Functional

Functional indicators describe the capacity of species to produce and regulate ecological processes including primary production, habitat provisioning, and climatic regulation. Functional indicators are increasingly used in post-restoration monitoring (Perring et al., 2015) particularly in highly modified landscapes where local conditions might preclude the return of historical plant assemblages but nonetheless allow ecosystem service provision. Equations derived from empirical observations can be used to convert SVI values into an ecosystem function estimate. For example, Mexicano et al. (2013) estimated the evapotranspiration of a costal wetland in Mexico by multiplying its NDVI by the evapotranspiration potential of local plant canopies measured empirically. Some remote sensing data sets also provide pre-calculated ecosystem functions. For example, MODIS (Table 2) offers Gross Primary Productivity (MOD17A3) and Net Primary Productivity products (MOD17A3HGF), both estimating primary productivity from dominant growth forms and SVI values. Hyperspectral and active sensors can be particularly beneficial in assessing ecosystem functions, thanks to their sensitivity to plant functional traits (Andrew et al., 2014). For example, Byrd et al. (2018) used data from Sentinel-1 (a synthetic aperture radar satellite; section 4.2.2) and Landsat to estimate the carbon sequestration capacity of tidal wetlands in the United States based on their vegetation properties (e.g., height, growth form).

Phenology is another commonly used indicator of vegetation recovery and is an essential biodiversity variable (Pereira et al., 2013) that can be easily monitored from remote sensing data. Phenological variations through time and space can reflect the vegetation response to stress and climate change (White et al., 1997; Pettorelli et al., 2005) and capacity to provide key functions including habitat provisioning and carbon sequestration. To model phenology, studies first apply a filter (Pettorelli et al., 2005) or a phenological model to a time series of satellite images to obtain a smooth, continuous curve representing the growth season of a plant community (Pettorelli et al., 2005). Phenological metrics can subsequently be identified using pre-determined thresholds (White et al., 1997) or by detecting changes in the inflexion of the growing season curve marking a “greening”, “browning”, or vegetation stabilization near peak biomass (Pettorelli et al., 2005). To validate phenological metrics derived from satellite time series, researchers and project managers can conduct frequent field surveys of vegetation to identify key phenological events, use phenological cameras, or higher resolution and higher frequency satellite data sets (White et al., 1997; Hufkens et al., 2012).

Phenological metrics can, in some instances, detect short-term disturbances or plant community shifts that do not otherwise significantly alter aggregated measures of vegetation structure. For example, Chen et al. (2019) monitored fluctuations in peak SVI over an 8-year period to distinguish the short-term (i.e., temporary reduction in growth that may be followed by a recovery) and long-term impacts (i.e., significant long-term impact on crop yield) of floods on crop productivity. In other studies, phenological metrics have indicated transformations in the composition of plant communities following succession, management change, or land-use conversion (Kariyeva & van Leeuwen, 2012; Steinaker et al., 2016). Although few field-based post-restoration monitoring efforts focus on the phenological characteristics of restored ecosystems, phenological assessments could nonetheless provide clues on site response to interventions and stressors, as illustrated in previous examples.

4.2 | Sensors

As open-access and low-cost remote sensing products become increasingly available, managers and scientists must decide which spectral, spatial, and temporal resolutions are best suited to their management question or hypothesis, study extent, target plant characteristics, and change driver (Figure 4, Q1, Step B). Luckily, cloud-based platforms such as Google Earth Engine (Gorelick et al., 2017) enable the batch processing of large remote sensing data sets and facilitate their analysis, comparison, and in some cases, fusion. Most studies reviewed here—particularly those focusing on multiple sites or a regional to global scale—utilized open-access optical sensors (e.g., MODIS, Landsat, Sentinel-2; Table 2; section 4.2.1) which provide free satellite images summarizing spectral information into tens of broader bands. Some studies also used active sensors (i.e., sensors emitting their own radiation) including LiDAR and radar (section 4.2.2), whereas others used hyperspectral sensors (i.e., satellites summarizing spectral information into hundreds of narrow bands; section 4.2.4). Finally, some used commercial sensors (e.g., IKONOS, WorldView; Table 2) and UAVs (section 4.2.3).

4.2.1 | Optical open-access sensors

With frequent (16–30 days) image acquisition since 1972, NASA's Landsat program offers the longest global record of remote sensing data (Table 2) and is consequently the most widely used across this sample of studies. This time span is well suited to monitoring site responses to climate change (Guo et al., 2017; Copeland et al., 2019) or examining factors promoting site resilience (Chen et al., 2014; Fernández-García et al., 2018). With its 30–60-m resolution, Landsat was used throughout this sample to monitor vegetation properties at various scales ranging from site level to the global level. With between 4 and 11 bands in the visible, near-infrared, shortwave infrared, and thermal portions of the electromagnetic spectrum, Landsat products can be used to monitor a variety of plant community properties. Landsat products are commonly used to measure fluctuations in vegetation structure and abundance using SVIs based on visible, near-infrared, and shortwave bands. Landsat's frequent data acquisition and long time span can detect seasonal variations and phenological indicators, long-term changes and interannual variations (e.g., recovery indices), although MODIS and Sentinel-2 have better temporal resolution. Throughout its 30+ years, the Landsat program has operated different sensors that vary slightly in spatial, spectral, and temporal resolution. Long-term analyses thus warrant pre-processing to harmonize early images captured at a coarser resolution (e.g., Landsat MSS; 1972–2013; 60 m) with later ones captured at a 30-m resolution (e.g., TM, ETM+, OLI; 1984–present). Equations developed by Roy et al. (2016) enable users to calibrate Landsat sensors with different bandwidths.

The MODIS sensor aboard the Terra and Aqua platforms was also commonly used across this sample. MODIS provides daily surface reflectance data in 19 bands at a 250–500-m resolution (Table 2). Users can download pre-calculated products including SVIs to estimate vegetation structure and abundance or indicators of ecosystem functions including Gross Primary Productivity (section 4.1.3). With this coarser spatial resolution, MODIS enables regional (Qiu et al., 2017; Ni et al. 2019) to global monitoring (Zhang et al., 2016) of key drivers of ecosystem change. MODIS has been capturing images since 2000. Its frequency, with daily image acquisition, is well suited to studies focusing on plant phenology which rely on frequent observations to identify key events in the growing season. Its frequency can be particularly beneficial for monitoring in regions with high cloud cover. However, its coarser resolution compared with Landsat or Sentinel-2 can be limiting when trying to monitor plant communities with a patchy distribution.

Few of the studies reviewed here used the multispectral instrument (MSI) Sentinel-2, probably because of its shorter archival time span (5+ years), which currently limits its application for the long-term assessment of restoration progress. Sentinel-2 has offered 12 spectral bands at a 10-m resolution since 2015 (Table 2). It provides better temporal (one image every 5–10 days) and spatial resolution (10 m) than the Landsat constellation. As such, Sentinel-2 is likely to become an important data source for post-restoration monitoring. Because Landsat and Sentinel-2 have similar bands and bandwidth, several studies have combined them (see section 4.2.5) to increase the temporal frequency of images in regions with high cloud cover, expand the temporal scope of analyses, or improve spatial resolution (Zhang et al., 2021). For example, Zhang et al. (2021) fused Landsat 8 OLI and Sentinel-2 data to map small-scale disturbances in a tropical forest with frequent cloud cover. Furthermore, Sentinel-2 provides additional spectral bands representing the red-edge portion of the electromagnetic spectrum, which in previous studies showed sensitivity to vegetation condition and response to disturbances (Abdullah et al., 2019; Evangelides & Nobajas, 2020).

Lastly, a few studies reviewed here leveraged remote sensing data captured by commercial sensors (e.g., WorldView; IKONOS; Table 2). Commercial data sets generally offer more spectral bands and a finer temporal and spatial resolution. Such properties can be particularly useful when mapping and monitoring distinct plant communities (Ballanti et al., 2017; Chapple & Dronova, 2017). However, using commercial sensors over a large spatial extent or long period can rapidly increase monitoring costs. Consequently, the studies using commercial sensors focused on one site and assessed vegetation change over few images, instead of relying on data-heavy approaches such as phenological assessments or breakpoint analysis (Chapple & Dronova, 2017; Ballanti et al., 2017).

4.2.2 | Active sensors

Some studies used LiDAR systems typically mounted on an airplane or UAV, which enable data acquisition at custom spatio-temporal extents. LiDAR instruments emit their own pulse to measure their distance to various surfaces on Earth. Variations in the intensity of the return signal can help detect land surfaces and their properties. This enables LiDAR systems to estimate the three-dimensional structure of surfaces, including canopies and their different layers. Such information can be particularly useful when monitoring vegetation recovery after disturbance or restoration. For example, Räpple et al. (2017) used a LiDAR system mounted on a UAV to monitor the three-dimensional expansion of vegetated riparian habitats following a flood event. Similar methodological approaches could be used to track vegetation expansion and height in restorations.

Radar sensors emit microwave pulses at regular time intervals and then record the portion of the signal that is backscattered and at what speed. This allows the sensors to estimate their distance from a given surface. As such, radar systems are particularly useful in detecting variations in canopy height and density (Bergen et al., 2009), while their sensitivity to structural heterogeneity might help estimate the diversity of ecological communities (Bae et al., 2019). Radar systems have the chief advantage of using longer wavelengths that can penetrate through clouds, making their use particularly appealing in regions of the globe with frequent cloud cover. Sentinel-1 is commonly used to map plant communities and their dynamics thanks to its high spatial and temporal resolution (Table 2). A few of the studies reviewed here (Griffiths et al., 2010; Jenkins et al., 2014) also used data from the ERS-1 and ERS-2 sensors (Table 2), but the sensors unfortunately ceased operation in 2000 and 2010, respectively.

4.2.3 | Unoccupied aerial vehicles

UAVs (i.e., aircrafts controlled remotely and commonly called drones) can further promote rapid and repeated assessments of site condition, floristic health, and composition (Anderson & Gaston, 2013) to monitor restoration success and inform adaptive management. UAVs can detect certain species-specific characteristics including distinct phenology or physical and chemical differences (e.g., water, chlorophyll, carotene content), enabling the identification of some individual species and an estimation of diversity (Calderón et al., 2013; Whiteside & Bartolo, 2018). Users can customize the frequency, timing (e.g., focusing on certain phenological stages during which species can best be identified), and spatial extent of data acquisition, thus offering a more flexible approach and finer resolution than governmental satellites. Furthermore, some studies reviewed here used UAVs with several cameras, which enabled them to track both the spectral properties and three-dimensional biomass distribution of plant canopies (Calderón et al., 2013; Whiteside & Bartolo, 2018; Reis et al., 2019). For example, Calderón et al. (2013) used a combination of thermal and multispectral cameras to measure the impact of a fungus on the leaf chemistry and physiology of olive orchards. Whiteside and Bartolo (2018) used multispectral and LiDAR cameras to track the recovery of woody species following the rehabilitation of a mine. However, UAVs present challenges that might curb their use in particular sites or ecosystems. For example, species identification can be difficult in ecosystems with dense vegetation, tall trees masking the understory, or very short vegetation (Durgan et al., 2020). The limited autonomy of UAVs (i.e., length of flight before needing a battery change or recharge) is not suited to the monitoring of large sites. Country-specific and local regulations (summarized in Stöcker et al., 2017) can require permits and piloting licenses and restrict their use in high-density areas or near certain federal facilities.

4.2.4 | Hyperspectral sensors

Hyperspectral sensors record spectral information within hundreds of narrow bands sensitive to various plant characteristics including pigment, water, and nitrogen content (Andrew et al., 2014). As such, they are well suited to studies seeking to map plant diversity or detect changes in the composition of a plant community following a disturbance. Such properties can also be useful in assessing the response to disturbance and recovery patterns specific to individual species. For example, Numata et al. (2011) used hyperspectral data from the sensor Hyperion (Table 2) to derive spectral indices sensitive to forest water and pigment content, to assess the rapidity with which forested plant communities recovered from burn damage. Luckily, researchers and managers now have access to an increasing number of open-access hyperspectral data sets including PRecursore IperSpettrale della Missione Applicativa (PRISMA; 30-m resolution and 249 bands), Environmental Mapping and Analysis Program (EnMAP; 30-m resolution and 242 bands), and Hyperion (10–20-m resolution and 128 bands), among others (Transon et al., 2018). The increasing availability of these sensors and their sensitivity to various plant characteristics make them particularly appealing in the context of restoration monitoring.

4.2.5 | Data fusion and combination

Some studies in this sample used a combination of remote sensing data sets with complementary properties. For example, Sato et al. (2016) used LiDAR to measure forest biomass recovery within burn scars identified using MODIS images. LiDAR can thus offer more detail on the structure of vegetation canopies where optical sensors such as MODIS and Landsat may be impacted by a saturation effect. Similarly, Morgan et al. (2021) used data acquired by a UAV as ground-truthing to estimate changes in vegetation cover across a 30-year Landsat time series. Some studies utilized commercial sensors with finer spectral and spatial resolution to generate training samples, particularly where a large spatial scope precluded an extensive field survey. For example, Chu et al. (2016) identified areas with low to high burn severity within WorldView-2 images to serve as training samples to detect and classify burn within Landsat images.

Emerging data fusion approaches will also improve capacities for vegetation monitoring and trajectory analysis. The harmonized Landsat–Sentinel-2 combines images acquired by Landsat 8 OLI and Sentinel-2 MSI, both of which have similar spectral characteristics, into new data sets with more frequent images (5–16 days) (Claverie et al., 2018). The data set now covers 5+ years of data. This can be particularly useful for phenology analysis requiring high temporal frequency or in regions of the globe prone to frequent cloud coverage. Similarly, the Spatial and Temporal Adaptive Reflectance Fusion Model (STRAFM) joins Landsat and MODIS imagery to create a data set with medium–high resolution (30 m) and a higher temporal frequency conducive to disturbance assessment and phenological analyses (Gao et al., 2006).

4.3 | Model vegetation trajectories

Complete time series can help assess how indicators of vegetation condition (section 4.1) are changing over time. To generate a complete time series from satellite observations, assess its general properties (Figure 4, Q1, Step C), and minimize outliers, studies can fit linear trends to annual SVI and spectral values (section 4.3.1), and use more flexible nonlinear models (section 4.3.2) or piecewise models (section 4.3.3) sensitive to different phases in vegetation recovery. These approaches to trend detection and analysis seek to characterize the direction, magnitude, and duration of phases in the vegetation response to management, restoration, or press and pulse disturbances.

TABLE 3 Approaches to modeling vegetation trajectories, their applications, and metrics with associated references

Model type	Modeling approaches	Type of information you can derive	Applications: Vegetation response	Applications: Change drivers
Linear regression	Theil–Sen regression (Fernandes & Leblanc, 2005)	Rate of change Direction of change Contribution of individual change drivers (Liu et al., 2014)	Gradual and consistent	Press
Nonlinear models	Asymptomatic (Storey et al., 2016) Unimodal (Chasmer et al., 2018) Smoothing spline (João et al., 2018) Wavelet analysis	Rate of change Direction of change Time needed to meet threshold	Response rate fluctuates over time	Press, pulse
Piecewise regression	BFAST (Verbesselt et al., 2010) LandTrendr (Kennedy et al., 2010)	Source of disturbances (Bernardino et al., 2020) Rate of change (Meigs et al., 2011) Direction of change Length of response (Meigs et al., 2011) Timing of transition in vegetation response phases (Bernardino et al., 2020)	Response rate fluctuates over time	Several pulse and press change drivers

Remote sensing is a particularly useful tool to model vegetation trajectories because it can provide repeated observations at a consistent time interval and over long periods. Across the studies reviewed here, trajectory detection was commonly used to assess the time needed for an ecosystem to re-cover to a pre-disturbance benchmark following a short-term, time-bound disturbance (i.e., pulse disturbance) such as a wildfire (João et al., 2018), drought (Bernardino et al., 2020), or flood (Cai et al., 2018a). Other studies used trajectory analyses to assess the impacts of press disturbances on ecosystem properties of interest. Such disturbances included climate change, successional changes, or modifications to management practices (Hutchinson et al., 2015; Vinatier et al., 2018).

4.3.1 | Linear models

Linear regressions (Table 3) can model the general direction of vegetation change, fill gaps in time series, and smooth noisy data points (Zhu, 2017). They are best suited to the modeling of gradual vegetation responses to press disturbances because they assume a continuous change in a constant direction and at a constant rate (Zhu, 2017). Across this review, linear regressions helped detect plant responses to climate changes, land conversions, and restoration efforts (Qiu et al., 2018; Pastick et al., 2019). Theil–Sen regression—which identifies the trend as the median value across slopes computed among pairs of points (Fernandes & Leblanc, 2005)—is commonly used to detect linear trends in time series because it is less sensitive to outliers than least square regression analysis (Fernandes & Leblanc, 2005). Wilcoxon–Mann Whitney (Pastick et al., 2019) or Mann–Kendall (Yi et al., 2013; Qiu et al., 2017) statistics can subsequently be used to assess the significance of linear trends. Studies can then compare the direction (i.e., upward versus downward) and slope (i.e., rate of change) of trends observed across the study area to disentangle pixel responses to different drivers of change (Qiu et al., 2018; Pastick et al., 2019). Multivariate linear models can also be leveraged to assess the relative contribution of different change drivers. For example, Liu et al. (2014) used a partial least regression model, which reduces explanatory variables into a smaller set of uncorrelated predictors, to assess the impact of temperature and precipitation on net primary productivity in Hunan Province, China. Copeland et al. (2019) used linear mixed models to assess the impact of climatic conditions, invasive species, and management on the post-restoration recovery of drylands.

4.3.2 | Nonlinear models

Nonlinear models (Table 3) can account for fluctuating rates of change over time, whereas linear models assume that change remains constant (Zhu, 2017). Disturbances and restoration can trigger an asymptomatic response characterized by an initial upward trend as vegetation benefits from empty niches followed by a stabilization in spectral signal as colonization and plant growth slow (Figure 1a).

For example, Storey et al. (2016) fit an asymptotic model that characterized the recovery of shrublands after a fire (i.e., increase in greenness as vegetation expands until it stabilizes). Sun et al. (2012) used a similar function to model the recovery of forested pixels following an ice storm in China. Immediately after the ice storm, milder temperature, abundant precipitation, and nutrients left by decaying vegetation enabled the rapid regrowth of vegetation. Other sites may follow a unimodal trajectory (Figure 1b) in which an initial upward trend in vegetation growth is followed by a decrease as a new stressor arises. Across this literature review, some studies sought to identify pixels that conformed to a pre-determined hypothetical nonlinear model or compare the fit of different models (Chasmer et al., 2018).

Some studies preferred more flexible gap-filling (i.e., interpolation of missing values using prior and subsequent observations) and curve smoothing techniques. From the resulting continuous curves, the studies can then generate different indices describing the recovery of the ecosystem (João et al., 2018). Such techniques can be classified into broad categories including filtering, threshold-based, and decomposition approaches. Filter-based approaches (e.g., Whittaker smoother, Savitzky–Golay filter) use a local (i.e., portion of the time series) temporal interpolation to fill in gaps between observations and correct extreme values. Threshold-based techniques (e.g., BISE) reject outlier values based on a pre-determined threshold. Finally, decomposition models (e.g., wavelet analysis) use a global approach (the model is applied to the entire time series) to decompose the time series into a multiscale temporal pattern.

4.3.3 | Piecewise regressions

Piecewise linear models (Table 3), which segment time series into several linear trends or phases, can detect both abrupt and gradual changes, and upward and downward trends, whereas linear and nonlinear models focus on one generalized response to drivers of change (Zhu, 2017). As such, piecewise linear models can identify multiple sources of disturbance operating at different schedules. In this review, applications included separating different pest outbreaks, detecting successional changes, and disentangling the impact of various management practices (Meigs et al., 2011; Hutchinson et al., 2015). Commonly used algorithms to conduct piecewise linear regressions include Breaks for Additive Season and Trend (BFAST; Verbesselt et al., 2010) and Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr; Kennedy et al., 2010). Both algorithms seek to segment time series by identifying breakpoints separating trends varying in slope, direction, or fluctuations. Bernardino et al. (2020) used BFAST to identify trajectories in dryland responses to landscape transformations and climate change. In their study, deforested pixels were characterized by a period of relative stability in greenness (pre-deforestation) followed by a decline. By contrast, agriculture abandonment and subsequent restoration was characterized by decreasing greenness followed by an upward trend. Meigs et al. (2011) used LandTrendr to identify different forested pixel responses to pest outbreaks (e.g., long decline followed by recovery, long decline, short decline, and recovery) and separate the impact of different insect mortality agents (e.g., pine beetle versus western spruce budworm).

Statistics can characterize different phases, or time series segments, separated by breakpoints. The direction and slope of individual segments might help distinguish different drivers of change. Similarly, the duration of the different segments can distinguish disturbances and indicate whether they result in an abrupt or gradual vegetation response. Studying how the frequency of breakpoints varies throughout the study area can reveal locations prone to more disturbances, successional shifts, or landscape transformations. For example, Bernardino et al. (2020) identified "hotspots" in the frequency of breakpoints associated with changes in the ecological functioning of drylands, which corresponded to areas subject to increased anthropogenic pressure and rapid climate change. Piecewise linear regressions could be applied in the ecological restoration context to detect "turning points" in restoration projects and identify their potential causes. For example, an upward increase followed by a decrease has been attributed in field-based studies to a lack of connectivity and its impact on propagule availability and to an increase in aggressive coverage and its impact on plant diversity and coverage (Hubbell et al., 19991999aMatthews et al., 2009c; Matthews, 2015).

4.4 | Thresholds and benchmarks

Once a time series revealing trends and fluctuations in vegetation properties is generated, project managers can identify when the site meets a pre-determined target (Figure 4, Q2, Step E) or falls below a certain value suggesting an arising source of stress. Managers can also identify within time series inflexions marking transitions in the spectral properties of vegetation resulting from succession, disturbance, or other ecological processes (Figure 4, Q3, Step F; breakpoints).

4.4.1 | Thresholds and benchmarks

Thresholds (Table 4) mark a tipping point between two stable states (i.e., different combinations of biotic and abiotic characteristics that can persist at a location) following a disturbance modifying biotic structure and interactions or abiotic conditions (Briske et al., 2006). Beyond this threshold, interventions are likely needed to recover pre-disturbance conditions (Briske et al., 2006a). In the remote sensing literature, thresholds typically consist of a spectral value (e.g., SVI, burn index) used to separate the undisturbed and disturbed states of a pixel or distinguish its "disturbed" state from its "recovery". Thresholding enables a quasi "real-time" identification of disturbances and restoration progress because it relies on pre-determined values beyond which the pixel shifts to its disturbed or recovered state (Zhu, 2017). Thresholds are most useful to identify abrupt drivers of changes (e.g., fire, flood) triggering a rapid vegetation response.

TABLE 4 Applications of thresholds and breakpoint analysis and their data needs

Indicator	Applications	Data needs	Drivers of change
Thresholds	Identify disturbances (Scheffer et al., 2012; Yi et al., 2013)	Spectral information from previous or nearby disturbances or historical data	Abrupt events triggering rapid vegetation response
	Separate noise in time series from "real" change (Villa et al., 2012)	Long-term time series	Abrupt events triggering rapid vegetation response
	Identify when site has met goals	Spectral information from reference site	Restoration, management
Breakpoints	Detect multiple disturbances (Verbesselt et al., 2010)	Complete time series	Various drivers of changes
	Identify factors impacting vegetation recovery (Niu et al., 2019)	Complete time series	Various drivers of changes

Ground-truthing can determine spectral thresholds associated with an observed plant response to disturbances, including shifts in successional stage, dominant species, or decreases in plant coverage and density. Shifts in alternative stable states, for example, can modify tree density and dominant growth forms, thereby impacting the tree cover observable from satellite images (Scheffer et al., 2012). For example, vegetation removal due to fire and the subsequent deposition of ash can trigger a decrease in the NDVI sensitive to plant biomass and increase surface temperatures (observable from thermal sensors such as Landsat; Table 2) or burn indices. Once spectral values associated with site-level signs of vegetation disturbance are identified, they can be used to assess other instances in time and space.

Where a large spatial scope precludes the representative acquisition of field samples, studies instead use thresholds based on historical averages or reference sites; an approach also commonly used to set restoration targets. Ideally, "historical thresholds" should be based on an average or median spectral value over several years to account for fluctuations in vegetation biomass and atmospheric conditions. For example. Yi et al. (2013) used a 2-year pre-fire NDVI average as a benchmark to identify fire damage. Studies can also use reference sites to set a threshold between disturbance and recovery. Pre-determined thresholds of greenness variation can separate noise from "real" variation in greenness indicating a vegetation response to disturbances. For example, Villa et al. (2012) used a threshold of vegetation coverage, based on the SVI values of undisturbed areas, to separate tsunami damage from normal fluctuations in SVI driven by tidal fluctuations.

Thresholds are context dependent (Bestelmeyer, 2006): some sites might be inherently greener than others because of their environmental conditions, the plant communities those conditions support, or the presence of water bodies and anthropogenic features. Recognizing this, Yang et al. (2018) used a site-specific coefficient of variation in SVI (ratio of site standard deviation to mean) rather than an absolute value to identify a realistic threshold of plant damage specific to each site. Similarly, thresholds might need to be dynamically evaluated because landscape transformation, climate change, and other drivers of change continue to impact ecosystems and their spectral properties.

4.4.2 | Breakpoints

Breakpoints (Table 4) are used in piecewise regressions to separate trends differing in direction, slope, or fluctuations. Breakpoints might occur where extreme disturbances mark a transition from an upward trend in greenness to its rapid decline (Figure 1b). Similarly, successional transitions triggered by a disturbance can impact trend slope and direction, resulting in a series of breakpoints (Greig et al., 2018). Finally, a breakpoint between a gradual increase in greenness and a steeper one might reflect the positive impact of a management policy on plant communities (Bernardino et al., 2020). Whereas thresholding relies on pre-determined values to identify shifts in ecosystem states, breakpoints use complete time series to identify past instances of community shifts. As such, they do not allow for "real-time" monitoring of ecosystem shifts, but rather can assess factors triggering changes in plant communities. To assess whether breakpoints are occurring in the time series, studies can use the ordinary least squares residuals-based Moving Sum (OLS-MOSUM)—which detects potential breakpoints based on the moving sum of residuals—then test different iterations of breakpoints until an optimal solution (e.g., a solution that minimizes the Bayesian Information Criterion; Verbesselt et al., 2010) is met. In the restoration context, breakpoint analysis can help compare the recovery time of different sites and assess how disturbances impact recovery. For example, Niu et al. (2019) used breakpoint analysis to assess how vegetation growth in northern China was impacted by regional restoration efforts, dust storms, and land management.

4.5 | Application in restoration science and practice

Once trajectories are identified, breakpoints detected, and trends measured, several of the approaches described here can be tailored to the restoration context to help project managers identify factors modulating the trajectories of plant communities (Figure 4, Q4, Step G).

4.5.1 | Identify sites and landscape drivers

Clustering sites with similar trajectories could reveal local and regional constraints to vegetation recovery. Previous efforts to cluster sites based on field observations have shown the incidence of landscape context, management, and land legacies, all of which may not be immediately evident when focusing on the response of one site alone (Matthews, 2015). Time series extracted from satellite observations can facilitate site clustering at low cost and across broader gradients of environmental conditions than is achievable using field observations alone. For example, Qiu et al. (2017) clustered pixels showing similar trajectories to highlight how regional constraints, including climatic and topographic patterns, had modulated the local outcomes of a national afforestation program. Clustering can expand the temporal scope and frequency of site monitoring to deepen our understanding of how press disturbances and the combined actions of multiple stressors impact vegetation dynamics. Chasmer et al. (2018) grouped pixels with a similar trajectory to examine how watershed characteristics (e.g., topography, soil) regulated vegetation response to drought in Canada. Different indices of trajectory similarity—including correlation indices, descriptive statistics, and distance-based similarity indices—can identify pixels or sites with analogous temporal responses (see Lhermitte et al., 2011). Correlation indices (e.g., Pearson's cross-correlation; Lhermitte et al., 2011) determine whether two time series are generally moving in the same direction. Statistics describing trajectories (e.g., slope, duration, direction, average) can serve as a starting point to group pixels or sites. Once these statistics are generated for each unit of analysis, multivariate clustering approaches (e.g., classification and regression trees, principle components analysis) can group sites. Distance-based similarity indices (Lhermitte et al., 2011) can group trajectories based on their distance at different time steps.

4.5.2 | Assess restoration progress

The trajectory approach could establish when restoration goals are met and promote a more flexible evaluation of restoration success. Site capacity to meet certain thresholds is context dependent because local constraints (e.g., topography, adjacent land uses) can limit maximum potential vegetation density. Furthermore, a trajectory approach could offer more flexible targets in landscapes with shifting baselines. Benchmarks and reference conditions are typically based on one sampling campaign or very few years of sampling, thus not always accounting for the impact of extreme climate events, landscape transformations, and climate change on the plant communities of reference and restored sites. Although monitoring plant dynamics in both reference and restored sites can be resource-intensive, remote sensing can be leveraged to dynamically assess whether restored sites are deviating or otherwise approaching the conditions of reference sites. The same similarity indices that can guide site clustering (4.5.1) could be used to this effect. Where reference sites are not readily applicable, an alternative approach could be to develop an "expected" trajectory based on several restored projects (i.e., range of trajectories). Open-access optical sensors can help characterize broad signals of plant community health and response to interventions. UAVs, which typically provide a better spatial resolution than open-access products, will also become increasingly useful in helping project managers track the responses of target species and identify the role of local factors on their recovery (Neumann et al., 2021).

4.5.3 | Test ecological hypotheses

Future studies could leverage the trajectory approach to test ecological hypotheses pertaining to patterns of vegetation recovery and their drivers (Figure 4, Q4, Step H). Different ecosystem processes, disturbance types, and forms of management are likely to produce a contrasted site response and long-term spectral signal. The restoration literature reports various responses to restoration interventions, with some sites showing an asymptotic trajectory (Figure 1a), whereas others show a linear or unimodal response (Figure 1b). Model fitting (i.e., testing which mathematical model best fits the general trend of observed values) can help identify where such responses are occurring, to tease their potential drivers. For example, Meigs et al. (2011) generated hypothetical trajectories describing how vegetation responses to two pests (mountain pine beetle and western spruce budworm) were mediated by different environmental conditions (e.g., frequency of pest outbreaks, initial site productivity). Similarly, Qiu et al. (2017) formulated hypothetical trajectories representing different landscape transformations and sought to identify where these different trajectories were occurring to assess broad patterns of landscape change. Furthermore, assessing the characteristics of vegetation trajectories (e.g., slope, direction, time before stabilization) can help measure the incidence of different environmental drivers. For example, Cai et al. (2018) assessed how the recovery rate of burned forest varied with local seed availability and presence of environmental filters to seed dispersal. Copeland et al. (2018) assessed how the post-fire recovery rate (i.e., time needed to recover to pre-disturbance greenness) of drylands varied with biological invasions, soil characteristics, and extreme weather.

4.6 | Limitations

Although a trajectory approach could expand the spatio-temporal scope of restoration monitoring at low cost, its ease of use might vary with ecosystems and geographic regions. Most studies reviewed here focused on forests, while fewer papers looked at ecosystems with shorter canopies (e.g., grasslands), sparse vegetation (e.g., drylands), or water exposure and fluctuations (e.g., wetlands). Both spectral indicators of vegetation properties and algorithms for time series analysis have been thoroughly tested in—and often developed for—forests, giving future studies extensive literature to rely upon. The structural characteristics of forests—including generally a high coverage and leaf area index—facilitate the separation of disturbed and undisturbed states characterized by a decline in greenness. In ecosystems with a sparse or heterogeneous vegetation distribution, it becomes more challenging, but not impossible, to detect vegetation in mixed pixels (e.g., pixels covered by vegetation and bare ground) or separate disturbances from natural fluctuations.

Geographic variations in the availability of cloud-free data might also make the use of trajectory analysis somewhat challenging when relying on passive sensors. Some regions are characterized by more cloud coverage, limiting the availability of cloud-free data to generate SVIs. In these regions, indicators relying on frequent observations (e.g., phenological metrics) might be difficult to generate, but studies can instead focus on aggregated indices (e.g., annual maximum greenness) or rely on one cloud-free image per year, preferably captured at peak growing season. Spatial variability in cloud cover might also be challenging for studies focusing on a national or global scope. For such studies, it might be prudent to conduct a sensitivity assessment to determine whether their selected indicators of vegetation properties are affected by the availability of cloud-free images or leverage radar sensors, which are not impacted by cloud cover.

Finally, open-access remote sensing data sets with a long time span and frequent data acquisition (Table 2) typically have a coarser resolution. They are consequently more suited to the monitoring of total vegetation coverage, or the average phenology or ecosystem functions of plant communities, rather than their composition. UAVs and commercial sensors with higher spectral resolution (Table 2) could help detect some changes in species composition or diversity, but their use is best suited to studies with a limited extent. Research wishing to study temporal changes in species composition could use a trajectory approach to target field monitoring efforts, notably by detecting signs of ecosystem stress or unexpected trajectories.

5 | CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Restoration interventions can elicit a plant community response similar to that triggered by fire, flood, or hurricanes; vegetation removal opens new niches and increases resource availability. This favors seed bank emergence and colonization from nearby populations, thereby increasing vegetation biomass, coverage, and their spectral indicators. As such, remote sensing approaches used to monitor vegetation response to press and pulse disturbances could be integrated into post-restoration monitoring efforts. Monitoring post-restoration vegetation trajectories at the pixel or site level could enable project managers to detect when a site is meeting targets or diverging from them suggesting a need for adaptive management. Comparing the trajectories of several sites could help identify the factors modulating their recovery that would otherwise be challenging to identify using site monitoring alone. Finally, a trajectory approach could set more flexible restoration targets by monitoring conditions in reference and restored sites simultaneously, thereby accounting for the impact of landscape changes on the vegetation potential of both sites.

To support the widespread use of a trajectory approach in restoration monitoring, future studies could tailor indicators and methods that are already used to monitor vegetation response to natural disturbances to the specific context of restoration. Spectral indicators of vegetation structure are already used in some post-restoration studies, but recovery and phenological indicators are used more sparingly. Future studies could test the application of existing recovery indices, or develop similar ones, to offer guidance on how to select the baseline conditions to be integrated to the recovery index. Similarly, future studies could assess how specific phenological metrics (e.g., growing season length, rate of spring green up, maximum greenness) respond to post-restoration changes (e.g., succession, fluctuations in species diversity) to promote their use as indicators of recovery.

Another important avenue for research is developing early warning signals of ecosystem shifts (i.e., tipping points) in restored ecosystems. Breakpoint analysis, although helpful for understanding when and how vegetation has responded to specific drivers of change, relies on a complete time series. Thresholds can identify signs of disturbance but rely on previous data (i.e., an understanding of how specific disturbances impact spectral characteristics). Current literature counts several attempts to develop early signals of ecosystem shifts notably by assessing changes in spatial patterns (Kefi et al., 2018), but few have tested their applicability using real-world data (Nijp et al., 2019) or in restored ecosystems.

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

Appendix S1. Number and list of studies identified with different search keywords and filtered through different search criteria.

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