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REVIEW ARTICLE

Time series analysis to demonstrate restoration outcomes and system change from satellite data

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Abstract

Introduction: Restoring functions to degraded ecosystems is needed to maintain a sustainable planet. Although restoration efforts are widespread, the majority of restoration projects are not monitored, limiting the ability to assess outcomes, adaptively manage, and improve future restoration projects. Remote sensing, with its multi-decadal data and global extent, offers new opportunities for restoration monitoring. However, remote sensing data require analytical approaches that may be unfamiliar to ecologists and practitioners.
Objectives: We present a guide to applying time series analysis to assess restoration outcomes via change point detection, using publicly available remote sensing data.
Methods: We demonstrate a range of time series analysis techniques for quantifying change at a river corridor restoration site.
Results: The tools we present can detect if and when change occurs, what type of changes might be expected if restoration were performed at a similar site, and if restoration treatments cause measurable change. We introduce a flow diagram to help restoration professionals determine which change point detection method is most useful for their needs and software with an example to get started.
Conclusions: We provide recommendations for choosing between different types of models for ecologists and practitioners interested in monitoring, assessing, and communicating restoration outcomes.

Implications for Practice: Remote sensing time series cannot replace in situ data collection, but can provide low-cost ways for monitoring high-level outcomes of restoration projects between visits. Available software packages for time series analysis provide complementary, but different, information about restoration outcomes, and choosing the correct method for understanding change is non-trivial. Continuous monitoring of sites is essential for quantifying change, and evaluating restoration impacts with remote sensing time series can help to understand and communicate these changes. While we present these tools for analyzing remote sensing time series, they are equally applicable to time series data collected in situ or any other pertinent source.

Key words: change point detection, monitoring, remote sensing

Introduction

Humanity is rapidly pushing the Earth beyond its biophysical limits, interrupting the Earth System processes that sustain life. At all scales, ecosystem functions are at risk due to anthropogenic environmental change: land cover and land use change (Pimm et al. 2014), climate change (Arneth et al. 2020), alteration of hydrological processes (Wohl et al. 2024), and unsustainable extraction and resource use (IPBES 2019). In this era, humanity is faced with the incredibly daunting task of monitoring, managing, and restoring the Earth System processes that sustain life as we know it.

Concerted efforts to restore ecosystem processes are underway at local, regional, and global scales (Higgs et al. 2014; Fischer et al. 2021). Restoration projects often seek to make ecosystems more resilient in the face of increasing disturbances and stressors, including mitigating the effects of a changing climate (Krosby et al. 2018). Adaptive management is often lauded as a successful approach to ecosystem restoration efforts, particularly as projects evolve and outcomes vary (Bestelmeyer et al. 2019). A framework for periodically revising restoration activities based on social-ecological outcomes, adaptive management requires a commitment to monitor restoration outcomes and revise targeted practices (and expectations) accordingly (Bestelmeyer et al. 2019). Approaching restoration through the lens of restoring physical and ecological processes ("process-based restoration") aligns well with adaptive management frameworks and acknowledges the variability of dynamic systems rather than aiming to restore a system to a single reference state (Lengyel et al. 2020). Despite its potential, adaptive management efforts like process-based restoration are

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challenging to implement well (Nagarkar & Raulund-Rasmussen 2016), especially due to the need for extensive data collection, analysis, and interpretation.

Measurements of incremental changes over time are integral to effective adaptive management of any restoration effort and mandatory for monitoring variability in dynamic systems. Continuous measurements at inter- and intra-annual scales provide insights into a system's resistance and resilience to disturbances. However, measuring changes that result from restoration projects requires resources that can come at the expense of implementing new restoration projects (McKenna et al. 2023). Continuous monitoring of subtle changes in ecosystems as they occur is an even larger challenge as projects are implemented in more remote regions and increase in number and size (Holl & Brancalion 2020). These challenges lead to many projects with irregular or non-existent monitoring plans, leaving little opportunity for managers to quantify and evaluate the outcomes. For example, out of tens of thousands of river restoration projects, only 10% include a monitoring plan (Bernhardt et al. 2005).

Time series of remote sensing data provide a solution to some monitoring challenges because satellites continuously collect consistent data over large areas. Applying remote sensing data to quantify ecological change has never been easier with a variety of satellite-based ecosystem monitoring products now available, including annual maps of land cover, vegetation, biomass, and carbon (Sturm et al. 2022). Publicly available, preprocessed time series have opened low-cost avenues for ecological monitoring by removing the need for extensive processing before satellite data can be used. Novel sources of error, however, complicate analysis and assessment of remotely sensed data (Van Cleemput et al. 2025).

Change point analysis to identify the timing and magnitude of changes is particularly relevant for restoration monitoring. It can take advantage of long time series of data while accounting for seasonality and noise present in satellite observations. The literature presents a wide range of techniques for change point detection, each varying in their requirements and assumptions. Approaches to change point detection can be distinguished by requirements for input data, statistical assumptions, and relevance of output to different research questions, and offer distinct advantages and disadvantages for change point detection.

While change point analysis can detect when the highest probability of an ecosystem state change occurred, additional analyses may be required to definitively attribute change to restoration interventions. The ideal way to assess causality, including the impact assessment of restoration treatments, is to pair treatments with equivalent control units. In observational studies, determining these control units can be difficult, if not impossible (Shackelford et al. 2024). Control selection is complicated because restoration treatments do not occur randomly, but are often driven by social and biophysical settings leading to unobserved biases that can confound inferences (Ribas et al. 2021). Quasi-experimental techniques provide a solution to control selection in observational studies by estimating a counterfactual scenario, representing how a system would have behaved in the absence of treatment (causal inference) (Simler-Williamson & Germino 2022; Siegel & Dee 2025).

A major barrier to more widespread application of time series analysis for restoration assessment is a lack of guidance on how to apply change point analysis and quasi-experimental techniques to satellite-based products. Here, we seek to address the difficulties that arise when measuring the outcomes of ecosystem restoration. We recognize that it can be difficult to compare across sites with different treatments, restrictions, and reference conditions. In this article, we (1) outline considerations for identifying appropriate analysis parameters and (2) demonstrate the utility of various publicly available quantitative methods for analyzing change at sites that aim to restore ecosystem processes. We also aim to provide a glossary of terms relevant to change point analysis for restoration, a list of change point analysis methods and their key features, a list of freely available satellite-based products that could be used in different ecosystems, and a "decision-tree" diagram of how and when to use different time series techniques.

Methods

Time Series Analysis Methods

Although there are many time series analysis methods available, we focus on four that are straightforward to apply in R (R Core Team 2021). Figure 1 provides guiding questions to lead the restoration practitioner to the appropriate method for their application: (1) Bayesian Change Point (BCP) (Erdman & Emerson 2008), (2) Breaks For Additive Season and Trend (BFAST) (Verbesselt et al. 2010), (3) Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) (Zhao et al. 2019), and (4) Bayesian Structural Time Series (BSTS) (Brodersen & Hauser 2017). The following sections provide more detail about each method and highlight the particular differences in their input data requirements (Table S1).

Bayesian Change Point. BCP returns the probability that the mean value has changed for any given point in the time series. Given a sample of observations over a period of time, BCP can identify the magnitude and timing of change in a system. It can be used in an exploratory manner to determine when an ecosystem experienced a high probability of state change, and can be helpful for practitioners to establish reasonable expectations for an ecosystem's response to restoration. BCP can be applied to univariate or multivariate data, and the parameter values in different blocks of data need to be independent. A Markov Chain Monte Carlo (MCMC) sampling approach is used to estimate population parameters at each possible change point for every point in the time series. The array of values resulting from MCMC is then used to estimate real population parameters. Importantly, BCP cannot handle missing values, so a choice must be made prior to using this method to either impute missing values or to delete them and proceed with an irregular time series. If neither is appropriate, other analysis techniques should be considered.

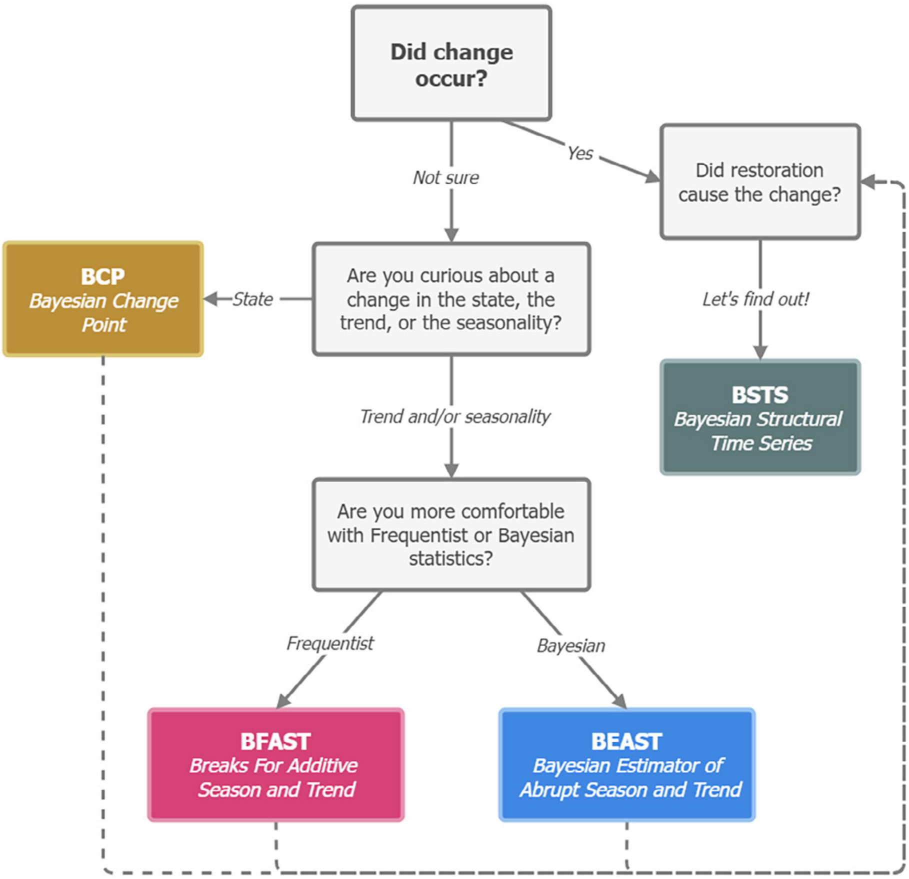

Figure 1. This flowchart illustrates how to choose a time series analysis method to investigate change at a restoration site. Starting at the top with "Did change occur?" work through the questions to choose an analysis. If you already know that change occurred and when it began, skip straight to using Bayesian Structural Time Series (BSTS) to find out if restoration caused the change observed. Otherwise, use Bayesian Change Point (BCP), Breaks For Additive Season and Trend (BFAST), or Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) to find out if change occurred and when.

Breaks for Additive and Seasonal Trend. Breaks for Additive and Seasonal Trend (BFAST) decomposes time series into trends, seasonal variation, and error, and can accurately respond to highly variable inputs in the magnitude of both trend and seasonality (Verbesselt et al. 2010). BFAST estimates constant seasonal variation relying on a piecewise-linear model to describe trend and a piecewise harmonic model to describe seasonality. Through this estimation, this algorithm works with the entire time series rather than needing to reduce datasets to specific seasons (Verbesselt et al. 2010). BFAST identifies the point in time a change occurred, the magnitude, and the direction of change (Mendes et al. 2022). It can also identify multiple discrete change points and broad changes within a single time series without supervision (i.e. a known, defined event date) (Zhu 2017). BFAST has been applied successfully in many disciplines and ecosystems and is widely used.

Shortcomings of BFAST include its limitation as a univariate method, meaning only a single predictor, time, is considered to explain variation in the outcome (Zhu 2017). Further, Li et al. (2022) note that practitioners need to have the necessary domain knowledge to assign the maximum number of change points and minimum separation interval. Model parameters, such as maximum number of iterations, can also affect change point estimation, and BFAST outputs can vary dramatically depending on the parameters chosen. Further drawbacks of BFAST include its inability to detect subtle changes, deal with missing data, and its computational costs (Li et al. 2022) though these have been addressed with different versions of the algorithm including BFAST Monitor (Verbesselt et al. 2012; Li et al. 2022) and BFAST Lite (Masiliūnas et al. 2021). One final consideration is that while the other algorithms we outline in this paper are Bayesian, BFAST relies on frequentist methodologies, including determining change based on an arbitrary threshold or p value.

Bayesian Estimator of Abrupt Change, Seasonal Change, and Trend. The Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) algorithm is a Bayesian (see Box 1) ensemble model designed to detect abrupt changes in the trend and/or seasonal components of a time series (Zhao et al. 2019). BEAST constructs many piecewise-linear models

Box 1 Glossary of key terms for change point analysis for restoration projects.

Term	*Definition*	*Plain language definition*	*References*
Change point	A moment in a time series where a change occurs. These changes can be abrupt or gradual and detection type and frequency differs based on the algorithm used.	A moment when something in a pattern shifts—like a sudden jump in temperature or a change in how fast something is happening. The change can be big or small, sudden, or gradual.	Mendes et al. (2022); Verbesselt et al. (2010)
Counterfactual	A well-defined hypothetical scenario different from what actually happened. For restoration, this would typically be a hypothetical time series where an intervention did not occur.	A "what if" scenario—imagining what would have happened if something had been different. For example, how would ecological conditions be different for a restored site if it had not received an intervention.	Dashti et al. (2024); Siegel and Dee (2025)
Frequentist statistics	Statistical approach where probabilities are assigned to the data. This approach tests against a null hypothesis of no effect and results in *p* values and confidence intervals.	A way of analyzing data that focuses on testing whether a pattern is just random or actually meaningful. It does this by comparing data to a "no effect" scenario (the null hypothesis) and using tools like *p* values and confidence intervals to measure uncertainty.	Fornacon-Wood et al. (2022)
Bayesian statistics	Statistical approach where probabilities are assigned to the hypotheses and prior knowledge is taken into account.	A way of analyzing data that updates what you already know with new evidence. Bayesian outputs represent how sure we are that a model is supported by the data.	Fornacon-Wood et al. (2022)
Trend component	Gradual change across a time series or portion thereof (e.g. rising global temperatures and ecological succession).	The overall direction your data are headed. For example, global temperatures may vary by day, but overall they are getting hotter.	Cleveland et al. (1990)
Seasonal component	Variation in data around the trend line on a seasonal frequency; often, this is annual variation in climate or phenology.	The predictable way that environmental data changes throughout a year. For example, temperatures are colder in winter and warmer in summer each year.	Cleveland et al. (1990)
Harmonics	Sine and/or cosine waves optionally used to model a seasonal component by capturing an annual high and low relative to the time series trend.	A common way to show the shape of data across a year. Every year will have one or more peak value(s) and low value(s) that alternate.	Zhao et al. (2019)
Error component	Remaining variation in the data beyond the seasonal and trend components.	The trend and seasonal estimates for data will not be perfect because they have to fit a specific shape, such as a wave pattern, and real data are messy. Error components are the difference between model estimates and actual data.	Cleveland et al. (1990)
Posterior distribution	Best understood as a weighted average between knowledge about the parameters before data is observed (which is represented by the prior distribution) and the information about the parameters contained in the observed data (which is represented by the likelihood function).	An updated belief about a system considering what is already known (the prior) and the new data. It can be thought of as an educated guess that is adjusted based on new evidence. Posterior distributions represent probabilities of model output, given the data.	Glickman and van Dyk (2007)
Posterior mean	A point estimate for the posterior distribution in a Bayesian analysis, representing the average of posterior samples.	The best guess for a value after combining what is known with the new data. It represents the average value of all the possible values.	Glickman and van Dyk (2007)
Latent state	An unobservable system state estimated from observable environmental data.	A hidden or alternative (ecosystem) state.	Auger-Méthé et al. (2021)

composed of line segments and harmonics to describe the trend and seasonal components of a time series, respectively. BEAST then averages these models, estimating the probability of each detected change point in the time series trend or season. By averaging, BEAST is capable of estimating nonlinear signals. BEAST can also be used without the seasonal component, which provides a way to calculate change points in the trend with missing data. BEAST has been applied in study areas around the globe to describe many types of remote sensing time series changes, including land surface temperature (Li et al. 2022), vegetation indices (Lyu et al. 2024), and precipitation indices (Di Nunno et al. 2024).

BEAST has a number of unique features compared to the other algorithms presented, such as its capability of estimating changes in the magnitude (i.e. annual extremes becoming more similar/divergent), timing (i.e. annual shifts in maximums), and/or harmonic order (i.e. a shift in the number of cycles per cycle) of the seasonal trend of a time series. Further, BEAST can handle missing values in the time series. The BEAST algorithm assumes the number of change points is unknown through a uniform prior and estimates the number of change points, a useful feature if the number of change points is unknown, as could easily be the case if other variables beyond restoration are affecting the site.

However, BEAST has limitations that may be undesirable for some analyses (Zhao et al. 2019). A large amount of computational power is required to estimate the many parameters in BEAST models. For local computing environments, BEAST is best suited to either global coarse-resolution or local high-resolution remote sensing time series, as too many resources would be needed otherwise. BEAST also struggles with noisy data, which can result in reduced probabilities for pattern changes, especially if the trend is weak (Zhao et al. 2019), and may require the user to eliminate false breakpoints (methods in Li et al. 2022). BEAST is a descriptive model; that is, it cannot attribute change to any particular drivers. Finally, BEAST is currently a univariate model, though support for detecting common change points in multivariate time series (i.e. multispectral bands, ancillary climate information) is in development (Hu et al. 2019).

Bayesian Structural Time Series. The BSTS algorithm tests if a known event in a time series caused a change in the outcome by constructing a counterfactual scenario. BSTS analyzes and forecasts time series data by decomposing the data into key components such as trend, seasonality, and an error component. BSTS is a specialized framework that represents time series data as observations of an underlying latent (hidden) state that evolves over time (Haqbin & Khan 2024). BSTS is widely used for causal impact analysis, allowing researchers to measure the effect of specific events on a time series by generating a counterfactual to represent the latent state of the system (Gianacas et al. 2023). This flexibility makes BSTS particularly useful for applications such as climate change (Haqbin & Khan 2024) and ecosystem recovery (Dashti et al. 2024), where understanding both gradual and punctuated change is crucial.

BSTS relies on three key techniques: the Kalman filter to estimate trends and seasonality, spike-and-slab regression to identify the most important external variables that influence the time series, and Bayesian model averaging to improve forecasting by considering multiple possible models. These techniques allow the model to adjust parameters over time, as well as to handle a large number of predictors. This accurately reveals the stochastic behavior of the time series, uncovering not only correlations but also causal relationships within the underlying data.

The effect of the intervention is estimated as the post-intervention difference between the counterfactual and observed outcome time series using Bayesian estimation methods (Dashti et al. 2024). Unlike other counterfactual estimation techniques that rely on matches or synthetic time series derived from real-world observations, BSTS estimates the latent state had an event not occurred. However, this approach has some limitations. First, BSTS can be computationally intensive, especially with large datasets. Second, BSTS is multivariate and requires inclusion of predictor variables, beyond time, which require careful selection based on domain knowledge. Inappropriate or irrelevant predictors may lead to the incorrect attribution of observed outcomes to the intervention (Gianacas et al. 2023). We suggest researchers use a directed acyclic graph to determine which variables can be represented in the model without introducing bias into the model (Van Cleemput et al. 2025). Finally, BSTS requires that the change point in the time series is known beforehand, so it can generate a counterfactual time series starting from the time of change. In the case of a restoration treatment, the change point should be known a priori—most likely to be chosen as the time restoration began. If the change point(s) in your time series are unknown, BSTS can be paired with an exploratory algorithm like BEAST to first identify change points and then generate a counterfactual time series (Dashti et al. 2024).

Data

We present a non-exhaustive list of remote sensing time series data products that can be used to monitor landscape changes, including information about each product that determines its suitability for each of the time series analysis methods (Table S2). While the methods we present are similarly applicable with in situ and other data sources, remote sensing time series are readily available and diverse with regards to what they describe (e.g. vegetation rigor [Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), etc.], burned area [Normalized Burn Ratio (NBR)], surface water [Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), etc.]).

To demonstrate the applicability of the aforementioned methods for time series monitoring, we use the Landsat Monthly MRRMaid, an outcome dataset that estimates mesic vegetation cover, developed specifically for monitoring the outcomes of mesic ecosystem restoration efforts in the semiarid Intermountain Western United States (Kolarik et al. 2024). This dataset is the output of machine learning regression models that estimate the proportion of mesic vegetation present in each Landsat pixel, assumed to be indicative of ecologically available water, and represents one choice of many similar products derived from the Landsat time series that are readily available for monitoring land cover changes as a result of restoration activities or policy changes (Table S2).

Case Study

River corridor restoration efforts are occurring globally to help reestablish the physical and biological processes that have been altered or interrupted by historical and contemporary human alterations to the landscape (Skidmore & Wheaton 2022). In particular, many river corridors across the Western United States are in highly degraded states due to the extirpation of beaver, the creation of log flumes for timber extraction, mining legacies, agricultural operations, and the modification and simplification of valley bottoms and river channels that have created highly efficient conduits for water to exit the system (Wohl 2021).

To demonstrate the use, outputs, and interpretation of the methods presented, we apply them to a restoration site on the Yankee Fork, a tributary to the Salmon River in Custer County, Idaho, United States. The Yankee Fork Pond Series 3 Side-channel Project is an example of river restoration considered to be successful by project managers and the community (Fig. 2). Between 1940 and 1952, mining companies heavily dredged five and a half miles of floodplain to extract gold and left piles of mine tailings and disconnected pools behind. The floodplain was disconnected from the main channel, leaving negligible salmonid habitat and little riparian vegetation (Colyer 2021). As part of concerted efforts across the region to restore habitat for native salmonids, Trout Unlimited partnered with federal, state, and tribal agencies to increase lateral and longitudinal floodplain connectivity and instream habitat heterogeneity. This project involved historical channel reconstruction, riparian plantings, and the addition of large wood to increase complexity from 2012 to 2015 (C. Wood, personal communication). These activities also happened to create suitable habitat for beaver, as they were observed returning to the reach in 2015. A 100-year flood event occurred in 2017, and in subsequent years the project area seemed to have been transformed toward a wetter state replete with mesic vegetation. With this detailed restoration history and knowledge shared by project managers, we can identify analysis techniques suitable for detecting changes in the data that correspond with field observations.

We applied BCP, BFAST, BEAST, and BSTS to the Monthly MRRMaid time series at the Yankee Fork restoration site to quantify how the proportion of mesic vegetation changed after restoration treatments. We present outputs with both aggregated and individual pixel values. Where necessary, we imputed values for missing observations and applied the algorithms described in Section 2. We then provide recommendations for the application of each analysis method based on their role as exploratory, prediction, and inferential tools.

Results

Bayesian Change Point

Using the BCP approach, we observed a 25% probability of a change in the mean value of mesic vegetation cover at the restoration site at the onset of the channel reconstruction in 2012 (Fig. 3). Similarly, we see another low probability of change

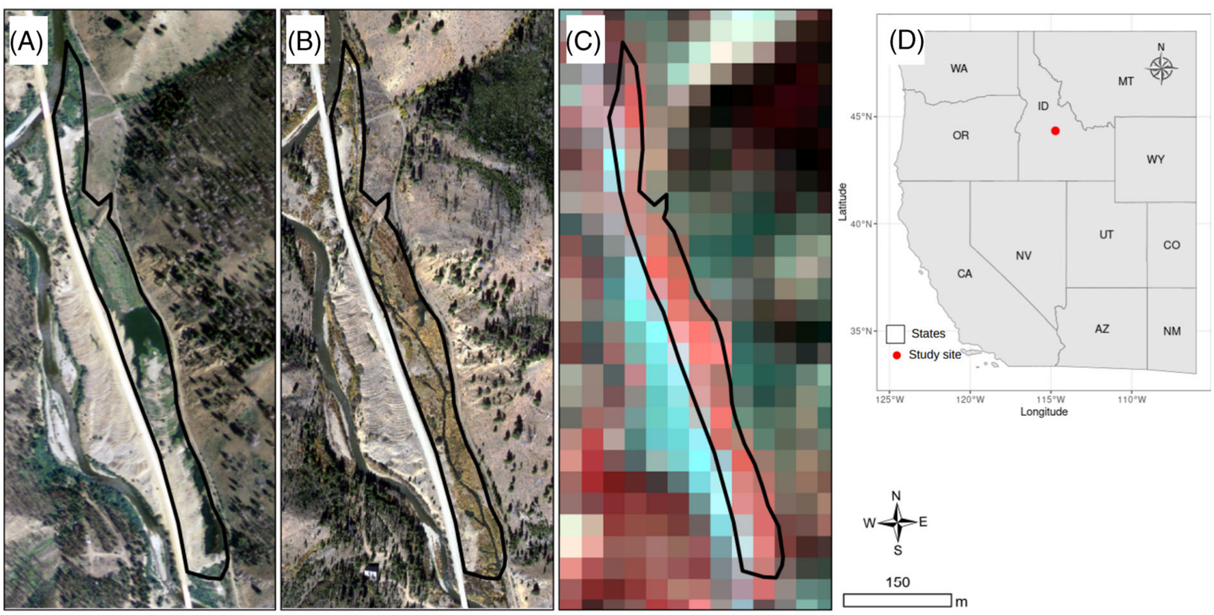

Figure 2. (A) National Agricultural Imagery Program (NAIP, 1 m) image on 12 August 2004 (beginning of time series). (B) NAIP image on 29 September 2021 (post-time series). (C) False color (near infrared, red, green; 30 m) Landsat 8 composite image on 24 September 2021 with the project area shown in black in (A–C). (D) Location of the case study.

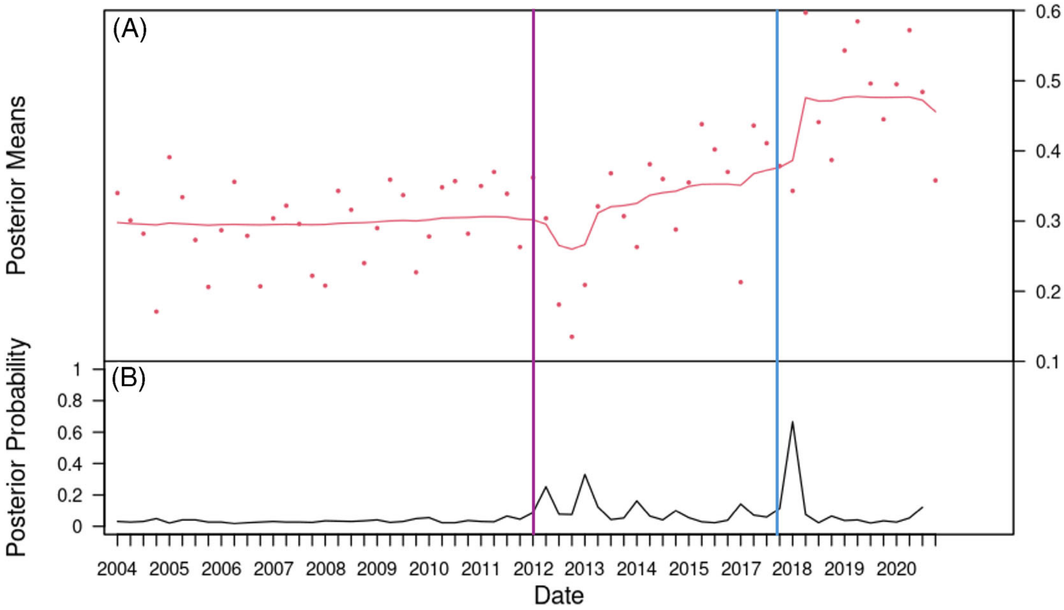

Figure 3. BCP output. (A) Observed data (points) and posterior means (line) of mesic vegetation proportion (right y-axis). (B) The probability of a change point in the mean of the time series at any given location (left y-axis).

(29%) following the planting of riparian vegetation in 2013. We observed the highest probability of change in the system following the high flow flood event in 2017, where we estimate a 57% probability of an overall change in the mean value of the time series, corresponding with the state change observed by practitioners. The pre-restoration mean is estimated to be 30% mesic vegetation cover, and the post-flood mean is 47% mesic vegetation. The maps in Figure S1 show results of a univariate analysis similar to that in Figure 3, with independent algorithms applied to each pixel through the time series. These maps show spatial differences in restoration outcomes, including the largest changes in mesic vegetation cover (>50%) in the downstream portion of the restoration reach. In Figure S2, we demonstrate the application of a supporting predictor variable (Palmer's Drought Severity Index [PDSI]) in a multivariate approach.

Breaks for Additive Seasonal and Trend

We identified a change point in the time series at the beginning of the restoration process in 2012 using the BFAST algorithm (Fig. 4). The results separate the data into seasonal, trend, and error components, then identify abrupt changes in the overall time series (Fig. S3). With this frequentist approach, we observe a statistically significant ($\alpha = 0.05$) difference in trends before and after the intervention. Before the restoration, BFAST estimated that mesic vegetation was increasing at a rate of 0.7% per year. After the restoration, BFAST estimated that mesic vegetation decreased by 9% of the total restoration reach in the short term, aligning with the channel reconstruction timeline, but then began increasing at a rate of 3.9% per year shortly thereafter. The maps shown in Figure S4 first show the overall shift in vegetation cover that occurred from the beginning of the time series in 2004 to the end in 2020 (panels A and B). Panels (C) and (D) demonstrate declines in mesic vegetation associated with the channel reconstruction in 2012 and also the subsequent rebounds that align with riparian vegetation plantings and large wood introduction from 2013 to 2015. We observed an increase in large-magnitude changes further out in the floodplain following the return of beavers and a large flood event in 2017.

Bayesian Estimator of Abrupt Change, Seasonal Change, and Trend

The BEAST output displays a median of one change point in the seasonal component of the time series. The algorithm estimated a 16% chance of a change point following the flood event in 2017 (Fig. 5), implying a phenological change (either in magnitude or timing) in the vegetation at the restoration site. In our case, BEAST estimated a 16% chance that annual mesic vegetation maximums are approximately 13% higher in the early season than in the later season, while before the seasonal change point, mesic vegetation maximums were approximately 10% higher in the peak of the growing season than in the end, indicating a possible shift in the vegetation community. In the trend component, we observed a median number of three change points that align with the onset of channel reconstruction in 2012 (46% probability of change), revegetation efforts in 2013 (33% probability of change), and the system response to the flood event in 2017 (49% probability of change) (Fig. 5E). At each of these detected change points, panel (H) describes the directions of these changes, with a 49% probability that the slope is decreasing following the channel reconstruction in 2012 (41% flat slope, 10% increasing). Following the vegetation planting in 2013, we observed a 74% probability that the slope

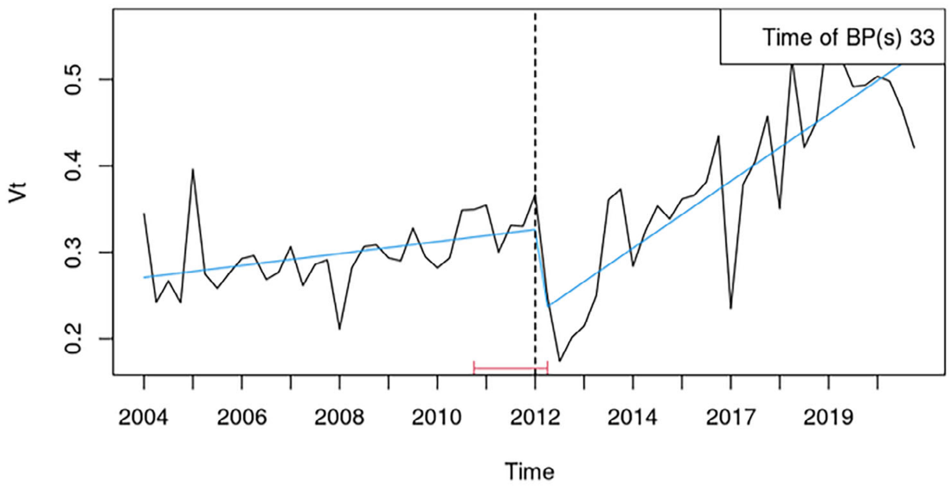

Figure 4. BFAST trend output. Observed data (black) plotted along with the fitted lines (blue), where the *y*-axis (labeled Vt) corresponds to vegetation proportion, demonstrating the slopes before and after the restoration began (2012). Also included is the 95% CI of when the change point occurred (red). The caption in the upper right explains that the estimated breakpoint (BP) is estimated at observation 33.

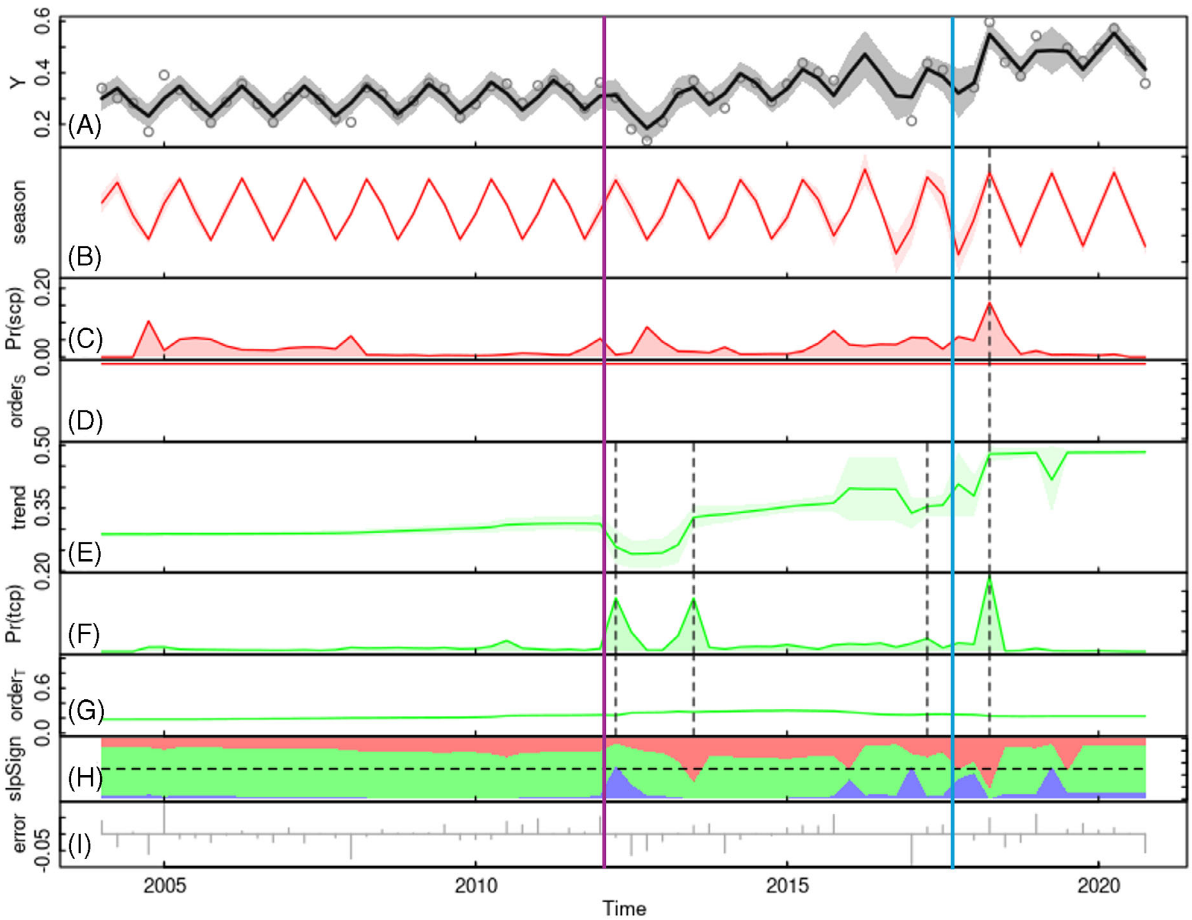

Figure 5. BEAST output. (A) Data (Y) with fitted model (solid line) and 95% credibility intervals (shaded region), (B) seasonal component, (C) the probability of change in the seasonal component; Pr(scp), (D) the number of sine/cosine waves needed to characterize seasonal cycles(order$_s$), (E) trend component, (F) probability of change in trend; Pr(tcp), (G) the magnitude of the trend component (order$_t$), (H) the probabilities of the slope being positive (red), flat (green), and negative (blue) (slpSign), (I) error (unexplained) variance in the bottom panel. Vertical dashed lines are estimated change points. The purple vertical line indicates the beginning of restoration activities, and the blue vertical line a flood event. Please see Figures S6-S8 for alternate BEAST parameterizations.

has changed to positive (26% flat, 0% negative). We observed another slope change following the flood event in 2017, where the models estimate an 87% probability that the slope has changed again, although the slope maintains a positive direction (13% flat, 0% negative). Figure S5 shows the locations of the single largest magnitude of change in the vegetation trajectory (panel A), along with the probability of this change (panel B) and when it occurred (panel C).

Bayesian Structural Time Series

The BSTS outputs indicate a high probability of the intervention causing change in mesic vegetation (Fig. 6). The observed proportion after the intervention was 0.38 on average; whereas the predicted values, assuming no intervention, were 0.29 on average (95% credibility interval [CrI] 0.28–0.30; Fig. 6). In general terms, the intervention led to a 31% increase (25–38% CrI). Furthermore, the posterior probability of a causal effect is extremely high at 99.8%, strongly suggesting that the observed changes were not due to random fluctuations but rather a direct result of the restoration.

In Figure 6A, we interpreted the data alongside the counterfactual predictions for the post-treatment period. We observed that after the intervention date, the actual data begins to deviate from the expected trend (95% Crl), indicating a disruption in the regular patterns and a noticeable impact of the intervention. Subsequently, Figure 6B shows the difference between observed data and counterfactual predictions; this is the pointwise causal effect where the 95% CrI of the departure from the counterfactual scenario does not include zero following the flood event that occurred in 2017. Finally, the cumulative impact (Fig. 6C) follows a similar pattern as described using the previous methods: an initial dip following the channel reconstruction in 2012 followed by a rebound and a steady increase in mesic vegetation cover thereafter. The cumulative impact describes the sum of the pointwise differences following the intervention.

Data availability plays a crucial role in the selection of certain models. In this scenario, we evaluated the performance of BSTS by omitting the missing data from 2016 to assess the model's reliability. Despite this adjustment, we observed a similar pattern, which could be corroborated by obtaining the posterior probability of a causal effect (99.8%), suggesting the model's robustness in handling data gaps. Figure 7 highlights the shifts in mesic vegetation across space, associated with the 2012 channel reconstruction and the subsequent recoveries aligning with riparian vegetation plantings and the addition of large wood and structures. The estimated counterfactual scenario for September 2020 is shown in panel (B) and demonstrates the "business-as-usual" scenario, where the pointwise differences are shown in panel (C), which clearly show mesic vegetation increases within the project boundary.

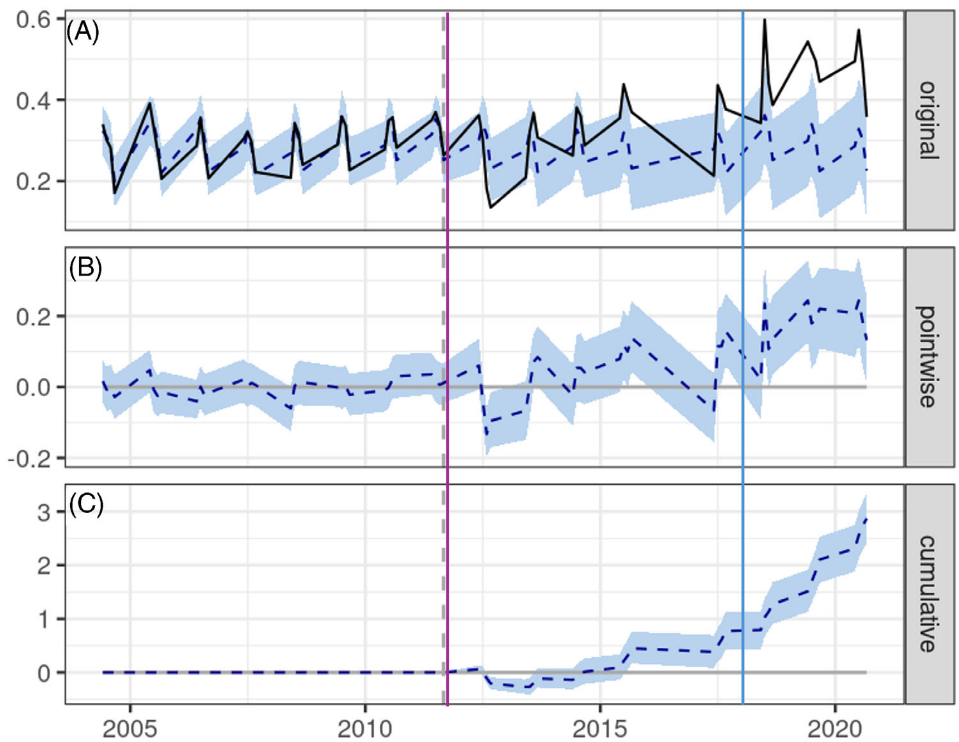

Figure 6. BSTS output. (A) Observed data (black) and the modeled predictions for the time series (blue shading, pre-intervention indicated left of dotted line, post to the right) and the 95% credibility interval for the predictions with mesic vegetation proportion on the y-axis. (B) The difference between observations and the modeled time series with difference in mesic vegetation on the y-axis. (C) The cumulative (sum of middle panel) effect of the intervention. The purple vertical line indicates the beginning of restoration activities, and the blue vertical line a flood event. See Figure S9. for output without accounting for the missing data period.

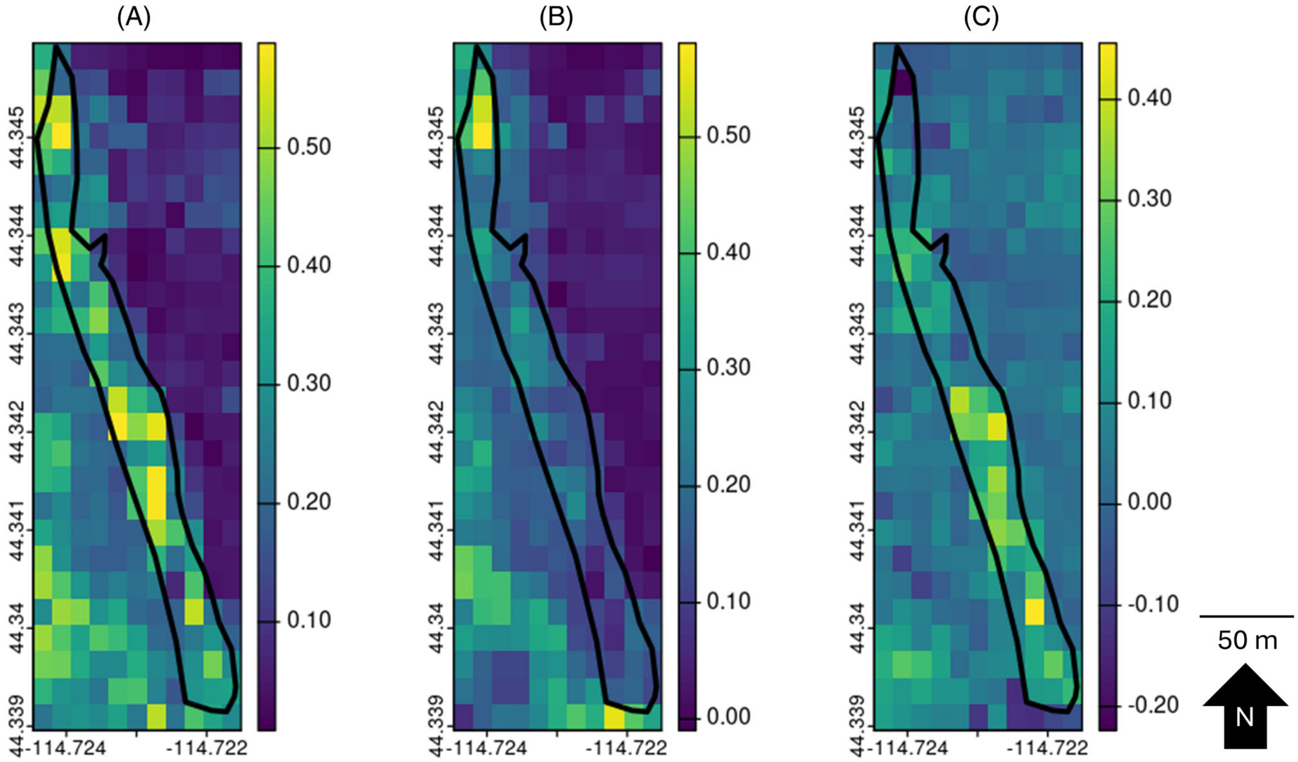

Figure 7. BSTS outputs on a per pixel basis with the project area overlaid in black in all panels. (A) The observed mesic vegetation proportion in September 2020. (B) The counterfactual, latent state predictions for September 2020. (C) The pointwise differences in each pixel across the case study region.

Discussion

Restoration projects rarely include long-term monitoring, making it difficult to evaluate outcomes. Satellite time series offer a way to track ecosystem change, but using them effectively requires models that can detect and interpret those changes. We demonstrate how four contemporary time series analyses—BCP, BFAST, BEAST, and BSTS—can detect ecological signals in satellite-derived time series, with relevance to restoration. This suite of models offers a starting point for practitioners to assess long-term restoration outcomes, tailored to their data and objectives.

Results from the case study we present reveal how change point models vary in their goals, sensitivity, and assumptions, as well as what each of these methods offers in terms of communication of restoration outcomes. All uses of remote sensing datasets to communicate outcomes at local scales should be corroborated with local knowledge or in situ measurements. BCP and BEAST identified moderate probabilities of change following active restoration interventions (e.g. channel reconstruction and revegetation) and a more pronounced shift following the 2017 flood, supporting observations from project managers. BFAST estimated significant breaks in the trend component at the time of intervention and showed a steeper increase in mesic vegetation cover post-flood, while BEAST provided insight into both phenological (seasonal) and trend shifts in the system. Finally, BSTS offered strong evidence for a causal effect of restoration activities.

Taken together, these analyses suggest that the Yankee Fork restoration catalyzed a directional ecosystem shift toward a wetter, more mesic state—consistent with both field observations as described by the project manager and theoretical expectations of process-based restoration. We observe a change in trend at the onset of restoration in 2012 with both BFAST and BEAST. With BCP, we observe a change in the mean mesic vegetation cover and habitat following the beaver colonization and subsequent flood in 2017 as described by the project manager. With the BSTS, we infer that without the restoration activities, the vegetation in this reach would indicate a much drier, less connected valley bottom. The pixel-level applications of each method revealed spatial heterogeneity in system responses, underscoring the value of combining remote sensing with robust statistical tools. These results also show how restoration outcomes can be incremental, nonlinear, and vary across space with additive effects from multiple interventions and natural events contributing to long-term ecological change. As time series from high-resolution data collected with newer platforms get longer, the ability to describe restoration outcomes with greater precision will also increase.

A first step in selecting between different change point techniques is to identify the main objective of the analysis. If the goal is to explore potential state changes and interannual seasonal variation is less important, BCP is appropriate. For the Yankee Fork, BCP outputs identify two periods of relatively stable means: before restoration and after a large flood event. The highest posterior probability of state change after a large flood followed by low posterior probabilities and a horizontal line representing posterior means is indicative of a new stable state. Between these, a period of disturbance from restoration and a changing system is characterized in the outputs by several small peaks in posterior probability and a rising posterior mean, indicating dynamic conditions. Although BCP does not evaluate changes in trend explicitly, the output can be qualitatively interpreted to identify the time period during which change is occurring in addition to the point in which the highest probability of a new stable state is reached. The simplicity of its output may be desirable for practitioners presenting to a lay audience.

If the goal of analysis is to identify a point when change started (e.g. change in trend), either BFAST or BEAST can be implemented. One application of BFAST and BEAST could be to test whether the algorithm-identified change point matches the known timing of a restoration intervention. For the Yankee Fork, BEAST identified three changes in trend in the time series that corresponded to discrete events at the site in 2012, 2013, and 2017, as well as directional estimates for each of these changes. BFAST is nearly a decade older, but is still widely used and has borne modified versions such as BFAST monitor and BFAST Lite (Verbesselt et al. 2012; Masiliūnas et al. 2021). BFAST provides a simpler output and identified only a single change point at the start of channel reconstruction in 2012.

An important difference between BFAST, BEAST, and BCP lies in their ability to detect seasonal changes. BFAST and BEAST are capable of modeling interannual variation, a defining characteristic of many ecosystems. Variation in temperature, photoperiod, wind, and precipitation among years leads to variations in human activity, resource pulses, and vegetation greenness (White & Hastings 2020). These are often key outcomes or indicators of restoration success, including resource availability synced with species migration timing (Barker et al. 2022), transition from xeric to mesic phenologies surrounding restored streambeds (Wohl 2021), and shifted phenological timings that indicate the absence of early-germinating exotic plant species (Wainwright et al. 2012). Changes in seasonal timing are of particular interest in the context of climate change, such as detecting changes in the timing of the last frost of the year or the timing of snowmelt in spring (Li et al. 2024). Changes in seasonal patterns were previously difficult to monitor because they required multiple data collection efforts per year, but time series remote sensing provides low-cost continuous monitoring that makes this type of seasonal change detection possible.

BFAST, BEAST, and BCP are useful for exploratory purposes, including identifying change in time series data. However, without appropriate reference sites, it is impossible to infer whether change occurred due to restoration activities. We recommend the BSTS as a way to estimate a counterfactual outcome. Counterfactual outcome estimation methods such as matching, differences in differences, and regression discontinuity design are increasingly used to minimize hidden biases associated with ecological treatments (Siegel & Dee 2025). BSTS provides a dynamic estimation of causal impacts, making it particularly effective for capturing gradual ecological changes, such as those resulting from conservation policies. Because BSTS models latent state components, it is relatively resilient to baseline mismatches where other counterfactual estimation methods that require direct control units are not (Brodersen & Hauser 2017). Furthermore, its adaptive counterfactual approach dynamically reweights hypothetical control units over time, enhancing accuracy when variable relationships evolve. These advantages position BSTS as a particularly powerful tool for analyzing interventions with delayed, nonlinear, or context-dependent effects that are prevalent in ecological systems.

The complexity of all four of the algorithms we explore raises a question: how much do practitioners actually need to understand the inner workings of these models to apply them? In ecology, a widespread gap exists between statistical training and the rapid evolution of quantitative methods, potentially limiting adoption of powerful but technically demanding analyses (Touchon & McCoy 2016). An advantage of BCP, BEAST, BSTS, and BFAST is that all are well-documented, flexible, and widely used. Researchers commonly employ them for a wide variety of environmental outcomes with varying estimates of a variety of disturbance events, some with multiple changes (Mendes et al. 2022; Dashti et al. 2024; Di Nunno et al. 2024).

One notable difference is that BFAST uses a frequentist approach, while the others use a Bayesian approach. The prevalence of Bayesian statistics in time series analysis stems from their ability to fit complex models with contemporary Monte Carlo algorithms, including models with nonlinear and latent states common in ecological time series (Clark 2005). The frequentist approach used to identify change points in the BFAST algorithm involves p values, with a default threshold of 0.05—a convention increasingly scrutinized (Amrhein et al. 2019). In the context of predicting change, such thresholds can lead to the exclusion of variables that improve predictive performance (Tredennick et al. 2021). Still, the familiarity of frequentist methods may make BFAST results more accessible to many scientists and practitioners. In contrast, Bayesian posterior probabilities can be directly interpreted as the probability of a model given the data, a formulation some consider more intuitive (McElreath 2020). Regardless of paradigm, clear communication and appropriate interpretation of uncertainty are essential when evaluating model-based outcomes of restoration projects (Brudvig & Catano 2021).

All remote sensing analyses have inherent challenges due to the uncertainty that results from aggregating land cover to discrete pixels and inescapable error in classification. While user-friendly products with easily interpretable land cover products are increasingly available, it is important to keep in mind that all of these products present sources of uncertainty that are absent in on-the-ground measurements. We advocate for using the outputs of tools we present in this study as only one line of evidence of restoration outcomes, particularly when trying to infer ecosystem state changes, as there are no substitutes for ground survey or local expert knowledge. Most time series data available at the landscape level are derived from moderate or coarse-resolution imagery, leading to mixed pixels and biased fractional estimates (Applestein & Germino 2022). To further complicate these limitations, researchers commonly mask clouds, shadows, and smoke from input images, which leads to missing data and irregular time series (Zhu & Woodcock 2014). Many of the available analysis tools, including several we highlight in this paper, are equipped to handle missing data in the time series (e.g. BFAST, BEAST, and BSTS), but some are not (e.g. BCP). Further, some of the methods we review in this paper require or benefit from the use of ancillary predictors of the outcome in a multivariate approach (e.g. BCP, BSTS). Choosing datasets and scales to represent these drivers can also be difficult, especially when there are spatial or temporal mismatches among outcome processes and available data (Stuber et al. 2017). State space models, including the Kalman filter implemented by the BSTS algorithm, address the challenge of remote sensing error by modeling a latent state that represents the "true" state of the system. A productive avenue for future work could involve fitting state space models by combining satellite-based remote sensing with data that is more accurate but lacks spatiotemporal coverage, such as aerial lidar (Caughlin et al. 2021).

In this paper we outline and suggest ways to incorporate change point detection and counterfactual estimation into restoration monitoring, but many questions remain as to how further to utilize these tools. One future avenue of investigation is how to use outcomes of projects across space and time to better predict plausible restoration outcomes before a project is implemented (Brudvig & Catano 2021). Reducing the uncertainty of outcomes, inferences, and data sources holds great potential for improving our understanding of restoration processes and is an ongoing issue for ecological remote sensing endeavors (Van Cleemput et al. 2025). The analyses we present are relatively straightforward, but more complexity could be added to improve model fit and performance. Finally, researchers and land managers could utilize various change point analyses to elucidate and avoid detrimental regime shifts (Bauch et al. 2016). Detecting potential changes at all scales will help support global efforts led by the UN Decade on Ecosystem Restoration and protect global systems from irreversible changes (Aronson et al. 2020).

Conclusion

Our findings reinforce the critical role of sustained monitoring in adaptive restoration frameworks. By leveraging freely available satellite products and appropriate statistical methods, practitioners can detect subtle shifts, evaluate intervention timing and magnitude, and establish more reliable links between restoration actions and ecological outcomes. The methods we present—when paired thoughtfully with restoration histories—offer a scalable, transparent, and repeatable framework for evaluating change across diverse landscapes and restoration strategies.

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Supporting Information

The following information may be found in the online version of this article:

Table S1. Requirements for each method of analysis, description, and key citations.
Table S2. A non-exhaustive list of remote sensing time series products that can be used as outcome datasets.
Figure S1. BCP outputs on a per pixel basis with the project area overlaid in black in all panels.
Figure S2. Multivariate—BCP output using PDSI as a predictor as well as time.
Figure S3. BFAST output.
Figure S4. BFAST outputs on a per pixel basis with the project area overlaid in black in all panels.
Figure S5. BEAST outputs on a per pixel basis with the project area overlaid in black in all panels.
Figure S6. Same as Figure 5 without accounting for the missing data period (2016).
Figure S7. Same as Figure S6 but allowing the precision parameter (inverse gamma distribution) to vary randomly for each trend and season with a uniform distribution.
Figure S8. An alternate way to model our time series in BEAST to compare to Figure 7.
Figure S9. Same as Figure 6 without accounting for the missing data (2016).

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