Rethinking Ecosystems Disturbance Recovery: what it was or what it could have been?

Hamid Dashti[1], Min Chen[1*], William K Smith[2], Kaiguang Zhao[3], David JP Moore[2]

[1]Depratment of Forest and Wildlife Ecology, University of Wisconsin-Madison, Madison, WI, USA

[2]School of Natural Resources and the Environment, University of Arizona, Tucson, AZ, USA

[3]School of Environment and Natural Resources, Ohio State University, Columbus, Ohio, USA

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***Corresponding author:** Email: min.chen@wisc.edu; Phone: +1 (765) 430-5774; Address: Russell Labs, 1630 Linden Drive, Madison, WI 53706

Author contributions

H.D. and M.C. conceptualized the study and designed the research and methodology and wrote the initial draft of the paper. K.Z. provided technical support for the use of BEAST analysis. All authors reviewed and edited the paper and made substantial contributions to the improvement of the paper.

Data availability

The original, high-resolution Landsat land cover data can be obtained from ORNL DAAC at the link: https://daac.ornl.gov/ABOVE/guides/Annual_Landcover_ABoVE. Similarly, the original Landsat NDVI data is available for download from ORNL DAAC at: https://daac.ornl.gov/ABOVE/guides/Annual_Seasonality_Greenness. Additionally, the resampled and post-processed versions of the land cover and NDVI datasets can be accessed through the public GitHub repository associated with this study, located at: https://github.com/hamiddashti/greeness.

Abstract

The time it takes for an ecosystem to recover is a key aspect of environmental disturbance. Conventionally, recovery is defined as a return to the pre-disturbance state, assuming ecosystem stationarity. However, this view does not account for the impact of external forces like climate change. We propose a counterfactual approach, viewing recovery as the state the ecosystem would achieve without the disturbance. This redefines recovery time as the period until the ecosystem reaches its counterfactual state. Through a case study on the greening of the Arctic and Boreal regions, we present evidence demonstrating significant disparities between counterfactual and conventional recovery time estimates. The well-documented greening of the region serves as an external force, introducing non-stationary dynamics that result in a counterfactual recovery time twice as long as the conventional view. We advocate for embracing the counterfactual definition of recovery, as it aligns more realistically with informed decision-making.

Introduction

Disturbance is any distinct event that disrupts the structure, function, or composition of an ecosystem, community, or population, and alters resource availability or the physical environment (Turner 2010; P. S. White and Pickett 1985). Disturbances can be caused by abiotic (e.g., wildfires and tornadoes) or biotic pulse events (e.g., pathogens), with long-term pressing impacts on ecosystem function (Kautz et al. 2017; Harris et al. 2018). Natural disturbances are essential for maintaining key ecosystem functions (Moi et al. 2020). However, the disturbance pattern including severity, frequency, and timing is rapidly changing (Johnstone et al. 2016; Turner and Seidl 2023; Turner 2010). For example, globally, there has been an increase in the frequency and intensity of disturbances such as wildfires (Pechony and Shindell 2010; Westerling 2016), insect outbreaks (Kautz et al. 2017), and drought (Millar and Stephenson 2015). These shifts have been shown to impact ecosystems in various degrees, resulting in significant loss of key life-sustaining ecosystem services.

One key aspect to understand, mitigate, and adapt to a changing disturbance regime is the time it takes for ecosystems to recover. But what is recovery? In its most intuitive form, the Oxford dictionary defines recovery as a "return to a normal state" (https://languages.oup.com/). However, in the context of ecology, the term "normal" is not always unambiguous. In most studies, the time to return to normal is considered as the duration it takes for a state variable of a disturbed system to bounce back to its pre-disturbance state (Pérez-Cabello, Montorio, and Alves 2021; Yi and Jackson 2021; Moreno-Mateos et al. 2017). A more general definition of recovery is that disturbed systems reach a stable state. The post-disturbance stable state could be similar to the pre-disturbance state, or it could be a different stable state (McDowell et al. 2020; Seidl and Turner 2022).

The conventional definition of recovery is fundamentally limited by the unrealistic assumption of ecosystem stationarity, where ecosystems remain in equilibrium within a fixed historical range of variability (Milly et al. 2008; Rollinson et al. 2021). This concept originated from early studies on ecosystem resilience and disturbance where a steady state was envisioned, implying that changes in a state variable over time closely approximate its average (Fraccascia, Giannoccaro, and Albino 2018; Rykiel Jr 1985; Nimmo et al. 2015; Yi and Jackson 2021). The core idea is the resiliency of an ecosystem depends on its capacity to recover to pre-disturbance state(Nimmo et al. 2015; Matos et al. 2020). However, this definition overlooks external forces such as climate change. These external forces may impose a non-stationary dynamic on the ecosystem and can shift the state of an ecosystem regardless of disturbance occurrence. In the event of a disturbance, these external forces can either shorten or lengthen the recovery time (Cheng, Ganapati, and Ganapati 2015). However, the conventional view confounds the impact of these forces with that of the disturbance itself.

An alternative definition of recovery that goes beyond the stationary assumption, is the counterfactual definition, which defines the recovery time as the duration it takes for an ecosystem to reach its "counterfactual state." In this context, the counterfactual definition of recovery poses the question: What would the state of a disturbed ecosystem have been if the disturbance had not occurred? Unlike the conventional definition, which compares the current state of an ecosystem to its pre-disturbed state, the counterfactual method compares it to a hypothetical, undisturbed state, considering the influence of external forces. This concept disentangles the contribution of external forces and the disturbance on recovery.

The two perspectives on recovery have significant implications for ecosystems management and decision-making. The conventional view of recovery is reactive and introduces a trade-off between the speed and the quality of the recovery process (Cheng, Ganapati, and Ganapati 2015; Olshansky 2006). In this view, the primary objective is to restore the ecosystem to its pre-disturbance state (normal state) as rapidly as possible, often without considering the quality of the recovered state; the new normal imposed by other forces. This approach is fundamentally backward-looking and implies returning the ecosystem to the vulnerable conditions that existed before the disturbance. Decisions based on this conventional recovery view may inadvertently exacerbate the disturbance cycle.

In contrast, the counterfactual perspective is more proactive, where the quality of recovery holds equal importance alongside the speed of recovery. Unlike the conventional view, the counterfactual approach evaluates the post-disturbance recovery against a hypothetical state that a disturbed ecosystem would have reached if the disturbance had never occurred. The counterfactual recovery approach empowers decision-makers to plan for the future (Cheng, Ganapati, and Ganapati 2015; Olshansky 2006) and aligns more closely with the goal of promoting the resilience of ecosystems. For example, there is a body of evidence indicating that protected and managed regions can recover to their original state (as per the conventional view) more rapidly (McClanahan 2008; Senf, Müller, and Seidl 2019; Su et al. 2022). However, these management practices may simultaneously compromise the ecosystem's resistance to future disturbances (Côté and Darling 2010; Senf, Müller, and Seidl 2019). Resilience depends on seeking a balance between resistance (quality) and the speed of recovery, and the counterfactual view implicitly considers both critical aspects.

Ecologists have long recognized the influence of external factors like climate change on recovery (Gaiser et al. 2020; Turner and Seidl 2023; Turner et al. 2020; Albrich et al. 2020). However, there is a gap in developing quantitative frameworks to analyze these external forces' impact (Fick et al. 2021; Iglesias and Whitlock 2020). To address this gap, we introduce an approach based on time series impact analyses to quantify counterfactual recovery time estimates. We emphasize the divergence between counterfactual and conventional perspectives using an illustrative example: the recovery time for greenness in North American Arctic and boreal ecosystems. Over three decades (1984-2013), these ecosystems have faced diverse disturbances, including wildfires, permafrost thaw, insect outbreaks, and human activities(Foster et al. 2022; Zhang et al. 2022). Regardless of the trigger, a key consequence of disturbance in this region has been altered land cover composition (Jonathan A. Wang et al. 2020). We focus on the recovery of the annual maximum normalized difference vegetation index (NDVI), a proxy for ecosystem greenness and photosynthetic potential, following land cover disturbances. We demonstrate the significant discrepancies in NDVI recovery time estimates between counterfactual and conventional approaches. The framework presented in this study has the potential to be applied to encompass the recovery of other remote sensing or ecological variables.

Materials and Methods

Study area and datasets

The study region is the core domain of the NASA Arctic-Boreal Vulnerability Experiment project, encompassing most of Alaska and a large portion of western Canada (Figure S1), with a total area of slightly more than four million km^2. The land cover map used in this study has a 30 m spatial resolution and covers the period 1984-2013 (J. A. Wang et al. 2019). The data can be downloaded from the ORNL DAAC (10.3334/ORNLDAAC/1691). This product has ten different land cover types (Table S1), including evergreen forest (EF), deciduous forest (DF), shrublands, herbaceous vegetation, sparsely vegetated areas, barren land, fens, bogs, shallow/littoral areas, and water classes. Since our primary interest is NDVI, we only focused on vegetative categories.

The NDVI data in this study is the annual maximum NDVI that was developed for the region (E.K. Melaas et al. 2019) with 30 m spatial resolution, and has been used in various studies (Eli K. Melaas, Sulla-Menashe, and Friedl 2018; E.K. Melaas, Friedl, and Sulla-Menashe 2018). The NDVI values from 1984 to 1998 are based on the Landsat TM sensor, and from 1999 to 2013 on the Landsat ETM+ sensor. There is an inconsistency between the two sensors, as the NDVI values of ETM+ are generally higher. This could introduce a spurious upward trend in the analyses. To correct for this bias, we calibrated the ETM+ NDVI using the following linear correlation which was originally developed for the region and the Landsat dataset (Sulla-Menashe, Friedl, and Woodcock 2016) used in this study:

$$NDVI_{cor} = (NDVI_{obs} + 0.015)/1.095$$

Where $NDVI_{cor}$ and $NDVI_{obs}$ are the corrected and observed NDVI ETM+, respectively.

We divided the region into 0.05° × 0.05° grids, each covering approximately 17,000 pixels with 30-meter resolution. Within each grid, we calculated the percent cover of each land cover type by counting the number of pixels of a specific land cover type and dividing it by the total number of enclosed pixels. We also calculated the average NDVI in each grid. In this study, we defined a 10% change in net land cover change between two consecutive years as a disturbance. If a grid experienced at least one change greater than 10% between two consecutive years, we considered it a disturbed grid. Note that the 10% threshold is subjective, since our goal was to demonstrate how the ecosystem recovers from a significant land cover composition change. Despite the subjectivity of the disturbance threshold, the map of disturbed areas produced in this study (Figure S1) is very close to the comprehensive map of disturbance recently derived for the region (Zhang et al. 2022).

It is worth mentioning that while normalized burned ratio (NBR) is commonly used in recovery studies across the region (Frazier et al. 2018; J. C. White et al. 2022; J. C. White, Hermosilla, and Wulder 2023), our focus was on NDVI. We chose NDVI because, in comparison to NBR, it exhibits a relatively rapid recovery (Frazier et al. 2018), allowing for an assessment of both traditional and counterfactual recoveries during the study period. Furthermore, NDVI is extensively utilized in the analysis of greening (Fiore et al. 2020; K. Fred Huemmrich et al. 2023), disturbance and recovery (Bright et al. 2019; Shvetsov et al. 2019), and has demonstrated correlations with climate, productivity, leaf area index, and other ecological variables in the region (K. F. Huemmrich et al. 2010; Raynolds et al. 2012; Verbyla and Kurkowski 2019).

Trend estimation

The trend estimation in land cover time series and NDVI is conducted using the Bayesian Estimator of Abrupt Change, Seasonal Change, and Trend (BEAST) method (Zhao et al. 2019), which is implemented in Python. The code for this algorithm can be accessed at (https://github.com/zhaokg/Rbeast). BEAST is an ensemble algorithm that, instead of searching for the "best" time series model, fits numerous models and assesses the relative utility of individual decomposition models. It accomplishes this by leveraging all the models through Bayesian model averaging. Extensive testing on synthetic data and various remote sensing time series products has demonstrated that BEAST is capable of capturing realistic nonlinear dynamics within a time series (Zhao et al. 2019; Dashti et al. 2021; Li et al. 2022). Furthermore, this algorithm identifies potential change points (CPs) in trends. The CPs indicate the point in time when there is a significant change in the trend, attributable to various factors such as disturbances.

Estimating conventional and counterfactual recovery time

We defined conventional recovery time as the period for a variable (e.g., NDVI) to reach its mean value before a disturbance. In contrast, counterfactual recovery time is the duration for a variable to attain its counterfactual state, representing what the ecosystem's condition would have been without the disturbance. To predict this counterfactual state, we employed the Bayesian Structural Time Series (BSTS) model (Brodersen et al. 2015). BSTS was originally developed to assess the impact of interventions or external events on a time series. It has found applications in a wide range of fields, including assessing the impact of COVID-19 on ridership (Hu and Chen 2021), evaluating marketing campaign effectiveness (Mourtgos, Adams, and Nix 2022) and examining hurricane impact on mortality rates (Santos-Burgoa et al. 2018). An implementation of BSTS has been developed as an R package known as CausalImpact.

Inferring the impact of land cover disturbance on NDVI using BSTS involves a three-step process. Firstly, a model is established between NDVI and highly correlated variables before the disturbance occurs. The critical assumption is that these correlated variables remain unaffected by the disturbance. In our study, we assume that neighboring NDVI values (within a ~50 km radius) in the undisturbed region demonstrate a strong correlation with the NDVI of the disturbed area prior to the disturbance, and they remain unaffected by the disturbance, thus fulfilling the BSTS assumption. We then calculated the mean of all these undisturbed NDVI values and utilized this time series as the predictive feature. Secondly, we fit the model established in the preceding step to the undisturbed NDVI values post-disturbance to predict the counterfactual NDVI state. Thirdly, the posterior distribution of the pointwise impact of disturbance on NDVI post-disturbance was computed.

Lastly, we defined a counterfactual recovery time as the moment when the disparity between counterfactual predictions and observed NDVI post-disturbance approaches zero. In other words, counterfactual recovery marks the time when the actual and potential NDVI, accounting for the influence of external factors such as climate change, converge. All findings presented in our study are statistically significant (p-value < 0.01).

Results

Disturbance Drives Shifts in Vegetation Greenness

The NDVI dynamics were found to be closely linked with land cover changes and disturbances (Figure 1). The most prominent pattern in disturbance was the onset of a decline in evergreen forests (EF) in 1994, which persisted until the end of the study period (Figure. 1a). Over this period, the coverage of evergreen forest in disturbed areas decreased by approximately -54%, from an average of 60% in 1994 and earlier to 30% by 2013 (Figure. 1b). Concurrently, other vegetation types expanded. Notably, there was a sharp rise in sparse vegetation, which was subsequently moderated, while shrubs and herbaceous vegetation began to grow at an accelerated pace, gradually replacing sparse land cover. This pattern exemplifies a typical post-disturbance succession process. Figure 1c shows the increasing number of change points (CPs) around 1995, highlighting that disturbance led to a change in the general trend of land cover. A similar pattern, although less pronounced, can be observed for the year 2005. While herbaceous cover also increased relatively, from 4% to 6%, this increment is much less than shrubs and sparse vegetation. Thus, we did not show the CPs for this category. The pattern described here is consistent with above-ground biomass dynamics over regions disturbed by fire, as described by (Jonathan A. Wang et al. 2021). Their analysis shows that around 1995, the net forest cumulative above-ground biomass changes from positive to negative, implying a reduction in forest cover since that year.

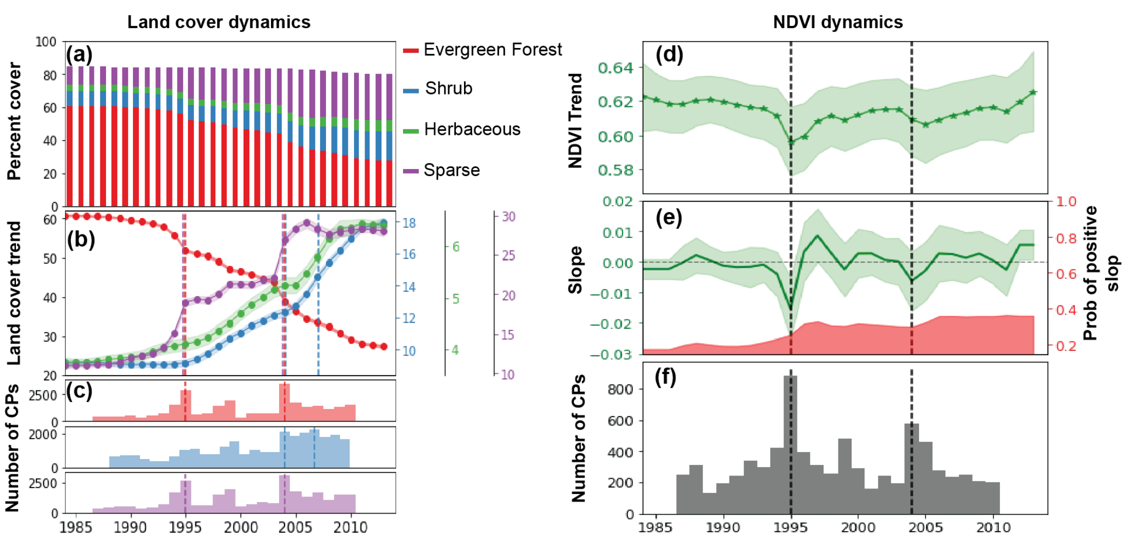

Figure. 1. (a) Temporal land cover composition, (b) mean of estimated trends for different land covers, (c) frequency of detected change points (CPs) in the estimated trend that are caused by abrupt changes, (d) NDVI trend, (e) average slope of NDVI trends at each point in time, and (f) detected CPs for NDVI. The

trends and CPs were estimated using the BEAST time series approach, and the shaded regions show the 95% confidence intervals. Vertical lines highlight the two most common years in which CPs are detected.

The land cover pattern over the disturbed area is also reflected in the NDVI dynamics (panel (d)). From 1994 to 1995, there is a sharp drop in NDVI, followed by a gradual recovery until 2004. At this point, another drop happens due to another smaller disturbance in land cover. In alignment with the land composition dynamics, the detected CPs in NDVI trend peak around 1995 and 2004. An interesting observation is the increase in the probability of finding positive slopes since 1994 in the NDVI trend (Figure. 1e) due to recovery process which is consistent with other studies.

Greenness Takes Significantly Longer to Recover Under Counterfactual View

Our analysis revealed a widespread disturbance across the region since 1994, as depicted in Figure 2. Upon focusing on regions affected by this disturbance, we observed significantly different estimates of the recovery time when considering conventional versus counterfactual perspectives. Achieving the counterfactual state required approximately 17 years, which was twice the time needed to reach the pre-disturbance mean NDVI in 8 years (see Figure 2d). At the onset of the disturbance, the actual disturbed NDVI experienced a sharp decline, deviating substantially from the counterfactual prediction (see Figure 2e). As the recovery process unfolded, the disparity between the actual and predicted NDVI gradually diminished. By 2002, the actual disturbed NDVI had returned to its pre-disturbance mean (NDVI = 0.57). However, during the same period, the predicted counterfactual NDVI slightly exceeded (NDVI = 0.6) the observed NDVI, suggesting that NDVI in the disturbed regions would have been slightly higher in 2002 (~5%) had the disturbance not occurred. Similar to undisturbed pixels (see Figure 2c), we observed a slight positive trend in the predictions of the counterfactual state (slope=0.0008). This "greening effect" contributed to a 0.03 difference between observed and predicted NDVI in 2002 and extended the disturbance recovery time from 8 years under the classical assumption to 17 years under the counterfactual definition of recovery.

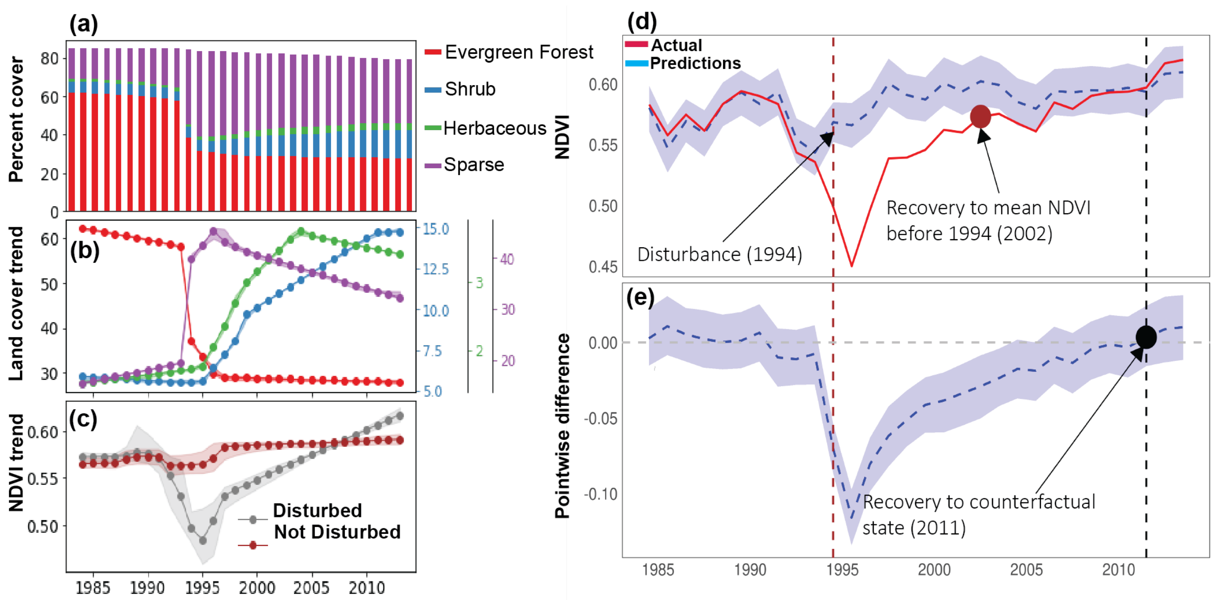

Figure 2. (a) Temporal land cover composition for regions that were disturbed in 1994, (b) the estimated trend for different land cover types as defined in Table S1, (c) the mean NDVI trend of disturbed and not disturbed neighboring grids, (d) the actual and the predicted counterfactual NDVI, and (e) the difference between the two. The brown and black circles show the conventional and counterfactual recovery points, respectively. The trend and the counterfactual predictions were estimated using BEAST and casual impact analyses, respectively.

Discussion

While our estimate of an 8-year recovery time for NDVI to return to the pre-disturbance mean aligns with findings from other studies conducted in the same region (Foster et al. 2022; Pickell et al. 2016; Jonathan A. Wang and Friedl 2019), our counterfactual recovery estimation of 17 years exceeds this estimate by almost a decade. It even surpasses the ~5-15 years of recovery time observed using slower pace indices such as NBR in the region (Frazier et al. 2018; J. C. White et al. 2022; J. C. White, Hermosilla, and Wulder 2023). We should note, these studies commonly employ the Years to Recovery metric (Kennedy et al. 2012), which defines the time needed for variable to return to 80% of its pre-disturbance mean. This definition is less conservative, implying faster recovery, than our definition, which demands a return to the pre-disturbance mean. Given the gradual recovery observed with NBR, it is reasonable to anticipate much longer counterfactual recovery timelines for this variable, necessitating longer time series than those employed in this study for a comprehensive investigation.

The discrepancy between conventional and counterfactual estimation of recovery time is primarily due to the well-known greening trend in the Arctic and boreal region observed in many studies (e.g. Piao et al. 2020; Ju and Masek 2016; Myers-Smith et al. 2020; Phoenix and Bjerke 2016). Greening acts as an external force constantly affecting NDVI values, gradually pulling them up (i.e. positive slope) in both disturbed and undisturbed regions. The conventional notion of recovery, which centers on returning to the pre-disturbance NDVI mean, overlooks this ongoing NDVI uptrend and non-stationary pattern. It implicitly assumes a stationary NDVI dynamic. While the positive trend is incremental and small, its cumulative impact becomes significant over extended timeframes. As shown in Figure 2, even with the relatively sharp post-disturbance NDVI increase, it takes 17 years for disturbed areas to reach to the NDVI value that would have existed if the disturbance had not occurred.

It's worth noting that the difference between NDVI values of 0.57 at the conventional recovery point and 0.6 at the counterfactual recovery point may seem insignificant at first glance. However, a more meaningful comparison involves considering the difference in NDVI alongside the slope of NDVI increase. The undisturbed NDVI slope is approximately 0.0008. Consequently, the 0.3 difference in NDVI is more than 37 times greater than the slope. This subtle yet consistent upward trend adds an additional 11 years to compensate for the 0.3 disparity. However, we recognize that a 0.3 difference in an ecological context may appear inconsequential, especially when considering that, in our case, the forest within the study timeline has never fully recovered to its pre-disturbance state. This is not surprising, as disturbed forested ecosystems typically require several decades to millennia to fully restore or there has been a permanent state transition due to multiple pressures (Turner et al. 2019; Cole, Bhagwat, and Willis 2014).

Our choice of NDVI over other common indices, such as NBR, for forest recovery estimates is twofold: First, NDVI recovers much faster, allowing us to achieve our primary goal of presenting a framework for counterfactual recovery analyses. Second, NDVI has been extensively used in greening (Fiore et al. 2020; K. Fred Huemmrich et al. 2023; de Jong et al. 2011; Myers-Smith et al. 2020). Since greening is the dominant external force in our counterfactual analyses, the selection of NDVI is justified. Nevertheless, the framework proposed in this study has the potential to be extended to encompass the recovery of other remote sensing or ecological variables.

We are living in an era of accelerated global changes due factors such as climate change and human activities. These external pressures introduce a non-stationary dynamic, potentially shifting entire systems toward a "new normal" over an extended timeframe (Seidl and Turner 2022; Milly et al. 2008; Turner and Seidl 2023). We propose that the adaptation to this new normal should be considered, as it presents a more realistic scenario, and as a community we should move away from assuming a constant state when assessing recovery. In some instances, the traditional perspective can lead to misleading conclusions. For example, in our example, greening resulted in a longer counterfactual recovery period compared to the traditional view. Conversely, in water-stressed regions, a general negative trend in greenness may occur. According to the conventional view, this would imply significantly longer recovery times or incorrect conclusions that the ecosystem failed to recover, when, in fact, a counterfactual recovery to a reduced state might happen more rapidly.

We acknowledge several limitations associated with the counterfactual recovery approach. Most notably, the counterfactual state is impossible to directly observe and relies on predictions, introducing uncertainty into the analysis. Depending on the context, various methods can be employed for counterfactual analyses. The simplest approach involves comparing disturbed and undisturbed regions using systematic methods such as quasi-experimental designs (Cheng, Ganapati, and Ganapati 2015; Grace et al. 2021; Xiao 2011). However, due to the intricate nature of ecological systems, finding two locations that are similar before the disturbance can limit the scope of such studies. In this study, we adopted a data-driven causal impact analysis approach, which requires predicting features that are unaffected by the disturbance and are highly correlated with the variable of interest. Therefore, this method is feasible when features for predicting the counterfactual state can be identified. An alternative method is to employ mechanistic models, such as Earth system models. For instance, Dobor et al. 2018, utilized a landscape model to demonstrate a 10-year difference in the recovery of total ecosystem carbon between the values before disturbance and those simulated under various climate change scenarios. These models are particularly useful for making longer-term predictions of the counterfactual state compared to other methods, and they offer more control over varying external forces such as different climate change projections. However, the challenge with most models lies in the number of parameters, model complexity, and the assumptions that underlie these models.

We envision and expect that this study leads to a rethinking of the recovery process and inspires further research on this topic, encouraging the exploration of various methods, including counterfactual analyses that do not assume stationarity, to improve our ability to realistically predict post-disturbance ecosystem recovery. The concept of counterfactual recovery is highly relevant to concepts such as ecosystem resilience, natural/engineering climate solutions, conservation and decision making.

Code availability

All code used in this study is accessible through the dedicated public GitHub repository at https://github.com/hamiddashti/greeness. The repository contains code written in both Python and R, utilizing various open-source libraries.

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