Global Change Biology

WILEY

Global Change Biology

REVIEW OPEN ACCESS

Monitoring Terrestrial Ecosystem Resilience Using Earth Observation Data: Identifying Consensus and Limitations Across Metrics

Katharina Runge[1,2] | Marlee Tucker[2] | Thomas W. Crowther[1] | Camille Fournier de Laurière[1,3] | Emilio Guirado[4] | Lalasia Bialic-Murphy[1] | Miguel Berdugo[1,5]

[1]Institute of Integrative Biology, ETH Zurich (Swiss Federal Institute of Technology), Zurich, Switzerland | [2]Department of Environmental Science, Radboud Institute for Biological and Environmental Sciences, Radboud University, Nijmegen, the Netherlands | [3]Department of Humanities, Social and Political Sciences, ETH Zurich (Swiss Federal Institute of Technology), Zurich, Switzerland | [4]Instituto Multidisciplinar para el Estudio del Medio "Ramon Margalef", Universidad de Alicante, San Vicente del Raspeig, Spain | [5]Departamento de Biodiversidad, Ecología y Evolución, Universidad Complutense de Madrid, Madrid, Spain

Correspondence: Katharina Runge (katharina.runge@usys.ethz.ch)

Received: 18 September 2024 | **Revised:** 15 January 2025 | **Accepted:** 29 January 2025

Funding: This research was supported by a grant from Stichting DOB Ecology (ID18626) to Thomas W. Crowther, funding from the Bernina Initiative through the ETH Foundation (202-2F-S318) to the Global Ecosystem Ecology Lab, and funding from the Spanish Government under a Ramón y Cajal contract (RYC2021-031797-I) to Miguel Berdugo.

Keywords: biomes | Earth observation | recovery | resilience | resistance | terrestrial vegetation

ABSTRACT

Resilience is a key feature of ecosystem dynamics reflecting a system's ability to resist and recover from environmental perturbations. Slowing down in the rate of recovery has been used as an early-warning signal for abrupt transitions. Recent advances in Earth observation (EO) vegetation data provide the capability to capture broad-scale resilience patterns and identify regions experiencing resilience loss. However, the proliferation of methods for evaluating resilience using EO data has introduced significant uncertainty, leading to contradictory resilience estimates across approximately 73% of the Earth's land surface. To reconcile these perspectives, we review the range of methods and associated metrics that capture aspects of ecosystem resilience using EO data. Using a principal component analysis, we empirically test the relationships between the most widely used resilience metrics and explore emergent patterns within and among the world's biomes. Our analysis reveals that the 10 resilience metrics aggregate into four core components of ecosystem dynamics, highlighting the multidimensional nature of ecosystem resilience. We also find that ecosystems with slower recovery are more resistant to drought extremes. Furthermore, the relationships between resilience metrics vary across the world's biomes and vegetation types. These results illustrate the inherent differences in the dynamics of natural systems and highlight the need for careful consideration when evaluating broad-scale resilience patterns across biomes. Our findings provide valuable insights for identifying global resilience patterns, which are critically needed to inform policy decisions and guide conservation efforts globally.

Lalasia Bialic-Murphy and Miguel Berdugo should be considered joint senior authors.

1 | Introduction

Resilience is a feature of ecosystem dynamics that captures a system's ability to retain and recover its function and structure following environmental perturbations (Capdevila et al. 2020; Holling 1996). Holling's definition of resilience has been interpreted in different ways across subdisciplines (Hodgson et al. 2015), with some studies focusing on the speed of recovery to an equilibrium following large perturbations (Lees et al. 2021), and others including a broader sense definition that includes the capacity of a system to absorb small-scale perturbations and environmental stochasticity (Seddon et al. 2016).

The most frequently applied definition of resilience in ecology is *engineering resilience*, which captures resilience around a single equilibrium to which a system always converges (Dakos and Kéfi 2022; Holling 1996). According to this definition, resilience can be equated to the ability of ecosystems to resist and recover from environmental perturbations (Figure 1). Both resistance and recovery are non-mutually exclusive measures of resilience, as they collectively represent two crucial aspects of ecosystem dynamics. Slowing down in the speed of recovery over time has been proposed as an early-warning signal of abrupt transitions (e.g., a system flipping from one state to another; Figure 1; S. R. Carpenter and Brock 2006; van Nes and Scheffer 2007) and is closely aligned with the *ecological* definition of resilience, whereby a system is not inherently assumed to return to its local basin of attraction (Holling 1973). These core components of resilience have been widely used to characterize system-level responses across scales of ecological organization, including population, community, and ecosystem dynamics (Capdevila et al. 2022; Gazol et al. 2017; Isbell et al. 2015; Poorter et al. 2021). For example, a species' resistance to buffer against environmental change has been characterized by its ability to maintain high fitness in variable environments. Similarly, niche differentiation and species complementarity have been theoretically linked to a community's ability to maintain high net primary productivity (NPP) in response to changing environments (Isbell et al. 2015).

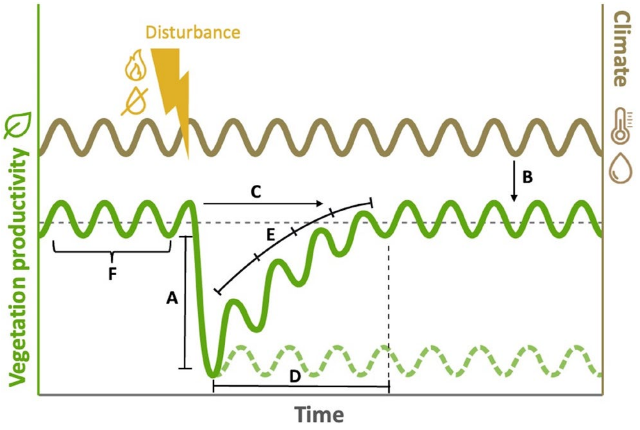

FIGURE 1 | General conceptual diagram of resilience summarizing how resilience is currently measured in EO-based studies. The green line depicts the system state that fluctuates over time, which is affected by climatic variability (brown), gets disturbed (yellow), and recovers (upper green line) or changes state (lower dashed green line). The dynamic responses of the system to perturbations, its resilience, involves different aspects that can be captured with different metrics—resistance can be captured as the system's magnitude of change (A) and its sensitivity to climatic variability (B); recovery can be captured as the recovery time (C), recovery rate (D), and approximated with statistical signals of temporal autocorrelation (TAC) and variance (D); changes in recovery rate can be captured with a change in TAC and variance (E), which, together with change in kurtosis and skewness, are also used to detect critical slowing down in the vicinity of a tipping point (F) leading to a state change (dashed green line).

Our understanding of ecosystem resilience has been traditionally derived from local-scale studies. While foundational for our understanding of resilience, the small spatial scale has limited our ability to identify unifying patterns across biogeographic gradients and distinctive ecological systems. However, Earth observation (EO) data now provide long-term dynamic information that allows us to scale up assessments of resilience to detect variation at the regional and global scale. As a result, EO has the potential to generate cost-effective data, which is relevant for setting and evaluating international policy targets on ecological health and resilience. This is especially relevant for progressing on the global goals on adaptation established in article 7 of the Paris Agreement and guided through the UAE Framework for Global Climate Resilience, as well as reaching the Aichi biodiversity target 15 and goal A established in the Kunming-Montreal Biodiversity Framework for maintaining and enhancing ecosystem resilience (Conference of the Parties to the Convention on Biological Diversity 2022; Intergovernmental Panel on Climate Change 2022; Thompson 2009).

The recent evolution of EO datasets has transformed our capacity to measure resilience at the ecosystem level across large spatial scales. Based on the reflected light from vegetation, studies have applied various indices that track the state of vegetation over time at high spatial and temporal resolutions (up to 10 m and 5 days, respectively; see Box 1). Using time series data, studies capture resilience at the regional to global scale by measuring the ability of a system to resist and absorb climate variability (sensitivity analysis, Seddon et al. 2016). Other commonly used indicators capture a system's ability to recover from environmental perturbations, namely, the time and rate of recovery (Schwalm et al. 2017; Wu and Liang 2020), which can be approximated by measuring the temporal autocorrelation (TAC) and variance within vegetation time series data (Smith et al. 2022; Verbesselt et al. 2016). Changes in TAC and variance are used to assess trends in resilience (Smith et al. 2022; Wang et al. 2023) and have also been interpreted as critical slowing down (CSD), signaling a loss of ecological resilience in the vicinity of tipping points (Dakos and Bascompte 2014; Flores et al. 2024; Forzieri et al. 2022). All these indicators capture aspects of dynamic variability in NPP and can be theoretically used to characterize aspects of ecosystem resilience over time and space. The inherent speed of a system is also thought to be predictive of resilience, whereby systems with faster-growing species with more rapid selection potential are commonly thought to have a higher adaptive capacity to ongoing environmental change (Chaparro-Pedraza 2021; Dakos et al. 2019).

With such a wide range of indicators, there are big inconsistencies in spatiotemporal trends among previous works (Box 2), with disagreement on the direction of resilience change for 73% of the land surface across three example studies (Figure 2). Although small differences in technical and methodological decisions may be one cause of disagreement

BOX 1 | Vegetation indices frequently used for measuring resilience.

When measuring resilience using EO data, it is important to note that the choice of an appropriate vegetation index for monitoring resilience depends on the type of ecosystem studied and spatial and temporal data needs and requires us to consider what vegetation parameter a given index can capture and what it can not (Table S2). Most studies so far have used the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI) for estimating resilience, which are especially suitable to reflect the resilience of fast-responding vegetation (e.g., perennial grasslands) but are thought to overestimate the resilience of forests (capture the recovery of greenness, which includes grass replacing a forest post-perturbation, rather than the return to the initial forest density). Other studies have thus combined NDVI with vegetation optical depth (VOD) (Table S2) to include changes in aboveground biomass (leaves and stems) to capture the resilience of slower-responding vegetation (i.e., trees). Which index is most appropriate depends on the context of the study; for example, leaf area index (LAI), instead of NDVI, can be more suitable for quantifying resilience if one wants to capture the indirect effect of CO_2 fertilization on plant biomass (Zhang et al. 2022; Zhu et al. 2016). In this study, we have focused our efforts on assessing NDVI/EVI derived resilience metrics, which capture the dynamics of vegetation greenness. By doing so, we aim to investigate the different facets of resilience when maintaining the same ecosystem component (vegetation greenness) as the state variable.

between studies, another widely recognized explanation is that these indicators capture different "facets" of resilience (i.e., ability to absorb small perturbations vs. recovery from large disturbances etc.; Box 2). While we know from theoretical (Dakos and Kéfi 2022) and empirical studies (Capdevila et al. 2022; Gazol et al. 2017; X. Li et al. 2020; Yao et al. 2022) that different resilience facets are related, the relationship between these resilience indicators using EO data has not been explored. Resolving the considerable discrepancies between the patterns emerging from different metrics remains a central challenge to guide both scientific (S. Carpenter et al. 2001; Pimm et al. 2019) and political decision-making (Donohue et al. 2016; Lecina-Diaz et al. 2024).

Here, we review the methodological approaches that are currently used to capture resilience at large scales. The central objective is to provide an intuitive understanding of the alignment between key metrics of resilience. To frame resilience in this review, we draw on a broad sense definition that considers engineering resilience to be a function of the resistance and recovery of a system to a local equilibrium. These expectations are grounded in foundational theories in community ecology (Hodgson et al. 2015; Holling 1996; Khoury and Coomes 2020) and have been further developed in EO resilience research (Gazol et al. 2018; Smith et al. 2022). EO resilience research can benefit from such a bivariate framework that incorporates resistance and recovery as part of resilience, which offers a more comprehensive perspective of the multifaceted nature of ecosystem responses to environmental disturbances in a changing world. In the following sections, we refer to engineering resilience as resilience if not specified otherwise.

BOX 2 | Global resilience patterns across studies.

Across studies assessing resilience with EO data, we observe discrepancies in the resilience patterns, making it at least problematic to obtain meaningful conclusions for ecosystem management due to the unclarity of which places are in fact losing resilience and require management intervention (Figure 2). It is unclear whether those inconsistencies come from differing methodological approaches, such as the use of different time intervals, EO products, or whether they are due to the use of different indicators to capture resilience. For example, two studies that use change in TAC and variance across different time intervals come to different conclusions about patterns of resilience losses and gains. Smith et al. (2022) observe an overall reduction of resilience mainly in higher latitudes and an increase in the tropics between 1992 and 2017 (Figure 2a), while Forzieri et al. (2022) find different trends; resilience declines in tropical and temperate forests and increases in boreal forests between 2000–2010 and 2011–2020 (Figure 2b).

When studies use different resilience indicators, we observe more discrepancies. While Forzieri et al. (2022) observe a resilience increase in boreal forests, two studies measuring CSD using a composition of metrics (TAC, standard deviation, kurtosis, skewness [and variance]) found that tundra and boreal forests undergo the greatest loss in resilience (Feng et al. 2021; Rocha 2022). A different study shows high resilience (measured as TAC) to climate change in boreal forests and the tundra biome (D. Li et al. 2018), while another study finds that boreal forests, tundra, and tropical areas are highly sensitive to climate variability (Seddon et al. 2016). Furthermore, Forzieri et al. (2022) observed declining resilience for arid forests. However, when resilience is measured as the response to drought disturbances, they were found to be more resistant to, but recovering more slowly from droughts (Yao et al. 2022). These discrepancies indicate that different indicators capture different aspects of ecosystems' dynamics and responses to disturbances.

Our review builds on previous work, which discussed the practical and computational challenges of resilience assessments using EO data and focused primarily on metrics that serve as indicators of CSD (Bathiany et al. 2024). By developing an in-depth understanding of the theoretical and empirical alignment between the most widely used EO resilience metrics, which capture distinct aspects of resilience (e.g., resistance to small perturbations vs. the speed of recovery follow large disturbances), we aim to advance our understanding of current resilience trends and the mechanisms underpinning the commonalities and discrepancies among resilience assessments. Specifically, we review the most widely used metrics using EO data, highlight which aspect of resilience each metric captures (i.e., resistance and recovery) and critically discuss their core assumptions and limitations. Second, we use a principal component analysis (PCA) to evaluate the alignments among the core aspects of ecosystem dynamics that are captured by these 10 resilience metrics, and we assess whether and how these metrics capture different facets of

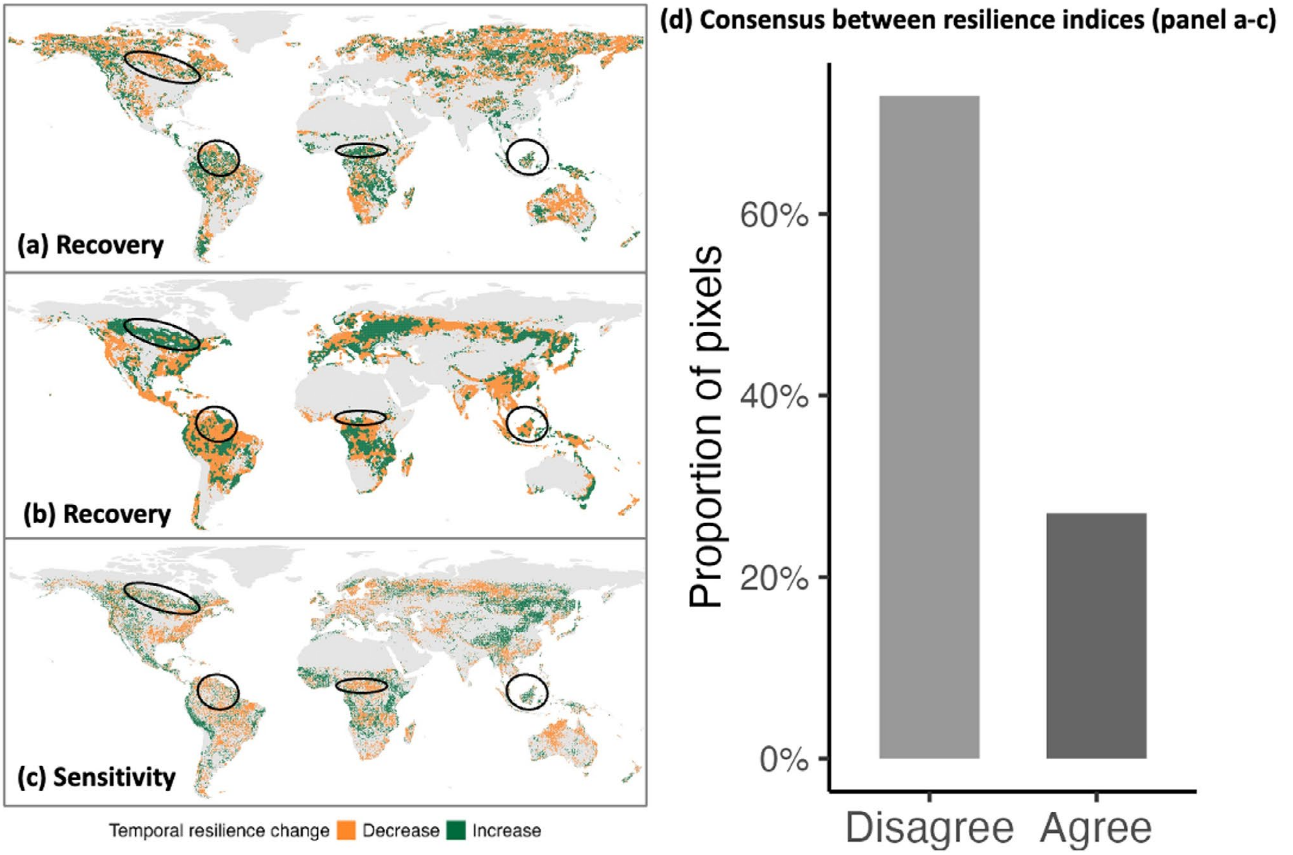

FIGURE 2 | Discrepancies in the temporal trend of three resilience indices from three different studies. We compared resilience trends of recovery (temporal autocorrelation [TAC]) from Smith et al. (2022) (a), recovery from Forzieri et al. (2022) (b), and sensitivity from Lauriere et al. (2023) (c). Map (a–c) show the binary resilience trend (decrease in orange, increase in green) extracted from the published maps of the three studies at 0.3° resolution. Black circles highlight areas of disagreement between resilience trends across (a–c). We assessed the proportion of pixels showing the same resilience trend (decrease/increase) across the three indices (27% agree). If at least one study showed a different trend, we considered it a disagreement (73%) (d). Any pixel that did not have a resilience value in at least one study was excluded from the comparison in (d). We note that one on one comparisons between the three studies result in a more even proportion of agreement and disagreement (see Table S3). See Table S4 for an overview of the data pre-processing steps of the three studies. See Supporting Information, methods for more information.

resilience. Moreover, we test this alignment within and across the world's dominant biomes to evaluate whether those dimensions are system specific. The 10 metrics are all derived from EO data capturing dynamics of vegetation productivity and greenness (NDVI and EVI). We conclude by highlighting considerations and gaps in how resilience is currently quantified with EO data and discuss which unasked questions should be addressed in future studies.

2 | Current State of the Art in Resilience Indicators Using EO Data

There has been a growing number of studies over the past several decades that characterize aspects of ecosystem resilience across broadscale biogeographic gradients using EO data (Table S1). Many of those studies focus on identifying processes driving resilience loss, such as changes in precipitation, water availability, and biodiversity (Boulton et al. 2022; García-Palacios et al. 2018; Khoury and Coomes 2020; Y. Li, Zhang, et al. 2023; Schwalm et al. 2017; Smith and Boers 2023; Verbesselt et al. 2016; Zhang et al. 2022), while others investigate how ecosystems resist and recover from individual disturbances (Gazol et al. 2018; Lees et al. 2021; H. J. White et al. 2020; Wu and Liang 2020; Yao et al. 2022). Another body of studies investigate changes in resilience over time (Boulton et al. 2022; Forzieri et al. 2022; Lauriere et al. 2023; Smith et al. 2022; Wang et al. 2023) and map emergent biogeographic resilience patterns (D. Li et al. 2018; Seddon et al. 2016; Wu and Liang 2020). Across studies, a variety of methodological approaches have been applied to characterize shifts in ecosystem-level dynamics. These core methodological approaches can be loosely grouped into two categories that are in line with classic resilience indicators. The first group of methodological approaches captures the ability of a system to absorb and resist disturbances (e.g., sensitivity to climate variability or resistance to shock disturbances), and the second group of methodological approaches captures the capacity of systems to recover from perturbations (e.g., recovery time, TAC, and variance). Several methodological approaches have also been developed to detect slowing down in the rate of recovery over time, which are also used as early-warning signals of abrupt transitions (e.g., a system flipping from one state to another). Interestingly, previous works using EO data have found discrepancies in broadscale resilience patterns (see Box 2; Figure 2). While still unclear, mixed results could be driven by differences in the methodological approaches (e.g., indicators that capture resistance vs. recovery) or mismatches in the timeframe used to infer resilience patterns across vegetation zones and biome types.

In the following two sections, we highlight the core set of methodological approaches that have been developed to capture the components of system dynamics assuming a return to an equilibrium state (i.e., resistance, recovery, and changes in the rate of recovery) and discuss their assumptions and limitations. We focus our discussion on those approaches that have been applied in the field of resilience assessments using EO data.

2.1 | Metrics Capturing Resistance

2.1.1 | Resistance to an Individual Shock Disturbance

Resistance has been defined as the ability of a system to withstand or stay unchanged and absorb external forces (Grimm and Calabrese 2011). It is often quantified by measuring how much the state variable is affected by a natural or experimentally created shock disturbance, a sudden and short-lived event like a drought. The unit of measure is the (relative) difference or ratio of change of NPP before and following a disturbance. It has been used, for example, to compare drought resistance between forest types across Spain (Khoury and Coomes 2020) and to quantify the maximum stress from which an ecosystem can recover on the global scale (Wu and Liang 2020).

Resistance is only one component of resilience and is often combined with metrics quantifying recovery to capture resilience more completely and to control one component to estimate the other (Gazol et al. 2018; Hodgson et al. 2015; Khoury and Coomes 2020; Senf and Seidl 2022; Wu and Liang 2020). Resistance captures the severity of a disturbance, which can impact the recovering process (Chu et al. 2017). Furthermore, one system can be resilient due to its fast recovery after a disturbance and another one because of its resistance to stress (Hodgson et al. 2015). Quantifying resistance and recovery to an individual disturbance has some caveats, which require consideration, such as making assumptions about the "normal state" of the system, defining the perturbation, and considering the interaction of multiple disturbances and resilience. We discuss these in Section 2.2.

2.1.2 | Sensitivity to Climate Variability

Using long-term vegetation and climate data from EO, Seddon et al. (2016) developed a sensitivity index that captures resistance as a system's response to climatic variability, including temperature and water availability (Figure 1). This sensitivity metric captures a system's ability to resist and absorb continuous perturbations and has been used to characterize spatial variation in ecosystems' sensitivity to climate variability along environmental gradients (D. Li et al. 2018; Seddon et al. 2016). Later, this approach has now been extended to characterize a system's sensitivity change over time due to the increased temporal coverage of EO vegetation data (e.g., sensitivity change of canopy greenness to precipitation, Zhang et al. 2022). It is important to note that sensitivity analyses are based on EO data that only cover a few decades. This is a relatively short period, especially with regard to climate sensitivities for slow-moving systems (forests) and to account for cyclic climate oscillations. Thus, sensitivity to climate variability using EO data only captures transient climate responses (Williams et al. 2022).

Measuring a system's sensitivity to climatic fluctuations requires methodological assumptions that give rise to two main caveats. First, the sensitivity metric assumes that the relationship between vegetation anomalies and climate is linear. However, ecological responses often follow unimodal patterns (Whittaker 1967) or are nonlinear (Scheffer and Carpenter 2003). Therefore, sensitivity may differ depending on the amplitude of climate variability, which may be particularly relevant in the context of long-term changes in climate and observed increases in the frequency of extreme events. Considering this aspect in the use of sensitivity metrics is an approach still missing within the literature. Second, sensitivity is based on a system's response to large-scale climatic factors and does not explicitly capture the influence of disturbance history and local-scale processes. However, local environmental changes and spatially variable site-level responses can be significant and can play an important role in ecosystems' resilience responses to large-scale climatic effects (Carnicer et al. 2021; Williams et al. 2022).

2.2 | Metrics Capturing Recovery and Slowing Down

2.2.1 | Recovery

Recovery is defined as a system's ability to return to its predisturbance state following a shock perturbation (Carnicer et al. 2021; Williams et al. 2022). Such shock events are substantially shorter than the characteristic time scale of the system. The most straightforward way to measure recovery is to define a reference state and measure how long it takes the system to return to its initial condition (Schwalm et al. 2017). To measure the time to recover requires the detection of a sufficiently large perturbation. This requires several assumptions, including the following considerations and methodological challenges.

2.2.1.1 | Equilibrium State. To detect a perturbation and measure recovery back to the "normal" reference state, one needs to define an ecosystem's equilibrium state. Some studies define the equilibrium state based on a long-term average, for example, Wu and Liang (2020), who define the normal state as the mean LAI value in each month over 34 years. Others use shorter time frames to define the normal state, for example, the average value of the normalized vegetation index (NDVI) for 3 years preceding the disturbance (Gazol et al. 2018) and the monthly mean gross primary productivity across the same number of months as the relevant disturbance event (Schwalm et al. 2017). Beyond this, climatology and seasonality influence what is considered a "normal" state (e.g., what is a normal vegetation cover in January in a particular place is different when one changes the place or month). For example, the literature on temperature extremes accounts for this aspect by controlling for deviations from a Gaussian distribution within a month (Gubler et al. 2023), an approach often absent in resilience studies.

2.2.1.2 | Extreme Perturbations.

To measure recovery requires us to identify perturbations that deviate from natural fluctuations in the state variable. The magnitude of response that can be considered a deviation from the equilibrium can be highly variable among systems (grasslands vs. forests), which makes it challenging to derive biologically reasonable differences in resilience among ecosystems (i.e., grasslands vs. forests, or tropical vs. boreal ecosystems). A methodological approach that has been developed to help identify extreme perturbations is the Palmer Drought Severity Index (PDSI), which defines dry periods as a drought disturbance when the precipitation of a place differs at a standardized deviation from the place's historical precipitation (Alley 1984). However, there is no a priori reason to think that a given precipitation deviation would cause the same disturbance in all regions, as differences in vegetation types have highly different responses and rates of recovery (Li, Piao et al. 2023). Detecting perturbation anomalies also requires sufficient time series data, and the length of time series data that is needed to differentiate between natural fluctuations and extreme events may differ among systems. In other words, assumptions and simplifications need to be made on what a disturbance is when extending it to the global scales using EO.

Another approach that has been used to identify large perturbations using EO data is to detect deviations from the typical vegetation state using time series data (Khoury and Coomes 2020; H. J. White et al. 2020). Delineating disturbances like this, however, has some limitations: (1) The type of disturbance is unknown, which is relevant information for evaluating the mechanistic process behind the system's response, and responses can vary depending on the disturbance type (J. C. White et al. 2022). (2) Because EO data only capture specific vegetation parameters, it may not detect certain disturbances to the ecosystem; for example, a drought can lead to a change in the species composition but is not as devastating to cause a change in NPP. Because only disturbances that are large enough to change NPP are detected, such an approach may be biased toward detecting systems with low resistance. (3) Because different data products (i.e., vegetation indices) do not describe the same vegetation parameters and hence do not respond identically to external shocks, depending on the vegetation index used, specific disturbances may be harder or easier to detect (e.g., water content measured with VOD index may respond more sensitively to drought than productivity measured with NDVI). To account for the complexity of defining disturbances worldwide, Li, Piao et al. (2023) delineated drought disturbances by identifying thresholds in soil moisture coinciding with anomalies in multiple EO vegetation proxies. This approach accounts for the fact that the extent to which the severity of a drought suppresses vegetation varies across different biomes (Li, Piao et al. 2023). Although such an approach has not derived resilience patterns yet, it highlights the scale and global variation of defining disturbances. Moreover, the sensitivity of the vegetation to environmental perturbations (required to define a disturbance and thus to infer resilience) is in itself a sign of resilience of the vegetation (Seddon et al. 2016), which adds to the complexity of the problem.

2.2.1.3 | The Interaction of Multiple Disturbances and Resilience.

Resistance and recovery are often assessed in terms of a system's response to a distinct, isolated shock disturbance. However, in reality, systems are continuously perturbed by a natural regime of shocks and fluctuations (e.g., fire, grazing, and gradual changes in the climate acting together) (Arani et al. 2021). Therefore, quantifying ecosystem responses to specific shock disturbances enables us to understand their resilience to such disturbances only and not their overall response to multiple pressures. While this concern is not exclusive to EO-based resilience assessments (Carpenter et al. 2001; Hodgson et al. 2015; Strickland et al. 2024; Walker 2020), it is an important caveat to consider as systems become more degraded and threatened by multiple stressors (Forzieri et al. 2022; Strickland et al. 2024).

An ecosystem's resilience is affected not just by multiple different disturbances, but also by changes in disturbance duration, frequency, and intensity. For example, increased disturbance frequency can prevent ecosystems from fully recovering to their pre-disturbance conditions (Senf and Seidl 2022) and more intense, frequent and longer droughts slow down the recovery across the Amazon forest (Van Passel et al. 2024). The duration of press and shock disturbances determines whether recovery occurs, or the system shifts to an alternative state (Ratajczak et al. 2017) and the combination of drought frequency and intensity affect the recovery time and resistance of dryland vegetation (Yao et al. 2022). On the global scale, Schwalm et al. (2017) showed that the complex interaction of drought severity and duration, post-drought climate conditions, carbon cycle dynamics and fire act on ecosystems' recovery time. Considering the interplay between multiple factors on ecosystems' resilience, that their duration, frequency, and intensity change over time and how they affect recovery and resistance differently is essential to gain a coherent understanding of ecosystems' vulnerabilities in a changing world (Ingrisch and Bahn 2018; Seidl et al. 2016).

A closely related metric to recovery time is the rate of recovery. It can be quantified by fitting an exponential function to the time interval between the perturbation and the time when the system has fully recovered (Smith et al. 2022). The rate of recovery can also be inferred from the internal fluctuations of a system as it is permanently adjusting to many small perturbations (Figure 1). EO time series provide long-term data that tracks the variability of a system and contains information about a system's response to external influences. A widely adopted approach to capture resilience using EO data is to assess TAC and variance of the state variable, which have been theoretically and empirically linked to a system's rate of recovery (Dakos et al. 2012; Scheffer et al. 2015; Smith et al. 2022). TAC measures the autocorrelative nature of time series data and, as such, captures an ecosystem's velocity (Figure 1; Dakos et al. 2011; Scheffer et al. 2009). A high TAC and variance indicate that a system is recovering slower (S. R. Carpenter and Brock 2006; Smith et al. 2022; Veraart et al. 2012). Previous EO-derived assessments have applied TAC and variance to characterize resilience change over time (Forzieri et al. 2022; Smith et al. 2022; Wang et al. 2023) and space (Verbesselt et al. 2016). It is important to note here that the rate of recovery inherently differs between systems due to unique evolutionary and environmental processes that have shaped the dynamics of natural systems (e.g., forests vs. grasslands), which makes it difficult to differentiate between inherently different dynamics (forest inherently recover slower than grasslands due to slow growth and differences in generational turnover rate) versus a signal of recovery loss (decline in resilience) due to external stresses.

The advantage of using the change in TAC and variance is that this approach is not spatially and temporally constrained to systems that have been perturbed by a shock disturbance and does not require strong assumptions about the system's initial condition. Those indicators pick up statistical signals in time series data and are thus considered generic resilience indicators that can be applied to a variety of different systems, ranging from populations to climate systems (Camarero et al. 2015; Scheffer et al. 2015). This makes it theoretically possible to scale resilience monitoring across vegetation zones and biome types. However, this approach does not provide insight to the mechanism causing a system to have a slower recovery, which is relevant information for ecosystem management and for differentiating between inherent differences among systems that can, in some cases, be highly adaptive (fast vs. slow systems). For example, even though one filters out the seasonal signal using statistical techniques, it is not possible to fully remove the influence of seasonality on the system's response. Whether a drought occurs in summer or in winter can affect an ecosystem very differently and thus results in different TAC and variance values, which may be due to this indirect seasonality effect rather than the ability of the system to compensate an environmental perturbation (Bathiany et al. 2024). To isolate the process of resilience change affecting the velocity of recovery from external perturbations picked up by TAC, Forzieri et al. (2022) filtered out the effect of TAC of climate drivers on TAC in NDVI. Doing so, however, requires strong assumptions about the climatic drivers that are thought to influence the system under study and how this may differ among systems (vegetation zones and biome types).

2.2.2 | Critical Slowing Down

Closely related to the rate of recovery is the concept of CSD. An increase in TAC and variance indicates a system's slower recovery back to its equilibrium and can be linked to the slowing down of the system close to a tipping point at which it flips into another state, which is associated with a loss of ecological resilience (Scheffer et al. 2009). For example, abnormally high TAC was often detected 6 to 19 months before forest mortality, thus proving useful as an early-warning signal in this context (Liu et al. 2019). Other related metrics are kurtosis and skewness that have been used to capture local stability. An increase in kurtosis and in absolute skewness indicates lower resilience of the local basin of attraction (Rocha 2022). CSD specifically picks up the dynamics of a system when an environmental parameter slowly pushes the system toward a tipping point and not when a system is perturbed by a shock disturbance (e.g., a fire or hurricane).

Analogous to the phenomenon of CSD, but less established, is the decrease in CSD indicators, which has been proposed to signal "critical speeding up" before a critical transition (Rocha 2022; Titus and Watson 2020; Van Passel et al. 2024). It is important to note that although the change in TAC, variance, kurtosis, and skewness is used as a CSD indicator and is strongly correlated with changes in the potential of the ecosystem's state (Dakos and Kéfi 2022), alone, it does not provide a precise prediction of critical transitions and often fails (Kéfi et al. 2013). For example, not all critical transitions are announced by CSD indicators and CSD can occur without a critical transition happening (Dakos et al. 2015). The occurrence of resilience loss does not necessarily imply that a place will undergo immediate critical transitions (Kéfi et al. 2013). However, whether or not an alternative equilibrium is known to exist, we can still apply CSD indicators to compare differences in the rate of recovery across similar systems or quantify changes in recovery rate over time (Dakos et al. 2015; Kéfi et al. 2013; Lenton et al. 2022). Especially TAC and variance have been frequently used for that purpose (see Section 2.2.1; e.g., Smith et al. 2022; Verbesselt et al. 2016).

3 | Relationship Between the Core Aspects of Ecosystem Dynamics Across the World's Biomes

Each indicator discussed above captures a different aspect of an ecosystem's resilience, including a system's ability to recover from and resist individual shock disturbances, its sensitivity to climatic variability, and its resilience change. The variety of processes captured is also reflected in the discrepancies in global resilience patterns between different indices (Figure 2; Box 2). While we know from theoretical (Dakos and Kéfi 2022) and empirical studies (Gazol et al. 2017; X. Li et al. 2020; Yao et al. 2022) that different resilience facets are related, the relationship between these resilience indicators using EO data has not been explored. Here, we test how 10 widely used resilience metrics are dynamically related within and among the world's biomes, and we explore whether and how these metrics capture different facets of resilience.

The metrics we compare all capture a system's dynamics around a local equilibrium—its sensitivity to climatic variability, its resistance to extreme droughts, its recovery rate, and change in recovery rate (Figures S1 and S9). We focus on those 10 metrics for several reasons: (1) they are the most used in EO-based resilience studies; (2) they are, to a certain degree, comparable (e.g., they can all be calculated using vegetation data capturing greenness and productivity and across the same timespan); (3) they capture the main two components of resilience, resistance and recovery; (4) they have differences in their conceptualization (generic vs. disturbance-based indicators), but also similarities (e.g., sensitivity to water deficit is conceptually similar to resistance to extreme drought).

To compare the alignment among these facets of resilience, we conducted a PCA of the 10 resilience metrics. These metrics were calculated using EO time series data across 63,480 randomly sampled site locations. We compared the alignment among these 10 resilience metrics at the entire global scale, as well as among biome types and climate and vegetation zones. The metrics we included are lag-1 TAC, variance, change in lag-1 TAC, variance, kurtosis and skewness, resistance to extreme droughts and the Seddon et al. sensitivity index (2016) disaggregated into sensitivity to cloudiness, to temperature and to water availability (see Supporting Information for a detailed methodology).

Our analysis reveals that 10 of the most widely used EO resilience metrics align along four core axes (Figure 3; Figures S3–S8), which capture over 60% of the variation and provide

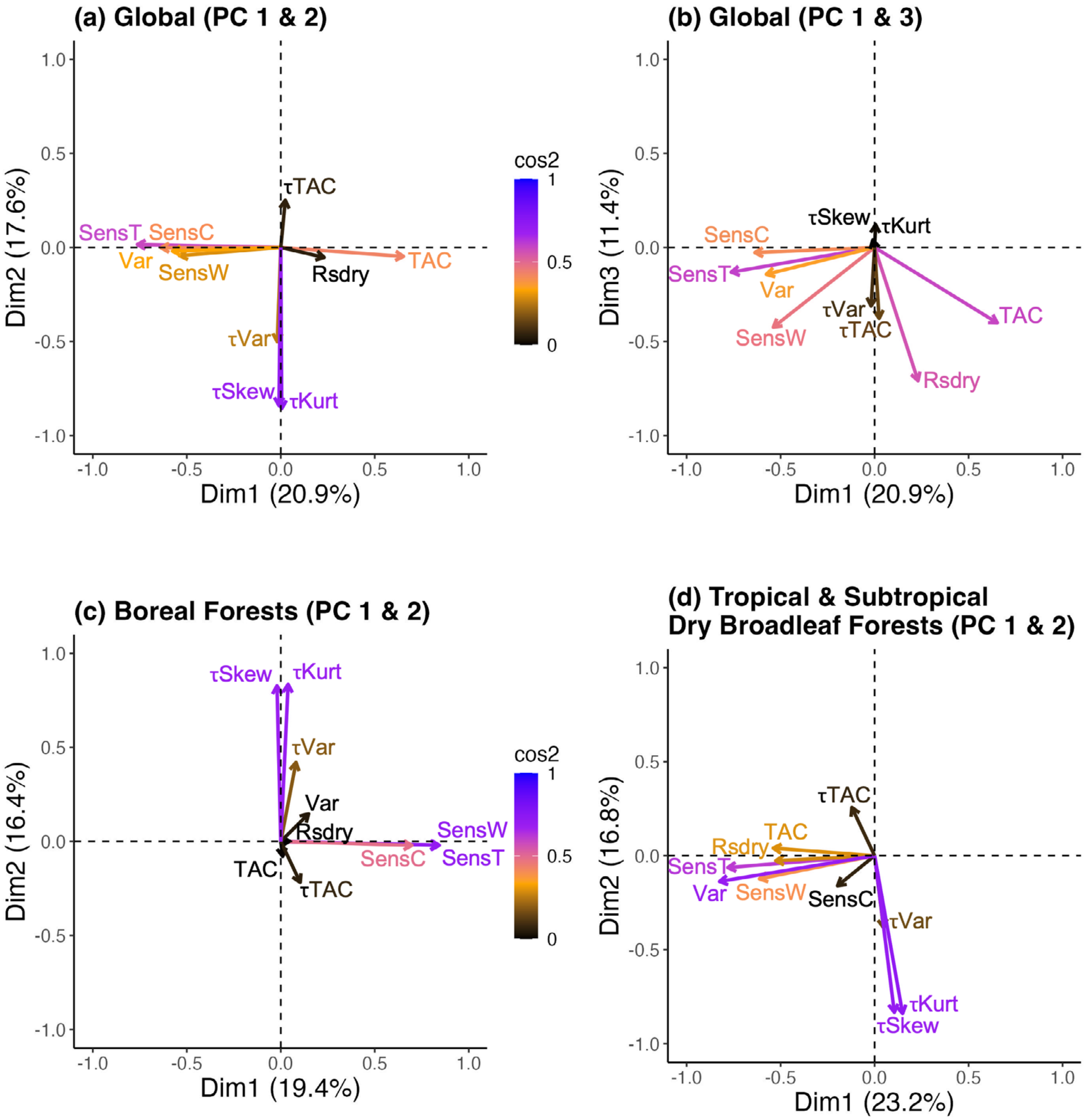

FIGURE 3 | The main axes and relationships across 10 resilience metrics. We provide examples of biplots of the principal component analysis (PCA) results of principal component (PC) 1 and PC 2 on the global level ($n = 63{,}480$) (a), PC 1 and PC 3 on the global level (b), PC 1 and PC 2 for boreal forests ($n = 7614$) (c) and PC 1 and PC 2 for tropical & subtropical dry broadleaf forests ($n = 1468$) (d). Colors depict how much each metric is represented on each PCA axis, which is estimated based on the squared cosine. The arrow length is proportional to the loadings of the metrics considered. Rsdry, resistance to extreme droughts; SensC, sensitivity to cloudiness; SensT, sensitivity to temperature; SensW, sensitivity to water availability; TAC, lag-1 temporal autocorrelation; Var, variance; τKurt, temporal trend in kurtosis; τSkew, temporal trend in skewness; τTAC, temporal trend in lag-1 temporal autocorrelation; τVar, temporal trend in variance. The PC loadings for the global level and each biome can be found in Table S5.

novel insights into the relationship between a system's ability to resist and recover from environmental perturbations. The first axis is strongly driven by a system's ability to absorb climatic fluctuations (PC loadings $L_{\mathrm{SensT}} = -0.53$, $L_{\mathrm{SensC}} = -0.44$, $L_{\mathrm{SensW}} = -0.37$) and a system's variability ($L_{\mathrm{Var}} = -0.40$) and negatively associated with its velocity/recovery rate ($L_{\mathrm{TAC}} = 0.45$; Table S5; Figure 3). This association between a system's ability to absorb climate variability and its velocity supports the idea that slower-moving systems are less vulnerable to climatic variability (Figure 3a). PC 2 is strongly driven by the change in recovery rate ($L_{\tau\mathrm{Kurt}} = -0.65$, $L_{\tau\mathrm{Skew}} = -0.63$, $L_{\tau\mathrm{Var}} = -0.38$), similarly to PC 4 ($L_{\tau\mathrm{TAC}} = -0.7$, $L_{\tau\mathrm{Var}} = -0.49$; Figure 3a,b). PC 3 is strongly weighted by the resistance to extreme droughts ($L_{\mathrm{Rsdry}} = -0.66$) and is positively associated with TAC ($L_{\mathrm{TAC}} = -0.38$).

At the global scale, sensitivity to temperature, water availability, and cloudiness strongly weighs on the first axis (Figure 3a; Table S5), which suggests that a system's ability to resist and absorb fluctuations of these climatic factors is related. While the responses to these climatic factors are tightly coupled across biomes, vegetation, and climate zones, the responses to temperature, water availability, and cloudiness are more coupled in the boreal, temperate, and cold zones (Figure 3c;

Figures S2–S4) and weakly coupled in the tropics and the evergreen broadleaf forests (lower correlations between variables on PC 1; Figure 3d; Figures S2–S4). Together, these results suggest that the individual and joint effects of these climate drivers are needed to characterize the ability of tropical systems to absorb and resist ongoing changes in climate variability. Conversely, a more generic sensitivity analysis may be sufficient to capture the ability of boreal and temperate systems to absorb climate variability.

Consistent across our global- and biome-scale analyses, we find a positive relationship between τTAC and τVar and between τKurt, τSkew, and τVar (Figure 3; Table S5). All these metrics have been used to capture losses and gains of local resilience (Feng et al. 2021; Rocha 2022; Smith et al. 2022; Smith and Boers 2023; Wang et al. 2023) and thus match the expectation that there should be a tight relationship between these metrics. Interestingly, contrary to theory, τTAC does not strongly align on the same axis with the other metrics that capture change in recovery rate over time (Table S5; Figure S9).

The velocity and recovery rate (TAC, lag-1 TAC) are strongly related to the resistance to extreme droughts, and this relationship is consistent at the global-, biome-, climate-, and vegetation zone-level (Figure 3; Table S5). Systems that are slower (high TAC) are more resistant to extreme droughts (Figure 3c,d; Figure S1). These emergent patterns support classic theory and suggest that faster-moving systems (grasslands vs. forests) that recover faster following perturbations (Smith et al. 2022) may be more vulnerable to more frequent and extreme events (drought, etc.). This negative relationship between the ability to recover and resist has been observed, for example, in forests and grasslands in China (Yao et al. 2022) and in forests in the Northern Hemisphere (Gazol et al. 2017).

On the biome-, climate-, and vegetation zone-level, we find that the relationship between a system's velocity (TAC) and change in recovery over time (τTAC and τVar) is changing depending on the system type (captured by PC correlation, Table S5). Across dryland regions, high mean TAC is coinciding with an increase in τTAC. Conversely, across tropical forests, TAC and τTAC are not strongly aligned with one another (Figure 4). While further investigation is needed to understand this emergent pattern, it likely suggests that the global variation in the rate of recovery is jointly influenced by (1) inherent, and arguably adaptive, differences among biomes and vegetation types (slow moving forest systems vs. fast moving grasslands) and (2) shifts in resilience due to external forces. Together, these trends highlight the need for careful considerations in how to use the rate of recovery to derive global patterns of resilience.

Furthermore, our analysis suggests a weak association between the ability to resist/absorb climatic variability (i.e., sensitivity) and to resist extreme droughts (Figure 3), which indicates that the resistance to continuous perturbations is a separate mechanism from the resistance to an individual extreme shock disturbance. The tropical regions of the world generally appear to be less resistant to small water availability fluctuations, while drylands are less resistant to large (shock) water availability fluctuations, i.e., extreme droughts (Figure 5). This contradicts the expectation that climate-sensitive systems are also sensitive to extreme disturbances and requires further investigation into the mechanistic processes and perturbation strengths giving rise to these divergent responses.

The four dimensions, revealed by the PCA, provide a tangible link between the emerging EO datasets and our conceptual understanding of resilience theory. The PCA shows the relationships and independence of different resilience aspects and the

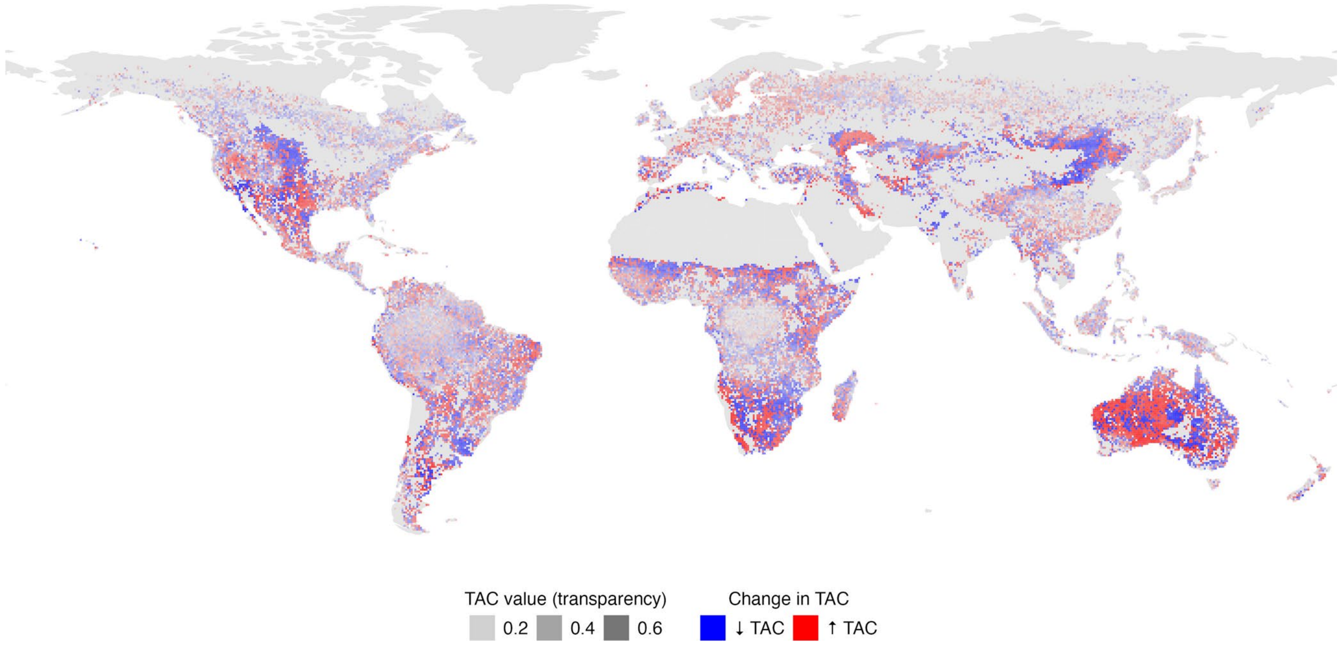

FIGURE 4 | Global pattern of the relationship between the magnitude of temporal autocorrelation (TAC) and direction of the change in TAC (τTAC). Red reflects places where τTAC is increasing (slower recovery) and blue represents places where τTAC is decreasing (faster recovery). Transparency corresponds to the TAC values, with higher transparency representing lower TAC and more opaque regions representing higher TAC. In gray are places without measurements. The map is in 500 m resolution.

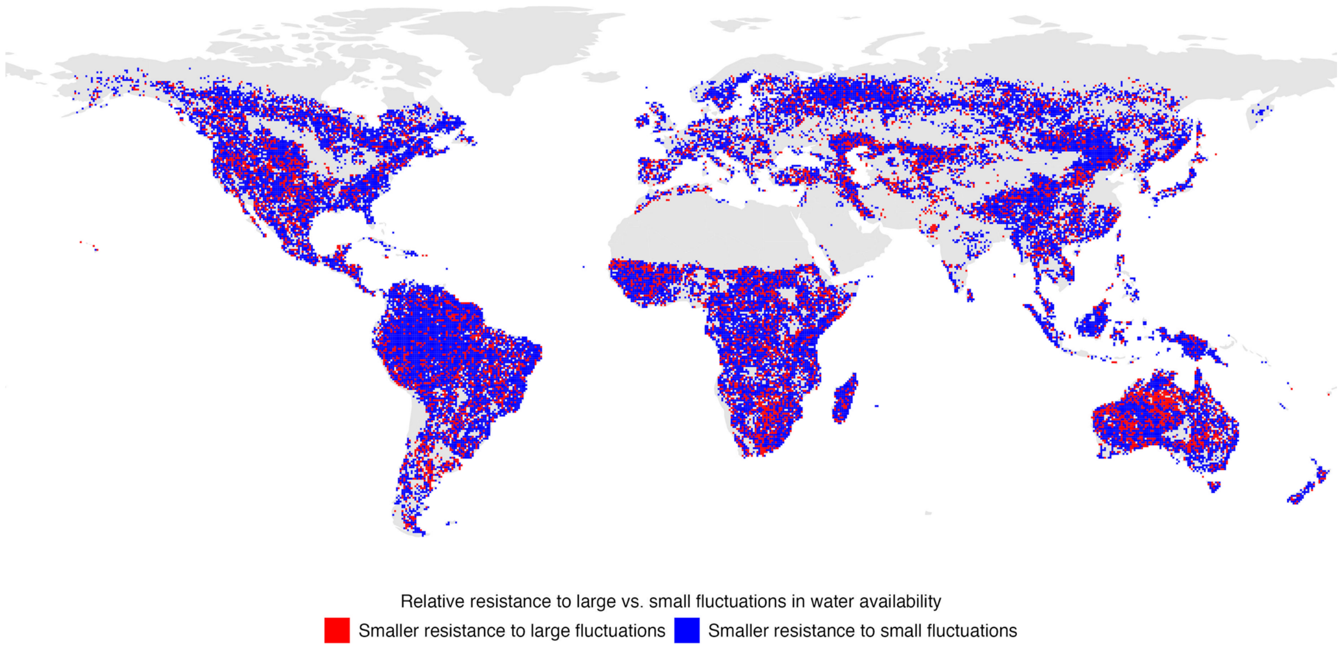

FIGURE 5 | Global pattern of relative resistance to large versus small fluctuations in water availability. We first standardized SensW (sensitivity to water availability) and Rsdry (resistance to extreme droughts) to make them comparable. Then we calculated for each pixel (at 500 m resolution) the ratio of Rsdry over SensW. In red we show places that are less resistant to large fluctuations (extreme droughts) than to small fluctuations in water availability (Rsdry > SensW). In blue, we show places that are more resistant to large fluctuations and less resistant to small fluctuations in water availability (Rsdry < SensW). Rsdry, resistance to extreme droughts.

context-dependent nature of this dependency. By identifying the appropriate metric to represent each of these dimensions, we believe that scientists can generate a more comprehensive and holistic understanding of resilience that considers the multidimensionality of system dynamics.

4 | Considerations and Future Directions of EO-Based Resilience Monitoring

4.1 | Scaling Resilience Assessments Across Inherently Different Systems

The PCA showed the general relationship between EO-derived metrics, which reflect the multidimensional nature of resilience, i.e., resistance, speed of recovery, and change in recovery rate (gains or losses in resilience over time) (Figure 3). We find that they capture several facets of resilience that match classic theory and that the relationships of metrics vary across biomes. Our findings suggest the importance of diversifying how we quantify resilience when scaling resilience assessments across inherently different vegetation zones. Other metrics that have not been applied in EO-based studies, like adaptive capacity (Chaparro-Pedraza 2021; Dakos et al. 2019), could provide additional insights into resilience and may reveal more facets.

Our findings highlight several important methodological challenges that should be carefully considered when scaling resilience assessments across inherently different vegetation zones and biome types. For example, the strong association between systems' speed and their resistance to extreme droughts, as well as the difference in the relationship between sensitivity metrics across systems, observed in the PCA, emphasizes the importance of considering inherent dynamical differences between systems for meaningfully assessing resilience. Several methodological considerations are discussed in-depth by Bathiany et al. (2024).

Among the most important considerations is to meaningfully delineate systems based on their dynamic similarity. This is crucial for separating out differences in the dynamics of systems that influence their resilience response, which makes resilience assessments difficult for deriving biologically reasonable comparisons across dynamically different systems. Especially when using a space-for-time approach to measure TAC and variance (e.g., Verbesselt et al. 2016), it is essential to restrict the space that we compare resilience values across to a well-defined system that is dynamically equivalent. For example, comparing TAC between a fast-moving grassland and a slow-moving forest may not give meaningful insights into the difference in their resilience (as discussed above), but only about how their dynamics differ. Furthermore, meaningfully delineating systems is necessary for defining biologically relevant deviations from a system's stable equilibrium and for determining how this may vary among systems, especially when making comparisons among systems with inherently different dynamics (fast moving grasslands vs. slow moving forests). These considerations are critical for defining extreme perturbations and detecting biologically meaningful differences in resilience loss over time and space (as well as CSD). Accounting for such system-specific differences can be done by identifying areas of resilience loss based on large deviations of a resilience indicator relative to its distribution within each biome (Rocha 2022).

Other important considerations when estimating resilience with TAC across systems are related to the methodological choices for the time series analysis. First, the use of sufficiently long time series is relevant to capture a biologically meaningful deviation from the equilibrium dynamics of a system. This time may vary across fast and slow systems, the latter requiring longer time series, such as forests with long regeneration times (Bathiany et al. 2024). Second, the choice of the time step and number of lags used to detrend and deseason the time series and to calculate TAC can lead to highly different trends. Whether we lag time steps of weekly, monthly, bimonthly, or yearly intervals will have a key influence on the extent to which seasonality and weather variations affect TAC. Additionally, longer cycles such as El Niño Southern Oscillation (ENSO) are important but difficult to account for as they can vary between two and 7 years. Short time steps capture fine-scale variability and short-term fluctuations, leading to high autocorrelation at short lags but potentially introducing noise. Thus, to capture the more rapid fluctuations in grassland systems, shorter time steps may be more appropriate. In contrast, longer time steps smooth out short-term noise, emphasizing long-term trends and seasonal patterns. Thus, they may be more relevant for capturing the slower fluctuations of forests. These system-specific differences in how the length of time step and number of lags for calculating TAC could influence the interpretation of resilience across different systems should be considered (Rocha 2022). One way of dealing with the complexities of different ecological systems (stemming from differences in seasonal variabilities, annual cycles or multidecadal oscillations) is to assess the dynamical complexity by approximating the influence of the past on the system (i.e., the period over which the lag should be estimated) (Takens 1981). This can be done by applying Autoregressive Integrated Moving Average (ARIMA) models or Sugihara's method to reconstruct the state space, which approximates the internal timing of each system (Sugihara and May 1990).

Studies applying resilience metrics using EO data should keep these complexities and caveats in mind when assessing a system's resilience. This is particularly relevant for large-scale assessments spanning a diversity of ecosystems. Overcoming these complexities is critically needed to inform scientific and policy-relevant communication of assessment outcomes (Lecina-Diaz et al. 2024) and should be the focus of future research. Indeed, our assessment highlights the importance of including a diversity of indicators that capture the different aspects of resilience in different ecological contexts.

4.2 | Integrating and Measuring the Concept of Ecological Resilience

The EO metrics discussed above are embedded into the definition of resilience as engineering resilience, which describes the stability of a system near an equilibrium and assumes that a system returns to its original state (Pimm 1984). A system with a low engineering resilience recovers slower from disturbances. Increased pressure from changing environmental conditions (e.g., increased intensity and frequency of droughts) can push the system across a tipping point into an alternative state, which means a loss of ecological resilience (Holling 1973). The existence of alternative states complicates the assessment of resilience due to nonlinear dynamics, asymmetric transitions between states, and the unpredictability of what state a system may tip into.

The change in TAC, variance, kurtosis, and skewness has been used as an early-warning signal that indicates a CSD associated with a loss of ecological resilience when a system is approaching a tipping point (Scheffer et al. 2009). However, they cannot prove the existence of alternative equilibria (see also discussion in Section 2.2.2; Kéfi et al. 2013). A regime shift can be caused by other factors that are unrelated to the presence of an alternative state or the loss of ecological resilience, for example, in the presence of a shock event (Dakos et al. 2015). Proving ecological resilience is challenging because it requires proving a bifurcation/tipping point. A recent review found that ecological resilience is measured less frequently than engineering resilience and that the assessment of both ecological and engineering resilience is almost absent, also in EO studies (Dakos and Kéfi 2022). This may stem from the difficulty of knowing if and when tipping has occurred in the EO data. Noise and uncertainties in EO data can lead to measurement and inference errors, which make ground truthing of tipping points detected with EO crucial. So far, identifying alternative states has mostly been based on studying probability distributions of ecosystem states and identification of potential thresholds (Hirota et al. 2011; Livina et al. 2010; Zou et al. 2024). However, going beyond these spatial approaches by measuring ecological resilience and applying temporal data to prove alternative states is an important field of research and has key implications for restoration goals. To apply the theoretical assumption that CSD increases when approaching a new equilibrium state, we need to test the CSD indicators using EO data on the thresholds emerging from fundamentally different states. Some evidence of clear thresholds comes from the theory of alternative biome states (the existence of alternative states of distinct vegetation growth forms—biomes—under the same environment, Pausas and Bond 2020). It offers a framework that infers clear thresholds separating biomes (grouping of vegetation types with the same dominant growth form), which may serve as initial hypothetical states of vegetation. Thus, we agree with recent studies that the emergence of big data from EO provides huge potential to probabilistically identify alternative states based on vegetation cover (Berdugo et al. 2017; Hirota et al. 2011; Scheffer et al. 2012). We emphasize that integrating such approaches with measuring resilience across the four axes we identified will help to better understand the dynamics of thresholds separating alternative states. Another promising indicator to quantify ecological resilience is the mean exit time, which is the time a system spends in a given state (Arani et al. 2021; Rocha 2022). Estimating this requires high-resolution time series data that cover dynamics of a system across different states (Dakos et al. 2008). State transitions between tropical forest and savannas have already been observed in EO data using space-for-time approaches (Hirota et al. 2011). But to observe alternative states throughout time of long-lived ecosystems, such as forests, we require data that spans very long time frames of several centuries (Pausas and Bond 2020), which we currently do not have (e.g., NDVI data covers around 20 years).

In real-world multi-dimensional systems that are subject to multiple stressors (Zhou et al. 2024), measuring resilience becomes even more complex. Apart from multiple states, ecosystem states are affected by multiple pressures simultaneously. Different stressors may lead to contradictory resilience signals, such as an increase in TAC on one dimension and a decrease in TAC on another dimension (Dai et al. 2015). In such instances, CSD indicators may fail to detect resilience loss. Our assessment somewhat manifests this complexity by pointing to the independence of resilience facets and to the context-specific nature of this independence (Figure 3). Yet, given the current limitations and methodological challenges of using EO data to identify bifurcations and assess tipping points and global resilience (i.e., limited years of data, etc.), we chose to focus on comparisons among local resilience indicators. However, an in-depth assessment of the commonalities and discrepancies among local and global resilience indicators is likely to become increasingly possible and is an exciting avenue for future research.

4.3 | Measuring Resilience Beyond Using EO Data of Greenness

Resilience assessments using EO data have primarily relied on NPP, often measured with NDVI (Table S1), to measure a system's state and response. However, NPP captures only one attribute of ecosystem health. As datasets improve, it is critical to consider other attributes, such as functional diversity and ecosystem structure that relate to total ecological resilience. Ultimately, resilience is an emergent outcome that results from the expression of multiple mechanisms interacting across different time scales and different levels of ecological organization, from the individual to the ecosystem. Thus, the aspect of ecological resilience that we choose to measure will determine the conclusions about the recovering and resisting ability of a system (Poorter et al. 2021). For example, because NDVI measures greenness, a system is thought to have recovered when its greenness returns, but its species composition could be completely different (e.g., forest replaced by grass) (Smith et al. 2022). Thus, studies focusing on greenness might overestimate the recovering ability of some ecosystems.

Advances in satellite sensors and data products derived from them (e.g., 3D structural data of forests from the Global Ecosystem Dynamics Investigation (GEDI) or up to 10-m-resolution data from Sentinel sensors) now allow us to measure resilience in terms of other ecosystem attributes, such as vegetation water content (Moesinger et al. 2020; Smith et al. 2022), soil moisture (Lees et al. 2021), and canopy height (Lang et al. 2023) across large spatial scales. Moreover, the finer spatial resolutions of new EO products allow us to measure more precisely certain ecosystems (today, with a resolution of 10 m it is more likely that within a pixel there is one ecosystem type, while with coarser resolutions used in the past, for example 250 m, a pixel likely contained multiple vegetation types) and enable us to move closer toward being able to capture community-level attributes, such as vegetation diversity. For example, remotely sensed spectral diversity (the variability of electromagnetic radiation reflected from plants) has been used to capture biodiversity (Kacic and Kuenzer 2022; Schweiger et al. 2018) and has the potential to capture the resistance and recovery of ecosystems' functional diversity (Fernández-Guisuraga et al. 2023) at resolutions of below 5 m (Kacic and Kuenzer 2022).

Capturing resilience in terms of functional diversity across large scales is especially important in light of global restoration goals aiming to establish functionally diverse ecosystems that can withstand and recover from global change. Yet, because resilience manifests differently at different scales of ecological organization (e.g., the resilience measured based on aboveground biomass (ecosystem level), does not necessarily mimic the resilience of an individual tree or the diversity of a forest community) (Kannenberg et al. 2019), field-collected data remain essential for capturing smaller-scale dynamics. Depending on the restoration goal, one or the other level of assessment is more suitable and guides the decision of which state variable is most appropriate to measure.

5 | Conclusion and Recommendations

Monitoring ecosystem resilience globally with EO data is becoming increasingly important for setting international policy targets, such as through the convention on biological diversity (CBD) (Thompson 2009) and the IPCC (Intergovernmental Panel on Climate Change 2022). However, to date, there is substantial uncertainty among global resilience indicators regarding where resilience is decreasing and increasing (Figure 2), with each indicator capturing a different facet of resilience. Our empirical analysis showed that the 10 most widely used resilience metrics aggregate into four core components of ecosystem dynamics, reflecting the multidimensional nature of resilience. Matching theory, we find that ecosystems with slower recovery are more resistant to drought extremes. Additionally, we show that the relationship between recovery rate and change in recovery rate over time varies across biomes and the alignment of sensitivity to different climate factors differs across boreal and tropical systems. Our findings highlight the importance of diversifying approaches to quantify resilience when scaling resilience assessments across inherently different vegetation zones. Such considerations aid in identifying priority areas to conserve and restore nature to enhance resilience at regional to local levels and for monitoring progress on nature-related sustainability targets (Ren et al. 2023). To capture a holistic perspective of ecosystems' resilience, recent advancements in EO measurements provide the opportunity to capture other features of resilience beyond NPP, including functional diversity and ecosystem integrity. This is especially relevant for assessing global restoration goals to establish functionally diverse ecosystems as an adaptation strategy to climate change. Furthermore, for restoration and conservation purposes, quantifying the possibility of regime shifts by measuring ecological resilience is highly relevant (Newton and Cantarello 2015). Finally, our results highlight the importance of diversifying resilience assessments to include a range of metrics across the four primary axes of ecosystem dynamics. We also emphasize the need to carefully account for inherently different dynamics when evaluating resilience across vegetation zones and biome types, as well as selecting time scales appropriate for each system. Integrating these considerations into EO resilience monitoring is crucial for scaling assessments across the world's biomes and for supporting policies that promote ecosystem health and sustainability.

Author Contributions

Katharina Runge: conceptualization, data curation, formal analysis, investigation, methodology, project administration, validation, visualization, writing – original draft, writing – review and editing. **Marlee Tucker:** conceptualization, supervision, writing – review and editing. **Thomas W. Crowther:** conceptualization, funding acquisition, resources, supervision, visualization, writing – review and editing. **Camille Fournier de Laurière:** conceptualization, data curation, writing – review and editing. **Emilio Guirado:** conceptualization, data curation, writing – review and editing. **Lalasia Bialic-Murphy:** conceptualization, formal analysis, methodology, supervision, validation, visualization, writing – review and editing. **Miguel Berdugo:** conceptualization, formal analysis, methodology, supervision, validation, visualization, writing – review and editing.

Acknowledgments

This research was supported by a grant from DOB Ecology to Thomas W. Crowther, funding from the Bernina Initiative through the ETH Foundation to the Global Ecosystem Ecology Lab, and funding from the Ramon y Cajal fellowship from the Spanish Ministry of Science (RYC2021-031797-I) to Miguel Berdugo. We would like to thank C. Runge for supporting the design of Figure 1. We thank the handling editor and the anonymous reviewers for invaluable comments on the improvement of the article.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data and code that support the findings of this study are available in Zenodo at https://doi.org/10.5281/zenodo.14892671. Vegetation datasets were obtained from the NASA EOSDIS Land Processes Distributed Active Archive Center at https://lpdaac.usgs.gov/products/mod13a3v061/(MOD13A3.061, NDVI), https://lpdaac.usgs.gov/products/mod13q1v006/ (MOD13Q1, NDVI), and https://lpdaac.usgs.gov/products/mod13c2v006/ (MOD13C2v006, EVI). Land cover data were obtained from the NASA EOSDIS Land Processes Distributed Active Archive Center at https://lpdaac.usgs.gov/products/mcd12q1v061/ (MCD12Q1v061). The Köppen–Geiger climate map was obtained from Figshare at https://doi.org/10.6084/m9.figshare.6396959. The Resolve biome data were obtained from the Earth Engine Data Catalog (https://developers.google.com/earth-engine/datasets/catalog/RESOLVE_ECOREGIONS_2017#description). The climate datasets to calculate the sensitivity index were obtained from NASA's Open Data Portal at https://doi.org/10.5067/MODIS/MOD06_L2.006 and the TerraClimate database (maximum and minimum temperature, reference and actual evapotranspiration) at https://doi.org/10.1038/sdata.2017.191. Data of the standardized precipitation evapotranspiration index (SPEI) were obtained from CSIC at https://doi.org/10.20350/digitalCSIC/15470.

References

Alley, W. M. 1984. "The Palmer Drought Severity Index: Limitations and Assumptions." *Journal of Applied Meteorology and Climatology* 23, no. 7: 1100–1109.

Arani, B. M. S., S. R. Carpenter, L. Lahti, E. H. van Nes, and M. Scheffer. 2021. "Exit Time as a Measure of Ecological Resilience." *Science* 372, no. 6547: eaay4895. https://doi.org/10.1126/science.aay4895.

Bathiany, S., R. Bastiaansen, A. Bastos, et al. 2024. "Ecosystem Resilience Monitoring and Early Warning Using Earth Observation Data: Challenges and Outlook." *Surveys in Geophysics*. https://doi.org/10.1007/s10712-024-09833-z.

Berdugo, M., S. Kéfi, S. Soliveres, and F. T. Maestre. 2017. "Plant Spatial Patterns Identify Alternative Ecosystem Multifunctionality States in Global Drylands." *Nature Ecology & Evolution* 1, no. 2: 1–10. https://doi.org/10.1038/s41559-016-0003.

Boulton, C. A., T. M. Lenton, and N. Boers. 2022. "Pronounced Loss of Amazon Rainforest Resilience Since the Early 2000s." *Nature Climate Change* 12, no. 3: 271–278. https://doi.org/10.1038/s41558-022-01287-8.

Camarero, J. J., A. Gazol, G. Sangüesa-Barreda, J. Oliva, and S. M. Vicente-Serrano. 2015. "To Die or Not to Die: Early Warnings of Tree Dieback in Response to a Severe Drought." *Journal of Ecology* 103, no. 1: 44–57. https://doi.org/10.1111/1365-2745.12295.

Capdevila, P., I. Stott, M. Beger, and R. Salguero-Gómez. 2020. "Towards a Comparative Framework of Demographic Resilience." *Trends in Ecology & Evolution* 35, no. 9: 776–786. https://doi.org/10.1016/J.TREE.2020.05.001.

Capdevila, P., I. Stott, J. Cant, et al. 2022. "Life History Mediates the Trade-Offs Among Different Components of Demographic Resilience." *Ecology Letters* 25, no. 6: 1566–1579. https://doi.org/10.1111/ELE.14004.

Carnicer, J., M. Vives-Ingla, L. Blanquer, et al. 2021. "Forest Resilience to Global Warming Is Strongly Modulated by Local-Scale Topographic, Microclimatic and Biotic Conditions." *Journal of Ecology* 109, no. 9: 3322–3339. https://doi.org/10.1111/1365-2745.13752.

Carpenter, S., B. Walker, J. M. Anderies, and N. Abel. 2001. "From Metaphor to Measurement: Resilience of What to What?" *Ecosystems* 4, no. 8: 765–781. https://doi.org/10.1007/S10021-001-0045-9.

Carpenter, S. R., and W. A. Brock. 2006. "Rising Variance: A Leading Indicator of Ecological Transition." *Ecology Letters* 9, no. 3: 311–318. https://doi.org/10.1111/J.1461-0248.2005.00877.X.

Chaparro-Pedraza, P. C. 2021. "Fast Environmental Change and Eco-Evolutionary Feedbacks Can Drive Regime Shifts in Ecosystems Before Tipping Points Are Crossed." *Proceedings of the Royal Society B: Biological Sciences* 288, no. 1955: 20211192. https://doi.org/10.1098/rspb.2021.1192.

Chu, T., X. Guo, and K. Takeda. 2017. "Effects of Burn Severity and Environmental Conditions on Post-Fire Regeneration in Siberian Larch Forest." *Forests* 8, no. 3: 76. https://doi.org/10.3390/f8030076.

Conference of the Parties to the Convention on Biological Diversity. 2022. "Kunming-Montreal Global Biodiversity Framework (Version 1)." https://doi.org/10.5281/ZENODO.3831673.

Dai, L., K. S. Korolev, and J. Gore. 2015. "Relation Between Stability and Resilience Determines the Performance of Early Warning Signals Under Different Environmental Drivers." *Proceedings of the National Academy of Sciences of the United States of America* 112, no. 32: 10056–10061. https://doi.org/10.1073/pnas.1418415112.

Dakos, V., and J. Bascompte. 2014. "Critical Slowing Down as Early Warning for the Onset of Collapse in Mutualistic Communities." *Proceedings of the National Academy of Sciences of the United States of America* 111, no. 49: 17546–17551. https://doi.org/10.1073/pnas.1406326111.

Dakos, V., S. R. Carpenter, W. A. Brock, et al. 2012. "Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS One* 7, no. 7: e41010. https://doi.org/10.1371/journal.pone.0041010.

Dakos, V., S. R. Carpenter, E. H. van Nes, and M. Scheffer. 2015. "Resilience Indicators: Prospects and Limitations for Early Warnings of Regime Shifts." *Philosophical Transactions of the Royal Society, B: Biological Sciences* 370, no. 1659: 1–10. https://doi.org/10.1098/RSTB.2013.0263.

Dakos, V., and S. Kéfi. 2022. "Ecological Resilience: What to Measure and How." *Environmental Research Letters* 17, no. 4: 043003. https://doi.org/10.1088/1748-9326/AC5767.

Dakos, V., S. Kéfi, M. Rietkerk, E. H. van Nes, and M. Scheffer. 2011. "Slowing Down in Spatially Patterned Ecosystems at the Brink of Collapse." *American Naturalist* 177, no. 6: 153–166. https://doi.org/10.1086/659945.

Dakos, V., B. Matthews, A. P. Hendry, et al. 2019. "Ecosystem Tipping Points in an Evolving World." *Nature Ecology & Evolution* 3, no. 3: 355–362. https://doi.org/10.1038/s41559-019-0797-2.

Dakos, V., M. Scheffer, E. H. Van Nes, V. Brovkin, V. Petoukhov, and H. Held. 2008. "Slowing Down as an Early Warning Signal for Abrupt

Climate Change." *Proceedings of the National Academy of Sciences of the United States of America* 105, no. 38: 14308–14312. https://doi.org/10.1073/pnas.0802430105.

Donohue, I., H. Hillebrand, J. M. Montoya, et al. 2016. "Navigating the Complexity of Ecological Stability." *Ecology Letters* 19, no. 9: 1172–1185. https://doi.org/10.1111/ELE.12648.

Feng, Y., H. Su, Z. Tang, et al. 2021. "Reduced Resilience of Terrestrial Ecosystems Locally Is Not Reflected on a Global Scale." *Communications Earth & Environment* 2, no. 1: 1–11. https://doi.org/10.1038/s43247-021-00163-1.

Fernández-Guisuraga, J. M., S. Suárez-Seoane, and L. Calvo. 2023. "Radar and Multispectral Remote Sensing Data Accurately Estimate Vegetation Vertical Structure Diversity as a Fire Resilience Indicator." *Remote Sensing in Ecology and Conservation* 9, no. 1: 117–132. https://doi.org/10.1002/rse2.299.

Flores, B. M., E. Montoya, B. Sakschewski, et al. 2024. "Critical Transitions in the Amazon Forest System." *Nature* 626, no. 7999: 555–564. https://doi.org/10.1038/s41586-023-06970-0.

Forzieri, G., V. Dakos, N. G. Mcdowell, A. Ramdane, and A. Cescatti. 2022. "Emerging Signals of Declining Forest Resilience Under Climate Change." *Nature* 608: 534–539. https://doi.org/10.1038/s41586-022-04959-9.

García-Palacios, P., N. Gross, J. Gaitán, and F. T. Maestre. 2018. "Climate Mediates the Biodiversity–Ecosystem Stability Relationship Globally." *Proceedings of the National Academy of Sciences of the United States of America* 115, no. 33: 8400–8405. https://doi.org/10.1073/PNAS.1800425115 /-/DCSUPPLEMENTAL.

Gazol, A., J. J. Camarero, W. R. L. Anderegg, and S. M. Vicente-Serrano. 2017. "Impacts of Droughts on the Growth Resilience of Northern Hemisphere Forests." *Global Ecology and Biogeography* 26, no. 2: 166–176. https://doi.org/10.1111/GEB.12526.

Gazol, A., J. J. Camarero, S. M. Vicente-Serrano, et al. 2018. "Forest Resilience to Drought Varies Across Biomes." *Global Change Biology* 24, no. 5: 2143–2158. https://doi.org/10.1111/GCB.14082.

Grimm, V., and J. M. Calabrese. 2011. "What Is Resilience? A Short Introduction." In *Viability and Resilience of Complex Systems: Concepts, Methods and Case Studies From Ecology and Society*, edited by G. Deffuant and N. Gilbert, 3–13. Springer. https://doi.org/10.1007/978-3-642-20423-4_1.

Gubler, S., S. Fukutome, and S. C. Scherrer. 2023. "On the Statistical Distribution of Temperature and the Classification of Extreme Events Considering Season and Climate Change—An Application in Switzerland." *Theoretical and Applied Climatology* 153, no. 3: 1273–1291. https://doi.org/10.1007/s00704-023-04530-0.

Hirota, M., M. Holmgren, E. H. Van Nes, and M. Scheffer. 2011. "Global Resilience of Tropical Forest and Savanna to Critical Transitions." *Science* 334, no. 6053: 232–235. https://doi.org/10.1126/science.1210657.

Hodgson, D., J. L. McDonald, and D. J. Hosken. 2015. "What Do You Mean, 'Resilient'?" *Trends in Ecology & Evolution* 30, no. 9: 503–506. https://doi.org/10.1016/J.TREE.2015.06.010.

Holling, C. S. 1973. "Resilience and Stability of Ecological Systems." *Annual Review of Ecology and Systematics* 4, no. 1: 1–23.

Holling, C. S. 1996. "Engineering Resilience Versus Ecological Resilience." In *Engineering Within Ecological Constraints*, 31–43. National Academies Press.

Ingrisch, J., and M. Bahn. 2018. "Towards a Comparable Quantification of Resilience." *Trends in Ecology & Evolution* 33, no. 4: 251–259. https://doi.org/10.1016/J.TREE.2018.01.013.

Intergovernmental Panel on Climate Change. 2022. *Climate Change and Land: IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*. 1st ed. Cambridge University Press. https://doi.org/10.1017/9781009157988.

Isbell, F., D. Craven, J. Connolly, et al. 2015. "Biodiversity Increases the Resistance of Ecosystem Productivity to Climate Extremes." *Nature* 526, no. 7574: 574–577. https://doi.org/10.1038/nature15374.

Kacic, P., and C. Kuenzer. 2022. "Forest Biodiversity Monitoring Based on Remotely Sensed Spectral Diversity—A Review." *Remote Sensing* 14, no. 21: 5363. https://doi.org/10.3390/rs14215363.

Kannenberg, S. A., K. A. Novick, M. R. Alexander, et al. 2019. "Linking Drought Legacy Effects Across Scales: From Leaves to Tree Rings to Ecosystems." *Global Change Biology* 25, no. 9: 2978–2992. https://doi.org/10.1111/gcb.14710.

Kéfi, S., V. Dakos, M. Scheffer, E. H. Van Nes, and M. Rietkerk. 2013. "Early Warning Signals Also Precede Non-Catastrophic Transitions." *Oikos* 122, no. 5: 641–648. https://doi.org/10.1111/j.1600-0706.2012.20838.x.

Khoury, S., and D. A. Coomes. 2020. "Resilience of Spanish Forests to Recent Droughts and Climate Change." *Global Change Biology* 26, no. 12: 7079–7098. https://doi.org/10.1111/GCB.15268.

Lang, N., W. Jetz, K. Schindler, and J. D. Wegner. 2023. "A High-Resolution Canopy Height Model of the Earth." *Nature Ecology & Evolution* 7, no. 11: 1–12. https://doi.org/10.1038/s41559-023-02206-6.

Lauriere, C. F., K. Runge, G. Smith, et al. 2023. "Uncovering Global Drivers Threatening Vegetation Resilience." *EcoEvoRxiv*. https://doi.org/10.32942/X2DP4R.

Lecina-Diaz, J., J. Martínez-Vilalta, F. Lloret, and R. Seidl. 2024. "Resilience and Vulnerability: Distinct Concepts to Address Global Change in Forests." *Trends in Ecology & Evolution* 39: 706–715. https://doi.org/10.1016/j.tree.2024.03.003.

Lees, K. J., R. R. E. Artz, D. Chandler, et al. 2021. "Using Remote Sensing to Assess Peatland Resilience by Estimating Soil Surface Moisture and Drought Recovery." *Science of the Total Environment* 761: 1–12. https://doi.org/10.1016/j.scitotenv.2020.143312.

Lenton, T. M., J. E. Buxton, D. I. Armstrong McKay, et al. 2022. "A Resilience Sensing System for the Biosphere." *Philosophical Transactions of the Royal Society B* 377, no. 1857. https://doi.org/10.1098/RSTB.2021.0383.

Li, D., S. Wu, L. Liu, Y. Zhang, and S. Li. 2018. "Vulnerability of the Global Terrestrial Ecosystems to Climate Change." *Global Change Biology* 24, no. 9: 4095–4106. https://doi.org/10.1111/GCB.14327.

Li, X., S. Piao, C. Huntingford, et al. 2023. "Global Variations in Critical Drought Thresholds That Impact Vegetation." *National Science Review* 10, no. 5. https://doi.org/10.1093/NSR/NWAD049.

Li, X., S. Piao, K. Wang, et al. 2020. "Temporal Trade-Off Between Gymnosperm Resistance and Resilience Increases Forest Sensitivity to Extreme Drought." *Nature Ecology & Evolution* 4, no. 8: 1075–1083. https://doi.org/10.1038/s41559-020-1217-3.

Li, Y., W. Zhang, C. R. Schwalm, et al. 2023. "Widespread Spring Phenology Effects on Drought Recovery of Northern Hemisphere Ecosystems." *Nature Climate Change* 13, no. 2: 182–188. https://doi.org/10.1038/s41558-022-01584-2.

Liu, Y., M. Kumar, G. G. Katul, and A. Porporato. 2019. "Reduced Resilience as an Early Warning Signal of Forest Mortality." *Nature Climate Change* 9, no. 11: 880–885. https://doi.org/10.1038/S41558-019-0583-9.

Livina, V. N., F. Kwasniok, and T. M. Lenton. 2010. "Potential Analysis Reveals Changing Number of Climate States During the Last 60 Kyr." *Climate of the Past* 6, no. 1: 77–82. https://doi.org/10.5194/cp-6-77-2010.

Moesinger, L., W. Dorigo, R. de Jeu, et al. 2020. "The Global Long-Term Microwave Vegetation Optical Depth Climate Archive (VODCA)." *Earth System Science Data* 12, no. 1: 177–196. https://doi.org/10.5194/essd-12-177-2020.

Newton, A. C., and E. Cantarello. 2015. "Restoration of Forest Resilience: An Achievable Goal?" *New Forests* 46, no. 5: 645–668. https://doi.org/10.1007/s11056-015-9489-1.

Pausas, J. G., and W. J. Bond. 2020. "Alternative Biome States in Terrestrial Ecosystems." *Trends in Plant Science* 25, no. 3: 250–263. https://doi.org/10.1016/J.TPLANTS.2019.11.003.

Pimm, S. L. 1984. "The Complexity and Stability of Ecosystems." *Nature* 307, no. 5949: 321–326. https://doi.org/10.1038/307321a0.

Pimm, S. L., I. Donohue, J. M. Montoya, and M. Loreau. 2019. "Measuring Resilience Is Essential to Understand It." *Nature Sustainability* 2, no. 10: 895–897. https://doi.org/10.1038/s41893-019-0399-7.

Poorter, L., D. Craven, C. C. Jakovac, et al. 2021. "Multidimensional Tropical Forest Recovery." *Science* 374, no. 6573: 1370–1376. https://doi.org/10.1126/science.abh3629.

Ratajczak, Z., P. D'Odorico, S. L. Collins, B. T. Bestelmeyer, F. I. Isbell, and J. B. Nippert. 2017. "The Interactive Effects of Press/Pulse Intensity and Duration on Regime Shifts at Multiple Scales." *Ecological Monographs* 87, no. 2: 198–218. https://doi.org/10.1002/ecm.1249.

Ren, L., J. Huo, X. Xiang, et al. 2023. "Environmental Conditions Are the Dominant Factor Influencing Stability of Terrestrial Ecosystems on the Tibetan Plateau." *Communications Earth & Environment* 4, no. 1. https://doi.org/10.1038/s43247-023-00849-8.

Rocha, J. C. 2022. "Ecosystems Are Showing Symptoms of Resilience Loss." *Environmental Research Letters* 17, no. 6: 065013. https://doi.org/10.1088/1748-9326/ac73a8.

Scheffer, M., J. Bascompte, W. A. Brock, et al. 2009. "Early-Warning Signals for Critical Transitions." *Nature* 461, no. 7260: 53–59. https://doi.org/10.1038/nature08227.

Scheffer, M., and S. R. Carpenter. 2003. "Catastrophic Regime Shifts in Ecosystems: Linking Theory to Observation." *Trends in Ecology & Evolution* 18, no. 12: 648–656. https://doi.org/10.1016/J.TREE.2003.09.002.

Scheffer, M., S. R. Carpenter, V. Dakos, and E. H. Van Nes. 2015. "Generic Indicators of Ecological Resilience: Inferring the Chance of a Critical Transition." *Annual Review of Ecology, Evolution, and Systematics* 46: 145–167. https://doi.org/10.1146/annurev-ecolsys-112414-054242.

Scheffer, M., M. Hirota, M. Holmgren, E. H. Van Nes, and F. S. Chapin. 2012. "Thresholds for Boreal Biome Transitions." *Proceedings of the National Academy of Sciences of the United States of America* 109, no. 52: 21384–21389. https://doi.org/10.1073/pnas.1219844110.

Schwalm, C. R., W. R. L. Anderegg, A. M. Michalak, et al. 2017. "Global Patterns of Drought Recovery." *Nature* 548, no. 7666: 202–205. https://doi.org/10.1038/nature23021.

Schweiger, A. K., J. Cavender-Bares, P. A. Townsend, et al. 2018. "Plant Spectral Diversity Integrates Functional and Phylogenetic Components of Biodiversity and Predicts Ecosystem Function." *Nature Ecology & Evolution* 2, no. 6: 976–982. https://doi.org/10.1038/s41559-018-0551-1.

Seddon, W. R., M. Macias-Fauria, P. R. Long, D. Benz, and K. J. Willis. 2016. "Sensitivity of Global Terrestrial Ecosystems to Climate Variability." *Nature* 531: 229–232. https://doi.org/10.1038/nature16986.

Seidl, R., T. A. Spies, D. L. Peterson, S. L. Stephens, and J. A. Hicke. 2016. "Searching for Resilience: Addressing the Impacts of Changing Disturbance Regimes on Forest Ecosystem Services." *Journal of Applied Ecology* 53, no. 1: 120–129. https://doi.org/10.1111/1365-2664.12511.

Senf, C., and R. Seidl. 2022. "Post-Disturbance Canopy Recovery and the Resilience of Europe's Forests." *Global Ecology and Biogeography* 31, no. 1: 25–36. https://doi.org/10.1111/GEB.13406.

Smith, T., and N. Boers. 2023. "Global Vegetation Resilience Linked to Water Availability and Variability." *Nature Communications* 14, no. 1: 1–11. https://doi.org/10.1038/s41467-023-36207-7.

Smith, T., D. Traxl, and N. Boers. 2022. "Empirical Evidence for Recent Global Shifts in Vegetation Resilience." *Nature Climate Change* 12: 477–484. https://doi.org/10.1038/s41558-022-01352-2.

Strickland, M. K., M. A. Jenkins, Z. Ma, and B. D. Murray. 2024. "How Has the Concept of Resilience Been Applied in Research Across Forest Regions?" *Frontiers in Ecology and the Environment* 22, no. 3: e2703. https://doi.org/10.1002/fee.2703.

Sugihara, G., and R. M. May. 1990. "Nonlinear Forecasting as a Way of Distinguishing Chaos From Measurement Error in Time Series." *Nature* 344, no. 6268: 734–741. https://doi.org/10.1038/344734a0.

Takens, F. 1981. "Detecting Strange Attractors in Turbulence." In *Dynamical Systems and Turbulence, Warwick 1980*, edited by D. Rand and L.-S. Young, 366–381. Springer. https://doi.org/10.1007/BFb0091924.

Thompson, I. D., ed. 2009. *Forest Resilience, Biodiversity, and Climate Change: A Synthesis of the Biodiversity/Resilience/Stability Relationship in Forest Ecosystems*. Secretariat of the Convention on Biological Diversity.

Titus, M., and J. Watson. 2020. "Critical Speeding Up as an Early Warning Signal of Stochastic Regime Shifts." *Theoretical Ecology* 13, no. 4: 449–457. https://doi.org/10.1007/s12080-020-00451-0.

van Nes, E. H., and M. Scheffer. 2007. "Slow Recovery From Perturbations as a Generic Indicator of a Nearby Catastrophic Shift." *American Naturalist* 169, no. 6: 738–747. https://doi.org/10.1086/516845.

Van Passel, J., P. N. Bernardino, S. Lhermitte, et al. 2024. "Critical Slowing Down of the Amazon Forest After Increased Drought Occurrence." *Proceedings of the National Academy of Sciences of the United States of America* 121, no. 22: e2316924121. https://doi.org/10.1073/pnas.2316924121.

Veraart, A. J., E. J. Faassen, V. Dakos, E. H. Van Nes, M. Lürling, and M. Scheffer. 2012. "Recovery Rates Reflect Distance to a Tipping Point in a Living System." *Nature* 481, no. 7381: 357–359. https://doi.org/10.1038/nature10723.

Verbesselt, J., N. Umlauf, M. Hirota, et al. 2016. "Remotely Sensed Resilience of Tropical Forests." *Nature Climate Change* 6, no. 11: 1028–1031. https://doi.org/10.1038/nclimate3108.

Walker, B. 2020. "Resilience: What It Is and Is Not." *Ecology and Society* 25, no. 2: 11. https://doi.org/10.5751/ES-11647-250211.

Wang, Z., B. Fu, X. Wu, et al. 2023. "Vegetation Resilience Does Not Increase Consistently With Greening in China's Loess Plateau." *Communications Earth & Environment* 4, no. 1. https://doi.org/10.1038/s43247-023-01000-3.

White, H. J., W. Gaul, D. Sadykova, et al. 2020. "Quantifying Large-Scale Ecosystem Stability With Remote Sensing Data." *Remote Sensing in Ecology and Conservation* 6, no. 3: 354–365. https://doi.org/10.1002/rse2.148.

White, J. C., T. Hermosilla, M. A. Wulder, and N. C. Coops. 2022. "Mapping, Validating, and Interpreting Spatio-Temporal Trends in Post-Disturbance Forest Recovery." *Remote Sensing of Environment* 271: 112904. https://doi.org/10.1016/j.rse.2022.112904.

Whittaker, R. H. 1967. "Gradient Analysis of Vegetation." *Biological Reviews* 42, no. 2: 207–264. https://doi.org/10.1111/J.1469-185X.1967.TB01419.X.

Williams, J. W., B. Huntley, and A. W. R. Seddon. 2022. "Climate Sensitivity and Ecoclimate Sensitivity: Theory, Usage, and Past Implications for Future Biospheric Responses." *Current Climate Change Reports* 8, no. 1: 1–16. https://doi.org/10.1007/S40641-022-00179-5.

Wu, J., and S. Liang. 2020. "Assessing Terrestrial Ecosystem Resilience Using Satellite Leaf Area Index." *Remote Sensing* 12, no. 4: 595. https://doi.org/10.3390/RS12040595.

Yao, Y., B. Fu, Y. Liu, et al. 2022. "Evaluation of Ecosystem Resilience to Drought Based on Drought Intensity and Recovery Time." *Agricultural and Forest Meteorology* 314: 1–12. https://doi.org/10.1016/j.agrformet.2022.108809.

Zhang, Y., P. Gentine, X. Luo, et al. 2022. "Increasing Sensitivity of Dryland Vegetation Greenness to Precipitation due to Rising

Atmospheric CO_2." *Nature Communications* 13, no. 1: 1–9. https://doi.org/10.1038/s41467-022-32631-3.

Zhou, G., N. Eisenhauer, C. Terrer, et al. 2024. "Resistance of Ecosystem Services to Global Change Weakened by Increasing Number of Environmental Stressors." *Nature Geoscience* 17, no. 9: 1–7. https://doi.org/10.1038/s41561-024-01518-x.

Zhu, Z., S. Piao, R. B. Myneni, et al. 2016. "Greening of the Earth and Its Drivers." *Nature Climate Change* 6: 791–795. https://doi.org/10.1038/NCLIMATE3004.

Zou, Y., C. M. Zohner, C. Averill, et al. 2024. "Positive Feedbacks and Alternative Stable States in Forest Leaf Types." *Nature Communications* 15, no. 1: 4658. https://doi.org/10.1038/s41467-024-48676-5.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.