Complex Realities, Simple Signals? Global Evaluation of Early Warning Signals for Forest Mortality Events

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Abstract.

Forests around the world are increasingly experiencing large-scale regional mortality events as a result of droughts and heat waves. Despite their considerable impacts on the material, non-material, and regulatory contributions of forest ecosystems to people, these mortality events remain difficult to predict. Temporal Early Warning Signals (EWS) based on the concept of Critical Slowing Down (CSD) have been applied widely to remotely sensed vegetation indices. These EWS have often been interpreted as indicators of resilience loss. In order to be of practical use in real-world ecosystem management, such EWS must demonstrate the capacity to reliably and robustly predict upcoming forest mortality events. Previous work has applied EWS for local cases of mortality, but to date, there is no global assessment of EWS on remotely sensed vegetation indices of forest mortality events. The objective of this study is threefold: 1) to provide an overview of various types of EWS as applied to forest mortality events in case studies around the world, 2) to empirically assess the effectiveness of different EWS in predicting globally distributed forest mortality events driven by droughts and heat waves using remote sensing time series, and 3) to conduct a driver analysis to evaluate which factors associated with the methodological setup, the characteristics of the mortality event and climatic conditions explain the performance of different EWS. We find that most previous work in predicting forest mortality events is based on tree ring data. In remote sensing applications, there is a significant lack of robust evaluation of CSD-based EWS using control cases. Our empirical analysis indicates that all of the EWS that were evaluated in this study are ineffective and lack the necessary robustness to serve as predictors of drought-induced forest mortality events. The primary factor that determines trends in EWS is the methodological setup employed. We conclude by calling for more caution in the application of system-agnostic CSD-based EWS, increased efforts to assess accuracy and uncertainty, and more consideration of the system characteristics and actual needs of ecosystem managers when assessing forest resilience and early warning systems.

1 Introduction

Climate change is predicted to increase both the frequency and magnitude of forest disturbances and mortality events around the world (Seidl et al., 2017, 2014; Allen et al., 2010). The main drivers of increasing mortality are increased mean temperatures, stronger heatwaves, and more and longer droughts caused by changes in the regional water cycle (Senf et al., 2020;

Hammond et al., 2022). These conditions are expected to become significantly more frequent as the climate warms, triggering or interacting with other drivers of mortality, such as wildfires and pests (Seidl et al., 2017; Hammond et al., 2022). Large regional forest mortality events often have wide-reaching negative consequences for the provision of nature's contributions to people (NCP) from local to global scales (Thom and Seidl, 2016; Oldekop et al., 2020; Millar and Stephenson, 2015; Swann et al., 2018). Locally to regionally, forest mortality events can affect all three categories of NCPs, by reducing material services such as food provision, non-material services such as recreation, and affecting regulating services such as water cycle mediation (Díaz et al., 2018; Williams and Torn, 2015; O'Connor et al., 2021). Forest mortality events can also affect the global climate system, by, for example, decreasing terrestrial carbon sequestration (Ke et al., 2024). In fact, in recent years, the effects of fires and droughts have caused forests to turn from carbon sinks to sources in certain regions, further fueling global warming (Gatti et al., 2021).

Predicting forest mortality events to prevent them or prepare adequately for their consequences requires an understanding of how stressed and how close to a die-off a forest ecosystem is. Often, a decline in internal resilience to small disturbances precedes such mortality events, which can be estimated in different ways. Individual droughts or heat waves often act as shocks. If previous stressors have already reduced forest resilience, the forest may not be able to absorb additional pressures. Shock events can then trigger large-scale and sudden mortality (Anderegg et al., 2020). Forestry research has focused on identifying early warning signals (EWS) of tree mortality based on physiological indicators of growth rates and water stress from the analysis of tree rings (Camarero, 2021). The performance of physiologically based EWS to predict mortality events is however mixed, with high variability between ecosystems, species, and locations (Cailleret et al., 2019; Camarero et al., 2020, 2015) Despite their significant impacts, forest mortality events thus remain hard to predict on the ground (Camarero, 2021). At the same time, satellite remote sensing data have been increasingly used for both the detection of mortality events and their EWS over larger areas (Torres et al., 2021; Bathiany et al., 2024). However, only certain characteristics of forest ecosystems such as 'greenness' can be observed with remote sensing data, particularly with the most widely used optical satellites (Torres et al., 2021), which limits what processes can be used as EWS (Runge et al., 2025).

EWS based on the concept of alternative stable states and the theory of Critical Slowing Down (CSD) have been proposed as a promising alternative approach to predict forest mortality events (Scheffer et al., 2009). Long-term observations have shown that many ecosystems can exhibit different stable states that are self-reinforced through internal feedback processes (Scheffer et al., 2001; Scheffer, 2009; Biggs et al., 2018). A classic example is the potential for both tropical forests and savannas to exist under the same environmental conditions, where each state reinforces itself through the structures and processes of the associated ecosystem, such as fire dynamics and ecological facilitation or inhibition of seedlings, preventing establishment of new trees (Hirota et al., 2011; House et al., 2003; Staver et al., 2011; Aleman et al., 2020). Similar dynamics exist in boreal forests, where low-density or high-density forests can exist within the same environmental niche (Scheffer et al., 2012; Rotbarth et al., 2025; Xu et al., 2015). A transition from one state to another qualitatively different one can be described mathematically as a 'bifurcation' (Boettiger et al., 2013; Ashwin et al., 2012). Although there are different types of bifurcations (see Boettiger et al.'s overview), a widely used type in conceptualizing ecological transitions is the saddle-node bifurcation. Here, a slowly and linearly changing external driver leads to the crossing of internal critical thresholds or tipping points, which causes a long-term qualitative change in ecosystem state (Scheffer, 2009). Saddle-node and other bifurcations are, in theory, preceded by CSD, which describes that before the bifurcation, the system's local stability, i.e., its capacity to recover after small disturbances, is eroded and it takes longer and longer for the system to return to equilibrium (Scheffer et al., 2009). Changes in local stability are often approximated with statistics such as variance and autocorrelation, interpreted as proxies of resilience (Scheffer et al., 2009; Carpenter and Brock, 2006; Dakos et al., 2008). While such theoretical insights were developed for low-dimensional systems, it is important to critically evaluate how applicable this theory actually is to real-world ecological transitions which are typically multi-dimensional.

Forest mortality events can be conceptualized as bifurcations (Hammond, 2020; Gonzalez et al., 2010; Allen et al., 2010) if the ecosystem that establishes after the collapse is qualitatively different and does not perform the same functions as the original ecosystem (Scheffer et al., 2001; Lloret and Batllori, 2021). It is therefore important to note that not every forest mortality event is always necessarily a bifurcation in this sense, if it does not lead to a significant change in, e.g., species composition or ecosystem functioning (Lloret and Batllori, 2021; Newton and Cantarello, 2015). However, large-scale reviews in temperate and boreal forests show that in a majority of cases after drought-driven mortality events, different species replace the originally dominating tree species, with only 21% of cases experiencing self-replacement of species within 5 years and 44% of case studies experiencing a shift to shrub-dominated, more drought-adapted (xeric) vegetation, leading to substantially altered ecosystem processes (Batllori et al., 2020; Lloret and Batllori, 2021; Anderegg et al., 2013). Although this is slightly more complex to evaluate in the tropics due to the high functional and biological diversity (Batllori et al., 2020), there are indications that ecosystems established after mortality events are dominated by different species, including significantly increased abundance of lianas that drastically affect ecosystem functions and services (Schnitzer and Bongers, 2011; Phillips et al., 2002; Van Der Heijden et al., 2015). For the purpose of our study, we assume that large-scale forest mortality events lead to a lasting change in community composition and ecosystem function, can be conceived of as bifurcations, and should theoretically be preceded by CSD.

CSD-based EWS have been widely applied to remotely sensed vegetation time series to detect large-scale changes in vegetation resilience without a clear connection to concrete mortality events (Smith et al., 2022; Lenton et al., 2022; Forzieri et al., 2022; Feng et al., 2021; Rocha, 2022; Van Passel et al., 2024). As outlined above, the indicators most commonly applied are temporal autocorrelation ($AC1$) and temporal variance (var), both of which are expected to increase over time as a system loses resilience (Scheffer et al., 2009; Dakos et al., 2023; Carpenter and Brock, 2006; Dakos et al., 2008). Recent work by Smith et al. established a clear connection between the indicators and empirical recovery rates of vegetation indices after specific disturbances using remote sensing data on Vegetation Optical Depth (VOD; a microwave-based indicator of vegetation water content and thus biomass; Frappart et al. (2020)), highlighting their applicability as indicators of resilience loss. However, the authors also discuss problems when applying these indicators to other types of remotely sensed vegetation indicators, such as the widely used Normalized Difference Vegetation Index (NDVI), due to its less direct connection to vegetation productivity. Nevertheless, concerningly, $AC1$ and var have been applied in many studies as indicators of resilience changes without additional validation against ground-truth, meaning that the statistical uncertainty and accuracy of previous early warning-based assessments have been omitted.

While CSD-based EWS have also been tested both in tree ring and remote sensing-based studies as direct precursors of local mortality events (e.g., Liu et al. (2019); Neycken et al. (2022); Schwarz et al. (2025)), they make up a minority in comparison to physiological EWS. However, these studies usually focus on a single case study, with the notable exception of Cailleret et al. (2019), who conduct an EWS analysis on a global tree ring database and find $AC1$ to be a poor predictor of mortality risk. Most remote sensing-based studies do not include a comparison of EWS detection on true positive cases of mortality and controls, i.e., locations where there was no dieback (Forzieri et al., 2022; Feng et al., 2021; Smith et al., 2022; Lenton et al., 2022). This is concerning, as to be useful for management applications, EWS need to be able to clearly distinguish between locations that are more and less likely to experience mortality, and do so with ample time before the event to allow for management interventions (Biggs et al., 2009). To make robust predictions of resilience loss, estimates of CSD should also have an assessment of accuracy and uncertainty that can only be obtained when compared to ground-truth data; a gap in current research that we aim to address.

In this work, we aim to answer the following questions:

1. Based on previous studies, how have EWS been applied to predict forest mortality events, and where did such approaches fall short?

2. Based on an empirical analysis, how well do commonly applied EWS serve as actual warning signals before events of forest mortality?

3. Which factors related to the methodological setup and the mortality event affect EWS performance?

To do so, we first conduct a literature review of previous work using EWS to predict forest mortality events. Next, we assess the performance of several commonly applied CSD-based EWS in predicting real globally distributed cases of forest dieback. The cases are curated from the Hammond et al. (2022) database on forest mortality, which includes only events caused by drought and heat stress, thereby excluding other anthropogenic drivers such as deforestation. We distinguish them from locations without mortality based on remotely sensed vegetation index time series, i.e., we construct a matching dataset of control points (true negatives). We evaluate which factors affect EWS performance and give recommendations on their application.

2 Methods

To record how EWS methods for forest mortality events have been applied in previous research, we conduct a literature search on Web Of Science (WOS) using the search term 'early warning* AND forest AND (mortality OR dieback OR collapse)'. We specifically focus on case studies and explicitly exclude all reviews and theoretical papers. We then record the location, the ecosystem type and dominant species, the main reason for the dieback, the data sources, the EWS indicators employed, whether the EWS was based on CSD, and whether there was an explicit comparison of the EWS performance between true mortality cases and control locations without mortality. Applying these criteria to our sample left us with 135 papers after the first round of screening based on titles, and 64 for the final analysis based on abstracts.

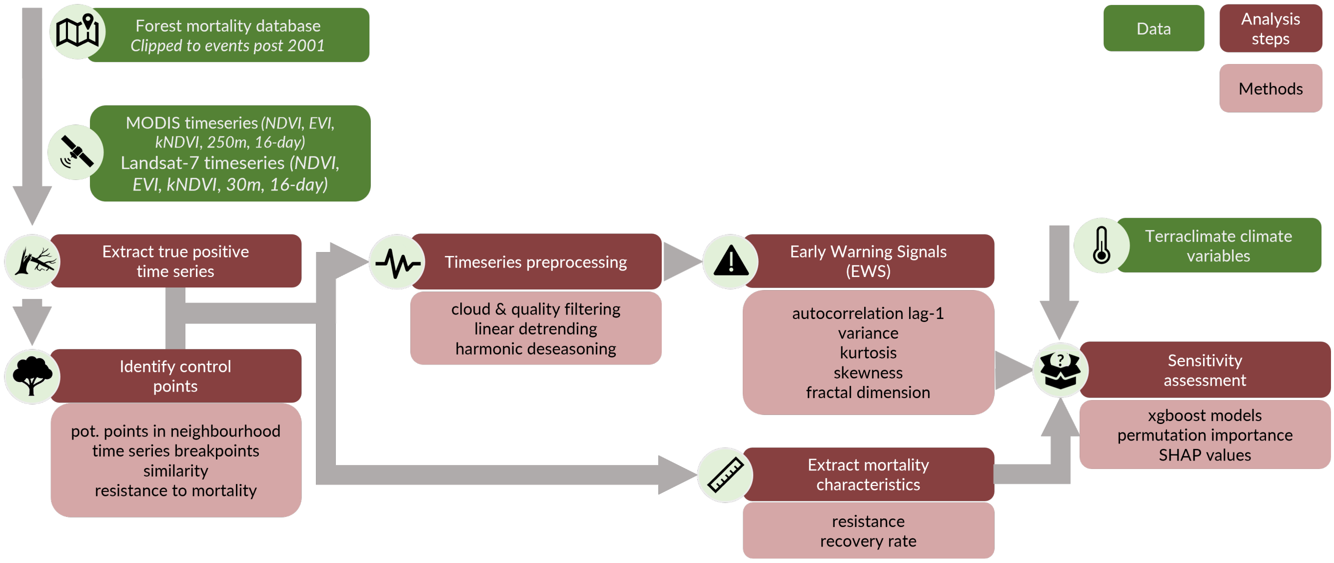

Figure 1. Overview of the analysis process of the empirical assessment of EWS performance. Colors indicate data, analysis steps, or methods.

For the empirical assessment of CSD-based EWS as precursors of forest mortality events, we use a multi-step procedure (Figure 1). We base this evaluation on the forest mortality database assembled by (Hammond et al., 2022), which records geo-referenced case studies of forest mortality as a result of drought or heat stress. The database contains 1300 cases between 1970 and 2018, with $>75\%$ recorded after the year 2000, across six continents. The cases have a strong bias towards subtropical (54% of observations between 23.4°and 35°) and temperate zones (37% of observations at $>35°$). For our analysis, we exclude diebacks that occurred before 2001, as we have no satellite coverage for the time period before, resulting in 941 case studies as shown in Figure 2**A**.

Around the dieback locations, we extract remote sensing time series of vegetation indices for the time period 2001 to 2024. We use the Normalized Difference Vegetation Index (NDVI) as well as the Enhanced Vegetation Index (EVI) of both NASA's Moderate-resolution Imaging Spectroradiometer (MODIS) $250\,\mathrm{m}$, 16-day product MOD13Q1 in a radius of $25\,\mathrm{km}$ around the recorded event (Didan, K., 2021). Based on NDVI, we also compute the kernel NDVI (kNDVI; Camps-Valls et al. (2021)), which is reported to provide more accurate and robust estimates of greenness. We conduct quality controls by masking out MODIS observations that have a Summary Quality Assessment score of >1 (Didan and Munoz, 2019).

Due to coarse spatial information on some dieback cases, we need to refine the coordinates of the true positives for those records where the precision of the location is lower than the pixel size of the satellite dataset (i.e., $250\,\mathrm{m}$ for MODIS). To do so, we select the area encompassed in the uncertainty range of the record and compute vegetation resistance r to the mortality event as the drop in mean vegetation index (VI) in the year of the dieback (t_0) in comparison to the three years preceding it (cf.Eq. 1 where x and y indicate spatial coordinates and t indicates time in years). Assuming that the mortality is strongest where we see the lowest resistance (i.e., the largest drop in vegetation index in the recorded year), we choose the location of the pixel with the lowest resistance as the adjusted true positive point.

$$r(x,y) = \overline{VI}_{[t_0,t_{+1}]}(x,y) - \overline{VI}_{[t_{-3},t_0]}(x,y) \tag{1}$$

Next, for each true dieback case, we identify a control location in the vicinity where no dieback occurred in the same year. This is necessary to explicitly evaluate false positive and false negative detection rates using EWS. It is a common procedure in studies based on traditional field data, but often lacking in remote sensing-based resilience analyses (cf.Section 3.1). To identify controls, we employ a four-step method (cf. also Figure 2**B** - **E**).

1. **Exclude pixels with vegetation cover change before dieback**: For all potential control points, we want to ensure there have been no major changes in vegetation dynamics or cover, such as, for example, due to deliberate deforestation or conversion to agricultural land. For this, we compute the number of outliers n_{out} on annual rolling means of the VI time series before the dieback year. We define an outlier as a mean annual NDVI value more than two standard deviations away from the long-term mean NDVI and compute this on all pixels within a radius of $20\,\mathrm{km}$ around the true mortality point. We keep only pixels as candidate controls that do not show an outlier in the time series before the dieback, as shown in Figure 2**B**.

2. **Find pixels with similar vegetation dynamics before dieback**: Out of all candidate control points, we want to keep those that show similar vegetation dynamics in the year before the dieback to be comparable (statistical matching). To do so, we compute the Mean Absolute Error (MAE) between the time series at the true positive point and all potential controls, as Figure 2**C** shows.

3. **Find pixels with high resistance**: The key distinction between the true positive and control points should be that the control point does not show a significant level of dieback in the relevant year. To distinguish this, we compute the vegetation resistance (r) on each candidate control point as outlined above in equation 1 and highlighted in Figures 2**D**, **F**, and **H**.

4. **Combine metrics**: To ensure our control point shows both high similarity before the collapse (i.e., low MAE) and high resistance to the environmental condition of the dieback (i.e., a small change in the VI), we combine the two metrics as a ratio (Eq. 2, where x and y denote spatial coordinates and shown in Figure 2**E**). We hence pick the point as control where the number of outliers is zero and this ratio is maximized.

$$control = \arg \max_{(x,y)\,|\,n_{\text{out}}(x,y)=0} \left(\frac{\left| r(x,y)^{-1} \right|}{\text{MAE}(x,y)} \right) \tag{2}$$

At the final true positive and control locations, we extract the time series of the vegetation indices. We detrend and deseason the time series by subtracting 5-year rolling mean values and third-degree harmonic oscillations (as shown in Figure 2**G** and **I**, Smith et al. (2023)). On these stationary time series, we then compute temporal autocorrelation at lag-1 ($AC1$), temporal variance (var), skewness ($skew$), kurtosis ($kurt$), and the fractal dimension (fd) as EWS over different temporal rolling

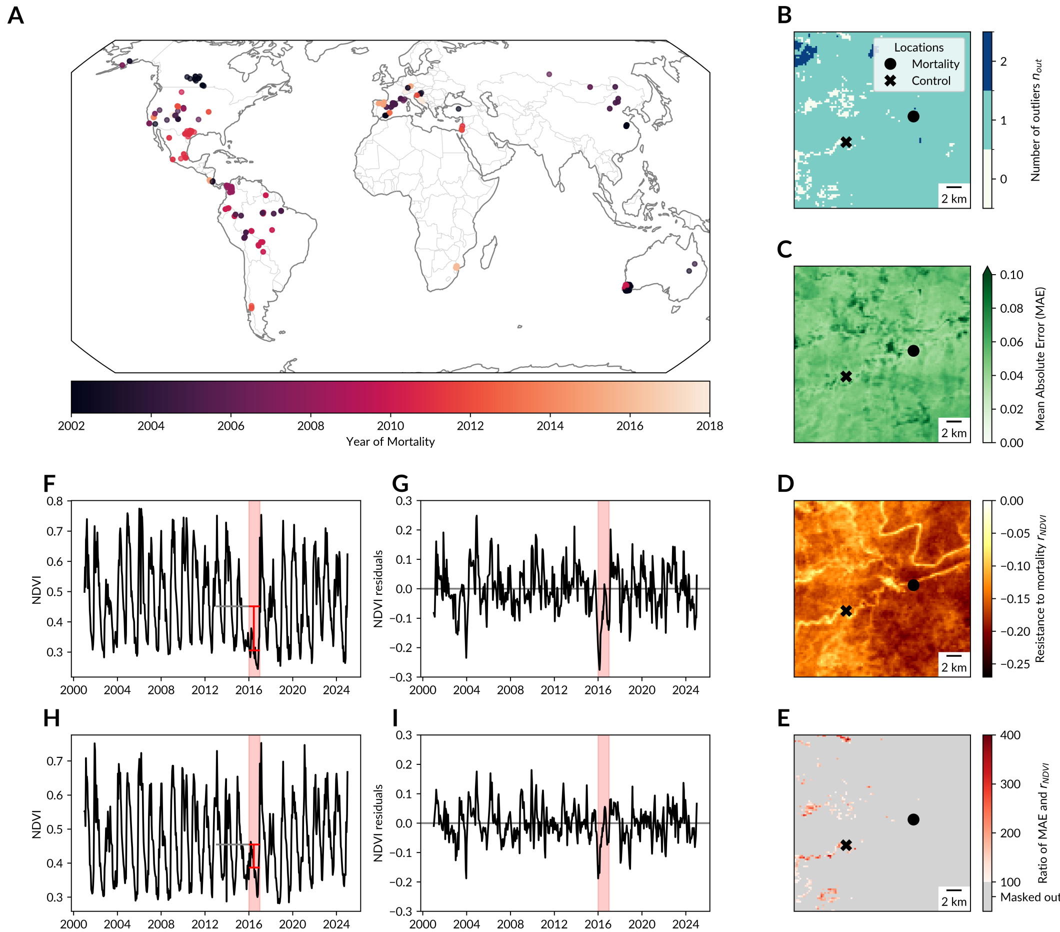

Figure 2. Overview of the forest mortality data points and selection procedure for control points. **A** shows the location of the mortality cases included in the analysis, colored by the year of the event. **B-E** selection criteria for the control point shown exemplarily for a location in South Africa that has undergone recent mortality in 2018. Specifically, **B** shows the number of outliers n_{out} in the time series before the mortality event, **C** shows the mean absolute error (MAE) between the time series before the mortality event and the true mortality location, **D** illustrates the resistance r_{NDVI} of vegetation to the climate extreme in the year of mortality, and **E** shows the joint decision criteria, showing the ratio of MAE and resistance, masked by the number of outliers. **F** and **H** show the time series of NDVI at the mortality location and the control point, respectively, with the recorded year of mortality shaded in red. The horizontal grey line indicates the mean NDVI in the three years before the mortality event, and the red vertical line denotes the size of the productivity drop in the year of mortality. **G** and **I** show the residuals of the NDVI time series after detrending and deseasoning, at the mortality and control location, respectively.

Table 1. Overview of the different computational setups used to compute EWS trends at the dieback locations.

Dataset	Spatial resolution	Rolling window length	Time frame before collapse
MODIS	250 m	1, 3, 5, 10	1, 3, 5, 10, all available years, mortality year

Table 2. Overview of the variables used in the driver analysis to assess their effect on EWS performance.

Driver category	Variable	Unit	Data source
EWS computational choice	Rolling window length	yrs	Different computational setups for computing EWS, either 1, 3, 5, or 10 years
	Time before mortality	yrs	Different computational setups for computing EWS Kendall tau trends, either 1, 3, or 5 years, all available years before mortality, or the mortality year itself
Mortality event characteristics	Relative resistance	-	Computed as $r_{rel} = r_{NDVI}/\sigma_{pre}$ where r_{NDVI} is defined following Eq. 1 and σ_{pre} is the standard deviation of NDVI values in the years before the mortality event
	Recovery rate		Computed from mortality event following Eq. 3
	Latitude	°	Absolute latitude of event
Climate characteristics	Actual evapotranspiration	mm	Terra Climate, mean value of the year before mortality
	Climate water deficit	mm	
	Soil moisture	mm	
	Downward surface shortwave radiation	$\mathrm{W\,m^{-2}}$	
	Maximum monthly temperature	°C	
	Vapor pressure deficit	kPa	
	Palmer Drought Severity Index	-	

windows (cf. Table 1 for an overview of the different setups used). Finally, we assess temporal changes in the values of the EWS by computing Kendall τ trends of each EWS over a range of time periods before the collapse time point.

To understand which factors influence the performance of the different EWS, we conduct a driver analysis on the role of climate influence, characteristics of the mortality event, the ecosystem type, and the computational EWS setup (cf. Table 2). If the EWS work to robustly predict mortality events, we would expect characteristics of the event, i.e., the resistance and recovery rate of the die-back, to be the key predictors of Kendall τ trends in all EWS, jointly with climate information. Computational setup should play only a minor role in a robust method.

Climate variables are extracted as annual mean values from TerraClimate at $4\,\mathrm{km}$ resolution at the true positive locations for the years before the mortality event (Abatzoglou et al., 2018). For the characteristics of the mortality event, we compute *resistance* as the drop in NDVI in the year of mortality in comparison to the mean of the three previous years (Eq. 1). Additionally, following Smith et al. (2022), we compute recovery rates r after the mortality event, as the negative exponents of an exponential function fitted to the residuals of the time series (cf. Eq. 3, where x_0 denotes the mean NDVI value in the year of mortality), following the detrending and deseasoning procedure described earlier. Computing recovery rates instead of recovery time in this way allows us to compare different biomes with different ecological dynamics and prevents us from having to make assumptions about which mean vegetation index value the system has to return to.

$$x(t) = x_0 * e^{-r*t} \tag{3}$$

Lastly, we extract information on latitude from the forest mortality database (Hammond et al., 2022). We use boosted regression tree models (xgboost) with the Kendall τ trend for each EWS and vegetation index as the target variable, and the predictors outlined in Table 2 as independent variables. We thus train 15 models (5 EWS $\times$ 3 vegetation indices) using 5-fold cross-validation and a train-test split of 80-20. To understand what feature dependencies the models have learned, we employ feature permutation importance (Breiman, 2001) and Shapley values (Shapley (1953); Lundberg and Lee (2017); for an introduction, see Molnar (2025)). All computations are conducted in Python 3.13.2, with driver modelling implemented with `scikit-learn` (Pedregosa et al., 2011) and `shap` (Lundberg and Lee, 2017).

3 Results

3.1 Literature review

Our **literature overview** (n = 64) reveals several key patterns in the prediction of forest mortality cases concerning the data sources, the usage of CSD-based indicators, and the incorporation of explicit true-negative control cases (cf. Figure 3). Note that here, we take EWS to mean any kind of early warning method, not only CSD-based ones. ***i) Data sources***: The majority of studies (48.4%, $n = 31$) rely on traditional tree ring analyses (including analyses of growth rates, growth sensitivity, and isotopes). These are followed by studies using remote sensing (RS) data (21.9%, $n = 14$), and a smaller fraction that employ mechanistic models (9.4%, $n = 6$). ***ii) Methods based on Critical Slowing Down (CSD)*** are used in a third of studies overall (37.5%, $n = 24$). CSD-based EWS are particularly common in mechanistic models (83.3%, $n = 5$ out of 6), and in RS-based studies (50%, $n = 7$ out of 14). In contrast, only 35% ($n = 11$ out of 31) of tree ring studies use CSD-based EWS. There is also a temporal trend: CSD-based studies have become more frequent in recent years, increasing from 23.5% of studies before 2019 (4 out of 17) to 42.5% after 2019 (20 out of 47). ***iii) Validation***: Most studies overall (64%, $n = 41$ out of 64) include an explicit comparison of EWS between mortality sites and control sites, thus incorporating a form of ground truthing using controls. However, this practice varies significantly across data sources and whether the EWS were based on CSD. While the

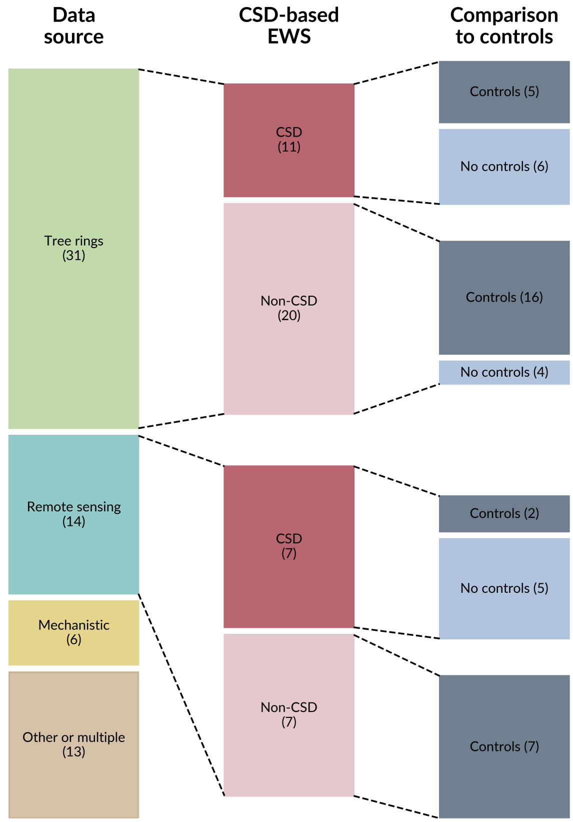

Figure 3. Selected results of the literature review. Studies were classified according to their data source, whether the EWS used were based on CSD, and whether there was an explicit comparison of EWS performance between true mortality locations and control points without mortality.

majority of tree ring (67.7%, $n = 21$ out of 31) and remote sensing (64.3%, $n = 9$ out of 14) studies employ explicit controls, most mechanistic models (83.3%, $n = 5$ out of 6) do not. Furthermore, 82.5% ($n = 33$ out of 40) of studies using non-CSD-based EWS apply explicit controls, compared to only 33.3% ($n = 8$ out of 24) of those using CSD-based approaches. This discrepancy is especially pronounced in studies based only on RS and using CSD-based EWS, where only 28.6% ($n = 2$ out of 7, Alibakhshi (2023); Rogers et al. (2018)) include explicit controls.

3.2 Evidence for mortality events and control point identification

For our empirical study, we identify control points such that we have 885 paired true positive and control observations. The control locations are at a mean distance of $3.2\,\mathrm{km}$ of the mortality points. 67% of the true mortality locations show a drop in the mean of all vegetation indices in the recorded year of mortality in relation to the mean of the three years preceding it (NDVI: 71.1%, EVI: 58.1%, kNDVI: 71.1%), in contrast to only 55% of control locations (NDVI: 53.7%, EVI: 53.7%,

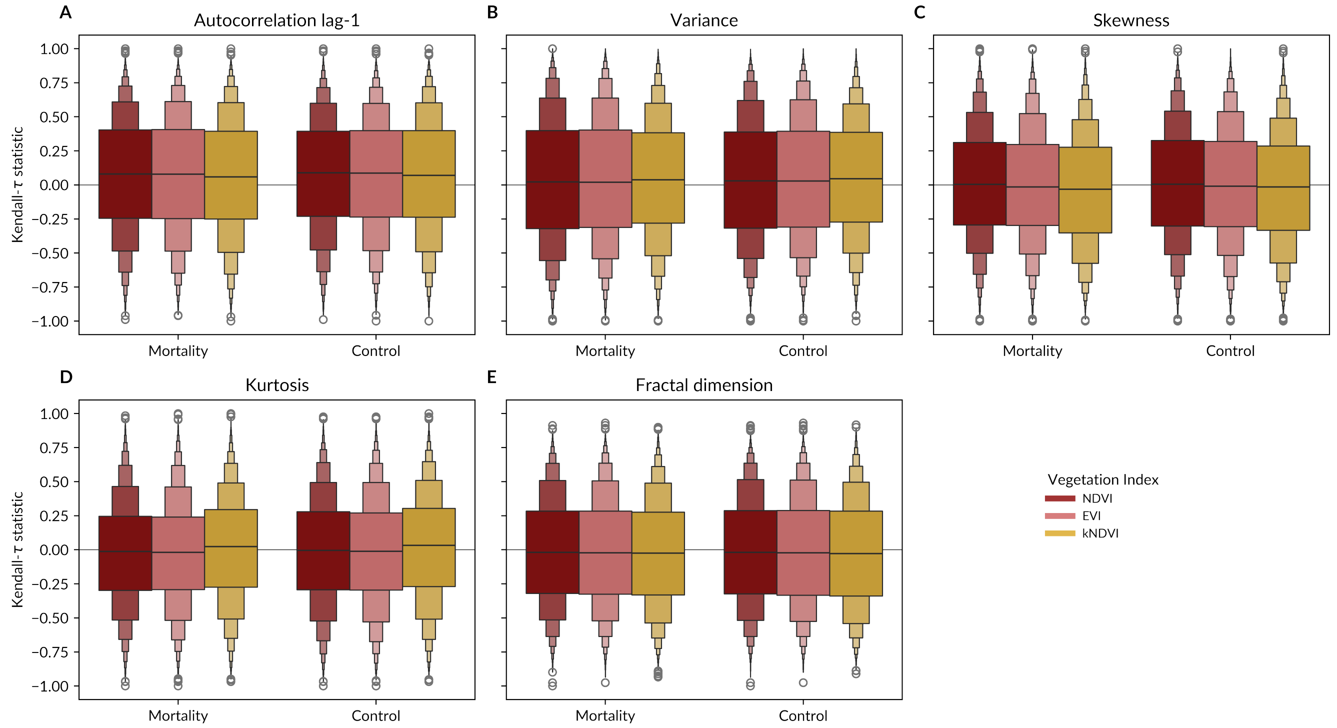

Figure 4. Distribution of Kendall τ trends for each Early Warning Signal (EWS) and vegetation index across different setups for rolling window length and computed over different time frames before the mortality year. Colors indicate the vegetation index. The widest box of each letter-value plot contains 50% of the values, with the center line indicating the 50th percentile. Each successively smaller box contains half of the remaining values, i.e., 25%, 12.5%, etc. (Hofmann et al., 2017). Figure A2 shows the distribution of Kendall τ trends when considering only statistically significant trends. Additionally, Figures A3-A7 show the detailed results per rolling window and time frame choice.

kNDVI: 56.0%), which constitutes a statistically significant difference ($p - value < 0.001$ as assessed with a two-sided t-test for each VI, Figure A1). On average, at true mortality locations, the mean NDVI (EVI, kNDVI) is 6.9% (6.3%, 10.9%) lower in the year of mortality than in the three years before. Evaluating just the time point of minimum productivity in the mortality year, we find that the NDVI (EVI, kNDVI) is on average 31.8% (37.6%, 48.7%) or 2.07 (1.46, 1.92) standard deviations lower than the mean of the three preceding years. The control points show **significantly higher resistance** to the mortality drivers in the given year than the true positives, with on average 40.9% less mortality effects, i.e., less decrease in NDVI at the controls ($p < 0.001$ as assessed with a paired t-test; Figure A1). As the climate effects that drive mortality usually act on larger geographic areas, we might still see some inhibition in growth even at the control points (cf. Figure 2**H**). However, the controls also show **significantly higher recovery rates** from these inhibitions, with recovery rates 421% higher ($p < 0.001$ as assessed with a paired t-test; Figure A1). This confirms that our selection of negative points achieves statistical matching and distinguishes well between points that underwent die-off events versus a shorter-term growth inhibition.

3.3 EWS performance

The performance of all EWS in predicting mortality events and distinguishing between true positives and controls is poor (cf. Figure 4 for the full results). At true mortality locations, only a minority of cases show a statistically significant increase in $AC1$ before the event ($41.7\% \pm 5.6\%$ as mean±standard deviation as assessed across 1, 3, 5, 10, and all years before the event for NDVI). Similarly, only $38.5\% \pm 7.7\%$ of points display a statistically significant increase in variance. The patterns are comparable for skewness ($34.2\% \pm 2.5\%$) and kurtosis ($30.2\% \pm 2.3\%$), as well as for the fractal dimension, for which we expect a decrease, which only $35.7\% \pm 4.8\%$ of points exhibit. Moreover, none of the EWS setups can reliably distinguish between true positive mortality events and true negatives. Across the 360 different setups (5 EWS $\times$ 3 different vegetation indices $\times$ 4 different rolling windows $\times$ 6 different time frames before the event to compute Kendall τ trends), comparing the statistically significant Kendall τ trends for complete true positive and control point pairs with a Mann-Whitney U test, no setup shows a statistically significant difference.

3.4 Driver analysis

The analysis of relevant drivers across all EWS and vegetation indices shows that methodological choices and climate conditions are more important in determining the Kendall τ trends in EWS than characteristics of the mortality event. Generally, our driver models show good model fits ($r^2 = 0.68 \pm 0.05$ as mean ±sd on the training set and $r^2 = 0.55 \pm 0.06$ on the test set) and thus explain a significant part of the variation in the EWS patterns. Using a permutation analysis that randomly shuffles the values of each individual predictor and computes the corresponding decline in model performance, we find that across all EWS and VI, the timeframe before the mortality event to compute the trend is the most important predictor of trend strength (0.44 ± 0.07 as mean permutation importance ± standard deviation), followed by the length of the rolling window used to compute the EWS (0.25 ± 0.06), as shown in Figure 5**A**. The resistance of the ecosystem to the climate extremes is the next most relevant predictor (0.17 ± 0.03), followed by the recovery rate (0.16 ± 0.03). These patterns of feature importance are broadly consistent across VI and EWS. The fractal dimension constitutes an exception, however, in that its trends are much less dependent on rolling window length than for the other EWS.

The SHAP analysis provides more detailed information on the direction and patterns of influence of different features on EWS performance. For $AC1$ and var, we find that EWS signals before mortality are stronger when using longer rolling windows and evaluated at longer time horizons before the mortality event, consistent across all VI, as shown in Figure 5**B** and **C** (results for all other EWS shown in Figure B1). The other EWS show no such clear trends. Effects of the resistance to the mortality event and the recovery rate are inconsistent across VI for each EWS (as shown in Figure 5**D** and **E** for $AC1$ and Figures B2-B6 for all other EWS). We see a slight positive effect of absolute latitude on $AC1$ trends, with high latitudes showing stronger positive Kendall τ trends (Figure 5**F**), but this is not visible for other EWS. The climate conditions in the year before mortality show complex and interacting effects on EWS performance (Figure B2–B6), with no clear derivable patterns.

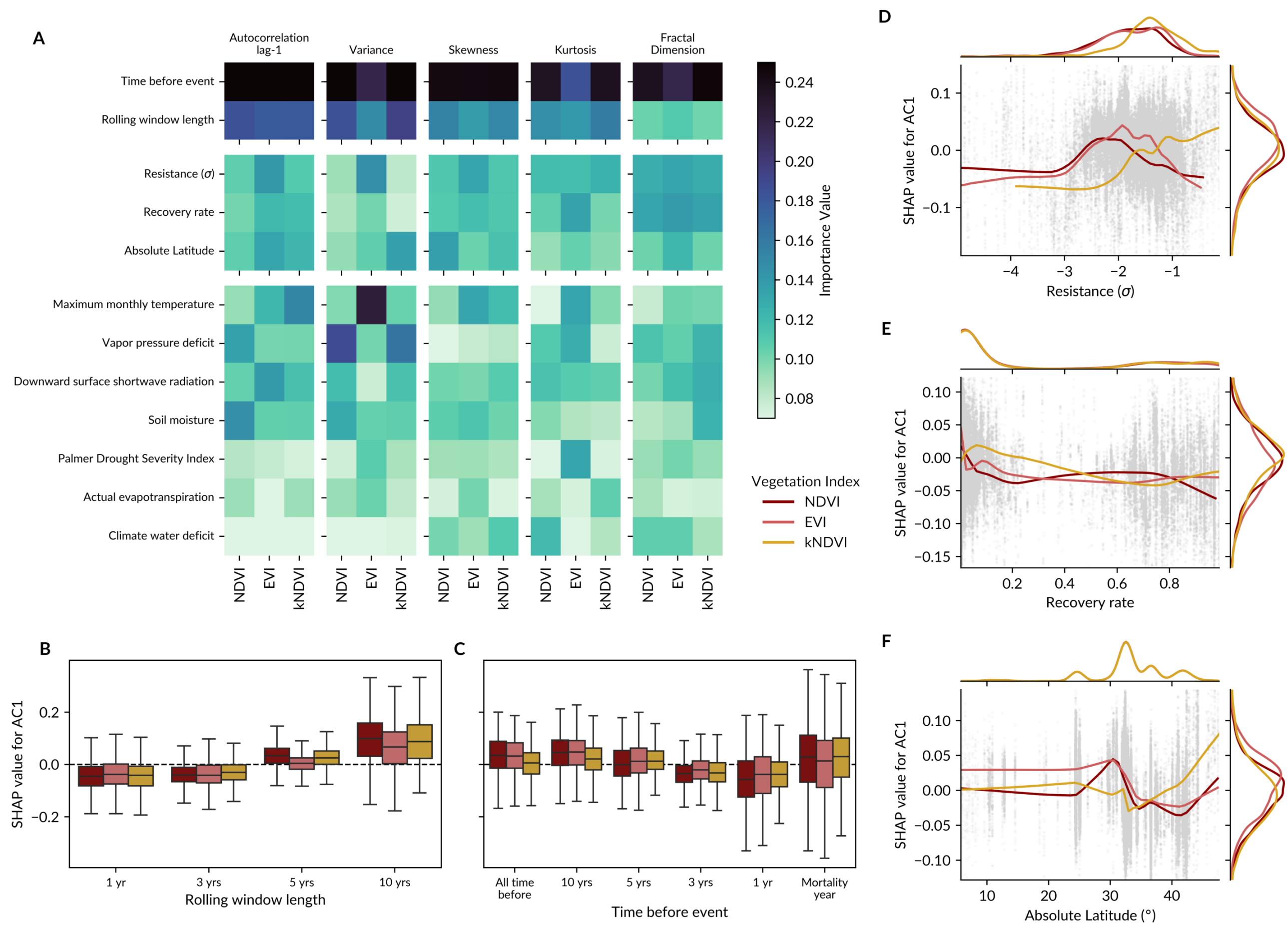

Figure 5. Results of the driver analysis. **A**: Feature importance of different predictors in determining Kendall τ trends of the EWS as assessed with a permutation analysis. **B**: SHAP values for $AC1$ for different methodological choices for rolling window length. **C**: SHAP values for $AC1$ for different time frames before the event over which Kendall τ trends were computed, colored by the vegetation index. Positive values indicate that this methodological choice contributed positively to Kendall τ trends. **D**-**F** show LOWESS (locally weighted scatterplot smoothing) curves of the SHAP values of $AC1$ trends for the three different vegetation indices. The points on which the LOWESS curves are computed are shown in light grey. The marginal plots show the density distribution of scatter points for each vegetation index. **D** shows the effect of resistance to the mortality event on Kendall τ trends in $AC1$, **E** shows the effect of recovery rates, and **F** shows the effect of the absolute latitude. Results for the SHAP analysis for EWS other than $AC1$ can be found in the Supplementary Material Figures B1 - B6.

4 Discussion

The commonly used time series-based EWS tested here perform poorly in predicting the forest mortality events in our data set from remotely sensed vegetation index time series (Figure 4). Such poor performance of EWS is not uncommon (Dakos et al., 2023; Boettiger and Hastings, 2012; Hastings and Wysham, 2010; Rietkerk et al., 2025), which is also shown by our literature review of previous CSD-based EWS applications on forest mortality events (e.g., Camarero et al. (2020); Cailleret et al. (2019); Camarero et al. (2015)). We will here explore a range of possible explanations, put our findings in the context of other evaluations of EWS performance for forests, and shine light on potential future pathways.

Bifurcation character of mortality events: How can one represent an ecological event such as forest mortality mathematically, and how does this influence our ability to predict its occurrence using CSD-based EWS? As outlined earlier, we assume for this study that the forest mortality events can be considered bifurcations, i.e., significant qualitative shifts in the system state. However, for the analysis of a multidimensional and spatio-temporally complex system such as a forest, it is important to note that this is, in fact, a difficult question to assess. There are multiple different analytical levels on which to evaluate a qualitative shift - focusing on genetic diversity, species abundance, diversity or interaction, ecosystem structure, or more abstract ecosystem services such as biomass or carbon fixation, which all follow different dynamics (Spake et al., 2015; Ibáñez et al., 2019). The time span considered for evaluating the persistence of a shift is also relevant and a value-driven choice. For example, multi-decadal time frames are common from a forest management perspective, whereas for a single, potentially threatened species, seasonal time frames may be sufficient to cause local extinction (Reyer et al., 2015).

Even for idealized, theoretical systems, mathematically not all types of bifurcations are expected to be preceded by CSD (e.g., chaotic crises or Maxwell point transitions; Boettiger et al. (2013)), while on the other hand CSD is also expected to precede non-catastrophic shifts such as continuous bifurcations or second-order transitions (Kéfi et al., 2013). While we can distinguish between different types of bifurcations in mechanistic, equation-based models and therefore determine whether one would expect to see CSD, such a mathematical distinction is challenging in a real, multi-dimensional, and multi-scalar ecological system. The translation of a complex ecological process, such as a forest mortality event, into mathematical terms is therefore challenging, as is the question of why these events show no CSD-based EWS. In the following, we will evaluate the characteristics of the mortality event, our methodological choice of measuring the ecosystem's state, and the dynamics of the driving factors of mortality.

Quality of mortality and control events: Our analyses indicate that the combination of the in-situ mortality dataset and remote sensing time series both captures real, measurable mortality events and shows that the size or severity of these events is not a key determinant of poor EWS performance. The quality of the mortality dataset and its associated control points in terms of location, timing, and size of the mortality event is an important potential source of error that needs to be carefully evaluated. The Hammond et al. (2022) database does not contain information about the spatial extent of the recorded events, but generally uses a threshold of $\geq 15\%$ standing dead of mature trees (Hammond et al., 2022). As demonstrated in Section 3.2, our remote sensing time series do show significant drops in all vegetation indices in the year of mortality at the true positive points. Although the average drop in vegetation indices at the true positives in the mortality year is low in relative terms, this likely reflects a strong increase in greenness after the initial mortality event, as understory vegetation benefits from the increased light availability and grows more strongly (cf. Figure 2**F**, Anderegg et al. (2012); Facciano et al. (2023)). This post-mortality greening is an expected phenomenon, and therefore, the combination of the in-situ dataset of locations and remote sensing time series can still be considered to pick up real, measurable mortality events. Furthermore, as shown in Section 3.2 and Figures A1, we also find that our control points show significantly higher resistance and recovery rates, indicating higher resilience to the climate conditions. The effect of these variables on EWS performance is assessed in our driver analysis (cf. Section 3.4), where we find no consistent influence of resistance and recovery rate on EWS performance across EWS methods and vegetation indices. This demonstrates that insufficient size or severity of the mortality event is not a key determinant of poor EWS performance.

Relevance of remotely sensed indicators: We used MODIS optical vegetation indices (NDVI, EVI, kNDVI) to approximate forest ecosystem dynamics, as they provide a suitable compromise between spatial resolution, temporal coverage, and global extent for detecting local mortality events. Optical vegetation indices such as NDVI, EVI, and kNDVI are indicators of chlorophyll and are indicative of ecosystem primary productivity. While there are well-known technical limitations of the NDVI, such as cloud coverage and saturation, particularly in highly productive areas such as the tropics, these are somewhat mitigated by the improvements made in the EVI and kNDVI (Camps-Valls et al., 2021). Nevertheless, as optical indices, they are not ideal measures of biomass (Box et al., 1989), cannot account for vegetation structure, and cannot distinguish between different species (Smith et al., 2023). Given the species-specific responses to environmental drivers (Esquivel-Muelbert et al., 2020), and evidence from our literature review showing species-specific or group-specific performance of different EWS to predict mortality (Cailleret et al., 2019; Liu et al., 2019; Rogers et al., 2018), this presents an important caveat. Smith et al. (2022) therefore argue that NDVI is not a good measure to assess resilience losses and recovery after disturbance and propose the use of Vegetation Optical Depth (VOD) instead. VOD is a microwave-based measure of vegetation water content and structure and captures true biomass significantly better than NDVI (Moesinger et al., 2020). However, currently, the global products for VOD (VODCA v2, SMOS L-VOD) are limited by their coarse spatial resolution (at most $9\,\mathrm{km}$), are multi-sensor products, which might introduce artifacts to higher statistical moments such as autocorrelation (Smith et al., 2023; Rietkerk et al., 2025), or are limited in terms of temporal extent with observations only starting in 2010 (Zotta et al., 2024; Hu et al., 2024). VOD data can therefore be suitable for large-scale or global analyses (Smith et al., 2022; Verbesselt et al., 2016), but neither for the local mortality events assessed here nor for management applications. Hence, we decided here to use the optical index data from MODIS, despite their limitations, as they are still widely applied (e.g., Rogers et al. (2018); Seddon et al. (2016); Forzieri et al. (2022); Verbesselt et al. (2016)) and provide a good tradeoff between spatial and temporal resolution and extent. While we do find that the MODIS time series capture the mortality events well (cf. Section 3.2), the poor approximation of biomass and productivity and the lack of differentiation between multiple species groups in NDVI, EVI, and kNDVI likely contribute to the poor performance of the EWS here (Smith et al., 2023).

Characteristics of the driving factors of mortality: The theoretical foundations of CSD-based EWS are based on assumptions for one-dimensional systems with one slowly varying, external driver (Brock and Carpenter, 2010) and stationary noise. For real cases of forest mortality, we need to carefully consider how far these assumptions are met.

First, droughts and heat stress, the main mortality drivers examined here, do not perfectly match this template, but they do share several key characteristics of CSD drivers. While the physiology of tree mortality as a result of drought is complex and species-specific (Choat et al., 2018), there is a known threshold behaviour with certain levels of low water availability causing abrupt and non-linear increases in tree mortality (Senf et al., 2020; Camarero, 2021). There is also ample evidence for drought legacy effects in affecting future susceptibility of a forest to additional droughts (Kannenberg et al., 2020). While these vary strongly in scale and effect direction, there is mostly a negative effect of past droughts on future forest sensitivity, which can be interpreted as eroding forest resilience over time (Kannenberg et al., 2020). At the same time, both droughts and heatwaves can vary in intensity and speed, and can in some cases act as shocks to a system rather than slowly varying linear drivers (Cailleret et al., 2019, 2017). Taken together, this suggests that while droughts may not fully conform to the assumptions of CSD theory, they nevertheless exhibit key properties —threshold behaviour and cumulative legacy effects — that make them suitable candidates for testing EWS in forest ecosystems.

Secondly, however, the multivariate and interactive nature of forest ecosystems and their drivers is likely a major reason for the poor EWS performance observed in this study. Ecosystems are complex, multivariate systems affected by multiple, interacting drivers and often non-stationary noise (Bathiany et al., 2024; Dakos and Kéfi, 2022; Boettner and Boers, 2022; Rocha et al., 2015b, a), with climate conditions affecting vegetation growth via various direct and indirect pathways (Cailleret et al., 2019). The hotter droughts identified as key drivers of mortality in the Hammond et al. (2022) database are acting through changes in both temperature and water availability, and therefore already constitute two-dimensional impacts on the forest system. Reviews also show that there are significant interactions between different biological and physical disturbance agents acting on forests (Seidl et al., 2017), and it is hence likely that the mortality cases used in this study also contain potential influences of biological mortality agents such as bark beetles. Once a system has more than one driver, theoretically expected EWS (increase in $AC1$ and var) can fail or give contradictory signals (Dai et al., 2015; Bathiany et al., 2025; Titus and Watson, 2020; Rocha, 2022). In our real-world application, these complexities therefore likely contribute to the poor EWS performance observed here.

Comparison to other work on forest resilience, disturbance, and EWS: Recent years have seen an increase in work employing temporal EWS on remote sensing data of vegetation indices (Lenton et al., 2022; Smith et al., 2022; Forzieri et al., 2022; Feng et al., 2021), with variable findings and critiques of the methods. We will focus here on setting our results in the context of three key recent publications that we deem relevant for the evaluation of EWS performance for forest resilience and mortality.

EWS on tree rings for individual tree mortality (Cailleret et al., 2019): In line with our results, this global, bottom-up, individual tree-level study finds that most classical temporal EWS performed poorly in predicting mortality. In this work, the authors test temporal autocorrelation, annual growth variability, and growth synchrony as EWS of individual tree mortality on a global dataset of tree rings at 198 sites. This method has been commonly applied in a range of case studies around the world (cf. Section 3.1) with mixed results, but this is the largest and only global study using EWS on tree rings. The authors find changes in autocorrelation to be a poor predictor of mortality risk for all species, while for gymnosperms, an increase in growth variability and decrease in growth synchrony are found as precursors of mortality (Cailleret et al., 2019). These results underscore that variability in species-level physiological responses can produce diverse temporal EWS patterns, a pattern consistent with our own observations (Cailleret et al., 2017; Augusto et al., 2014; Adams et al., 2017).

EWS as empirical indicators of vegetation resilience (Smith et al., 2022): Temporal EWS, as demonstrated by Smith et al. (2022) in this work, can capture *engineering resilience*, the short-term ability of ecosystems to recover after disturbances, but we find that these same indicators do not reliably signal declines in *ecological resilience*, which reflects the system's capacity to absorb stress until a major shift occurs. In this piece, the authors compute empirical recovery rates after identified abrupt drops in the vegetation indices and find broad agreement with VOD-based trends in $AC1$ and var, with significantly poorer performance of NDVI-based EWS. This analysis constitutes an important global assessment of EWS empirical grounding for vegetation resilience. However, their analysis focuses on local stability (engineering resilience) - as the ability of a system to return to a previous equilibrium state after a disturbance, whereas our study evaluates these indicators as measures of the size of the basin of attraction (ecological resilience) (Holling, 1973; Pimm, Stuart L., 1984). Even though the two concepts are closely related (Bathiany et al., 2024; Dakos and Kéfi, 2022), they are mathematically distinct (Krakovská et al., 2024). As our driver analysis shows, we do find that for $AC1$, there is an overall slight negative relationship between recovery rates and EWS trends (cf. Section 3.4). This means that generally, cases with lower engineering resilience are also more likely to exhibit EWS before the mortality event. Taken together, these results indicate that while EWS can capture short-term recovery dynamics, they do not provide reliable early warnings of large-scale shifts in threshold-driven mortality events.

EWS preceding abrupt transitions derived from remote sensing time series (Forzieri et al., 2022): In this study, the authors show that positive trends in NDVI-based $AC1$ only weakly precede abrupt declines in forest productivity, a pattern that is consistent with our findings and suggests limited usefulness of these EWS for practical applications. Forzieri et al. analyse trends in NDVI autocorrelation in forests globally and evaluate their occurrence prior to abrupt declines in productivity identified from remote sensing time series. They find that overall, the probability that a pixel will experience an abrupt decline in NDVI given a positive trend in $AC1$ is only slightly higher than 50% - i.e., a random guess - and increases with increasing severity of the decline. However, this pattern is observed only in boreal forests; in tropical forests, abrupt declines are not associated with increasing trends in $AC1$. The authors suggest that boreal disturbances are mainly driven by insect outbreaks, frequently favored by droughts, whereas tropical disturbances are more often caused directly by fires and droughts (Gauthier et al., 2015; McDowell et al., 2018). As we are only focusing on mortality events driven by droughts and heat stress, these results are hence not fully comparable. In contrast to their results, we do not find an effect of the strength of the abrupt decline (i.e., resistance) on EWS trends (cf. Sect. 3.4). However, we do find a slight positive effect of latitude on $AC1$ trends, with higher latitudes showing more positive trends, possibly due to higher residual seasonality in the data. Overall, both studies indicate that temporal NDVI-based EWS provide limited early-warning capability for abrupt vegetation declines, reinforcing our conclusion that they are of limited value for monitoring or management purposes.

Considerations for future developments and applications of EWS: Caution is called for when applying EWS and interpreting the results as vegetation resilience. Future applications should carefully consider how far the underlying assumptions for CSD-based EWS are fulfilled regarding the dimensionality of the ecosystem and its drivers. Moreover, one should critically evaluate whether the measured state variables do in fact capture the ecosystem properties of interest well and at the relevant spatio-temporal scales (Runge et al., 2025). As shown above, NDVI is limited in its representation of ecosystem processes and species composition, but newer developments in remote sensing are providing a range of additional metrics (Runge et al., 2025) related to e.g., ecosystem structure (such as LiDAR measurements from GEDI; Dubayah et al. (2020)), species composition and biodiversity (such as hyperspectral satellites; Crofts et al. (2024); Ghiyamat and Shafri (2010)), or vegetation health (for example, vegetation water content; Wang et al. (2023)). Unfortunately, these new datasets do not yet come with the long time series needed to leverage CSD-based methods. New EWS that work on short time series, or that combine spatial and temporal information, are needed to utilize newer high-resolution products. Regarding the resilience indicators to be applied, recent work has also shown progress in developing deep learning approaches as EWS for different bifurcation events (Bury et al., 2021; Liu et al., 2024). While these models are mostly trained on simulated data, they show promising first applicability on real-world systems such as forest-savannah transitions as well (Liu et al., 2024). The success of machine learning approaches, in particular supervised learning, relies on carefully annotated datasets of true positives and true negatives. Here, we provide a methodology to identify control points in real-world settings.

Lastly, taking one step backwards, researchers should also critically reflect on the implications and usefulness of promoting theory-based, overly simplified resilience indicators and EWS for ecosystem management. While resilience is widely called for as an ecosystem management goal in policy, it is not as frequently employed in actual forest management practice (Nikinmaa et al., 2020) due to a largely theoretical, sometimes overly conceptual focus, and a lack of operationalization (Rist and Moen, 2013; Newton and Cantarello, 2015; Reyer et al., 2015). Hence, there is a significant disconnect between the methods favored by forest research and forestry practice to manage forests for resilience (Nikinmaa et al., 2024; Sousa-Silva et al., 2018). The development of any early warning system needs to also take into account its usefulness - providing indicators that are robust, include an uncertainty estimate, and provide a warning early enough to actually implement management changes (Biggs et al., 2009). Further research should therefore also aim to move beyond theoretically motivated applications of simple EWS and focus on expanding and operationalizing the concept of forest resilience in a practically applicable way.

5 Conclusions

The global increase in forest disturbance and mortality events under climate change highlights the need for robust methods to predict such events in a sufficiently timely manner to enable opportune action. In this study, we demonstrate that despite their extensive utilization and ease of application, system-agnostic Early Warning Signals based on Critical Slowing Down are ineffective and non-robust predictors of forest mortality events on a global scale. The primary reasons for this can be attributed to the poor approximation of ecosystem dynamics from optical vegetation indices and the multivariate character of real ecosystems. We suggest that future applications should focus on critically evaluating the performance of EWS before their application. More research efforts should be devoted to the evaluation of the performance, accuracy, and decrease in uncertainty of these EWS in relation to real-world observations.

Code and data availability. All data used in this study are publicly available, with the tree mortality database taken from Hammond et al. (2022), the MODIS remote sensing data available from NASA Earthdata, and the TerraClimate data downloaded from Climatology Lab. The code to run this analysis and produce all outputs can be found on Github and will be made available upon acceptance of this study.

Appendix A: EWS assessments

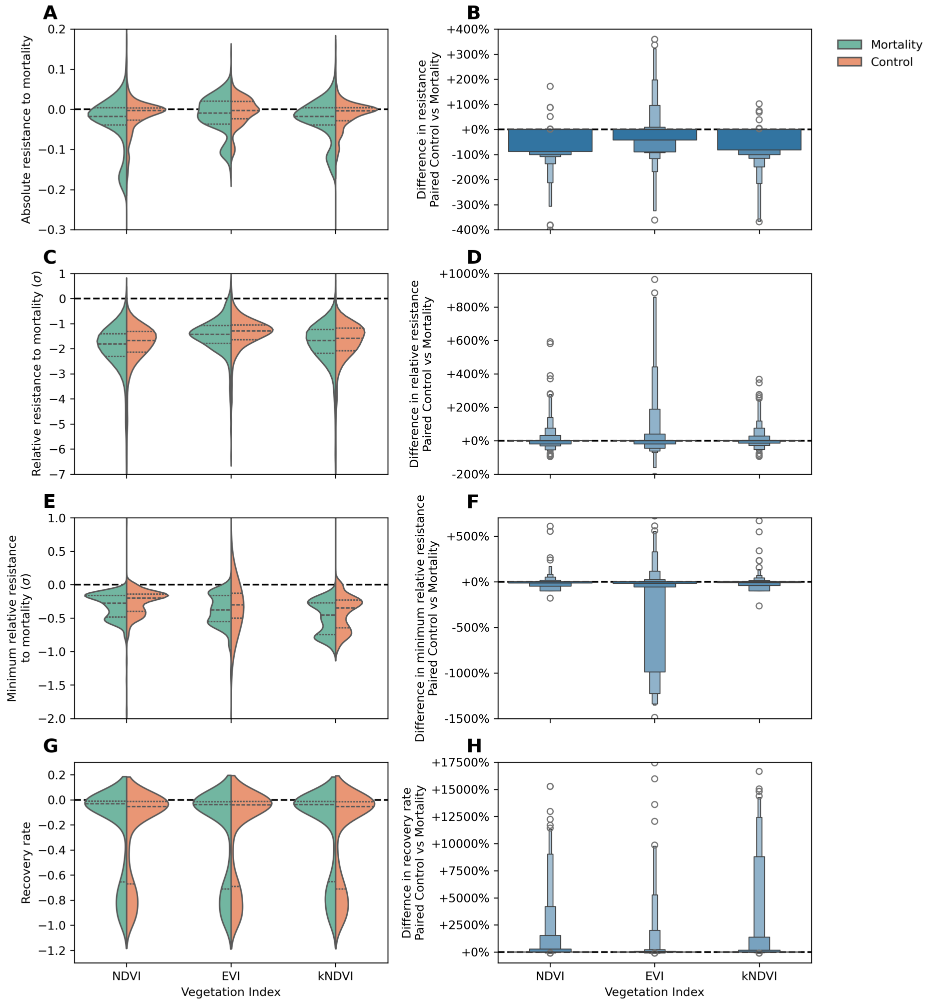

Figure A1. Comparison of true mortality points and controls. **A**: Absolute resistance (i.e., change in mean vegetation index in the year of mortality in comparison to the mean of the three preceding years) at mortality and control locations. The dashed line in the violin plots represents the 50th percentile, with the dotted lines representing quartiles. **B**: Percentage difference in absolute resistance between controls and true mortality locations as assessed for each paired location. The widest box in the letter-value plot contains 50% of the values, with each subsequently smaller box containing half the remaining values. **C**: Relative change in vegetation index in the year of mortality as normalized by the standard deviation of the three years preceding the mortality event for true mortality locations and controls. **D**: Percentage difference in relative resistance between controls and true mortality locations. **E**: Minimum relative resistance (i.e., difference between the minimum value of each vegetation index in the year of mortality and the mean of the three preceding years) at mortality and control locations. **F**: Percentage difference in minimum relative resistance at paired locations. **G**: Recovery rate at mortality and control locations. As these are computed as exponents of an exponential function fitted to the time series of the vegetation index, larger negative values indicate faster recovery. **H**: Percentage difference in recovery rates at paired locations of mortality and control.

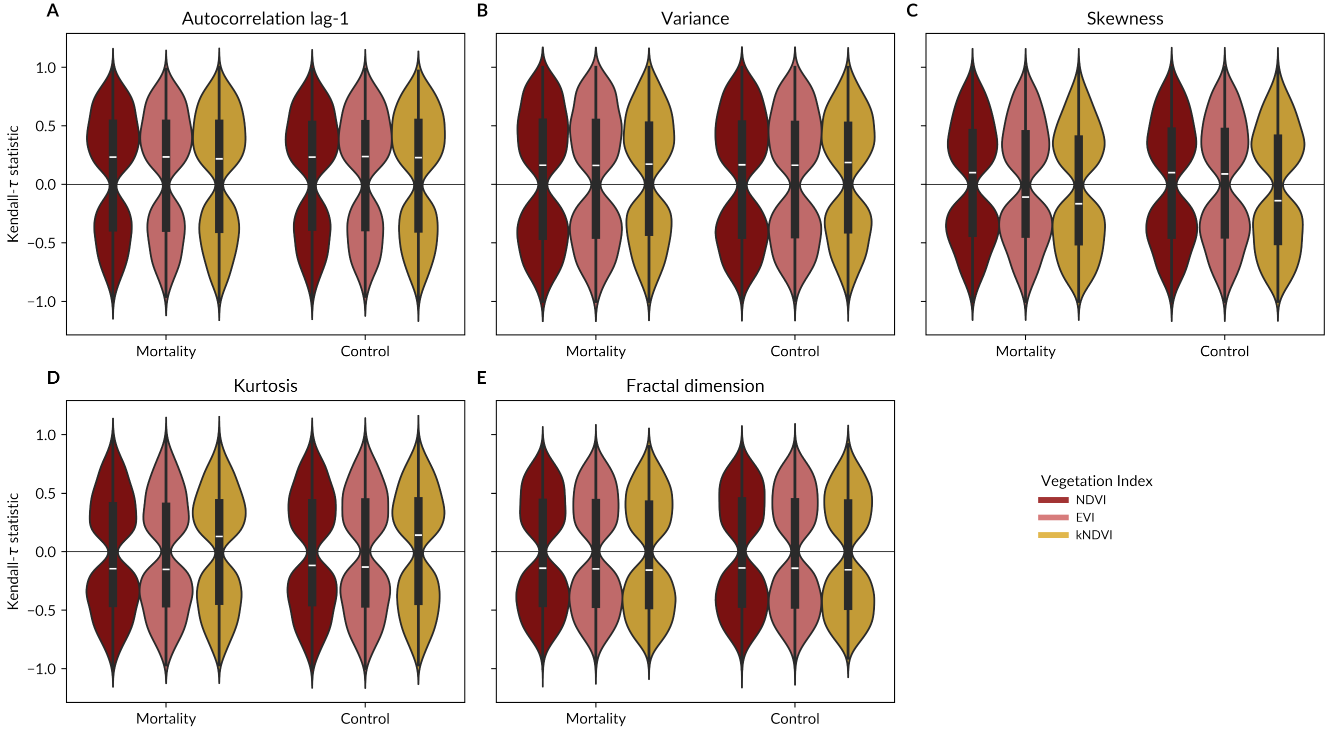

Figure A2. Distribution of Kendall τ trends for each Early Warning Signal (EWS) and vegetation index across different setups for rolling window length and computed over different time frames before the mortality year. Colors indicate the vegetation index. Note that the figure only shows statistically significant trends ($p < 0.05$), in contrast to Figure 4.

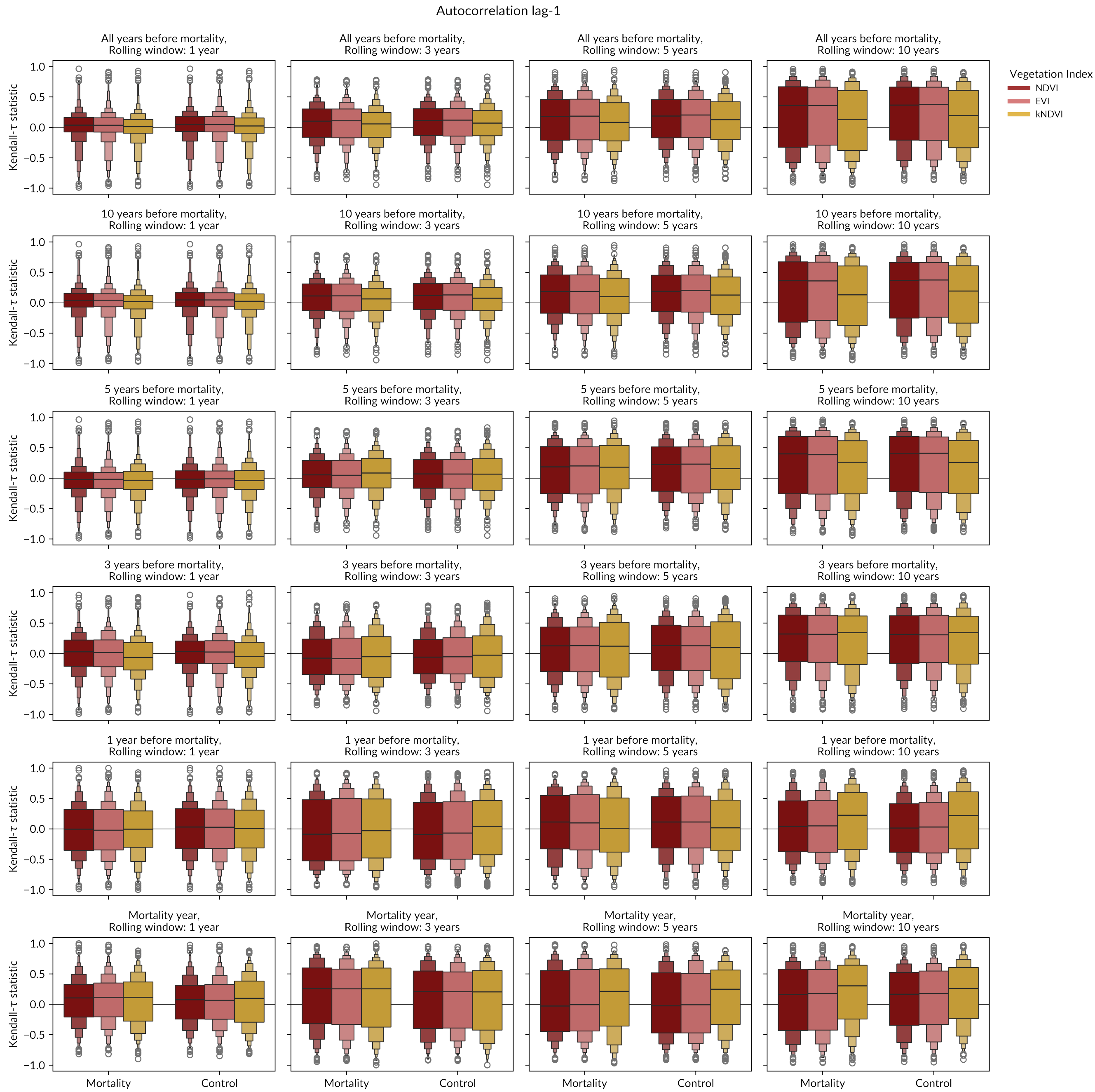

Figure A3. Distribution of Kendall τ values for $AC1$ at mortality and control locations, per choice of rolling window and time frame before the mortality event to compute trends. Note that this plot also includes statistically non-significant trend values.

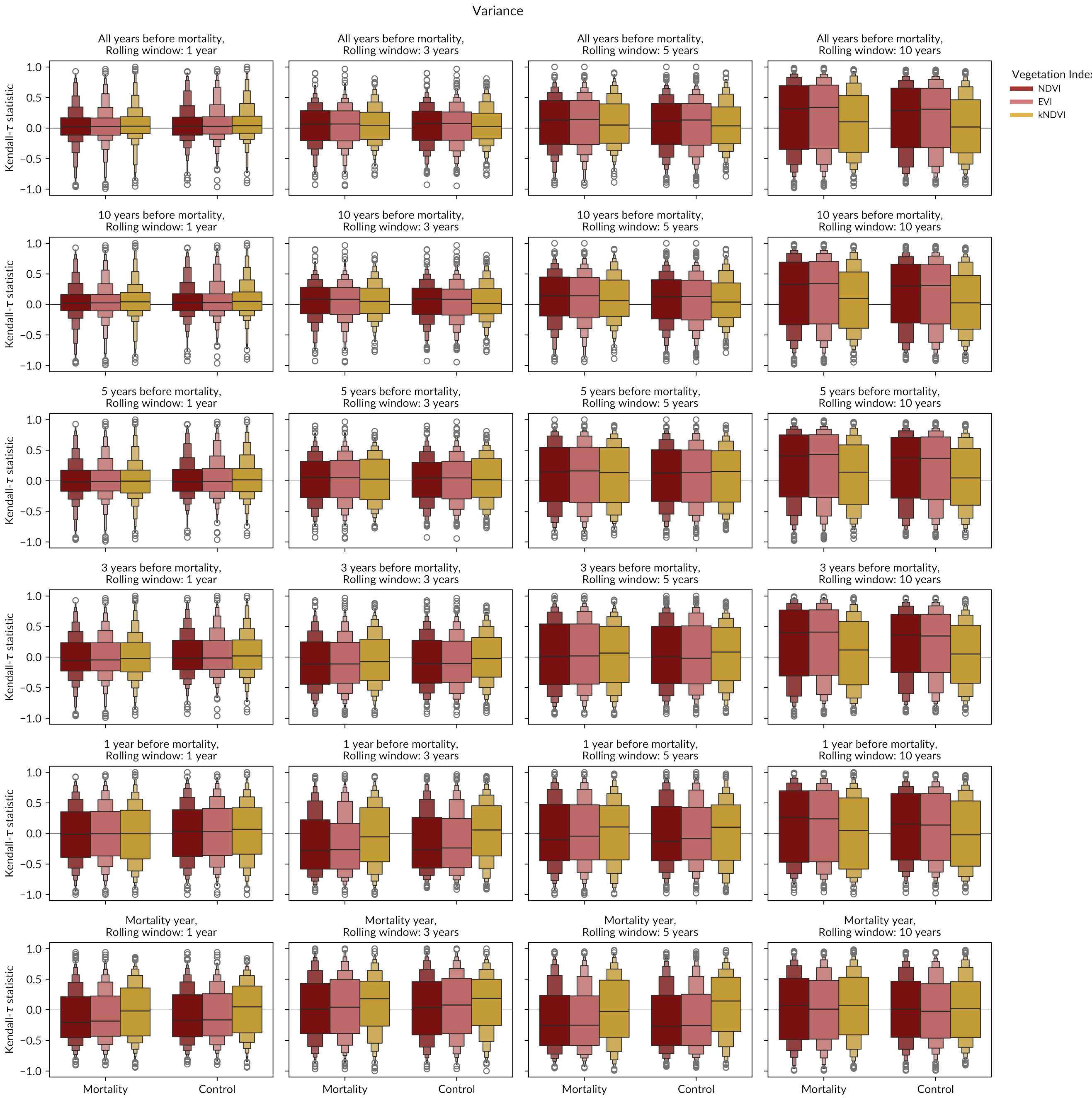

Figure A4. Distribution of Kendall τ values for variance at mortality and control locations, per choice of rolling window and time frame before the mortality event to compute trends. Note that this plot also includes statistically non-significant trend values.

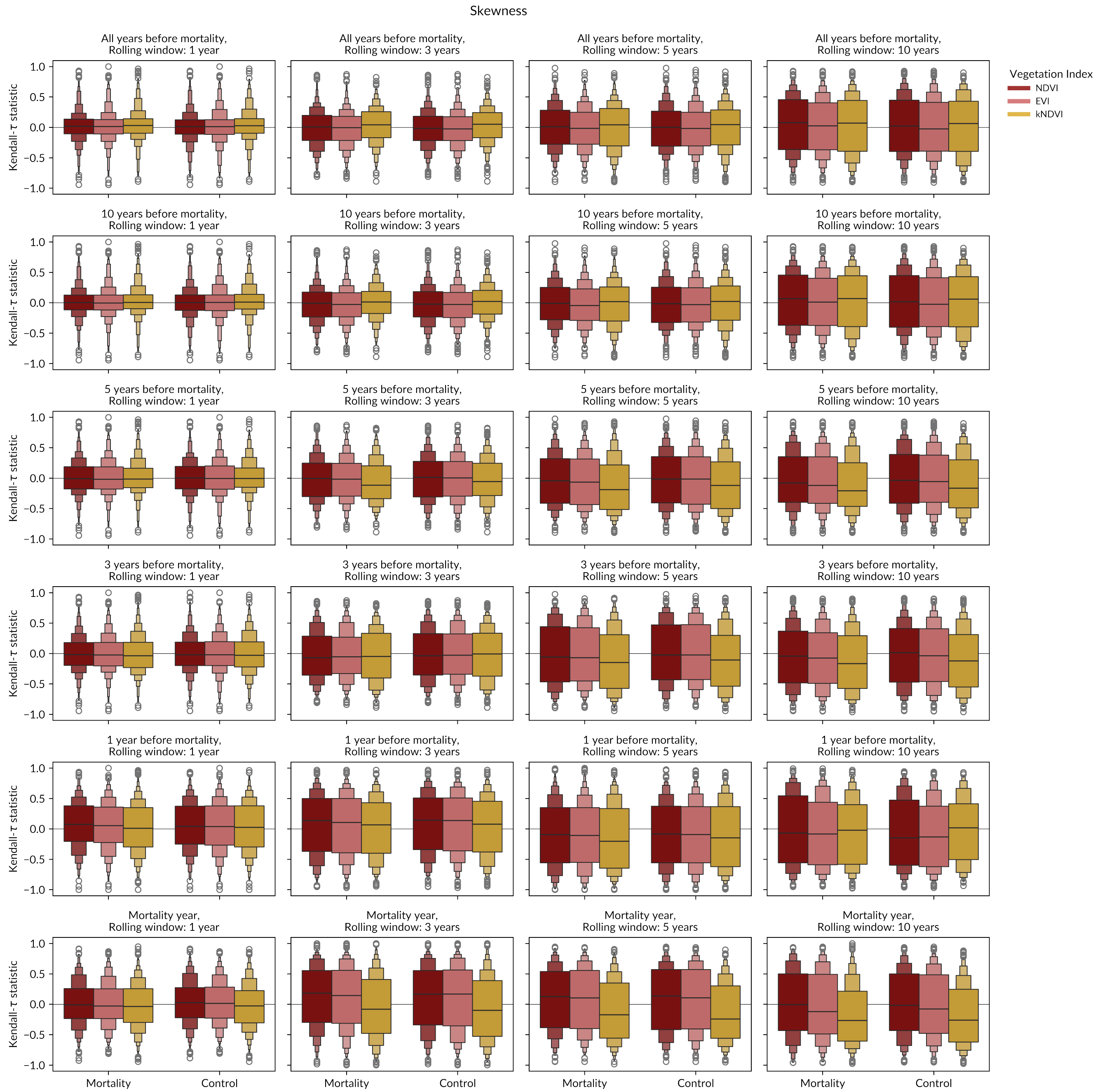

Figure A5. Distribution of Kendall τ values for skewness at mortality and control locations, per choice of rolling window and time frame before the mortality event to compute trends. Note that this plot also includes statistically non-significant trend values.

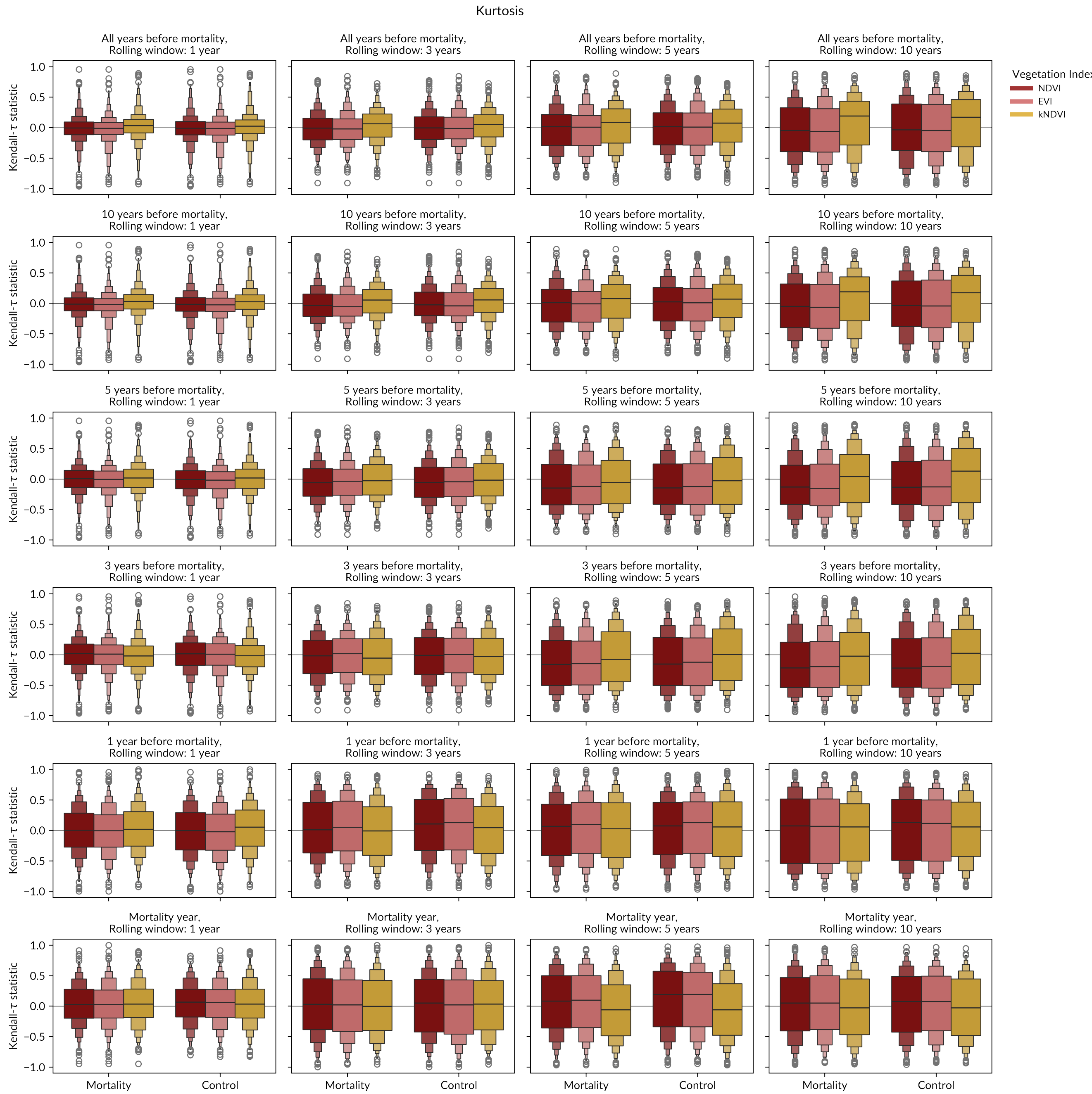

Figure A6. Distribution of Kendall τ values for kurtosis at mortality and control locations, per choice of rolling window and time frame before the mortality event to compute trends. Note that this plot also includes statistically non-significant trend values.

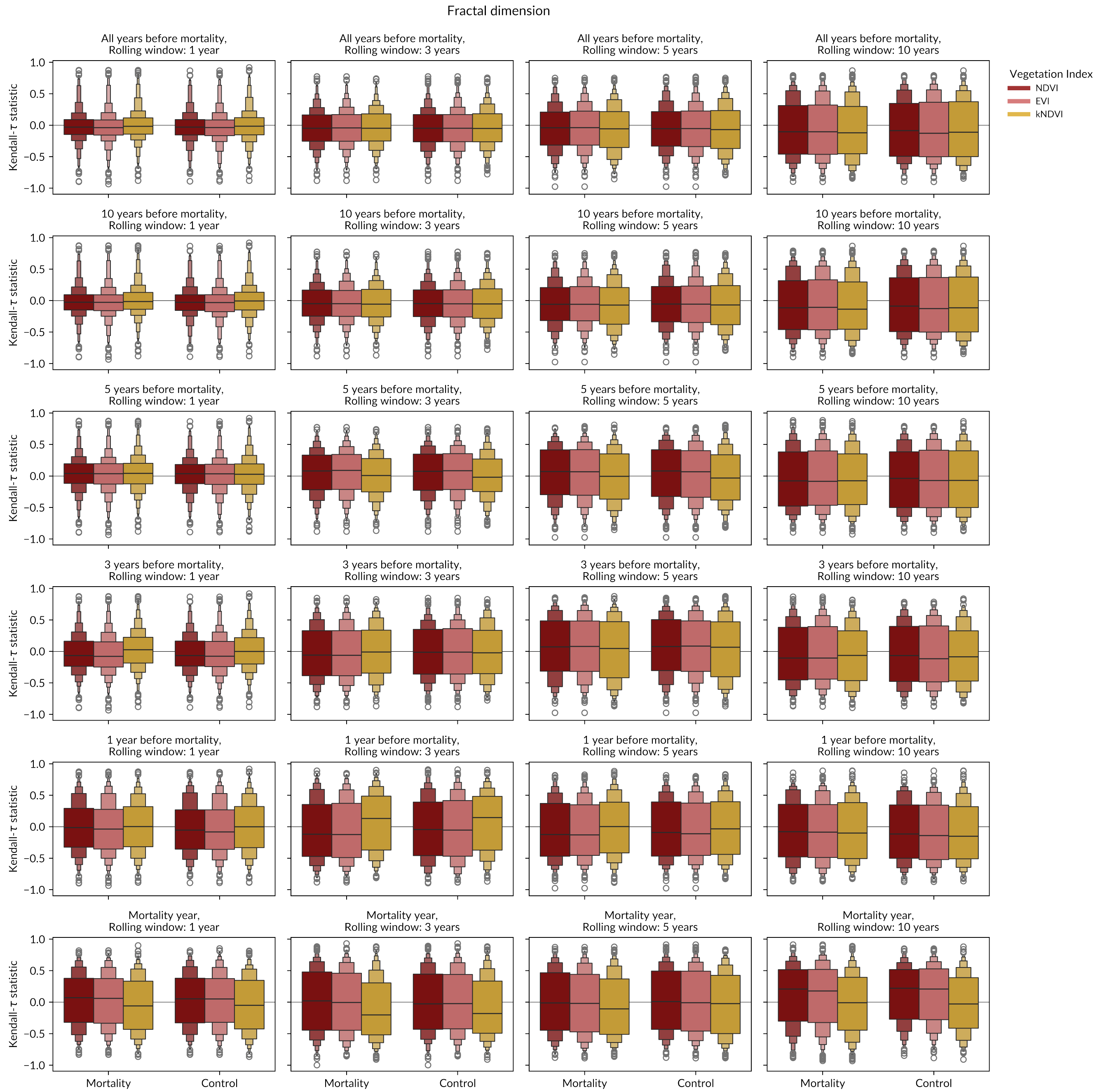

Figure A7. Distribution of Kendall τ values for the fractal dimension at mortality and control locations, per choice of rolling window and time frame before the mortality event to compute trends. Note that this plot also includes statistically non-significant trend values.

Appendix B: Driver analysis

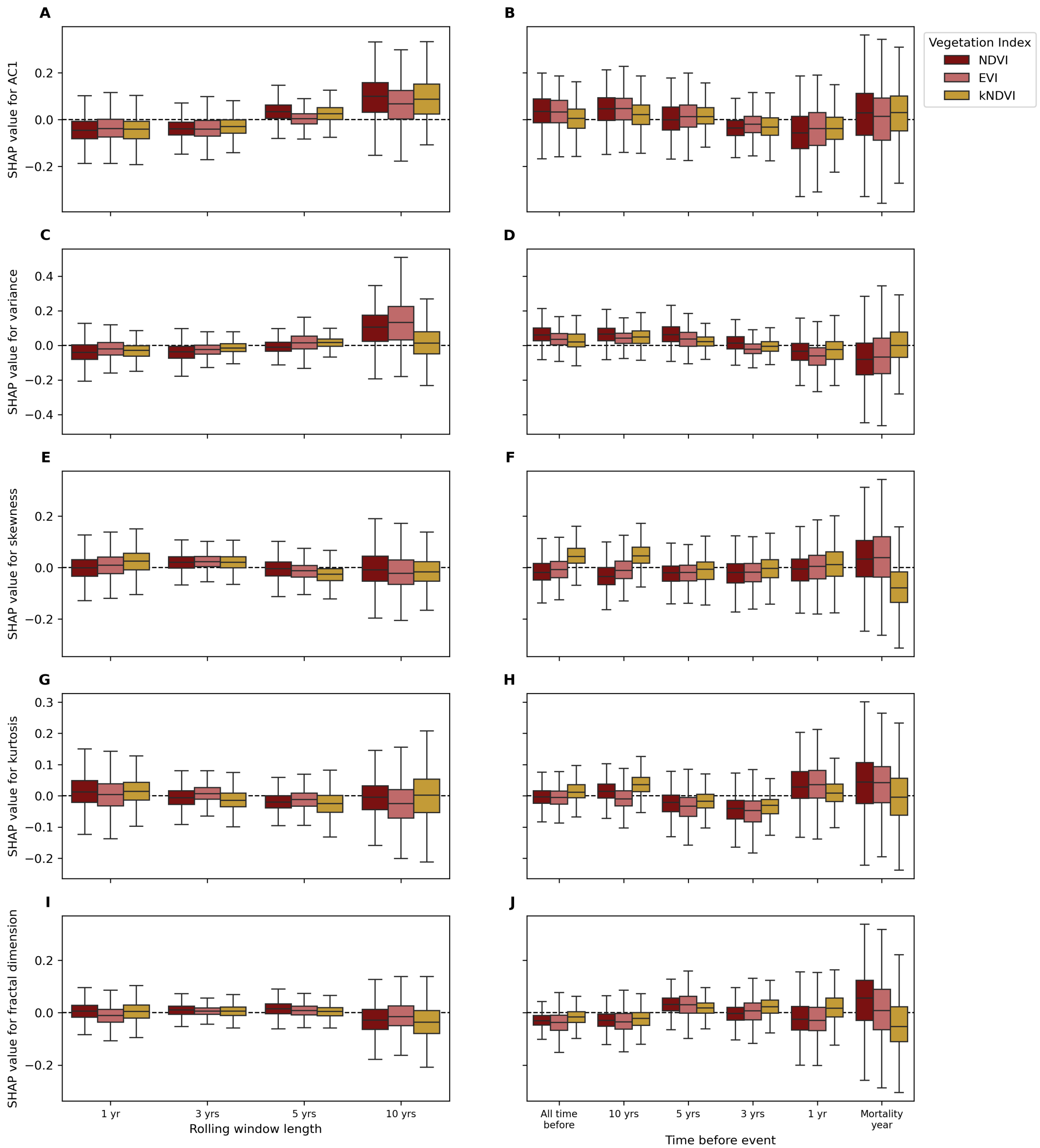

Figure B1. SHAP values for the driver models for the methodological choices per EWS and vegetation index.

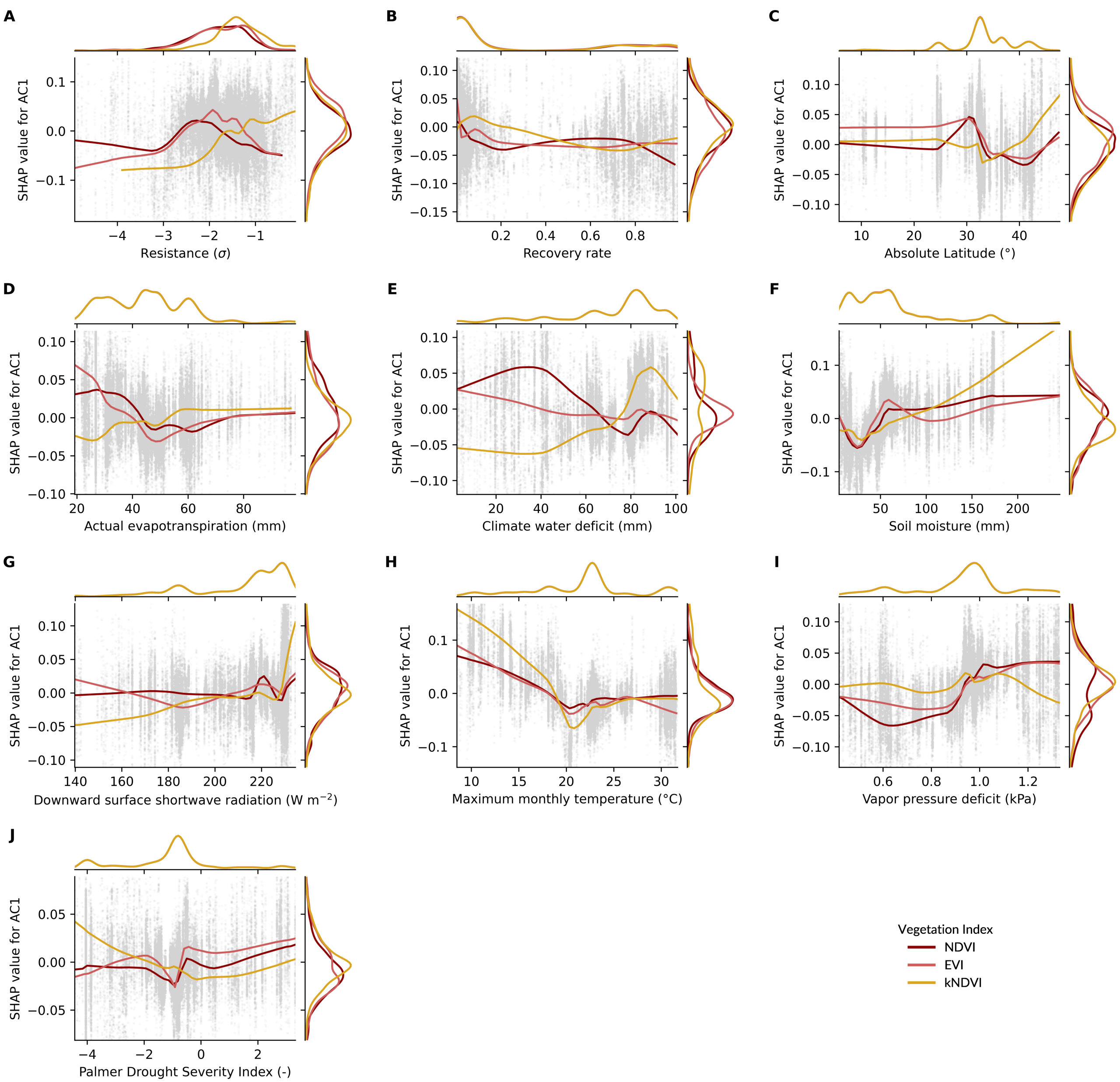

Figure B2. SHAP curves for **AC1 models** for the different continuous drivers and resolved per vegetation index. Smooth curves in the plot represent LOWESS (locally weighted scatterplot smoothing) curves computed on the SHAP values which are shown as scatter plot in light grey. Marginal plots show density curves of the scatter plot distribution per vegetation index. The axis limits are clipped to the 99th percentile on each dimension.

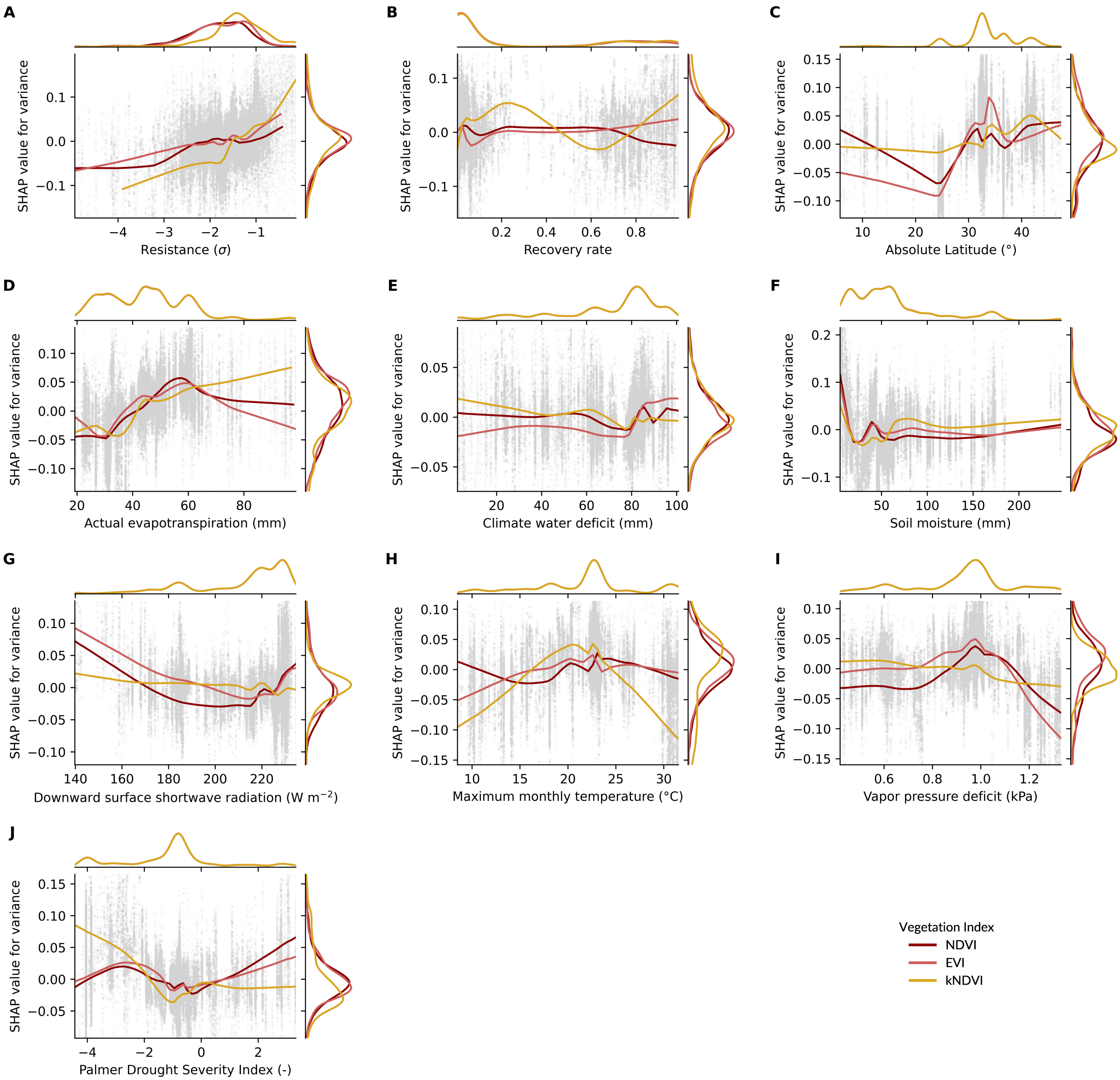

Figure B3. SHAP curves for **variance models** for the different continuous drivers and resolved per vegetation index. Smooth curves in the plot represent LOWESS (locally weighted scatterplot smoothing) curves computed on the SHAP values which are shown as scatter plot in light grey. Marginal plots show density curves of the scatter plot distribution per vegetation index. The axis limits are clipped to the 99th percentile on each dimension.

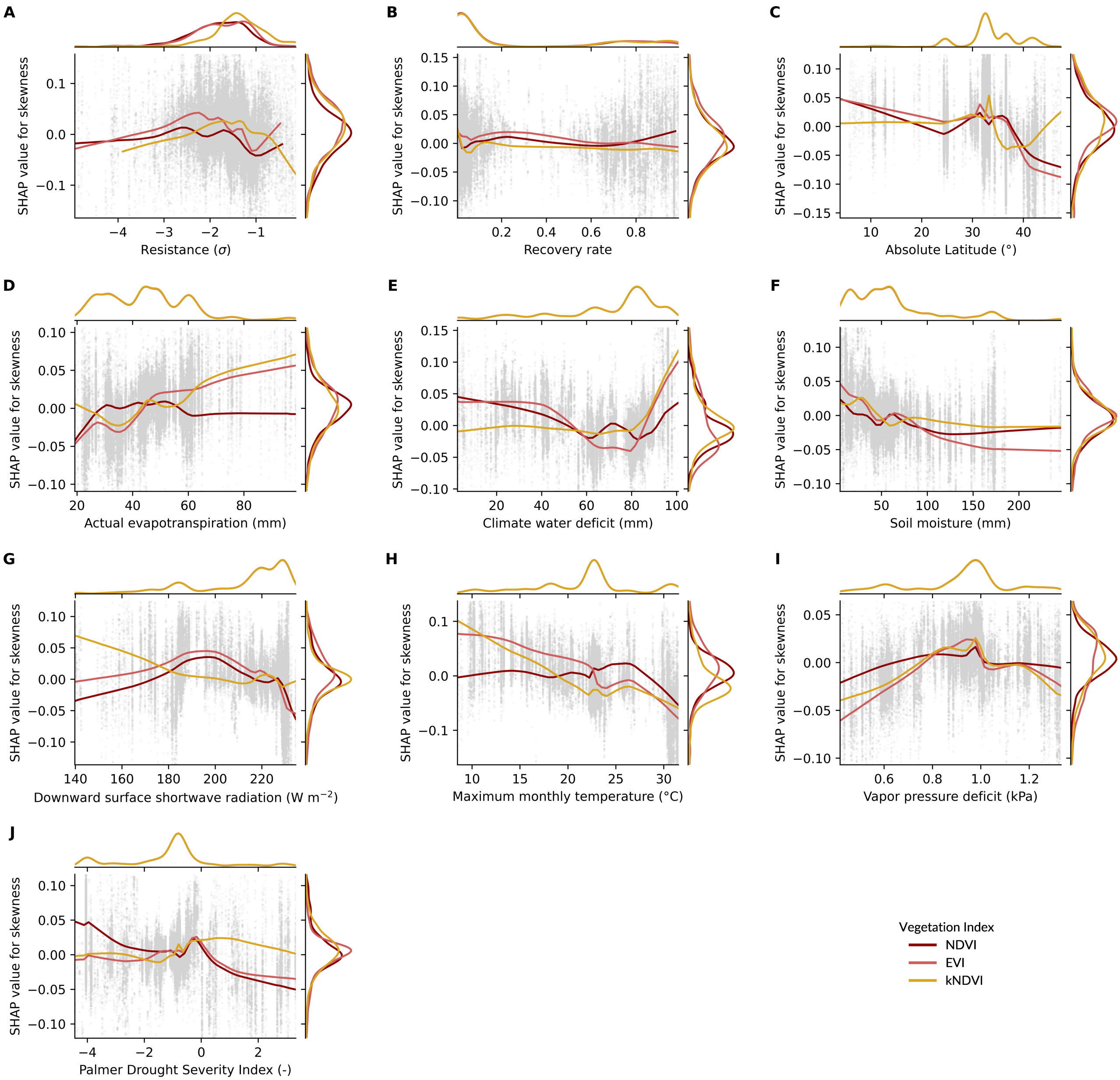

Figure B4. SHAP curves for **skewness models** for the different continuous drivers and resolved per vegetation index. Smooth curves in the plot represent LOWESS (locally weighted scatterplot smoothing) curves computed on the SHAP values which are shown as scatter plot in light grey. Marginal plots show density curves of the scatter plot distribution per vegetation index. The axis limits are clipped to the 99th percentile on each dimension.

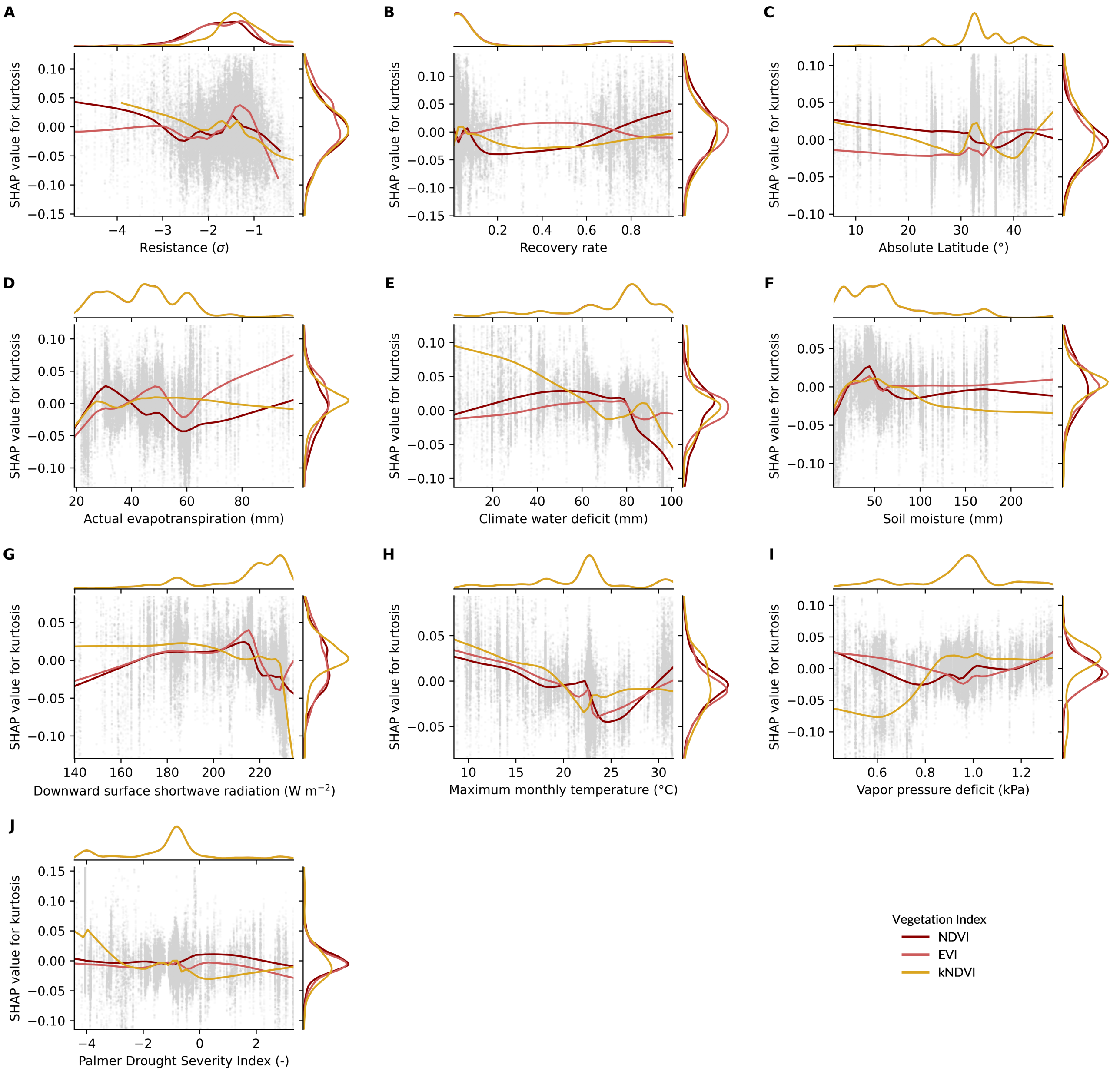

Figure B5. SHAP curves for **kurtosis models** for the different continuous drivers and resolved per vegetation index. Smooth curves in the plot represent LOWESS (locally weighted scatterplot smoothing) curves computed on the SHAP values which are shown as scatter plot in light grey. Marginal plots show density curves of the scatter plot distribution per vegetation index. The axis limits are clipped to the 99th percentile on each dimension.

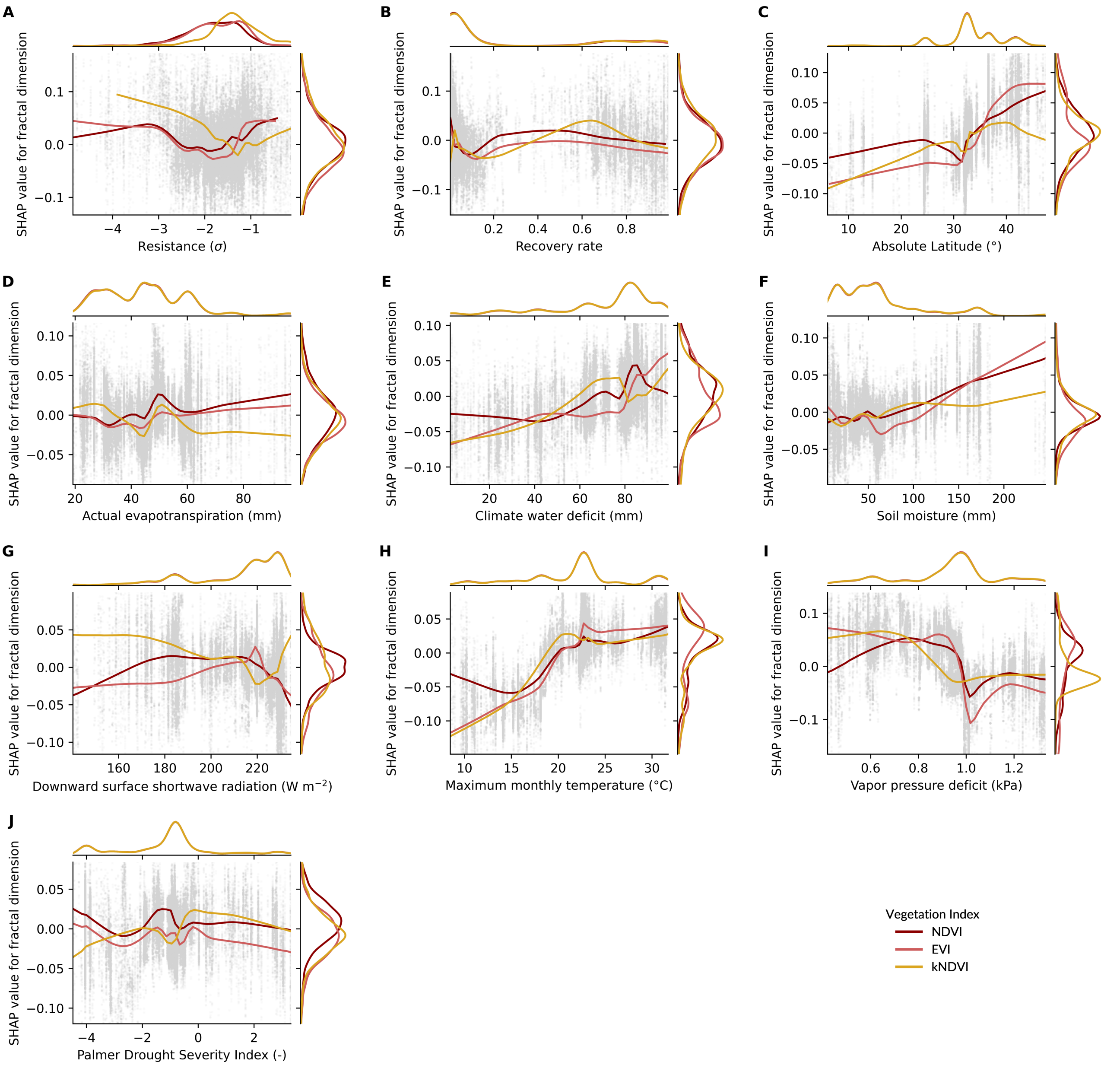

Figure B6. SHAP curves for **fractal dimension models** for the different continuous drivers and resolved per vegetation index. Smooth curves in the plot represent LOWESS (locally weighted scatterplot smoothing) curves computed on the SHAP values which are shown as scatter plot in light grey. Marginal plots show density curves of the scatter plot distribution per vegetation index. The axis limits are clipped to the 99th percentile on each dimension.

Author contributions. N.K. led the analysis and the writing of the paper. R.L. and I.F. contributed to the computations and editing of the manuscript. J.R. acquired funding support, oversaw the project progress, and contributed to interpretation and editing.

Competing interests. The authors declare that they have no competing interests.

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