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Detecting early warning signals of tree mortality in boreal North America using multiscale satellite data

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Abstract

Increasing tree mortality from global change drivers such as drought and biotic infestations is a widespread phenomenon, including in the boreal zone where climate changes and feedbacks to the Earth system are relatively large. Despite the importance for science and management communities, our ability to forecast tree mortality at landscape to continental scales is limited. However, two independent information streams have the potential to inform and improve mortality forecasts: repeat forest inventories and satellite remote sensing. Time series of tree-level growth patterns indicate that productivity declines and related temporal dynamics often precede mortality years to decades before death. Plot-level productivity, in turn, has been related to satellite-based indices such as the Normalized difference vegetation index (NDVI). Here we link these two data sources to show that early warning signals of mortality are evident in several NDVI-based metrics up to 24 years before death. We focus on two repeat forest inventories and three NDVI products across western boreal North America where productivity and mortality dynamics are influenced by periodic drought. These data sources capture a range of forest conditions and spatial resolution to highlight the sensitivity and limitations of our approach. Overall, results indicate potential to use satellite NDVI for early warning signals of mortality. Relationships are broadly consistent across inventories, species, and spatial resolutions, although the utility of coarse-scale imagery in the heterogeneous aspen parkland was limited. Longer-term NDVI data and annually remeasured sites with high mortality levels generate the strongest signals, although we still found robust relationships at sites remeasured at a typical 5 year frequency. The approach and relationships developed here can be used as a basis for improving forest mortality models and monitoring systems.

KEYWORDS
browning, dieback, drought, inventory, NDVI, pests and pathogens, productivity

1 | INTRODUCTION

Tree mortality from drought, heat, and pests and pathogens is increasing in many locations globally in response to global change drivers, primarily climate change (Allen et al., 2010; Brienen et al., 2015; Carnicer et al., 2011; Kautz, Meddens, Hall, & Arneth, 2017; Kharuk, Im, Oskorbin, Petrov, & Ranson, 2013; van Mantgem et al., 2009; McDowell et al., 2016). Tree mortality precipitates a cascade of ecosystem impacts relevant for carbon cycling, energy budgets, nutrient cycling, hydrology, habitat and food webs, and ecosystem

services (Adams et al., 2012; Anderegg, Kane, & Anderegg, 2013; Anderegg et al., 2016; Berner, Law, Meddens, & Hicke, 2017; Breshears, Lopez-Hoffman, & Graumlich, 2011; Edburg et al., 2012; Huang & Anderegg, 2014). If mortality occurs over large enough areas, it can accelerate shifts in biome distributions (Allen & Breshears, 1998; Clifford & Booth, 2015). Drought, including associated high temperature stress, is the primary climate characteristic associated with tree mortality (Allen et al., 2010; Williams et al., 2013). Although mortality from a single drought event can be severe (Anderegg, Plavcova et al., 2013; Michaelian, Hogg, Hall, & Arsenault, 2011), mortality is often associated with prolonged or repeated droughts (Bigler, Braker, Bugmann, Dobbertin, & Rigling, 2006; Gustafson & Sturtevant, 2013; Jump et al., 2017; Mitchell et al., 2013). Drought also combines with pests and pathogens that are able to exploit dry conditions to weaken and kill trees (Anderegg & Callaway, 2012; Anderegg et al., 2015; Hicke et al., 2012; McDowell et al., 2011; Poyatos, Aguade, Galiano, Mencuccini, & Martinez-Vilalta, 2013; Raffa et al., 2008). Despite its importance, our ability to model and forecast tree mortality at large scales is limited. Mortality representations in prognostic ecosystem models are evolving in complexity and realism (Chang et al., 2014; Davi & Cailleret, 2017; Manusch, Bugmann, Heiri, & Wolf, 2012; McDowell et al., 2013), but are still generally inadequate for many applications (Adams, Williams et al., 2013; McDowell et al., 2011).

Although they cannot be easily scaled across a landscape or region, plot-specific statistical models of mortality can have high predictive power (Bigler & Bugmann, 2003, 2004a,b; Cailleret et al., 2016; Carus, 2010; Gillner, Rueger, Roloff, & Berger, 2013; Ogle, Whitham, & Cobb, 2000; Wunder, Reineking, Matter, Bigler, & Bugmann, 2007; Yang, Titus, & Huang, 2003; Yao, Titus, & MacDonald, 2001). Their success comes from capturing early warning signals of mortality in productivity metrics. These signals most commonly consist of declining growth rates, but lower mean growth rates and subtle variations such as increased autocorrelation and variance in tree ring widths have been documented. Links between low growth rates and mortality have long been noted by ecologists and foresters (Wyckoff & Clark, 2000), and quantitative analysis using tree rings, repeat inventories, and wood anatomy details these signals years to decades before death (Berdanier & Clark, 2016; Bigler, Gricar, Bugmann, & Cufar, 2004; Bigler et al., 2006; Bond-Lamberty et al., 2014; Coyea & Margolis, 1994; Drobyshev, Linderson, & Sonesson, 2007; Heres, Martinez-Vilalta, & Claramunt Lopez, 2012; Kharuk, Ranson, Oskorbin, Im, & Dvinskaya, 2013; Kharuk, Im et al., 2013; Mamet, Chun, Metsaranta, Barr, & Johnstone, 2015; Pellizzari, Julio Camarero, Gazol, Sanguesa-Barreda, & Carrer, 2016). Typically, tree vigor is gradually reduced by an accumulation of drought and/or biotic-related stresses and a variety of predisposing genetic and environmental factors until an inciting event finally triggers mortality (Camarero, Gazol, Sanguesa-Barreda, Oliva, & Vicente-Serrano, 2015; Oliva et al., 2016; Pedersen, 1998a, 1998b; Suarez, Ghermandi, & Kitzberger, 2004; Voltas et al., 2013).

Remote sensing is capable of observing changes in ecosystem dynamics, such as forest productivity, from the level of individual plots to the large spatial scales often simulated by prognostic ecosystem models. Hence, remote sensing may offer a technique to provide direct observations and bridge the spatial gap between plot-based statistical models and coarse-scale ecosystem models of mortality for near-term forecasting (i.e., 5–20 years). The Normalized difference vegetation index (NDVI) is a widely used remote indicator of productivity. NDVI is sensitive to the fraction of absorbed photosynthetically active radiation (FAPAR) and can therefore serve as a proxy for gross primary productivity on relatively long timescales, such as a growing season (Gamon et al., 1995; Goetz & Prince, 1999; Myneni, Hall, Sellers, & Marshak, 1995; Tucker, 1979). NDVI can be derived from a variety of sensors covering decades of global imagery. Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and Landsat NDVI time series are widely used and now span 16–37 years. Each of these products has its own advantages and limitations related to spatial resolution, temporal coverage, radiometric and spatial fidelity, and processing requirements. To the extent that NDVI captures productivity, and productivity dynamics portend tree death, NDVI patterns should be capable of detecting such early warning signals. These relationships have been suggested (Huang & Anderegg, 2014; Vicente-Serrano et al., 2016), but never robustly explored using observational data.

Boreal forests are an important biome for mortality dynamics. They contain roughly one-third of global forested area and a similar proportion of terrestrial carbon stocks (Bradshaw & Warkentin, 2015; Kasischke, Christensen, & Stocks, 1995; Soja et al., 2007). Climate has been rapidly warming in these high latitude environments (Hartmann et al., 2013) and is projected to continue (Chylek et al., 2016; Collins et al., 2013). Climate feedbacks are amplified due to the large biophysical and biogeochemical impacts of disturbance (Betts, 2000; Randerson et al., 2006), making boreal forests a potential "tipping element" in the climate system (IPCC, 2014; Lenton et al., 2008).

Despite many boreal forests benefitting from recent warming (Barichivich et al., 2014; Zhu et al., 2016), there is an emerging understanding that productivity in the interior continental boreal regions, particularly Alaska and central-western Canada, is increasingly limited by moisture. Warmer and earlier springs cause higher immediate productivity (Buermann, Bikash, Jung, Burn, & Reichstein, 2013; Goetz, Mack, Gurney, Randerson, & Houghton, 2007; Randerson, Field, Fung, & Tans, 1999), but tend to result in drought stress and lower productivity later in summer (Barichivich et al., 2014; Beck, Juday et al., 2011; Buermann et al., 2013; Goetz, Bunn, Fiske, & Houghton, 2005; Parida & Buermann, 2014). Field-based studies using forest inventory, dendrochronology, and CO_2 fluxes from eddy covariance corroborate the temperature and drought sensitivity of boreal forests, with negative responses to temperature increasingly observed (Barber, Juday, & Finney, 2000; Lloyd & Bunn, 2007; Silva, Anand, & Leithead, 2010). Sensitivity to drought and high temperatures is species-dependent (Drobyshev, Gewehr, Berninger, & Bergeron, 2013; Girardin, Bouriaud et al., 2016; Huang et al., 2010; Welp, Randerson, & Liu, 2007) and generally highest in dry and interior sites (Grant et al., 2009; Hember, Kurz, & Coops, 2017a; Ma

et al., 2012; Ohse, Jansen, & Wilmking, 2012; Tei et al., 2017), but for some species all site types may be susceptible (Girardin, Hogg et al., 2016; Mamet et al., 2015; Walker & Johnstone, 2014; Walker, Mack, & Johnstone, 2015). As a result, NDVI records from AVHRR and MODIS show areas of the North American boreal forest to be browning (i.e., declining productivity during the growing season) since the early to mid-1990s, especially later in the growing season and in denser stands (Angert et al., 2005; Beck & Goetz, 2011; Bunn & Goetz, 2006; Goetz et al., 2005; Guay et al., 2014). Warming and drying have also resulted in extreme mortality events (Hogg, Brandt, & Michaellian, 2008; Worrall et al., 2013), increasing mean mortality rates (Peng et al., 2011; Zhang, Huang, & He, 2015), and associated loss of biomass in mature stands (Chen & Luo, 2015; Chen, Luo, Reich, Searle, & Biswas, 2016; Ma et al., 2012; Michaelian et al., 2011).

Here we assess the potential for NDVI to provide early warning signals of tree mortality in central-western boreal North America. Our overarching hypothesis is that early warning signals of mortality can be detected using long-term satellite imagery. We focused on this region because of its changing climate, drought sensitivity, potential feedbacks to climate, and proven relationships between forest productivity and NDVI. Several studies have related NDVI to site-scale productivity in boreal forests, including from coarse-scale AVHRR, with considerable success (Beck, Juday et al., 2011, 2013; Berner, Beck, Bunn, Lloyd, & Goetz, 2011; Bunn et al., 2013; Lloyd, Bunn, & Berner, 2011). Yet the relationships with other important ecosystem characteristics, and particularly the extent to which browning is related to mortality, are unknown. Deriving such relationships would advance a number of interrelated research disciplines and provide a foundation for monitoring, forecasting, and management. We focus strategically on two repeat forest inventories and three NDVI data sets to highlight a combination of sensors, metrics, and inventory characteristics that are most promising.

2 | MATERIALS AND METHODS

2.1 | Forest inventory data

We used two data sources with complimentary sets of repeatedly measured forest ground plots: the Cooperative Alaska Forest Inventory (CAFI) (Malone, Liang, & Packee, 2009) and the Climate Impacts on Productivity and Health of Aspen (CIPHA) study (Hogg, Brandt, & Kochtubajda, 2005). CAFI contains 612 permanent sample plots (PSPs), each covering 405 m^2 (66 × 66 ft) and arranged in sets of three per site spaced 30–63 m apart. Plots were established beginning in 1994 in interior and south-central Alaska including the Kenai Peninsula (Figure 1), and the majority (95%) were resampled every 5 years (the remaining were resampled between 4 and 10 years). We included inventory data through 2014, at which time 98% of the plots had been sampled at least twice, 78% were sampled at least three times, 35% four times, and 2% five times. Plots were dominated (in terms of biomass) by white spruce (*Picea glauca*, 34%), Alaska birch (*Betula neoalaskana*, 29%), quaking aspen (*Populus tremuloides*, 16%),

and black spruce (*Picea mariana*, 13%), with minor contributions from Kenai birch (*Betula kenaica*, 4%), balsam poplar (*Populus balsamifera*) or black cottonwood (*Populus trichocarpa*) (4%, not distinguished in the inventory), tamarack (*Larix laricina*, <1%), mountain hemlock (*Tsuga mertensiana*, <1%), and Lutz spruce (*Picea Lutzii*, <1%).

We excluded plots that were measured only once (2%), as they do not allow for temporally precise mortality measurements, as well as plots that burned within 50 years of being measured (12%) to avoid the effects of early stand succession. Fire history was determined by a combination of plot-scale information and fire polygons from the Alaska Large Fire Database (Kasischke, Barry, & Williams, 2002). We also excluded plots that were reported to have inventory errors or direct human disturbance (1%). We quantified plot-level stem density and aboveground biomass by species considering trees with a minimum diameter at breast height (DBH, 1.3 m height) of 3.8 cm (or 1.5", the original minimum used in CAFI). We used allometric relationships from Alexander, Mack, Goetz, Beck, and Belshe (2012) (white spruce if DBH ≥3.7 cm, Alaska birch, quaking aspen, black spruce, and balsam poplar if DBH ≥4.1 cm), Ung, Bernier, and Guo (2008) (white spruce, quaking aspen, and mountain hemlock), and Lambert, Ung, and Raulier (2005) (balsam poplar and tamarack). In each case the mean value from the collection of relevant allometric equations was used. Due to lack of data for certain species, we applied equations from Alaska birch to Kenai birch, western hemlock to mountain hemlock, and white spruce to Lutz spruce. Mortality was derived from status flags of individual remeasured trees and quantified as the number of trees and amount of aboveground biomass that died per year during every remeasurement interval.

CIPHA includes 150 plots within pure aspen stands with an average age between 40 and 80 years at plot establishment (Hogg et al., 2005). Plots cover 150–350 m^2 and are arranged in sets of two per site spaced 50–100 m apart and at least 50 m from the stand edge. Sites are further grouped into sets of three, spaced at a distance of 30 km or less, and aggregated into 25 study areas (Figure 1). Roughly half of the study areas (48%) reside in the aspen parkland with low to moderate canopy cover, and the other half in the more densely canopied boreal forest (Figure 1). Plots were established in 2000 across the western Canadian interior and resampled annually until 2012 (with the exception of 43 plots that were not remeasured between 2009 and 2011 but experienced relatively low mortality). We excluded one study area (Hartney) that was damaged by a tornado in 2007. Aboveground biomass was calculated using allometric equations from Lambert et al. (2005) for trees with DBH ≥7 cm, and mortality was calculated similar to CAFI but on an annual basis. Plots were dominated by aspen (98%), with minor contributions from balsam poplar and paper birch (*Betula papyrifera*). Further information can be found in Hogg et al. (2005, 2008). Because individual plots in both CAFI and CIPHA were designed to be spatially aggregated to sites, we calculated site-level mortality for our analysis. To do so, we simply averaged percent mortality across the relevant plots.

These repeat inventories are complimentary in several ways. CAFI includes a variety of boreal species and is relatively typical of other PSP networks in which plots are resampled every 5 or
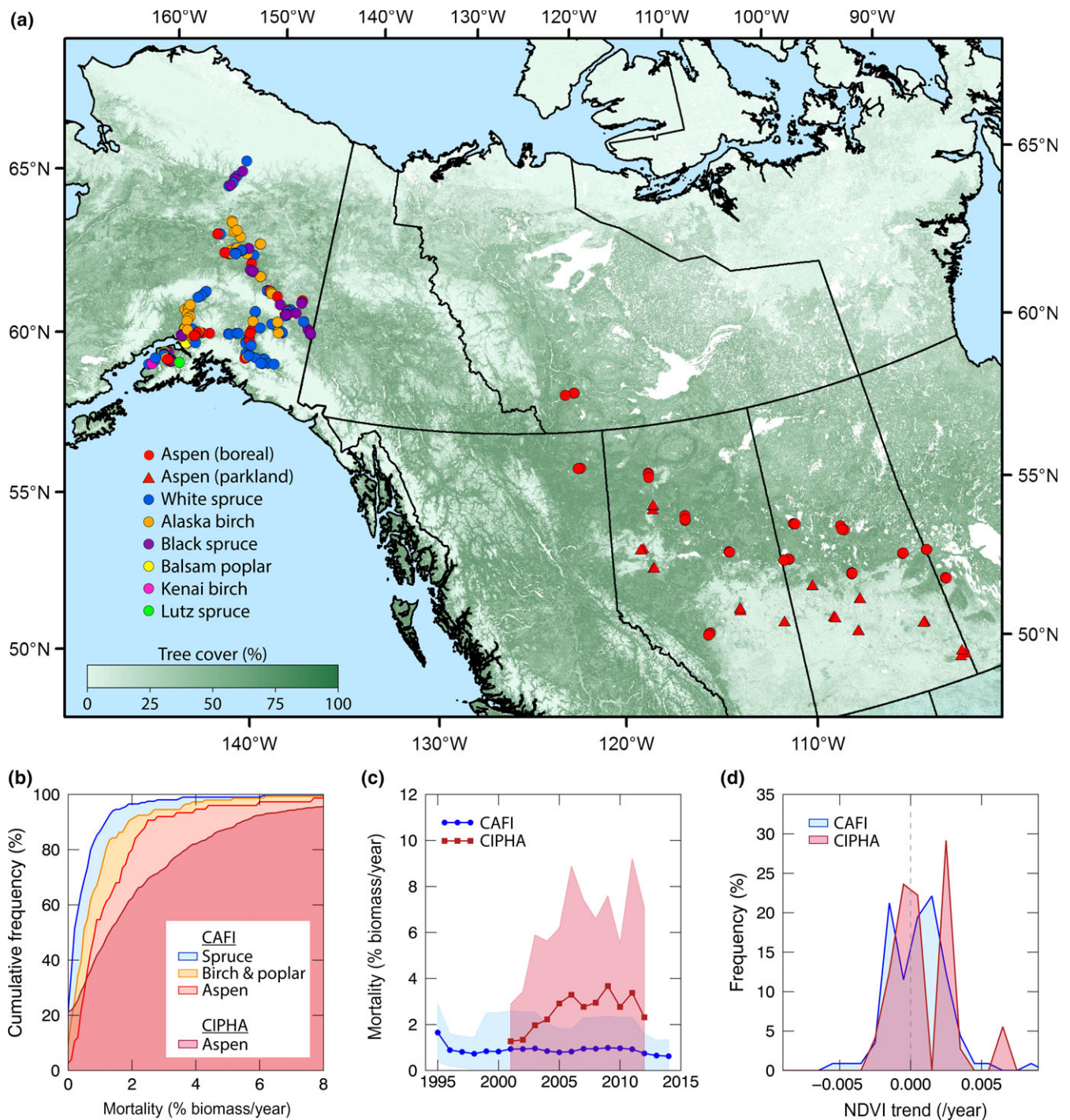
FIGURE 1 Spatial configuration (a), mortality dynamics (b,c), and Normalized difference vegetation index (NDVI) trends (d) at the Cooperative Alaska Forest Inventory (CAFI) and Climate Impacts on Productivity and Health of Aspen (CIPHA) sites. Sites in (a) are categorized by dominant species and region, and tree cover was derived from Moderate Resolution Imaging Spectroradiometer (MODIS) (MOD44B year 2014, version 6 (DiMiceli et al., 2015)). A cumulative distribution of mortality rates by species (b) shows clear differences between species groups, and particularly high mean mortality rates in CIPHA aspen plots from 2006 to 2011 (c). Shading in (c) represents one standard deviation. NDVI trends in (d) were derived from Global Inventory Modeling and Mapping Studies version 3 product (GIMMS$_{3g}$) from 1982 to 2014

10 years (e.g., Canadian Provincial networks and the US Forest Inventory and Analysis Program). Mortality can therefore only be defined within 5 year windows, which is a limitation for establishing relationships with remote sensing. CIPHA, on the other hand,

includes an ideal annual remeasurement frequency and only one dominant species (aspen). In contrast to the relatively steady mortality rates at CAFI (Figure 1c), a severe drought event in 2001–2003 in central Canada led to widespread aspen mortality, especially in

the CIPHA parkland sites (Hogg et al., 2008; Michaelian et al., 2011). However, CIPHA includes a shorter time series than CAFI, and the heterogeneity of the parkland prairie-forest landscape may present challenges for remote sensing, particularly using coarser resolution imagery.

2.2 | NDVI data

We derived annual NDVI time series from three commonly used satellite systems to explore the relationships with mortality: AVHRR, MODIS, and Landsat. In each case, we calculated mean NDVI during the months of July and August at the native resolution. We focused on mean July–August NDVI as it corresponds to peak summer productivity in northern ecosystems and is sensitive to drought (Buermann et al., 2013; Ju & Masek, 2016; Sulla-Menashe, Fried, & Woodcock, 2016). NDVI was averaged across the relevant plots for each site.

For AVHRR, we used the bimonthly maximum composite Global Inventory Modeling and Mapping Studies version 3 product (GIMMS$_{3g}$) from 1982 to 2014 (Pinzon & Tucker, 2014), which is produced at 1/12° or "8 km" resolution (approximately 4–5 × 9 km in the northern latitudes we considered). Although other AVHRR-based NDVI products are available, GIMMS$_{3g}$ is the most widely used and consistently one of the best performing when compared to Landsat, in situ data, and temporal consistency between sensors (Beck, McVicar et al., 2011; Marshall, Okuto, Kang, Opiyo, & Ahmed, 2016; Tian et al., 2015). GIMMS$_{3g}$ contains a number of improvements over its predecessor, GIMMS$_g$, including better snow detection and intersensor calibration in a Bayesian framework (Guay et al., 2014; Pinzon & Tucker, 2014). For MODIS, we used the 16 day Collection 6 vegetation indices product from Aqua (MYD13Q1) at 250 m resolution from 2002 to 2014 (Didan, 2015a). Although its time series is shorter than Terra's by 2 years, we focus on Aqua because of the documented sensor degradation in Terra that affects NDVI (Wang et al., 2012). Despite corrections in Collection 6, we observed more browning in Terra compared to Aqua for our region (Figure S1). We also performed the analyses with Terra (MOD13Q1; 2000–2014) (Didan, 2015b) for the sake of comparison. Finally, we used 30 m Landsat NDVI from Ju and Masek (2016) from 1984 to 2012. This included imagery from Landsat 5 (Thematic Mapper) and 7 (Enhanced Thematic Mapper Plus), processed with the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) with additional quality controls for clouds, cloud shadows, water, and snow, as well as a simple scaling factor to reduce bias between the two sensors. As a further quality control, and to avoid errors in plot geolocation, we averaged Landsat NDVI from a 3 × 3 pixel window surrounding each plot. Landsat data were almost universally available at the Canadian CIPHA sites beginning in 1984, but there were large gaps prior to 1999 at the CAFI sites in Alaska. We therefore excluded any Landsat observations before 1999 in Alaska.

These NDVI data sets are complimentary with respect to spanning a wide range of spatial resolution (30 m to 8 km) and radiometric fidelity. The coarse-scale AVHRR record, initiated in mid-1981,

includes a combination of different satellites and sensors with varying sensor calibrations and viewing geometries (Pinzon & Tucker, 2014). Additional issues stem from AVHRR's spectral configuration, sensor degradation, drifts in satellite overpass times, and its global area coverage (GAC) sampling and aggregation scheme (Fensholt & Proud, 2012; Hall, Masek, & Collatz, 2006; Ju & Masek, 2016). Landsat bypasses many of these issues and is theoretically superior by covering roughly the same time period (since 1984) at much higher spatial resolution (30 m). Nonetheless, Landsat has its own limitations, including a longer revisit frequency, sparse coverage in some locations, intersensor calibration, and large volumes of data that require careful processing (Ju & Masek, 2016; Sulla-Menashe et al., 2016; Zhang & Roy, 2016). Finally, MODIS NDVI products have high temporal frequency, robust atmospheric corrections, and a moderate resolution (250 m). However, sensor degradation has added uncertainty, and data are available only since 2000 (Terra) or 2002 (Aqua). Although comparisons of long-term trends between AVHRR and Landsat reveal differences across boreal North America (Fraser, Olthof, Carriere, Deschamps, & Pouliot, 2011; Ju & Masek, 2016; Olthof, Pouliot, Latifovic, & Chen, 2008), MODIS trends generally corroborate those from AVHRR (Barichivich et al., 2014; Beck & Goetz, 2011; Fensholt & Proud, 2012; Guay et al., 2014; Parent & Verbyla, 2010).

2.3 | Analysis

Our analysis was in the context of early warning signals (EWS) of threshold changes, in which loss of resilience proceeds state shifts in complex systems (Scheffer, Carpenter, Foley, Folke, & Walker, 2001) (note that throughout we use the term "EWS" in a broad sense to include any potential early warning signal of tree mortality). To that end, we quantified EWS metrics in NDVI time series prior to mortality "events" (e.g., Anderegg, Kane et al., 2013). We did not consider trends in field measurements of mortality, such as in van Mantgem et al. (2009) and Peng et al. (2011), as trends are generally not a threshold change, mortality tended to be episodic in the PSPs we considered, and temporal coverage did not allow for robust trend detection.

Because of their simplicity and intuitive relationships with known productivity dynamics prior to mortality, we focused primarily on trends and "jumps" in the NDVI time series prior to forest ground plot measurements (Figure 2). Negative trends can be indicative of declining productivity, which is frequently observed to precede mortality. We used simple linear regression to quantify NDVI trends. We also tested a nonparametric approach that is more robust against outliers, temporal autocorrelation, and normality. To do so, we applied the Theil–Sen trend method (Sen, 1968) after a prewhitening routine to remove lag-1 autocorrelation (Zhang, Vincent, Hogg, & Niitsoo, 2000) using the "zyp" package (Bronaugh & Werner, 2013) in R (R Core Team, 2012). Previous studies have used simple linear regression (e.g., Angert et al., 2005; Baird, Verbyla, & Hollingsworth, 2012; Beck & Goetz, 2011; Ju & Masek, 2016; Verbyla, 2008), augmented Dickey–Fuller and Vogelsang tests of stationarity (Beck &

Goetz, 2011; Bunn & Goetz, 2006; Goetz et al., 2005), and the Theil–Sen method (Berner, Beck, Bunn, & Goetz, 2013; Fensholt & Proud, 2012; Guay et al., 2014; Kim et al., 2014; Marshall et al., 2016) to estimate NDVI trends in boreal forests. To enable a more direct comparison between sites, we normalized trends to percent NDVI change per year using the mean for each site and NDVI product. For every mortality observation at every site, we varied the start date for trends depending on our analysis window (see below). To avoid including the year of mortality in our EWS metrics, we set the end date for trends to be 1 year prior to ground plot measurement for CIPHA. However, this was unavoidable in the case of CAFI's 5 year remeasurement strategy in which the specific year of mortality was unknown. We therefore set the end date for trends to be the midpoint of a given 5 year remeasurement interval after excluding the year of observation (i.e., year 2).

Negative jumps in the NDVI time series, or years with anomalously low NDVI, may represent inciting events such as drought or infestation. To quantify negative jumps, we first removed trends and other low-frequency variability by applying a 11 year Loess smoothing filter in R to the NDVI time series. Jumps were then estimated using z-scores of peak summer NDVI on the detrended time series (i.e., a larger negative z-score indicated a larger jump). End dates for jumps were set to 1 year prior to ground plot measurement for both CAFI and CIPHA. To help interpret results, we tested positive jumps using the same framework (note that positive trends are inherently included in our analysis). Because including the year of mortality in our EWS metrics was mostly unavoidable for CAFI, we tested its impact in CIPHA by setting the end date for both trends and jumps to the year of ground plot measurement.

Although we calculated mortality as both the percentage of live stems and biomass that died, we focused on biomass mortality because of its direct relationships with carbon cycling and ecosystem impacts. For a given remote sensing product and time window prior to inventory measurement, we excluded sites with at least two consecutive missing years or 25% missing years overall. In order to avoid the impacts of succession on satellite NDVI, we excluded sites for which the corresponding pixel experienced fire in the previous 50 years. Because of the smaller number of sites and therefore limited overlap between mortality observations and preceding NDVI time series, we excluded analysis of MODIS for CIPHA sites.

To assess how these EWS metrics are associated with mortality, we compared the percentage of sites that had negative trends or jumps (below a given z-score) and their magnitude between those classified as control and mortality events for each relevant inventory and NDVI product. We present this analysis in two primary ways. The first is a simple comparison of EWS metrics between mortality and control sites. Because this comparison relies on a suite of parameters, we employed a conservative Monte Carlo framework. In each case, we conducted 500 simulations by randomly selecting the following parameters using a relatively wide-ranging Latin hypercube: threshold for mortality events (2%–4% per year for CAFI and 2–20% for CIPHA); trend time window (8–15 years); jump time window (5–15 years); one-sided z-score threshold for jumps (−1.5 to −2); and, for CAFI, the end date for trends (30%–70% through the remeasurement interval after excluding the year of ground plot measurement). Significance was quantified using a bootstrap approach in which the population of differences (mortality minus control) from a set of Monte Carlo simulations was compared to zero, and p-values were defined by the fraction above or below zero (below for percentage and above for absolute). Secondly, to better represent the sensitivity of trends and jumps to the two dominant parameters, we present heat maps of the differences between mortality and control sites as a function of mortality threshold and time window.

Because transitions in boreal forest tree cover may proceed nonlinearly via threshold responses (Scheffer, Hirota, Holmgren, Van Nes, & Chapin, 2012), we also applied more complex EWS metrics from the literature designed to detect system state shifts (in our case mortality and subsequent loss of tree cover). This included the first-order autoregressive coefficient (AR(1)), density ratio, kurtosis, standard deviation, and skewness using the "earlywarnings" package in R (Dakos, Carpenter, Cline, & Lahti, 2014), as well as diffusion, jumps, total variance, and conditional variance from the Drift Diffusion Jump (DDJ) model (Brock & Carpenter, 2012; Carpenter & Brock, 2011; Dakos et al., 2012). Although some of these EWS metrics remain largely theoretical and without real-world examples (Scheffer et al., 2009), evidence from tree rings (Mamet et al., 2015; Ogle et al., 2000; Suarez et al., 2004) and broad-scale remote sensing (Verbesselt et al., 2016) suggests forests may display these dynamics prior to mortality. However, ground-based studies have shown mixed results (Camarero et al., 2015; Gillner et al., 2013), and remote sensing products may present problems due to relatively short time series (several decades as opposed to a century or more).

Finally, although some EWS metrics were calculated exclusively over a given time window (e.g., trends 10 years prior to inventory measurement), in other cases the entire NDVI time series was considered for parameter distributions and the metric of interest was then calculated over shorter time windows prior to inventory
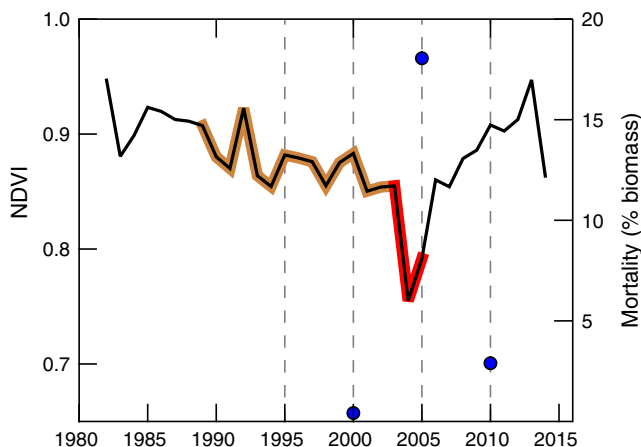
FIGURE 2 Example time series of NDVI (GIMMS$_{3g}$) and tree mortality in CAFI permanent sample plots (PSP 10036). A high level of mortality was observed in 2005, with a browning trend and jump (shown in red) prior to measurement. Note that each mortality measurement was incorporated into our analyses

measurement (e.g., jumps within a 10-year window after detrending the entire NDVI time series).

2.4 | Hypotheses

Within the context of our overarching hypothesis that early warning signals of mortality can be detected using long-term satellite imagery, we also tested the following secondary hypotheses:

1. Relationships between mortality and NDVI-based EWS metrics are strongest with finer spatial-scale and longer temporal-scale imagery.
2. Relationships with NDVI trends are detectable over longer time windows compared to jumps, as the former captures gradually declining vigor and the latter inciting events.
3. Relationships between mortality and EWS metrics are strongest in annually measured sites because longer remeasurement intervals add uncertainty as to the timing of mortality.
4. Relationships are strongest in aspen-dominated sites, and particularly those that are pure aspen (such as CIPHA). This is because (i) aspen's deciduous leaf habit results in more interannual variability in productivity (Welp et al., 2007) and leaf condition, as observed by NDVI, that responds more quickly to environmental stress compared to conifers (Gamon et al., 1995; Norman, Koch, & Hargrove, 2016); (ii) aspen are pioneer species and have comparatively high mean mortality rates, especially in later succession (Figure 1b) (Stephenson et al., 2011; Vanderwel, Zeng, Caspersen, Kunstler, & Lichstein, 2016); (iii) aspen die-off begins in the upper canopy (Anderegg & Callaway, 2012; Frey, Lieffers, Hogg, & Landhausser, 2004), which can be detected with multispectral imagery (Huang & Anderegg, 2014); (iv) aspen are clonal, meaning patches of genetically identical trees die together, and relatively quickly as a strategy for effective resprouting (Frey et al., 2004); (v) and finally, aspen have documented sensitivity to defoliation and drought, including mortality (Bell, Bradford, & Lauenroth, 2014; Chen et al., 2017; Hogg, Brandt, & Kochtubajda, 2002; Worrall et al., 2013).

3 | RESULTS

The percentage of negative trends and jumps in NDVI time series prior to inventory measurements was almost universally larger for sites with high mortality levels for both inventories and with all three NDVI products (Figure 3). The magnitudes of negative trends and jumps followed the same overall pattern, except that differences were substantially greater for trends compared to jumps (Figure 4). In only one case did the dynamics of these EWS metrics contradict our primary hypothesis (GIMMS$_{3g}$ trends for CIPHA). This specific case was due to the lack of a relationship using coarse-scale imagery in aspen parkland sites (Figure S2), which contain heterogeneous patches of aspen stands, grassland, agriculture, and other land uses. The boreal CIPHA sites displayed the expected relationship for

GIMMS$_{3g}$ trends, as did Landsat for both parkland and boreal sites (Figure S2). We note jumps with GIMMS$_{3g}$ in the parkland also behaved as hypothesized, suggesting coherent responses of punctuated drops in NDVI across these heterogeneous landscapes.

Differences in NDVI trends between mortality and control sites tended to become large and consistent when considering sites with higher mortality and at least 8 years of data prior to inventory measurement (Figure 5). With sufficient data, these patterns were mostly sustained until 15 years, and over 20 years in the case of CIPHA (Figure S3). Differences in the magnitude of trends were generally largest using shorter time windows compared to the percentage of negative trends, a result of trends becoming more steeply negative closer to mortality events (Figures 2,5, and S3). Similar overall patterns were observed for the percentage of sites exhibiting negative jumps (Figures 6 and S3), except that differences were generally observed using time windows as short as 2 years and, in the case of Landsat, largely disappeared with lower mortality thresholds and time windows longer than 11–12 years.

Gradients in trends and jumps as a function of mortality threshold were clearer and more consistent in CIPHA compared to CAFI. We attribute this to CIPHA's annual remeasurement strategy, which allowed for greater temporal accuracy and a wider range in annual mortality levels compared to CAFI, particularly when considering the severe regional drought in 2001–2003 and resulting mortality. The clarity of relationships observed for CIPHA may also be due its almost pure aspen stand composition, which we hypothesized to have the strongest species-specific relationships with EWS metrics from remote sensing. However, aspen, spruce, and birch/poplar-dominated stands in CAFI all displayed generally consistent relationships across sensors (Figure S4), suggesting EWS metrics of mortality can be applied across forest types. In terms of canopy cover, although the relationships using coarse-scale GIMMS$_{3g}$ trends broke down in the patchy aspen parkland, relationships in CAFI, although less significant, were relatively insensitive to low canopy cover. For example, the mean difference in % negative trends between mortality and control sites with GIMMS$_{3g}$ at CAFI sites was 11.4% using all sites and 7.6% using sites whose corresponding GIMMS$_{3g}$ pixels had at least 40% tree cover (55% of sites), derived from the MODIS tree cover product (DiMiceli et al., 2015).

In contrast to our hypothesis, and with the exception of GIMMS$_{3g}$ trends in the heterogeneous and human-affected aspen parkland, using finer-scale imagery did not necessarily lead to stronger results. Although Landsat trends showed greater differences between mortality and control sites compared to GIMMS$_{3g}$, the opposite was true for jumps (Figure 3). Thus, compared to Landsat, this suggests coarse-scale GIMMS$_{3g}$ NDVI is more sensitive to pulse disturbances that affect vegetation across a landscape, but is less sensitive to trends at any given site. Results were nearly identical when including the year of ground plot measurement for both CIPHA and CAFI (Figures S5 and S6). This provides evidence that the mortality events themselves did not affect our EWS metrics, and further highlights their long-term nature. When using stem mortality as opposed to percent biomass mortality, however, the
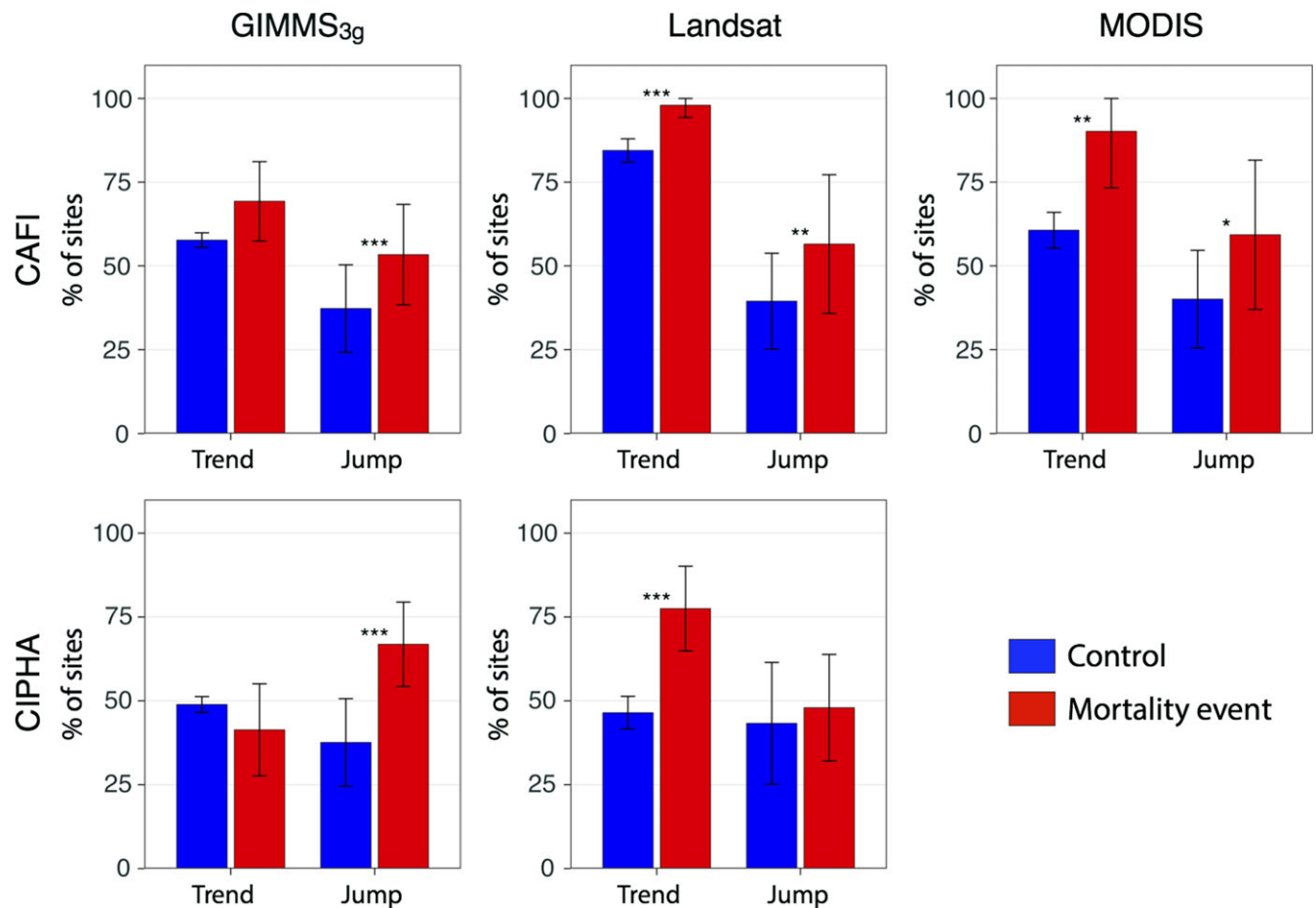
FIGURE 3 Percentage of mortality and control sites that displayed negative trends or negative jumps prior to inventory measurement. A Monte Carlo approach was used to vary several analysis parameters, including the mortality threshold used to define mortality events. Error bars represent one standard deviation from 500 Monte Carlo simulations. One, two, and three stars indicate one-sided significance at the $p < .1$, .05, and .01 levels, respectively. Note that we do not include analysis of MODIS at CIPHA sites due to lack of data [Color figure can be viewed at wileyonlinelibrary.com]

overall EWS patterns were evident but not as strong (Figure S7). Relationships using MODIS Aqua were also stronger than Terra (Figure S1), which could be due to issues with sensor degradation in MODIS Terra. Results using the Theil–Sen method with prewhitening for trend detection were qualitatively identical to using simple linear regression, but with reduced significance in the case of Landsat and MODIS ($p > .1$ for CAFI Landsat and MODIS, and $p < .1$ for CIPHA Landsat when assessing the differences in percent negative trends between mortality and control sites, as in Figure 3). We attribute the improved performance of linear regression to its sensitivity to negative jumps and increasingly steep slopes when approaching mortality events in the NDVI time series. This is evidenced by slightly more than expected nonnormal residual distributions (10% of residual distributions failed the Shapiro–Wilk test for normality at $p < .05$) and autocorrelation (12% of residual time series contained significant autocorrelation using the Durbin–Watson statistic at $p < .05$), especially close to severe mortality events (Figure 7). Because of its sensitivity, this suggests simple linear regression is well-suited to detect early warning signals of tree mortality.

Results using positive instead of negative jumps were similar in direction but smaller in magnitude and less significant. Across inventories and NDVI products, there were substantially more negative jumps than positive jumps using identical analysis parameters (39.5% vs. 21.8% in control sites), and differences between mortality and control sites were greater using negative jumps (16.8% vs. 4.4%). This supports the hypothesis that many negative jumps were related to acute stressors and that these stressors were often indicative of subsequent mortality. Combined with the trends analysis, this also suggests that positive trends or jumps in productivity, potentially indicative of structural overshoot that renders trees vulnerable to mortality (Jump et al., 2017), were a minor component of NDVI signals.

Several, although not all, of the more complex EWS metrics displayed consistent relationships with mortality (Figure 7). AR(1), density ratio, kurtosis, and conditional variance increased at sites that had higher mortality levels when using NDVI records with long time series (GIMMS$_{3g}$ for both inventories and Landsat for CIPHA). The remaining EWS metrics either did not display significant relationships with mortality, or the relationships were inconsistent across sensors and inventories.
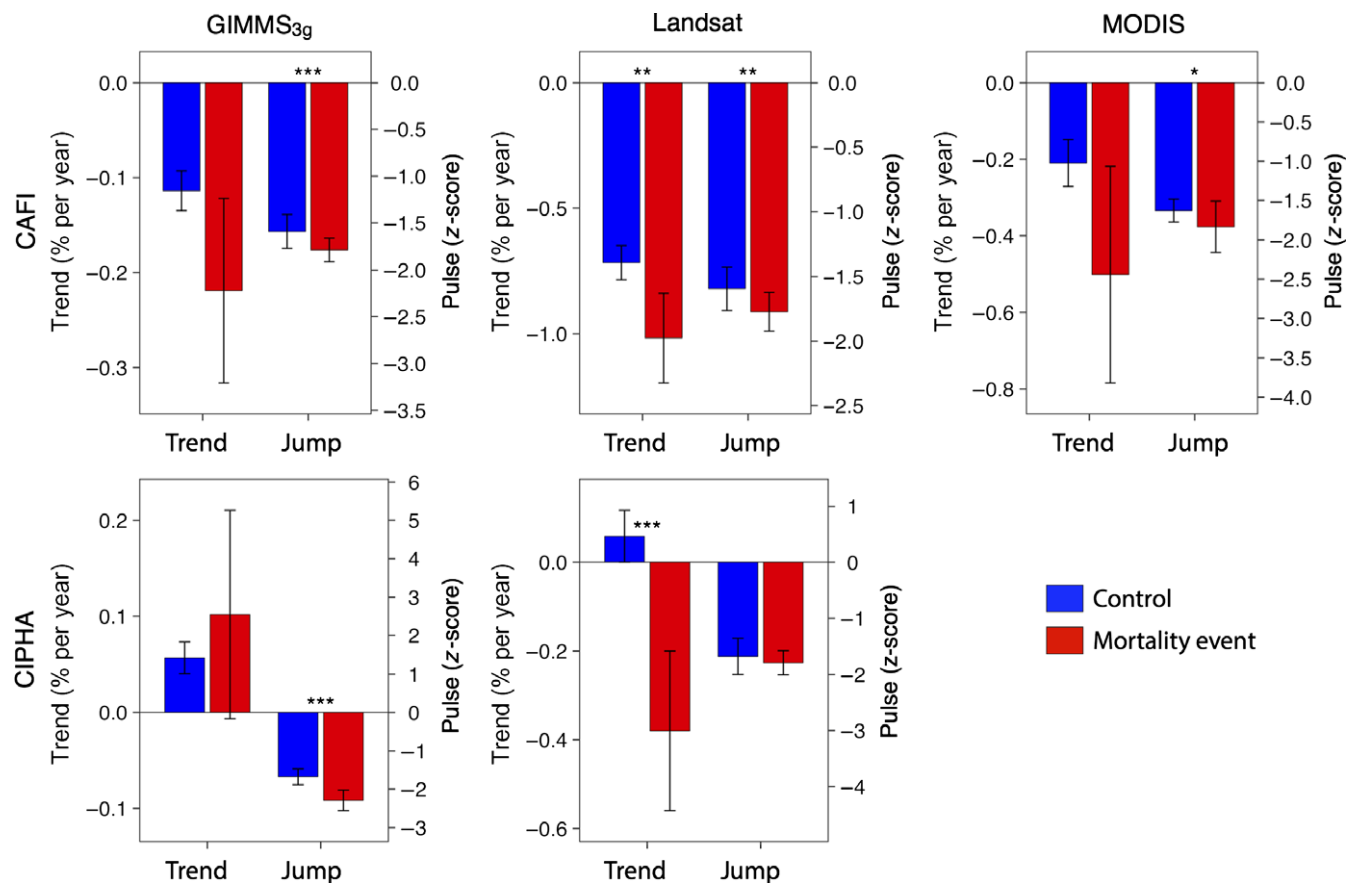
FIGURE 4 Magnitude of all trends and negative jumps (defined by the minimum z-score within a given time window) between mortality events and control sites. Error bars represent one standard deviation from 500 Monte Carlo simulations. One, two, and three stars indicate significance at the $p < .1$, $.05$, and $.01$ levels, respectively. The magnitude of negative trends and jumps was greater in mortality events, except for the case of trends in CIPHA GIMMS$_{3g}$ [Color figure can be viewed at wileyonlinelibrary.com]

4 | DISCUSSION

Boreal forests cover roughly one-third of all forests globally and are defined by cold climates where warming might be expected to be beneficial. Indeed, productivity in many boreal forests has been positively influenced by warming, and even negatively influenced by higher summer rainfall through its effect on surface insolation (Angert et al., 2005; Barichivich et al., 2013; Buermann et al., 2013, 2014; Jiang, Zhu, Zheng, Chen, & Fan, 2013; Myneni, Keeling, Tucker, Asrar, & Nemani, 1997; Wang et al., 2011). However, many interior and continental boreal forests for which moisture is more limiting are not responding favorably. This is especially the case in central-western boreal North America, where growing seasons have been lengthening (Barichivich et al., 2013; Buitenwerf, Rose, & Higgins, 2015; Zhang, Kimball, Kim, & McDonald, 2011; Zhao et al., 2015), spring snowpack has been decreasing (Brown & Robinson, 2011; Gan, Barry, Gizaw, Gobena, & Balaji, 2013), and water balance variables indicate a persistent drying since the mid-20th century (Dai, 2011; Girardin, Bouriaud et al., 2016; Hember, Kurz, & Coops, 2017b; Hogg, Michaelian, Hook, & Undershultz, 2017; Michaelian et al., 2011). Temperature optimums are often surpassed quicker than trees and many forests can adapt (Beck, Juday et al., 2011; D'

Arrigo et al., 2004; Juday, Alix, & Grant, 2015), such that the relationships between climate and productivity have frequently changed after the mid-20th century (Bi, Xu, Samanta, Zhu, & Myneni, 2013; D' Arrigo et al., 2004; D'Arrigo, Wilson, Liepert, & Cherubini, 2008; Porter & Pisaric, 2011).

As a result, tree mortality has generally been increasing in these boreal forests (Hember et al., 2017b; Peng et al., 2011), generating concern about their future condition and stability. The ability to forecast mortality is essential for multiple communities ranging from resource managers to Earth system modelers. However, our collective ability to do so is limited, in large part due to the complex pathways of death and highly variable physiological thresholds (Anderegg, Anderegg, & Berry, 2013).

Here we provide evidence that long-term NDVI time series have the potential to detect early warning signals of tree mortality using a variety of sensors, time scales, forest systems, and tree species in western boreal North America. The utility of NDVI for mortality forecasting has been suggested (Huang & Anderegg, 2014; Vicente-Serrano et al., 2016) and is consistent with known relationships between satellite-based NDVI (or similar indices) and drought, infestations, productivity, leaf senescence and partial dieback, and mortality (Beck, Juday et al., 2011; Berner et al., 2011; Breshears et al.,
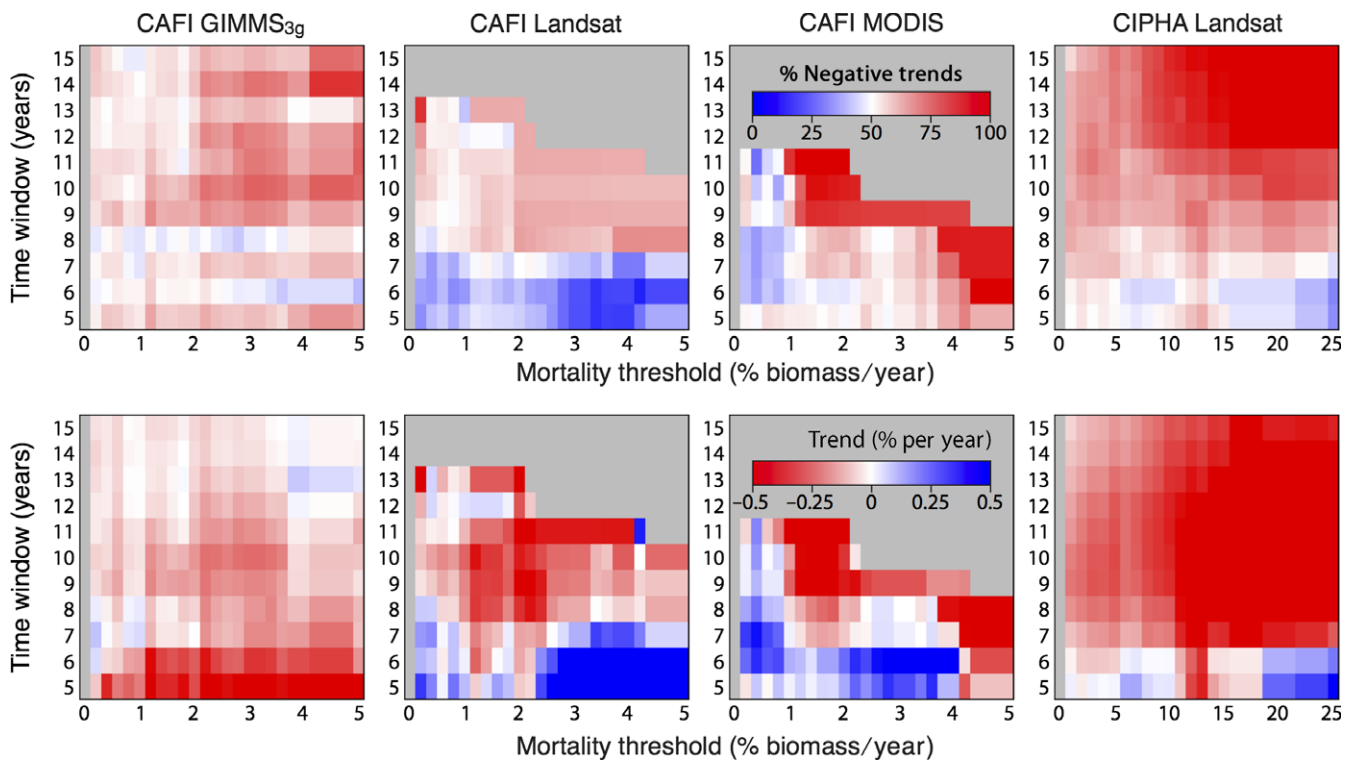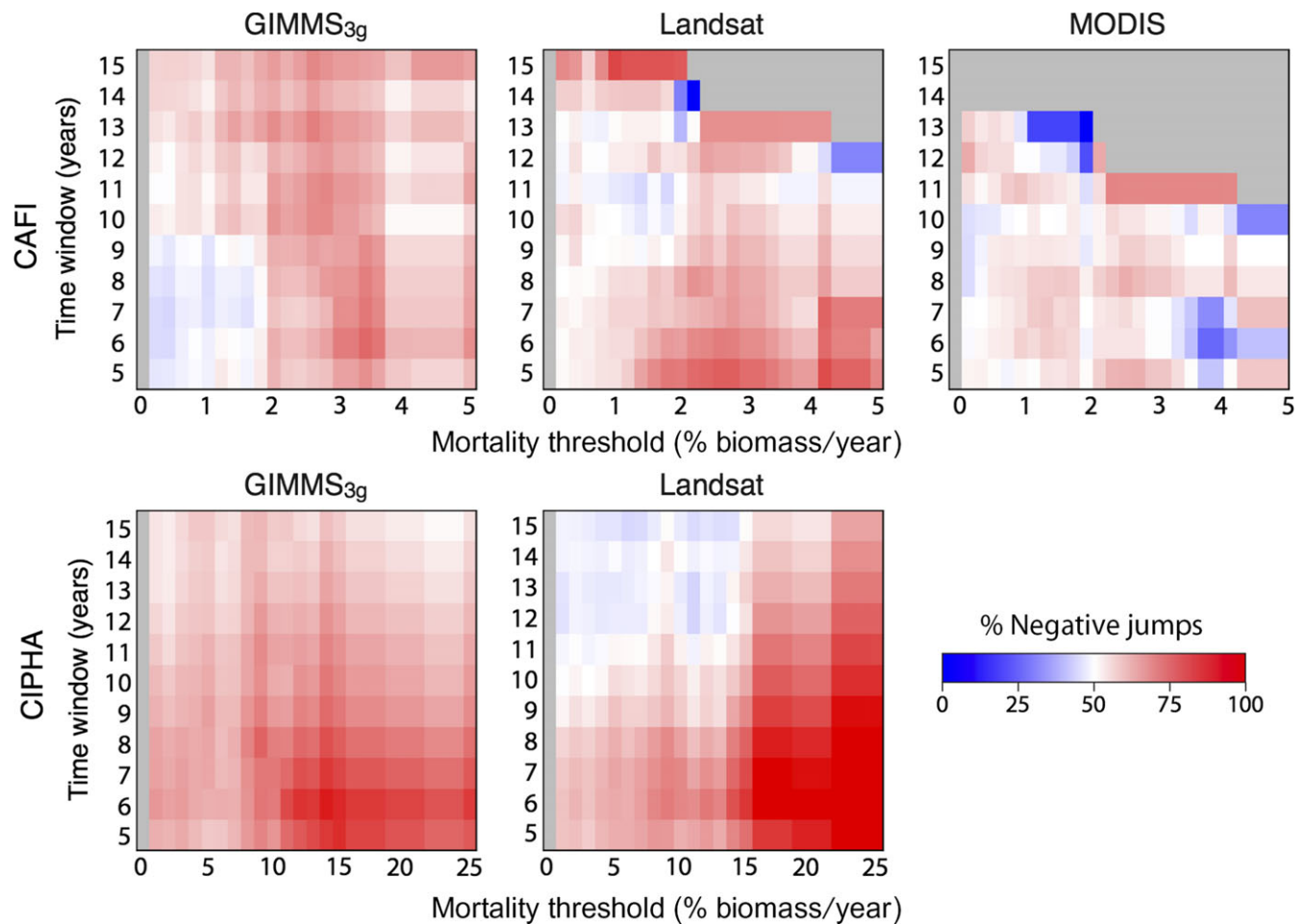
FIGURE 5 Heat maps showing the difference in NDVI trends between mortality and control sites as a function of mortality threshold and time window for analysis. The top row shows percent negative trends, and the bottom row shows the magnitude of trends. In each case, red represents conditions in which sites classified as mortality events had more or stronger negative NDVI trends relative to control sites, and blue represents the opposite. Note that there are no "control" sites with a mortality threshold of zero, which we therefore exclude, and that we do not show GIMMS$_{3g}$ trends at CIPHA due to the lack of consistent relationships

2005; Bunn et al., 2013; Foster, Walter, Shugart, Sibold, & Negron, 2017; Kharuk, Im et al., 2013; Lloyd et al., 2011; McDowell et al., 2015; Meddens & Hicke, 2014; Spruce et al., 2011; Vogelmann, Tolk, & Zhu, 2009). However, to our knowledge these relationships have not yet been documented beyond short-term (<5 years) associations during severe drought (Byer & Jin, 2017; Potter, 2016).

We found that moderate and coarse-scale imagery (250 m–8 km) was generally as useful as fine-scale imagery (30 m) for detecting EWS of tree mortality. There were subtle differences, however, including the better performance of fine-scale Landsat imagery for trends but coarse-scale GIMMS$_{3g}$ for jumps. This suggests Landsat is better able to detect the often subtle trends in vegetation productivity at any given plot, which may vary considerably within an 8 km GIMMS$_{3g}$ pixel (Ju & Masek, 2016). Yet our results also suggest that GIMMS$_{3g}$ is well-suited to detect anomalously low NDVI years that affect vegetation consistently within an 8 km pixel, such as drought events. We did not, however, comprehensively assess the impacts of lower revisit frequency for 30 m Landsat imagery, which resulted in fewer peak-summer observations and some data gaps. We also did not assess higher-resolution imagery that can detect individual tree crowns (e.g., Ikonos, QuickBird, or WorldView) because of its limited availability earlier than the past decade and its low frequency of repeat coverage. Nevertheless, our findings suggest that landscape-scale productivity (up to 8 km and potentially larger) is coupled to

site-level dynamics, which is in contrast to prior indications that AVHRR may misrepresent ecosystem dynamics (e.g., Kern, Marjanovic, & Barcza, 2016). Alternatively, our results corroborate studies showing strong correlations between AVHRR-based NDVI and annual productivity metrics in boreal forests (Beck, Juday et al., 2011, 2013; Berner et al., 2011; Bunn et al., 2013; Lloyd et al., 2011). MODIS is also promising for mortality EWS given its moderate resolution, high quality, and daily revisit frequency. However, we found that longer-term NDVI time series were generally more useful for detecting EWS, suggesting that the shorter time series of MODIS is limiting for multidecadal studies. Our results also show that stronger EWS relationships emerged when using forest inventory data with more frequent remeasurement intervals (e.g., CIPHA). Nonetheless, annual measurements are often not possible, and we found relationships were still relatively robust when using inventories with a more typical 5 year remeasurement frequency (e.g., CAFI). Finally, although EWS relationships were strong in aspen plots, we found that all tree species exhibited relatively consistent relationships in the CAFI database.

Our results suggest that early warning signals of mortality in NDVI data are evident shortly before death (2 years) in some EWS metrics, but may require at least 8 years of data for others (trends). Moreover, many EWS metrics can be detected up to roughly two decades before mortality (roughly 15 years in CAFI and 20–24 years
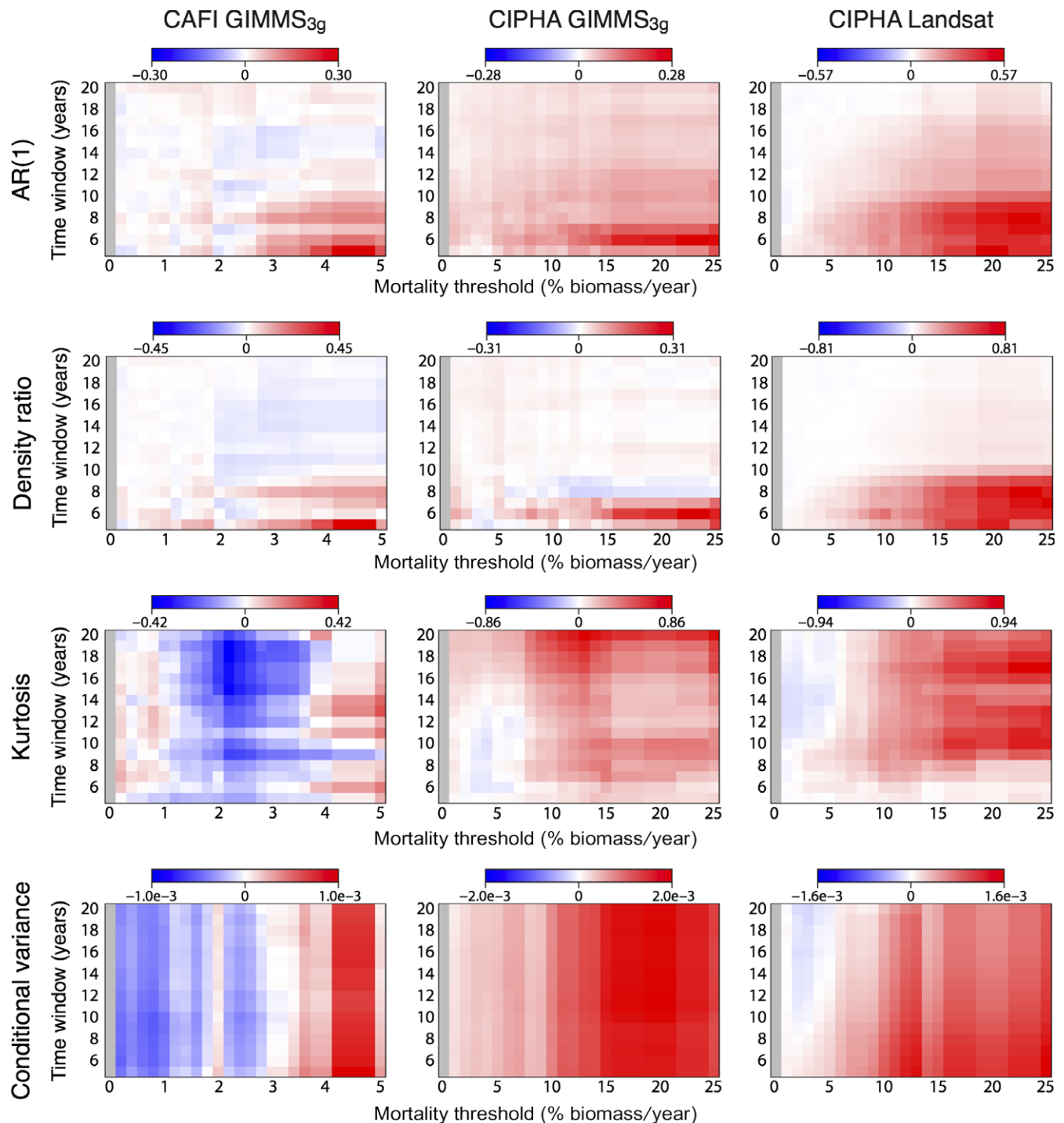
FIGURE 6 Heat maps showing the difference in percentage of sites that exhibited negative jumps between mortality and control sites for a given mortality threshold and analysis time window. A jump was defined by a maximum z-score of -1.5 after detrending the NDVI time series. In each case, red represents conditions in which sites classified as mortality events had more jumps relative to control sites, and blue represents the opposite. Note that we do not show heat maps for the magnitude of jumps as these were generally not significantly different between control and mortality plots

in CIPHA; Figures 5,6,7, and S3). In theory, the relationships between productivity and mortality should be apparent for many decades. Drought-related tree mortality, including the interactions with forest pests, is typically a complex process occurring over multiple years and often decades that involves interrelated physiological mechanisms that evolved to optimize carbon, water, and defense compounds (Adams, Germino et al., 2013; Anderegg, Berry, & Field, 2012; Anderegg, Berry et al., 2012; Herms & Mattson, 1992; McDowell, 2011; McDowell et al., 2008, 2011; Sala, Piper, & Hoch, 2010; Sala, Woodruff, & Meinzer, 2012; Sevanto, McDowell, Dickman, Pangle, & Pockman, 2014; Waring, 1987). This has been referred to as the "decline disease theory", "spiral of tree death", or "slow-decline" hypothesis (Franklin, Shugart, & Harmon, 1987; Houston, 1984; Manion, 1991), and is evidenced by plot-level deviations in productivity that can be detected in some cases 60–100 years before death (Bigler et al., 2004; Gillner et al., 2013). However, NDVI measurements are not available at these timescales, and our results suggest that confounding spectral signatures, likely related to forest demographics, become magnified after roughly two decades.

Overall, our analysis provides strong motivation for incorporating early warning signals from multisensor NDVI time series into predictive models of mortality. For example, a multiple linear regression model using the magnitudes of jumps and trends from GIMMS$_{3g}$ and Landsat with optimal time windows as predictors was able to model maximum annual mortality levels at the CIPHA sites with an r^2 of 0.38. Presumably, the integration of EWS metrics with additional environmental and forest demographic data would increase predictive power.

There are several uncertainties in our approach, and reasons why EWS of mortality from satellite imagery may be difficult to detect. Remote sensing registers signals from the entire plot or landscape, in which some trees may be stressed and dying while others are healthy and even benefitting from adjacent trees dying, as resources such as light, nutrients, and water are made available (Berg, Henry, Fastie, De Volder, & Matsuoka, 2006; Clark et al., 2016; Lloret, Escudero, Maria Iriondo, Martinez-Vilalta, & Valladares, 2012). NDVI signals are also disproportionately influenced by canopy dominants compared to understory trees. Mortality by age/size is often U-

FIGURE 7 Heat maps showing the differences in several early warning signals (EWS) metrics between mortality and control sites. In each case, red represents conditions in which sites classified as mortality events exhibited greater EWS metrics relative to control sites, and blue represents the opposite. For illustration purposes, we only show the combination of NDVI products and inventory data that resulted in long time series, and only the EWS metrics that displayed consistent relationships. Each heat map has a separate scale centered around zero

shaped as young/small trees are sensitive to competition for resources (Chen, Fu, Monserud, & Gillies, 2008; Dietze & Moorcroft, 2011; Hember et al., 2017b; Lines, Coomes, & Purves, 2010; Yang et al., 2003; Yao et al., 2001), but after escaping this phase are typically more resilient to drought than mature/large trees (Allen, Breshears, & McDowell, 2015; Bennett, McDowell, Allen, & Anderson-

Teixeira, 2015; Chen et al., 2016; Clark et al., 2016; Girardin, Guo, Bernier, Raulier, & Gauthier, 2012). Nonetheless, EWS relationships with mortality by stems, as opposed to biomass, were still relatively strong (Figure S7).

In forests with incomplete canopy closure, which tends to be the case at high latitudes (Scheffer et al., 2012), a significant portion of

the remotely sensed imagery is from understory vegetation, which may show different responses to climate and relationships with productivity (McDowell et al., 2015; Yuan et al., 2014). Indeed, tree-level growth is not always correlated with ecosystem productivity (Gea-Izquierdo et al., 2014). Although we found no negative effects of low canopy cover on the strength of our mortality–EWS relationships in the Alaskan CAFI sites, the heterogeneous and patchy aspen parkland presented problems for coarse-scale trends using GIMMS$_{3g}$. Noise is also introduced in that not all declining trees actually die, although their growth trends may be indistinguishable (Bigler et al., 2004). Finally, although we were able to exclude the year of mortality in our analysis with the CIPHA network, this was unavoidable in the case of CAFI, as it would be with most other repeatedly measured forest inventories. Nonetheless, our sensitivity analysis that included the year of observation in CIPHA, combined with the fact that the strongest early warning signals were observed using relatively long time windows (Figures 5,6,7, and S3), strongly suggests the year of mortality did not influence our results.

Collectively, our results suggest that some component of the browning trends in boreal forests that are not a direct result of land use, fire, or other landscape disturbances (Beck & Goetz, 2011; Carroll & Loboda, 2017; Goetz et al., 2005; Ju & Masek, 2016; Nitze et al., 2017; Raynolds & Walker, 2016) may be related to drought- and insect-induced tree mortality. We highlight the particular vulnerability of the interior southern boreal, where widespread browning trends (Guay et al., 2014; Ju & Masek, 2016; Sulla-Menashe, Woodcock, & Friedl, 2018) are coupled to recent mortality events, and projections suggest continued drought and potential transitions to open forest or grassland (Abis & Brovkin, 2017; Hogg & Hurdle, 1995; Lenihan & Neilson, 1995; Worrall et al., 2013).

Our approach may provide a foundation for using long-term remote sensing data to map and forecast mortality risk, which is a critical science and management need (Cailleret et al., 2016; Hogg & Bernier, 2005; Jump et al., 2017; Trumbore, Brando, & Hartmann, 2015). Although forest health assessments using remote sensing have made rapid developments, and many are operational (Brown, Wardlow, Tadesse, Hayes, & Reed, 2008; Hall, Castilla, White, Cooke, & Skakun, 2016; Lausch, Erasmi, King, Magdon, & Heurich, 2017; Mills, Hoffman, Kumar, & Hargrove, 2011; Norman et al., 2016; Pause et al., 2016; Spruce et al., 2011), they generally lack information on the cause and consequences of stress and cannot be used to forecast vulnerability. Statistical models of mortality are either plot-scale, based on tree growth and other demographic characteristics (Bigler & Bugmann, 2004a,b; Bigler et al., 2004; Cailleret et al., 2016; Carus, 2010; Gillner et al., 2013; Ogle et al., 2000; Wunder et al., 2007; Yang et al., 2003; Yao et al., 2001), or larger-scale based on climate (Gustafson & Sturtevant, 2013; Hember et al., 2017b). Remotely sensed early warning signals may therefore be able to bridge these scales and approaches, adding independent information that can be integrated into monitoring systems for resource management and broad-scale changes in vegetation conditions. Such novel approaches may also help validate and inform the development of gap models, dynamic vegetation models, and the

land components of Earth system models whose representations of mortality are generally too simplistic (Adams, Williams et al., 2013; Davi & Cailleret, 2017; Eamus, Boulain, Cleverly, & Breshears, 2013; McDowell et al., 2011; Thurner et al., 2017). Earth system models in particular do not generally capture the magnitude or spatial patterns of recent productivity declines and mortality in boreal forests (Anav et al., 2013; Mao et al., 2016; Murray-Tortarolo et al., 2013; Rafique, Zhao, de Jong, Zeng, & Asrar, 2016; Tei et al., 2017), implying inadequate representations of environmental sensitivity (Forkel et al., 2014) that cast doubt on projections of future greening (Charney et al., 2016) and carbon sinks (e.g., Friend et al., 2014; Qian, Joseph, & Zeng, 2010).

Developing improved methods to forecast mortality will become increasingly important as droughts (McDowell et al., 2016; Sheffield & Wood, 2008; Trenberth et al., 2014), pests and pathogens (Anderegg et al., 2015; Bentz et al., 2010; Berg et al., 2006; Cullingham et al., 2011; Pureswaran et al., 2015), and associated mortality and forest decline intensify with warming (Allen et al., 2015; McDowell & Allen, 2015; McDowell et al., 2011), particularly at high latitudes. These stressors may ultimately result in large-scale changes in vegetation and biome distributions, which may be starting to occur in many parts of the circumpolar boreal forest, including our study domain (Beck, Juday et al., 2011; Buma & Barrett, 2015; Chen et al., 2016; Sulla-Menashe et al., 2018). Robust early warning signals of these transitions can allow managers and policy makers to develop more effective strategies for mitigation and adaptation.

5 | SUMMARY

Long-term forest inventory and NDVI records have greatly advanced our understanding of carbon cycling, vegetation dynamics, and the impacts of global change on the terrestrial biosphere. We demonstrate another potentially important use of these data: detecting early warning signals of tree mortality. We show that sites varying in species composition, environmental conditions, and satellite sensors consistently displayed early warning signals prior to mortality events. We suggest this provides a foundation for more effective models and monitoring of tree mortality. Future work that could advance our findings includes (i) testing these relationships over a wider range of species and vegetation subject to varying environmental stressors; (ii) exploring the utility of additional remotely sensed indices and indicators of vegetation productivity and stress; and (iii) integrating these relationships into evolving diagnostic and predictive models of tree mortality.

distributors of NDVI products used in this study, including NASA and the US Geological Survey (USGS).

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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