Temporal Greenness Trends in Stable Natural Land Cover and Relationships with Climatic Variability across the Conterminous United States

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ABSTRACT: Assessment of temporal trends in vegetation greenness and related influences aids understanding of recent changes in terrestrial ecosystems and feedbacks from weather, climate, and environment. We analyzed 1-km normalized difference vegetation index (NDVI) time series data (1989–2016) derived from the Advanced Very High Resolution Radiometer (AVHRR) and developed growing-season time-integrated NDVI (GS-TIN) for estimating seasonal vegetation activity across stable natural land cover in the conterminous United States (CONUS). After removing areas from analysis that had experienced land-cover conversion or modification, we conducted a monotonic trend analysis on the GS-TIN time series and found that significant positive temporal trends occurred over 35% of the area, whereas significant negative trends were observed over only 3.5%. Positive trends were prevalent in the forested lands of the eastern one-third of CONUS and far northwest, as well as in grasslands in the north-central plains. We observed negative and nonsignificant trends mainly in the shrublands and grasslands across the northwest, southwest, and west-central plains. To understand the relationship of climate variability with these temporal trends, we conducted partial and multiple correlation analyses on GS-TIN, growing-season temperature, and water-year precipitation time series. The GS-TIN trends in northern forests were positively correlated with temperature. The GS-TIN trends in the central and western shrublands and grasslands were negatively correlated with temperature and positively correlated with precipitation. Our results revealed spatial patterns in vegetation greenness trends for different stable natural vegetation types across CONUS, enhancing understanding gained from prior studies that were based on coarser 8-km AVHRR data.

SIGNIFICANCE STATEMENT: Assessing vegetation trends, cycles, and related influences is important for understanding the responses and feedbacks of terrestrial ecosystems to climatic and environmental changes. We analyzed vegetation greenness trends (1989–2016) for stable natural land cover across the conterminous United States, based on vegetation index time series derived from coarse-resolution optical satellite sensors. We found greening trends in the forests of the east and far northwest and the grasslands of the northern central plains that correlated with increasing temperature in the regions. We observed browning and no trends mainly in the shrublands and grasslands across the northwest, southwest, and western central plains, associated with increasing temperature and decreasing precipitation. Future research should focus on vegetation greenness analysis using finer-resolution satellite data.

1. Introduction

Earth’s natural terrestrial vegetation greenness exhibits temporal trends and variability. Gradual changes in vegetation may be the result of atmospheric circulation generally occurring over years to decades (Nash et al. 2014; Wang et al. 2015; Ju and Masek 2016; Vogelmann et al. 2016), while abrupt change from disturbance occurs on time scales of days to weeks (Verbesselt et al. 2010; DeVries et al. 2015; McDowell et al. 2015; White et al. 2017). Understanding vegetation trends and variability over national, continental, and global terrestrial regions has largely been accomplished through the application of Earth observation data, especially the data collected via satellite sensors (Kim et al. 2014; Gonsamo et al. 2016; Thompson et al. 2017). Many natural and nonnatural factors have been shown to have relationships with vegetation productivity and greenness. Vegetation vigor and the timing and intensity of vegetation cycles are linked with climate and weather damage due to natural disasters such as floods, wildfires, and droughts, or land conversions caused by human activity and management (van Leeuwen et al. 2010; Ma et al. 2013; Xu et al. 2016; Zhu et al. 2016).

Many existing studies of vegetation greenness have relied on long-term satellite records of vegetation indices such as the normalized difference vegetation index (NDVI) (Tucker 1979) and the enhanced vegetation index (Huete et al. 2002). Although other useful vegetation indices exist, NDVI is the most frequently used in the scientific literature for geospatial inquiry of vegetation productivity, condition, and greenness (e.g., Reed et al. 1994; Nemani et al. 2003; Walker et al. 2014; Ju and Masek 2016; Wu et al. 2020). Satellite systems and
sensors with high temporal frequency, such as the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Visible Infrared Imaging Radiometer Suite (VIIRS), have collected lengthy and consistent data records of surface reflectance and vegetation indices, which support long-term global studies of dynamics over decadal and multidecadal periods.

Since the AVHRR record started in the 1980s, it has demonstrated value for studies of long-term vegetation trends and variations (Myneni et al. 1997; Neigh et al. 2008; Eastman et al. 2013; Kong et al. 2017; Pan et al. 2018). Although the newer generation sensors such as MODIS and VIIRS offer improved instrumental specifications, improved geometric registration, spectral calibration, and radiometric correction, AVHRR provides the longest record of all high-temporal-frequency sensors. Since the early 1980s, multiple AVHRR-derived global NDVI datasets have been developed for using in global vegetation monitoring, including global vegetation index (Tulipley 1991), Pathfinder AVHRR Land (PAL; James and Kalluri 1994), Global Inventory Modeling and Mapping Studies (GIMMS; Tucker et al. 2005). The AVHRR Land Long Term Data Record (LTDR) (combined with MODIS data) (Pedelty et al. 2007), Vegetation Health Product (VHP; Guo 2013), and Third Generation GIMMS NDVI (NDVI3g; Pinzon and Tucker 2014). However, all of these AVHRR datasets are based on the Global Area Coverage (GAC) level-1b data, although they are reprocessed in different ways. The GAC is one of the original AVHRR datasets and retains only one line of every three scanned lines and averages every fourth of five adjacent samples along the scan line, yielding a nominally 1 km × 4 km resolution (https://www.avl.class.noaa.gov/release/data_available/avhrr/index.htm). Although AVHRR datasets have proved very useful for investigating and monitoring global and continental vegetation dynamics, the very coarse resolutions (e.g., 8 km for PAL, GIMMS, and NDVI3g; 5 km for LTDR; 4 km for VHP) limited their application for more detailed subcontinental and regional vegetation studies. Because many pixels in these coarse-resolution images consist of mixed land surface signals, temporal trend analyses of these data can cause confusion especially where land-cover and land-use changes or disturbances occur at subpixel level. Moreover, the exact georectification of the sampled GAC pixels may not be consistent, which can confound mixed and pure pixels in the temporal compositing and thus add noise to the data (Wu et al. 2020).

Since 1989, the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center has produced a 1-km AVHRR dataset (referred to as “EROS AVHRR” herein) for the conterminous United States (CONUS; i.e., the lower 48 states) and Alaska (Eidenshink 1992; Eidenshink 2006; U.S. Geological Survey 2018). The dataset is processed through radiometric calibration, atmospheric correction (including corrections for effects of water vapor, ozone absorption, and Rayleigh scattering), geometric registration, cloud screening, and compositing that includes weekly and biweekly composites (Eidenshink 2006). A major advantage of the EROS AVHRR dataset is that it is produced from the higher-resolution 1.1-km local area coverage data and processed to 1 km (Hastings and Emery 1992). Relative to the GAC-based coarse-resolution AVHRR products, the 1-km EROS AVHRR dataset provides comparatively finer spatial detail, providing an advantage for investigating and monitoring vegetation conditions and dynamics at subnational and regional scales, especially for spatially heterogeneous regions such as mountain and dryland land cover found in the western United States (e.g., Yang et al. 1998; Schwartz and Reed 1999; Ji and Peters 2003).

Many studies have shown that because NDVI is proportional to fraction of absorbed photosynthetically active radiation, leaf area, vegetation fraction, and net primary productivity, it can be used to evaluate vegetation condition or greenness (e.g., Viña et al. 2011; Gitelson et al. 2014; D’Odorico et al. 2014). Time-integrated NDVI (TIN) is a proxy of photosynthetic potential in the vegetation canopy accumulated over a certain period and has been used to assess vegetation dynamics (e.g., Beck et al. 2006; Zhang et al. 2007; Brown et al. 2008; Barichivich et al. 2013). Furthermore, growing-season TIN (GS-TIN), or the time series NDVI integrated across the growing season, provides a measure of photosynthetic potential that is conceptually similar to net primary productivity summed across the season (e.g., Reed et al. 1994; Yang et al. 1998; Wessels et al. 2004; Wylie et al. 2008).

Since the late twentieth century, severe and extensive bark beetle outbreaks have caused dramatic tree mortality from Alaska to the western United States (Meddens and Hicke 2014; Hicke et al. 2015; Berner et al. 2017a). Previous studies reported that drought and warmth across western North America in the 2000s led to extensive insect outbreaks and mortality in many forest types including spruce, lodgepole, pinyon-juniper, and ponderosa, affecting 20 million ha and many tree species throughout the region (Allen et al. 2010; Bentz et al. 2010, Williams et al. 2013). In the western CONUS, tree mortality caused by bark beetle outbreaks may be a factor changing the dynamic vegetation greenness trends.

In this study, our goal was to analyze, clarify, and interpret multidecadal temporal trends in stable natural vegetation over the growing season over a 28-yr period (1989–2016) across CONUS and to assess relationships with weather and climate variability while reducing the influence of land management and disturbance. Our specific objectives were to estimate and evaluate 1) recent temporal trends in GS-TIN in major stable land-cover types across different geographic regions, 2) whether the GS-TIN trends were correlated to any trends found in temperature and precipitation time series, 3) the strength of the relationships of GS-TIN to temperature and precipitation, and 4) the impact of disturbance from bark beetle-induced tree mortality on the GS-TIN trends in the west. To reduce possible confusion resulting from human management practices and land-cover conversion, we focused only on stable natural vegetation cover including forests, shrublands, grasslands, and wetlands, but excluded burned landscapes and highly managed land cover. To assist interpretation, we summarized the results over geographic regions to inspect the diverse patterns of the GS-TIN trends and respective correlations with climate. This study is unique from previous studies of similar topics in three aspects: 1) the spatial
resolution of the AVHRR dataset we used allows more detailed land surface observations than other 8-km resolution AVHRR, and therefore, is able to depict finer variations in vegetation greenness trends; 2) The 28-yr EROS AVHRR time series is a decade longer than MODIS (19 years) providing more time to see richer variability and trends in vegetation greenness; 3) The combination of the temporal and spatial characteristics of the data enables closer examination and regional summaries of vegetation trends by specific land-cover types and the exclusion of disturbance including wildfire burned area.

2. Study area and datasets

a. Study area

The study area encompasses the CONUS land surface divided into seven geographic regions based on the Fourth National Climate Assessment (NCA4) Regions (Reidmiller et al. 2018), that is, Northwest, Southwest, northern Great Plains, southern Great Plains, Midwest, Northeast, and Southeast (Fig. 1). Deciduous forests are primarily distributed in the eastern regions (i.e., Northeast, Southeast, and Midwest), and evergreen forests are mainly located in the central and western regions (i.e., Northwest, Southwest, and northern Great Plains) and the Southeast. Shrublands are dominant in the four western regions, especially in the Southwest. Grasslands are mostly found in the Great Plains and the Southwest. The CONUS has large climatic variability, ranging from humid-subtropical in the Southeast, humid-continental in the Northeast and Midwest, semiarid in the western Great Plains, arid in the southwestern deserts, to Marine and Mediterranean along the western coast.

b. Land-cover data

We created a 1-km land-cover map to define stable natural vegetation types through the study period using National Land Cover Database (NLCD) and Monitoring Trends in Burn Severity (MTBS) data. NLCD provides land-cover datasets across CONUS at 30-m resolution (https://www.mrlc.gov/). The NLCD products consisted of four periods, NLCD 1992, 2001, 2006, and 2011, each created based primarily on the Landsat data of the corresponding years. The recently released NLCD 2016 and 7 integrated epochs of land-cover data were not available before our analysis was completed. Because NLCD 1992 used a different classification scheme (21 classes) from the other NLCD datasets, the NLCD 1992/2001 Retrofit Land Cover Change Product (Fry et al. 2009) was used to track the land-cover changes between circa 1992 and circa 2001. We used NLCD 1992 (retrofit), 2001, 2006, and 2011 to generate a 30-m stable cover map indicating locations with stable land-cover types. In the map, the changed cover was defined as the land cover that changed at any time from circa 1992 to circa 2011. The resulting land-cover map retained all stable natural vegetation classes (deciduous forest, evergreen forest, mixed forest, shrubland, grassland, and wetland) and open water, and grouped all other classes including agricultural land, urban, barren land, perennial snow/ice, and changed cover types through time.

The MTBS product, developed by the USGS EROS Center and the USDA Forest Service Geospatial Technology and

![FIG. 1. Map of stable natural vegetation for CONUS at 1-km resolution. The map insert indicates seven NCA4 regions: 1) Northwest (NW), 2) Southwest (SW), 3) northern Great Plains (NGP), 4) southern Great Plains (SGP), 5) Midwest (MW), 6) Northeast (NE), and 7) Southeast (SE). The map was created based on the NLCD products (NLCD 1992/2001 Retrofit, 2001, 2006, and 2011), MTBS burn-severity data (1989–2015), and MODIS burned-area data (2016).]
from “map for each year from 1989 to 2015 by merging all categories (Fig. 1), MTBS burned-area map (1989–2015) within CONUS. An annual burn map specifying burned and unburned pixels MODIS burned-area data (MCD65A1, Collection 6; Giglio et al. 2018) product as an alternative dataset for 2016. We summarized the 2016 monthly burned-area layers to generate an annual burn map specifying burned and unburned pixels within CONUS. Last, we combined the NLCD-derived land-cover map (Fig. 1), MTBS burned-area map (1989–2015), and MODIS burned-area map (2016) to generate a 1-km stable natural vegetation map. Our study focused on the stable natural vegetation cover including forest, shrubland, grassland, and wetland. Burned area and other cover were not analyzed because they represented nonvegetated, anthropogenic, or disturbed landscapes. The land-cover map was reprojected from the original projections to the Lambert azimuthal equal area (LAEA) projection, then resampled to 1-km resolution using a majority method. Derived from this map (Fig. 1), the total area of the stable natural vegetation cover in our analysis is 4,734,000 km², or 62.2% of all land surface area in the CONUS, including 440,000 km² (70.0% of the region) in the Northwest, 1,452,000 km² (81.9%) in the Southwest, 806,000 km² (67.3%) in the northern Great Plains, 625,000 km² (58.8%) in the southern Great Plains, 387,000 km² (33.7%) in the Midwest, 331,000 km² (65.6%) in the Northeast, and 691,000 km² (53.7%) in the Southeast. c. AVHRR NDVI data The EROS AVHRR dataset is processed through radiometric calibration, atmospheric correction, geometric registration, cloud screening, weekly/biweekly compositing, and gridded at 1-km resolution in LAEA projection (Eidenshink 2006). The products are produced using the maximum value compositing method with a data constraint that solar zenith angle (SZA) not exceed 80°. From the biweekly composite dataset, we retrieved the layers of atmospherically corrected reflectance bands 1 and 2 to create NDVI time series data (1989–2016). To reduce cloud contamination and atmospheric effects, we temporally smoothed the NDVI data using the weighted least squares regression method (Swets et al. 1999), generating a biweekly interval smoothed NDVI dataset.

The effect of orbital drift on the NDVI time series has been documented for National Oceanic and Atmospheric Administration (NOAA) satellites (McGregor and Gorman 1994; Privette et al. 1995; Kaufmann et al. 2000; Nagol et al. 2014; Sobrino and Julien 2016). Our previous study verified the influence of satellite orbital drift on the EROS AVHRR data compiled from the NOAA-11, NOAA-14, NOAA-16, NOAA-17, NOAA-18, and NOAA-19 satellites (Ji and Brown 2017). We reported that the NOAA satellite orbital drift caused SZA to increase toward the end of each satellite mission (Ji and Brown 2017). Specifically, SZA was found to be high in 1992–94 (last three years of the NOAA-11 satellite) and 1999–2000 (last two years of the NOAA-14 satellite), causing significant impact on the composites. That study concluded that SZA was highly correlated with phenological metrics, especially the NDVI-value metrics (e.g., start-of-season NDVI, end-of-season NDVI, maximum NDVI, and TIN), and recommended elimination of the five high-SZA years to minimize the influence of orbital drift on the AVHRR time series data. In our current study, we excluded the five high-SZA years (1992, 1993, 1994, 1999, and 2000) from the data analysis. d. Growing-season time-integrated NDVI data In this study, GS-TIN is defined as the sum of daily smoothed NDVI values (above the base NDVI value) between the start and end of the growing season:

\[
\text{GS-TIN} = \sum_{i=s}^{e} (\text{SNDVI}_i - \text{SNDVI}_b),
\]

where SNDVIi is the smoothed NDVI value on the ith day of the year, SNDVIb is the base value of the smoothed NDVI, s is the date of the start of the growing season, and e is the date of the end of the growing season. The dates of the start and end of the growing season are defined as the spring and autumn equinoxes, which occur around 20 March and 23 September, respectively. The SNDVIb was set to 0.1 in this study, which was derived from the long-term-averaged (1989–2016, excluding high-SZA years) smoothed NDVI value for barren land. Barren land was identified using the temporally consistent barren land pixels identified from the NLCD products of four periods. Because the smoothed NDVI time series had a time interval of 14 days, we linearly interpolated the daily NDVI values to create GS-TIN images. A map of multiyear-average (1989–2016) GS-TIN is shown in Fig. 2.

We applied spatially and temporally consistent dates to estimate the growing season to constrain the estimation of GS-TIN to a fixed period of vegetation growth. This method provides consistent intercomparison of NDVI integration across different locations and years while reducing the effects from phenological timing shifts on the NDVI integration. In this way, we focused primarily on the temporal trends in the magnitude of vegetation greenness rather than timing factors. Moreover, variable NDVI-based estimation of start and end of growing seasons might introduce uncertainties in GS-TIN, especially in very sparse or highly vegetated areas where the growing season was difficult to determine because of poor vegetation seasonality (Walker et al. 2014). e. Temperature and precipitation data We investigated the relationship between climate parameters and GS-TIN using monthly gridded data derived from
the Parameter–Elevation Regressions on Independent Slopes Model (PRISM) (Daly et al. 2008). We downloaded the PRISM AN81m product including monthly 2.5-arc-min mean air temperature and precipitation (1989–2016) datasets from the PRISM Climate Group website (http://www.prism.oregonstate.edu/). We calculated “growing-season temperature” (referred to as TMP herein), defined as the mean value of the monthly mean air temperature from April to September, and “water-year precipitation” (referred to as PPT herein) as the sum of monthly precipitation within a water year. The water year is defined as the 12-month period from 1 October of the previous year to 30 September of the current year (https://water.usgs.gov/nwc/explain_data.html). We created annual TMP and PPT data (1989–2016) that were reprojected to the LAEA projection and resampled from 4-km resolution to 1 km using a bilinear resampling method. The purpose of the resampling was to support the spatial detail needed for image processing and analysis to discover relationships with higher-resolution greenness data, and this did not mean that the true spatial resolution of TMP and PPT was increased to 1 km.

We selected air temperature and precipitation as the primary variables influencing natural vegetation greenness. Energy and moisture are the two primary factors controlling vegetation growth, which can be measured with air temperature and precipitation. Because there is substantial spatial variability in climatology, vegetation type, and landscape across CONUS, it is challenging to determine a common period when the precipitation or temperature have the strongest influences on vegetation growth for each specific region. We used growing-season (April–September) air temperature that matches approximately the GS-TIN defined by equinoxes for entire study area. The water-year precipitation was applied because the influences of precipitation on vegetation may involve water availability from winter season (e.g., snow and snow-meltwater) prior to the growing season.

f. Tree-mortality data

To interpret the potential impact of other disturbances on vegetation trends, we analyzed annual estimates of tree mortality due to bark beetles from 2003 to 2012 in western forests (Berner et al. 2017a). Tree mortality expressed as the amount of aboveground carbon (AGC) stored in trees killed by bark beetles was estimated at 1-km resolution by combining tree aboveground biomass data and tree canopy mortality data based on aerial surveys, forest inventory measurements, and high-resolution satellite imagery. Datasets from the Oak Ridge National Laboratory Distributed Active Archive Center (Berner et al. 2017b) were the basis for a 10-yr (2003–12) average map of tree mortality due to bark beetles (AGC; mg ha$^{-1}$ yr$^{-1}$). The map was then reprojected to the LAEA projection at 1-km resolution (Fig. 3). We calculated 10-yr-average tree mortality (AGC km$^{-2}$ yr$^{-1}$) based on the original annual data and then divided the average tree mortality into three levels: low (AGC = 0.1–10.0 Mg km$^{-2}$ yr$^{-1}$), median (AGC = 10.1–100.0 Mg km$^{-2}$ yr$^{-1}$), and high (AGC > 100 Mg km$^{-2}$ yr$^{-1}$).

We included the areas with bark beetle–induced tree mortality in the analysis because of the following three reasons. First, insect outbreaks in forests cause gradual changes in vegetation greenness, but they do not normally alter cover types.
Second, as part of the natural ecosystem, increased infestation by bark beetles leads to tree defoliation or mortality, which is induced mainly by abnormal climate conditions, such as drought or warmth, in western North America (Bentz et al. 2010; Williams et al. 2013). Last, the tree-mortality data are only available in a 10-yr record, that is much shorter than the entire AVHRR time series so we could not apply this analysis consistently to the entire study. However, the tree-mortality dataset provided a useful interpretation tool for some irregular negative trends in GS-TIN observed in western forests.

3. Methods

a. Trend analysis

Statistical distribution and autocorrelation are two crucial issues in time series analysis. In general, parametric statistical analyses rely on the assumption that the data resemble a normal distribution. Presence of the temporal autocorrelation in the time series would lead to overestimation of the significance of the temporal trends in those variables. We tested the data normality and temporal autocorrelation for the GS-TIN, TMP, and PPT time series of all pixels of stable natural vegetation in the study area. The two statistical tests are described in detail in appendix A.

We used a linear regression model to estimate the temporal trend of GS-TIN, TMP, and PPT over the 28-yr period, which is expressed as

$$Y_t = a + bX_t + e_t,$$

(2)

where $X_t$ is the predictor variable at time (year) $t$; $Y_t$ is the response variable GS-TIN, TMP, or PPT at $t$; $a$ is the intercept; $b$ is the slope; and $e_t$ is the residual at $t$. The slope $b$ indicates the time series trend. The $t$ statistic was applied to test the slope $b$ with $H_0 (b = 0)$ and $H_a (b \neq 0)$. The significance ($\alpha = 0.05$) of the slope was derived using the $p$ values based on the two-tailed $t$ distribution.

We addressed a concern about instrumental continuity due to sensor upgrade from AVHRR/2 (NOAA-11–NOAA-14) to AVHRR/3 (NOAA-15–NOAA-19). Because AVHRR/3 has
slightly narrower wavelengths in the red and near-infrared (NIR) channels than AVHRR/2, there is a possibility that the sensor change causes differences in NDVI and its derivative products (Trishchenko et al. 2002; Latifovic et al. 2012; Miura et al. 2013; Fan and Liu 2016). Therefore, we conducted a statistical test on the effect of the sensor change on the GS-TIN trends. The procedure for this test is described in appendix B. All statistical analyses involved in this study were performed using SAS 9.4 and ERDAS Imagine 2018.

b. Partial and multiple correlation analyses

To assess the influences of climatic variables on vegetation greenness, we performed partial correlation analyses for GS-TIN, TMP, and PPT. The partial correlation measures the degree and direction of the linear relationship between two variables, with the effect of one or more controlling variables removed from the analysis. The partial correlation coefficient \( r_{XY.Z} \) between variables \( X \) and \( Y \), controlling for variable \( Z \), is calculated as

\[
r_{XY.Z} = \frac{r_{XY} - r_{XZ}r_{YZ}}{\sqrt{1 - r_{XZ}^2} \sqrt{1 - r_{YZ}^2}},
\]

where \( r_{XY} \) is the correlation coefficient between \( X \) and \( Y \), \( r_{XZ} \) is the correlation coefficient between \( X \) and \( Z \), and \( r_{YZ} \) is the correlation coefficient between \( Y \) and \( Z \) (Pedhazur 1997).

To estimate the overall strength of relationship of GS-TIN with both TMP and PPT, we used the multiple correlation analysis. The multiple correlation coefficient \( r_{X.YZ} \) for \( X \) versus \( Y \) and \( Z \) is expressed as

\[
r_{X.YZ} = \sqrt{r_{XY}^2 - r_{XZ}^2 - 2r_{XY}r_{XZ}r_{YZ} - r_{YZ}^2}.
\]

The multiple correlation coefficient ranges from 0 to 1, indicating the association between GS-TIN and climatic variables from no relation to very strong relation.

The \( t \) statistic was used to test the partial and multiple correlation coefficients: \( \rho = 0 \) (\( H_0 \)) and \( \rho \neq 0 \) (\( H_a \)), where \( \rho \) is the population correlation coefficient. We performed partial and multiple correlation analyses for the GS-TIN, TMP, and PPT time series for all pixels in the study area. The results were shown as the maps of the correlation coefficients and significance level (\( \alpha = 0.05 \)).

4. Results

a. Influence of the AVHRR sensor change on the GS-TIN trends

The results of the statistical test for the influence of AVHRR sensor change (see the methods described in appendix B) shows that over all stable natural vegetation pixels in the GS-TIN time series images, 8.2% of the pixels rejected \( H_0 \) (the mean of the difference in the two sets of regression residuals is zero) at \( \alpha = 0.05 \) level for the matched pair \( t \) test. For 91.8% of the pixels that failed to reject \( H_0 \), there was no significant difference between the means of the two sets of residuals. These tests showed that the GS-TIN trends at those pixels were not significantly different whether the trends were estimated using the single regression or the two-segment piecewise regression (see appendix B). Because the piecewise regression did not significantly improve the estimation of the GS-TIN trends for those pixels, we considered that no substantial breaks existed between AVHRR/2 and AVHRR/3. Although 8.2% of the pixels showed significant breaks between the two segments, we expected that the difference was not artificial, but natural and local. Visually inspecting the image of the matched-pair \( t \)-test result, the distribution of the 8.2% pixels was noticed as scattered and random, with no relation to certain geographic locations or land-cover types. We assumed that if changes in the instruments could influence land surface observations, the impact would be geographically systematic and widespread.

b. GS-TIN, TMP, and PPT trends

We computed the Jarque–Bera (JB) statistic (Jarque and Bera 1987) for the GS-TIN, TMP, and PPT time series for all stable natural vegetation pixels in the study area (see appendix A for the description of the method). The JB test is a goodness-of-fit test for whether sample data have the skewness and kurtosis that match a normal distribution (Jarque and Bera 1987). Because the three variables are normally distributed in the time series at most pixels (98.4%, 99.6%, and 97.3% of all pixels in GS-TIN, TMP, and PPT, respectively) based on the test, conventional parametric statistics are adequate in our data analysis. For testing the presence of the temporal autocorrelation in the GS-TIN, TMP, and PPT time series, we applied the Durbin–Watson (DW) statistics (Durbin and Watson 1971) for all stable natural vegetation pixels (see appendix A). Most pixels (87.4%, 98.5%, and 99.2% of all pixels in GS-TIN, TMP, and PPT, respectively) do not show significantly positive first-order autocorrelation for the three variables. Therefore, the conventional linear regression model [Eq. (2)] is appropriate for the trend analysis.

The linear regression model indicates that significant positive GS-TIN trends occur over 35.0% of natural vegetation cover, much larger than the area with significant negative trends (3.5%). In general, GS-TIN shows significant positive trends in most forests except for the middle and southern Rocky Mountains where both positive and negative trends occur (Figs. 4a,b and 5). Western shrublands and grasslands display no significant trends or negative trends in GS-TIN, but the grasslands in the Great Plains demonstrate significant positive trends (Figs. 4a,b). For TMP, most areas of the country show positive trends with a few areas in the north-central region showing negative or nonsignificant trends (Figs. 4c,d and 5b). Negative or nonsignificant trends in PPT occur mainly in the western and southeastern CONUS, while positive trends are found in the north-central region (Figs. 4e,f and 5c). The characteristics of the GS-TIN, PPT, and TMP trends for each NCA4 region are summarized in Table 1.
Figure 4. Maps of (a),(b) GS-TIN trend; (c),(d) TMP trend; and (e),(f) PPT trend shown as (left) the slopes and (right) the significance tests of the slopes ($\alpha = 0.05$).
In general, GS-TIN is positively correlated with TMP across all vegetation cover types in the eastern CONUS (Northeast, Southeast, and Midwest) and the forests in the Northwest and the northern Great Plains (Figs. 6a and 7a). The greatest correlations between GS-TIN and TMP are observed in the forests of the Midwest and northeast regions. GS-TIN is negatively correlated with TMP in the central and western regions, mainly in the shrublands of the Northwest, Southwest, northern Great Plains, and southern Great Plains (Figs. 6b and 7b). The greatest negative correlations between GS-TIN and TMP are found in arid and semiarid areas, where long-term average GS-TIN is low, TMP is high, and PPT is low (Fig. 2). Correlation coefficients between GS-TIN and PPT show high values found mostly in the western regions, except for some pockets in the Pacific Mountains and the Rocky Mountains, where the forests show high negative correlations. For most areas of the eastern regions, correlations between GS-TIN and PPT are low, either positive or negative. Table 2 summarizes the characteristics of correlations of GS-TIN with TMP and PPT for each NCA4 region.

In summary of all NCA4 regions, the shrublands and grasslands in the west (Northwest, Southwest, and Great Plains) under arid and semiarid climate are negatively related to temperature and positively related to precipitation. Higher temperatures and lower precipitation are not favorable for shrub and grass growth in the west. The forests in the northern regions (Northwest, Midwest, and Northeast) and high-elevation regions in mainly cold climate conditions are more positively related to temperature. The increasing temperature appears to provide more beneficial conditions, especially for the northern forests.

d. Multiple correlations of GS-TIN, TMP, and PPT

The multiple correlation coefficient ($r_{X,Y,Z}$) indicates the overall strength of the relationship of GS-TIN with climate variables, that is, TMP and PPT in this study. Figure 6c shows the maps of the multiple correlation coefficients of GS-TIN versus TMP and PPT and the significance test of the correlation coefficients. Overall, the four NCA4 regions in the west have stronger multiple correlation than the three regions in the east. And in the west, shrublands and grasslands show much bigger multiple correlations than forests. The multiple correlation results are relatively low in the east, except for the northern extents of the Midwest and Northeast regions (Fig. 6c).

Figure 7c illustrates the average multiple correlation coefficient between GS-TIN and TMP/PPT for each vegetation type of each NCA4 region. On average, the multiple correlation coefficient is 0.54 across all stable natural vegetation we analyzed. The average multiple correlation coefficients are 0.61 and 0.35 in the west and east, respectively. For the entire CONUS, 67.7% of stable natural land cover shows significant multiple correlation between GS-TIN and TMP/PPT. Significant multiple correlation is found in 82.1% of the area in the west and 31.2% in the east.

This analysis indicates that seasonal temperature and precipitation are two important factors for the temporal trends and variations in stable natural vegetation greenness across the country. In general, the climatic influences on the vegetation trends are stronger in the west (Northwest, Southwest, and Great Plains) and the upper part of the east (Midwest and Northeast) than in the rest of CONUS.

e. Influence of tree mortality on GS-TIN trends

Although our analysis suggests that GS-TIN is significantly related to TMP and PPT in most areas, the GS-TIN trends are not fully explained by the TMP or PPT variations in some locations. Some forests with negative trends (e.g., many forested areas in the Rocky Mountains, Figs. 4a,b) do not show significant correlations with TMP or PPT, and the multiple correlations of GS-TIN versus TMP/PPT are relatively low (Fig. 6). Therefore, the decreasing trends in the forest GS-TIN in certain areas must be attributed to other factors besides climatic influences.

Visual comparison of the GS-TIN trends and the map of tree mortality caused by bark beetles exposed similar corresponding spatial patterns (Fig. 8). The tree mortality was estimated as the amount of AGC (Mg C m$^{-2}$) stored in trees killed by bark beetles annually from 2003 to 2012 (Berner et al. 2017a). In western CONUS, the areas with high tree mortality correspond well with areas with significant negative GS-TIN trends, especially in the Middle Rockies, Idaho Batholith, and South Rockies ecoregions (Fig. 8).
We quantitatively compared the areas with different levels of bark beetle–induced tree mortality in the entire western CONUS, Middle Rockies/Idaho Batholith ecoregion, and South Rockies ecoregion. In western CONUS, the areas affected by high-level tree mortality have a higher percentage of significant negative GS-TIN trends (23.1%) than significant positive GS-TIN trends (12.2%) (Fig. 8a). In the Middle Rockies/Idaho Batholith Ecoregion, areas with median/high level of tree mortality show much more negative GS-TIN trends (30.5%) than positive GS-TIN trends (4.6%) (Fig. 8b). Likewise, in the South Rockies Ecoregion, the areas with median/high level of tree mortality indicate 25.7% and 8.0%, respectively, of significant negative and positive trends (Fig. 8b). For the areas showing severe tree mortality during 2003–12, we postulate that tree die-off has caused a reduction in vegetation greenness and productivity, and thus a negative trend in the GS-TIN time series. However, the lack of tree-mortality data for the years before 2003 and after 2012 leads to uncertainty about the quantitative relationships between insect outbreaks and vegetation greenness.

### 5. Discussion

#### a. Comparison with previous studies

Vegetation greenness trends have been an important and popular research topic since the early 2000s when satellite data records had accumulated for a sufficiently long period (e.g., Lucht et al. 2002; Nemani et al. 2003; Slayback et al. 2003). There is ample literature about vegetation greenness trends at regional and global scales using coarse-resolution satellite data such as AVHRR and MODIS. Many recent studies cover the period from the early 1980s to early 2010s and can be compared with our current study. All those studies employed AVHRR data (mostly the GIMMS NDVI3g data at 8-km resolution) to investigate vegetation greenness trends from the late 1980s to early 2010s. Although these studies were at global scales, they provided continental and regional analyses that are similar to our study. Cook and Pau (2013) assessed the long-term vegetation greening and browning trends in global pasture lands using the annual leaf area index (LAI) derived from the GIMMS LAI3g dataset (1982–2008), and they reported that most pasture areas in western CONUS decreasing trends in western CONUS. Many investigators, including Eastman et al. (2013), Schut et al. (2015), Liu et al. (2015), Kong et al. (2017), Zhao et al. (2018), and Pan et al. (2018), used the NDVI3g datasets between 1982 and 2010–13.
Fig. 6. Map of (a), (b) partial correlation and (c) multiple correlation shown as (left) correlation coefficient and (right) significance test of the coefficient ($\alpha = 0.05$).
to analyze global greenness trends, and they all reported increasing temporal trends in CONUS Northeast, Southeast, and Great Plains. Zhao et al. (2018) also analyzed the relationship of the growing-season NDVI to air temperature and precipitation, but without removing the influence of land-cover change. Their results showed that NDVI and temperature correlation was significantly negative in western CONUS and significantly positive in the northeastern CONUS; the correlation between NDVI and precipitation was significantly positive in the West. Over our study area, all studies manifested significant greening trends in the Northeast, Southeast, and Great Plains, and negative or nonsignificant trends over the West. These prior studies based on 8-km AVHRR data-sets are consistent with our findings of GS-TIN trends across CONUS. However, these studies generally fail to remove the potential confounding influence of shifts related to land-cover modification, disturbance, and agricultural practices.

Supplementing these prior studies, ours provides more details about greenness trends and the relationship between vegetation and key climate variables related to specific geographic region and land-cover type. This study revealed non-uniform spatial patterns in vegetation greenness trends for different stable natural vegetation types across CONUS, enhancing existing understanding based on the less detailed 8-km AVHRR data. We employed a masking method to reduce possible confusion in interpreting greenness trends that might be caused by land-cover conversion or disturbance due to wildfire. Other types of land management activities not tracked in this study are not well mapped (e.g., forest plantation and harvest cycles) and may have an influence on vegetation greenness trends. As patterns of NDVI time series can be driven by long-term climate change, climate variability on short time scale, and anthropogenic land-cover conversions, reducing the effects of human influences and land-cover change is a useful strategy for revealing relationships of vegetation greenness to climate and weather.

b. Interpretation of the GS-TIN trends and their correlations with climate

We assessed vegetation greenness trends and their relationships with climate on lands presumed to have stable natural land cover through the study period that were not burned by wildfire. We removed developed and agricultural lands from the analysis because diverse surface characteristics linked to management influences over time would confuse interpretation of the trend results. The finer spatial resolution (relative to 8-km resolution) of the 1-km AVHRR data supported the screening of land-cover conversion and disturbance by wildfire.

We observed that significant positive GS-TIN trends were prevalent in the forested areas of the eastern third of the country and the far northwest. Additionally, a large proportion of the grassland in the northern Great Plains displayed significant greening trends correlating with significant precipitation increases. While the greening signal across eastern forests showed significant and positive trends, this appeared to correspond to increasing temperature in some locations (e.g., around the Great Lakes) or precipitation (which showed both increases and decreases). One uncertainty in this study could be shifts in dominant vegetation species in the context of stable land cover that might also be a source of greenness trends but not captured in this analysis. A recent study by Jones et al. (2020) revealed increases in percent cover of grasses/forbs in the northern Great Plains and trees in the southern Great Plains from 1999 to 2018, based primarily on 30-m Landsat, meteorology, and field observation data. The study reported large-scale woody plant encroachment in the western grasslands and shrublands in the past 20 years, which might have contributed to the positive trends in the vegetation greenness (Jones et al. 2020).

A large portion of the area showing negative GS-TIN trends was found in arid and semiarid areas in the western United States. Stable natural lands in the Southwest showed weakly decreasing or flat trends in GS-TIN, corresponding to significantly increasing trends in temperature for areas especially the Great Basin and the southern Rocky Mountains (Figs. 4c,d). Lack of significant GS-TIN trends in the Southwest may be partly due to the challenges in remote sensing of dryland vegetation (Smith et al. 2019). However, central and western shrublands and grasslands showed the greatest sensitivity to annual climate (Figs. 6c and 7c). Because shrublands and grasslands in those regions provide forage for livestock,

FIG. 7. Bar charts of the partial and multiple correlation coefficients between GS-TIN, TMP, and PPT summarized by NAC4 region and land cover: (a) partial correlation of GS-TIN vs TMP, controlling for PPT, (b) partial correlation of GS-TIN vs PPT, controlling for TMP, and (c) multiple correlation of GS-TIN vs TMP and PPT. The bar and the error bar, respectively, indicate the mean and standard deviation of the correlation coefficient for each vegetation type and each region. The vegetation types are as in Fig. 5.
these results have implications for the future condition of vegetation supporting the livestock industry (Derner et al. 2018; Havstad et al. 2018). Large areas in the Intermountain West also support ungulate species (e.g., deer, elk, and antelope) and their presence is significant to tourism and hunting (Torstenson et al. 2006). An increasing trend in greenness, as observed in various pockets in the Northwest, the Southwest, and the northern Great Plains (Figs. 4a,b), is indicative of improvements in the availability of vigorous herbaceous cover during the growing season.

The Southeast showed the largest area (88.8%) of positive GS-TIN trends over deciduous and evergreen forests but indicated weak correlation to either temperature or precipitation. Although there was some evidence of drying in the Southeast, most drying trends showed nonsignificant slopes. Sources of confusion include more local conditions leading to spatial heterogeneity in the 1-km AVHRR pixels such as the temporal cycle of planting and logging of coniferous forest plantations in this region (Napton et al. 2010). Our screening methods would likely not eliminate all harvested locations because the time step of the NLCD was not frequent enough (i.e., the 5-yr periodicity in NLCD), commercial forest use was not distinguished from natural forest in NLCD, or land-cover heterogeneity within the 1-km resolution spatial analysis.

In the Northeast, Southwest, and Midwest forests, further interpretation of the greening trends is needed as we did not observe significant correlations with temperature or precipitation. Although we reduced the impacts of anthropogenic influences and disturbance over the period, we were not able to fully eliminate other management impacts or species change. The Southeast, for example, has many commercial pine plantations dominated by periodic cycles of forest harvest, replanting, and growth that might underpin greenness trends (Sayler et al. 2016). Possible explanations from other research include CO₂ fertilization and radiation increases that occur with decreases in cloud cover (Nemani et al. 2003; Boisvenue and Running 2006), but further investigation is necessary to determine if this is the case in eastern CONUS.

Because land-use management is a complex practice with potentially large spatial and temporal variation, the influence of anthropogenic activities on vegetation greenness trends would benefit from further investigation. In stable natural land cover, human-induced changes can include forest fragmentation, forest or shrub thinning, invasive species, deforestation, urbanization, and grazing. According to the U.S. Department of Agriculture Forest Service’s report, the forested area in CONUS increased by approximately 134,000 km² from 1987 to 2012 (Oswalt and Smith 2014). The forest area change was attributed largely to forest management practices including planting, harvesting, conservation, and management.

### 6. Conclusions

We analyzed temporal vegetation greenness trends (1989–2016) and the relationships with climate for stable natural land cover using 1-km resolution AVHRR NDVI time series and gridded climate data. Temporal trend analysis of AVHRR-derived GS-TIN from 1989 to 2016 indicated
significant positive and negative GS-TIN trends varied depending on climate zones, land cover, elevation, and disturbance (e.g., tree mortality). In general, significant positive GS-TIN trends were shown within all land-cover types in eastern CONUS (Northwest, Southeast, and Midwest), the northern Great Plains, and the forests in the Northwest. Most shrublands and grasslands showed no significant trends or low negative trends in the western United States (Northwest and Southwest) and the southern Great Plains. Grasslands in the northern Great Plains showed significant positive trends in GS-TIN. The GS-TIN in shrublands and grasslands in central and western regions (Northwest, Southwest, and Great Plains) mainly correlated negatively with TMP and positively with PPT. The GS-TIN in the eastern forests (Northeast, Southeast, and Midwest) and the Northwest region was positively correlated with TMP but weakly correlated with PPT (except for the Northwest). The multiple correlation coefficients of GS-TIN versus TMP/PPT were relatively high in western and central CONUS (Northwest, Southwest, and Great Plains) and the Northeast. Shrublands and grasslands showed higher multiple correlation coefficients than forests. The results indicated that the GS-TIN over grassland and shrubland in western and central CONUS was more heavily influenced by climatic factors than in the east. The mixture of positive and negative GS-TIN trends in some western forested areas, for example the Rocky Mountains, were apparently linked to bark beetle–induced tree mortality. The insect outbreaks in the forests resulted in high tree mortality, decreasing the GS-TIN over time and leading to negative trends in the GS-TIN time series.

Because of the uncertainties in this research related to mixed pixels of land cover and land use based on 1-km-resolution AVHRR data, we recommend future research on vegetation greenness trends using long-term Landsat time series data. The Land Change Monitoring, Assessment, and Projection (LCMAP) project developed by the USGS EROS Center represents the next generation of land-cover mapping and change monitoring (Brown et al. 2020). LCMAP creates an integrated suite of annual land-cover and change products based on the entire Landsat time series record, providing an opportunity for investigation at finer spatial resolution. At the Landsat spatial scale, additional research can be done to delve into influences of topographic gradients and plant functional types on seasonal greenness trends.

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*Data availability statement.* The datasets such as AVHRR, NLCD, PRISM, MODIS, and tree mortality that we analyzed in the study are in the public domain and are freely available at the locations given in the reference section.

### APPENDIX A

**Tests of Data Normality and Temporal Autocorrelation**

We tested data normality for the GS-TIN, TMP, and PPT time series for all pixels of stable natural vegetation in the study area using the JB statistic (Jarque and Bera 1987). The tests calculated the probability that the time series samples were drawn from a normal population. The null hypothesis $H_0$ is that the samples are not different from a normal population. The alternative hypothesis $H_a$ is that the samples are different from a normal population.

The JB test was performed temporally for the time series at each one of all pixels (4,742,054) for stable natural vegetation. The results showed that GS-TIN rejected $H_0$ at the $\alpha = 0.01$ level for 1.6% of the total pixels. In other words, GS-TIN values were not significantly different from a normal distribution for 98.4% of the total pixels. As a result, the distribution of the GS-TIN time series was considered to be normal at the $\alpha = 0.01$ level for all pixel locations. The JB testing results also indicated that 0.44% and 2.7% of the total pixels in the TMP and PPT data, respectively, rejected $H_0$ at the $\alpha = 0.01$ level. That is, TMP and PPT in most areas (99.6% and 97.3%, respectively) did not show significant differences from normal distributions. Because the JB statistics indicated normal distributions in the GS-TIN, TMP, and PPT time series, conventional parametric statistics were considered to be adequate in our statistical analysis.

The DW statistic (Durbin and Watson 1971) was applied to test for presence of temporal autocorrelation for the GS-TIN, TMP, and PPT time series. The hypotheses for the DW test are that first-order positive autocorrelation does not exist ($H_0$) and first-order positive autocorrelation exists ($H_a$). We calculated the $d$ values and used the critical values based on the DW statistic table to indicate significance level of the time series. The temporal autocorrelation was tested on the GS-TIN, TMP, and PPT time series for all stable natural vegetation pixels. The results indicated that GS-TIN showed significant positive first-order autocorrelation for 12.6% of the total pixels. For TMP and PPT, only 1.5% and 0.2%, respectively, of the total pixels exhibited positive autocorrelation. Therefore, more-complicated statistical techniques adjusting for temporal autocorrelation were unnecessary in this study.

### APPENDIX B

**Test of the Effect of AVHRR Sensor Change on GS-TIN Trends**

We performed a statistical test on the GS-TIN time series. The procedure for statistical testing of the effect of sensor change from AVHRR/2 to AVHRR/3 on the GS-TIN trends is described below:

1. A trend analysis for the entire GS-TIN time series (1989–2016, excluding the high SZA years) was performed using the linear regression model [Eq. (2)]. The regression model generated a set of residuals.

2. The GS-TIN time series was partitioned into two segments: 1989–98 (AVHRR/2 on NOAA-11 and NOAA-14) and 2001–16 (AVHRR/3 on NOAA-16, NOAA-17, NOAA-18, and NOAA-19). A piecewise regression was run for the two-segment GS-TIN time series with a breakpoint between the two segments, generating another set of residuals.

3. A matched-pair $t$ test was run to compare the difference between the two sets of residuals, one from the regular regression and another from the piecewise regression. The hypotheses of the test were $H_0$ ($\mu_d = 0$) and $H_a$ ($\mu_d \neq 0$) where $\mu_d$ is the mean for the difference in the two matched residual sets.

4. If $H_0$ was rejected at $\alpha = 0.05$ level, we concluded that the difference between the two residual groups was significant. Thus, the residuals from the regular regression were significantly higher than those from the piecewise regression, implying that the GS-TIN time series was better fitted by two different trending lines. In this case, we considered the sensor change might have influenced the GS-TIN time series. Alternatively, if $H_0$ was not rejected in the test, we concluded that the difference between the two residual sets was not significant, implying that the GS-TIN time series was not significantly affected by the change of instruments.

5. This test was conducted temporally for the GS-TIN time series at each stable natural vegetation pixel in the images, resulting in maps of $t$ values and significance levels for the study area.

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