Ecological Applications, 27(5), 2017, pp. 1677–1693

Breaks in MODIS time series portend vegetation change: verification using long-term data in an arid grassland ecosystem

Dawn M. Browning,[1,2,3] Jonathan J. Maynard,[1] Jason W. Karl,[1] and Debra C. Peters[1,2]

[1]*USDA-ARS, Jornada Experimental Range, New Mexico State University, P.O. Box 30003, MSC 3JER, Las Cruces, New Mexico 88003 USA*

[2]*Jornada Basin Long-Term Ecological Research Station, New Mexico State University, P.O. Box 30003, MSC 3JER, Las Cruces, New Mexico 88003 USA*

Abstract. Frequency and severity of extreme climatic events are forecast to increase in the 21st century. Predicting how managed ecosystems may respond to climatic extremes is intensified by uncertainty associated with knowing when, where, and how long effects of extreme events will be manifest in an ecosystem. In water-limited ecosystems with high inter-annual variability in rainfall, it is important to be able to distinguish responses that result from seasonal fluctuations in rainfall from long-term directional increases or decreases in precipitation. A tool that successfully distinguishes seasonal from directional biomass responses would allow land managers to make informed decisions about prioritizing mitigation strategies, allocating human resource monitoring efforts, and mobilizing resources to withstand extreme climatic events. We leveraged long-term observations (2000–2013) of quadrat-level plant biomass at multiple locations across a semiarid landscape in southern New Mexico to verify the use of Normalized Difference Vegetation Index (NDVI) time series derived from 250-m Moderate Resolution Imaging Spectroradiometer (MODIS) data as a proxy for changes in aboveground productivity. This period encompassed years of sustained drought (2000–2003) and record-breaking high rainfall (2006 and 2008) followed by subsequent drought years (2011 through 2013) that resulted in a restructuring of plant community composition in some locations. Our objective was to decompose vegetation patterns derived from MODIS NDVI over this period into contributions from (1) the long-term trend, (2) seasonal cycle, and (3) unexplained variance using the Breaks for Additive Season and Trend (BFAST) model. BFAST breakpoints in NDVI trend and seasonal components were verified with field-estimated biomass at 15 sites that differed in species richness, vegetation cover, and soil properties. We found that 34 of 45 breaks in NDVI trend reflected large changes in mean biomass and 16 of 19 seasonal breaks accompanied changes in the contribution to biomass by perennial and/or annual grasses. The BFAST method using satellite imagery proved useful for detecting previously reported ground-based changes in vegetation in this arid ecosystem. We demonstrate that time series analysis of NDVI data holds potential for monitoring landscape condition in arid ecosystems at the large spatial scales needed to differentiate responses to a changing climate from responses to seasonal variability in rainfall.

Key words: arid ecosystems; Breaks For Additive and Season and Trend (BFAST); change detection; Jornada Experimental Range; long-term data; MODIS; time series; vegetation dynamics.

Introduction

Forecasted increases in the frequency and severity of drought episodes in the 21st century (Overpeck and Udall 2010, Cook et al. 2014) amplify the pressing need for data-informed strategies to mitigate the effects of variable climate. Capabilities to identify state transitions influencing ecosystem structure and function are needed to inform decisions and devise strategies to sustain natural resources (Bestelmeyer et al. 2011). Developing such capabilities requires an understanding of the drivers of long-term patterns in vegetation dynamics along with data needed to fuel the analytical approaches that build them (Carpenter et al. 2011). The ability to identify ecologically relevant shifts in vegetation structure and composition is predicated on distinguishing seasonal patterns from long-term directional trends in primary productivity (de Jong et al. 2012). Tools are needed that can characterize these temporal patterns of plant community dynamics, and to quantify deviations in a consistent way that can be applied over large spatial extents. Such tools would be especially valuable for forecasting landscape-scale responses to disturbance and environmental change (Herrick et al. 2013, Browning et al. 2015).

Remote sensing tools and products are a recognized means to detect landscape change and characterize disturbance in a consistent way over time that can improve the ability to identify state changes. Techniques that

Manuscript received 17 August 2016; revised 28 December 2016; accepted 8 March 2017. Corresponding Editor: Xiangming Xiao.

[3] E-mail: dawn.browning@ars.usda.gov

leverage the capabilities of long time series from remote sensing platforms and long-term ground observations are especially helpful (Woodcock et al. 2008, Brandt et al. 2015). Verbesselt et al. (2010*a*) described a time-series decomposition method for remotely sensed imagery known as Breaks For Additive and Season and Trend (BFAST) that characterizes time series patterns in land surface condition based on spectral vegetation index values (e.g., Normalized Difference Vegetation Index [NDVI]) and partitions these patterns into three components. The first component characterizes overall trends across the time period of interest. The second component represents seasonal or cyclical patterns in the data, and the third component represents the residuals or variance that remains once the trend and seasonal components are extracted (Verbesselt et al. 2010*b*). In addition to separating the trend and seasonal components in the time series, BFAST provides the ability to identify significant breaks in the modelled trend and seasonal components via a change in either the slope of the trend line or in the amplitude or frequency (i.e., shape) in the seasonal pattern.

The ability to distinguish seasonal patterns from those reflecting changes occurring at longer time scales (hereafter, "trend") strengthens change detection efforts. Landscape changes, from both anthropogenic and natural causes, occur over a range of temporal scales. We consider three classes of landscape change based on their temporal footprint: (1) abrupt changes that occur over days or weeks (e.g., deforestation, fires); (2) gradual changes (e.g., shrub encroachment, gradual land degradation) that occur over months or years; and (3) shifts in the seasonality of primary production that can be either abrupt or gradual (Verbesselt et al. 2010*b*). Changes in the timing, length, and shape of the growing season can potentially exhibit large influence on primary productivity and nutrient cycling (de Jong et al. 2013, Hufkens et al. 2016). Shifts in seasonality can be the result of different processes including high inter-annual climatic variability or changes in the dominance of plant functional groups (e.g., C_4 grasses vs. C_3 shrubs in the case of many grass and savanna systems worldwide). Changes in functional group dominance that result from shifts in the growing season (e.g., earlier start or later end) may serve as an indicator of vegetation state change or species invasion, and can affect a range of ecosystem services, including agricultural and forage yield, nutrient cycling, and plant–pollinator interactions (Morisette et al. 2009, Wolkovich and Cleland 2011).

There are two notable benefits of the BFAST method over other remote-sensing change detection techniques. First, it makes use of the entire time series rather than snapshots commonly used in change detection methods such as differencing two dates of imagery (e.g., Browning and Steele 2013). Second, the BFAST method requires specification of only a single parameter, the *h* value, which sets the minimum period between the breaks, thereby determining the potential number of breaks that can be detected in the time series. Selection of the *h* value should be based on the duration and frequency of the monitored processes (i.e., vegetation dynamics) and the length of the time series (Verbesselt et al. 2010*a*).

While the BFAST method has been used widely for a variety of research applications in a range of ecosystems (Verbesselt et al. (2010*a*) has been cited 256 times; accessed via Web of Science on 16 March 2017), there has not been an evaluation of BFAST's ability to detect changes in arid ecosystems based upon independent quantitative field data. There are three potential reasons for this research gap. First, validation of time series algorithms is complicated by the paucity of independent data sets for verification that span a long-term remote sensing record (Browning et al. 2015). Second, arid ecosystems are marked by high inter-annual variability in rainfall that make landscape patterns difficult to detect and make defining "average" conditions difficult (Sheppard et al. 2002). Third, relationships between primary productivity and environmental drivers in these water-limited ecosystems are non-linear and often exhibit lag effects, which are expressed differently across plant functional groups (Peters et al. 2007, Gherardi and Sala 2015*b*). Moreover, Verbesselt et al. (2010*a*) noted the reliability of detecting breaks is challenged in ecosystems with a low signal-to-noise ratio and recommended that the annual amplitude of the NDVI minimally exceeds 0.1 for the BFAST algorithm to work reliably. Arid landscapes commonly have a lower than average signal-to-noise ratio (SNR) and exhibit annual amplitudes in NDVI close to 0.1; high intra- and inter-annual variability in climate and sparse vegetation cover contribute to lower than average SNR.

Assessments of remotely sensed data using field data involve efforts to minimize effects of different spatial and temporal resolutions (Brandt et al. 2015, Browning et al. 2015). Differences in spatial resolution are inherent and are best evaluated in the context of spatial variability of the land surface (Karl et al. 2012). Landscape variability is more effectively characterized by imagery with smaller grain or pixel size while there is a trade-off with spatial resolution and consistency in sample frequency. Even so, we used 250-m MODIS imagery rather than 30-m Landsat imagery in this study because recent work at the JRN showed that the systematic grid field sampling employed at each study site effectively characterized the spatial variability present within 250-m MODIS pixels and MODIS circumvents the need for gap-filling that Landsat (with 30-m pixels) time series requires (Maynard et al. 2016).

In theory, we proposed that BFAST's trend component would be associated with inter-annual variability in plant biomass, while the seasonal component would be associated with intra-annual variability in plant phenology. While several studies have verified breaks identified in the trend component (typically abrupt high-magnitude changes) using records of forest management (Verbesselt et al. 2010*a*) or flooding and fire events (Watts and Laffan 2014), direct validation of trend and seasonal breaks with quantitative field data has been lacking. A recent study by DeVries et al. (2016) helps fill this gap in tropical forests in Ethiopia by leveraging data collected by local experts. The broader gap to include seasonal breaks from BFAST as well as applications in water-limited environments brings into question the ecological significance of identified seasonal as well as trend breaks and whether they can be used to inform management.

Objectives

We set out to determine whether the BFAST algorithm yields ecologically meaningful breaks when applied to MODIS 250-m NDVI imagery of an arid environment with a high inter-annual variability and a low annual amplitude of NDVI (but exceeding 0.1). Specifically, we predicted (1) breaks in the overall trend would reflect changes in total photosynthetic biomass (increases or decreases) and (2) seasonal breaks would identify shifts in dominance of plant functional groups exhibiting contrasting phenology patterns.

The Jornada Basin Long-Term Ecological Research site (JRN) in southern New Mexico is a model system to verify BFAST breaks derived from MODIS imagery in an arid environment. The JRN offers a long-term data record from 1990 to present including field-estimated biomass collected at 15 study locations exhibiting heterogeneity in fractional cover, plant biomass by species and functional type, and soils (Peters et al. 2012). In addition, extreme fluctuations in rainfall with a period of sustained below average rainfall (2000–2003) and a sequence of record-breaking rainfall years (2006 and 2008) resulted in a rearrangement of plant productivity between phenologically distinct plant functional groups at sites on the JRN (Peters et al. 2012, 2014). This "natural experiment" and documented shift in plant communities provide an opportunity to examine performance of both trend and seasonal breaks from the BFAST algorithm. We draw on expert knowledge of local vegetation dynamics and phenology at this arid site and leverage an independent long-term field data record in conjunction with moderate resolution MODIS NDVI time series to examine the utility and performance of BFAST in identifying ecologically significant breaks in the seasonal and long-term trends in biomass from 2000 through 2012.

Methods

Study site

The study was conducted on the JRN LTER site near Las Cruces, New Mexico (32.603° N, 106.776° W; Fig. 1). The JRN lies in the northern Chihuahuan Desert between the Rio Grande corridor and the San Andres Mountains within the southern Jornada del Muerto Basin in the Southern Desertic Basins, Plains, and Mountains Major Land Resource Area (USDA-NRCS 2010). Soils at study sites are dominantly sandy with variable surface sand content, soil depth, and subsurface clay accumulations (Bulloch and Neher 1980). Soils and landscape position strongly influence soil water dynamics at the JRN (Snyder and Tartowski 2006). Plant growth is primarily constrained by moisture and secondarily constrained by soil nutrients. Long-term (1990–2012) average annual rainfall was 233 mm with 53% of annual rainfall (123 mm) occurring from July to September. Mean maximum monthly temperatures range from 13.5°C in January to 35.0°C in July (Wainwright 2006).

Five ecosystem types distinguished by the dominant plant species characterize our study sites on the JRN: (1) *Larrea tridentata* shrublands, (2) *Flourensia cernua* alluvial flats, (3) *Prosopis glandulosa* dune systems, (4) *Bouteloua eriopoda* upland grasslands, and (5) grass-dominated dry lakes (*Pleuraphis mutica*) or playas (*Panicum obtusum*; Huenneke et al. 2002). Variation in environmental conditions across sites is reflected in the range of peak fall biomass from 65 to 257 g/m^2 between 1989 and 2014, percent bare (i.e., unvegetated surface) from 2% to 59%, surface gravel from 0% to 55% and plant-available water in the upper 50 cm of the soil profile from 1.7 to 9.4 cm (D. M. Browning et al., *submitted manuscript*).

Data used

Aboveground photosynthetic biomass was measured using non-destructive field methods at the same sites where rainfall data were collected. Plant biomass was compared to the seasonal and trend components of 250-m MODIS NDVI time series from BFAST over 13 yr (2000–2012). Changes in biomass and BFAST breaks were examined in the context of rainfall data collected at individual sites to enhance interpretation of patterns in this water-limited ecosystem. Biomass data and MODIS imagery are described in the following sections.

Field data.—The long-term field-based data record at the JRN used in this research comes from a study of aboveground net primary production (NPP) that began in 1989 (see Huenneke et al. 2002, Peters et al. 2012). The NPP study encompasses 15 sites established to capture a range of variability in species composition, biomass, soils, and landscape position at the JRN. Fourteen of 15 long-term sites are 70 × 70-m in area and include 49 1 × 1 m subplots; one playa site plot is 30 × 150 m in area with 48 1 × 1 m subplots. Biomass is estimated within subplots using allometric relationships defined in Huenneke et al. (2002) and refined by Peters et al. (2012). Biomass measurements are made three times a year: in winter (i.e., February) when perennial deciduous species are dormant, in spring (i.e., early to mid May) when C_3 shrubs have leafed out, and in late summer or early fall to capture peak biomass (i.e., mid to late September) when C_4 grasses are green.

To evaluate BFAST break dates with field-estimated biomass, we calculated the change in total mean biomass

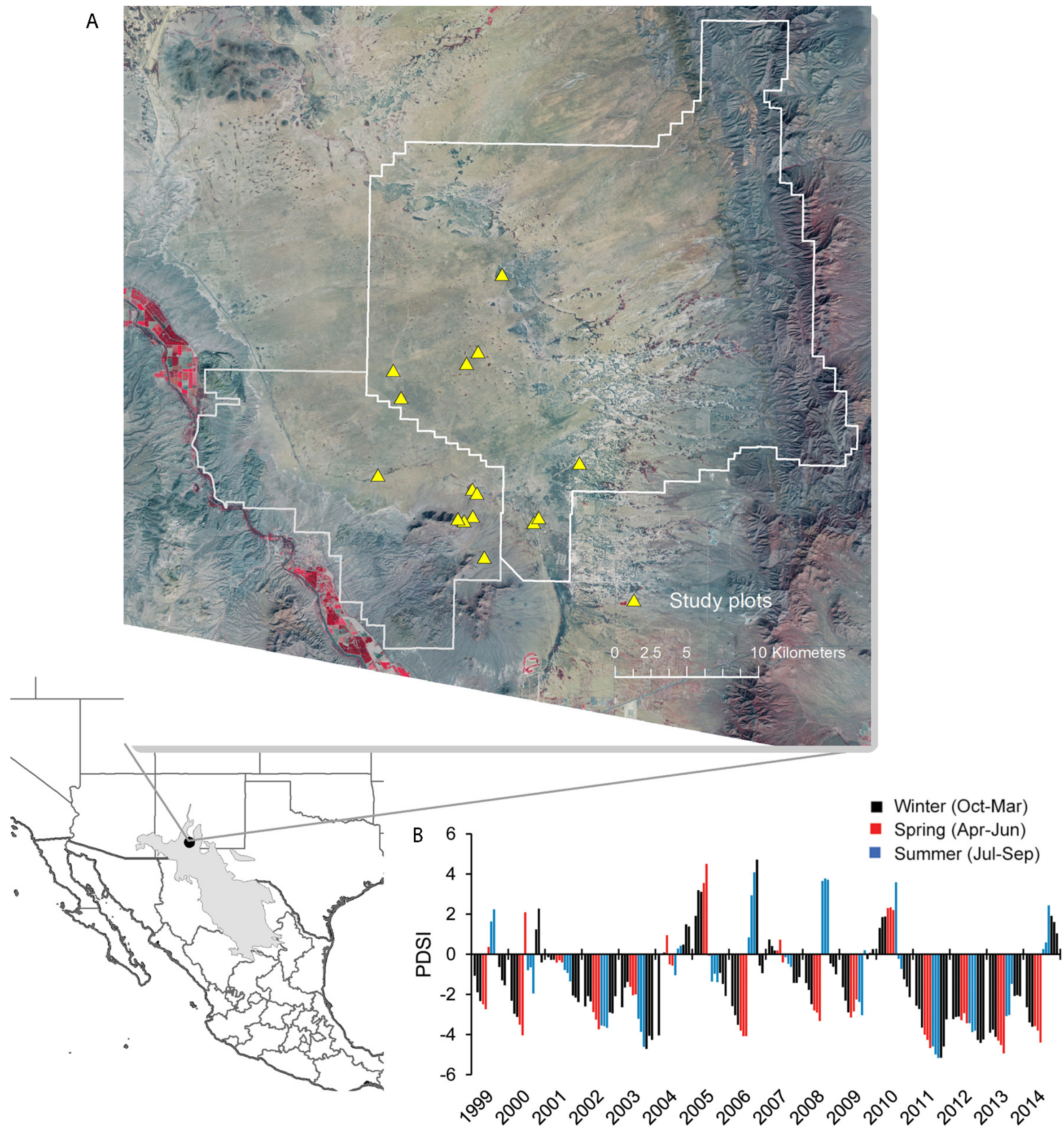


Fig. 1. (A) Jornada Basin LTER (JRN) with 15 long-term study sites (yellow triangles) atop a Landsat image acquired 17 October 2009 with (B) long-term patterns in Palmer Drought Severity Index (PDSI). PDSI was calculated monthly for the National Climate Data Center Southern Desert region (NM 8 at 46,495 km^2) for the Jornada Basin (http://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/) for the period 1999–2014. Negative values indicate drought and positive values denote wet months. [Color figure can be viewed at wileyonlinelibrary.com]

as the difference between successive field campaigns for each site. The median date for latest field campaign was assigned to the change in biomass value. To examine seasonal breaks, biomass was summarized by functional groups used in Peters et al. (2012) constituting species that demonstrate similar patterns of resource use. The four functional groupings were based on photosynthetic pathway and growth form to include perennial C_4 grasses, shrubs (deciduous and evergreen C_3 and CAM species), annual grasses, and annual and perennial forbs.

MODIS imagery.—The BFAST analysis of the 15 long-term sites was based on time series NDVI (Tucker 1979) from MODIS pixels covering the study sites. We acquired all 250-m resolution MODIS NDVI images (MOD13Q1 data product) between 2000 and 2012 (16-d resolution), totaling 269 scenes (H09V05). The MOD13Q1 NDVI product is a 16-d composite that uses a constrained view-angle maximum value composite method to reduce anomalies associated with cloud cover and low sensor view angles (Huete et al. 2002). The MOD13Q1 NDVI product includes quality assurance (QA) flags with statistical data that indicate the quality of the indices and input data. We used the QA flags to select only cloud-free data of optimal quality and replaced missing cloud-covered pixels by linear interpolation within each pixel time series to ensure a regular temporal measurement frequency for all pixels. MODIS data acquisition and preprocessing were performed using the MODIS R package (Mattiuzzi 2015, version 0.10-11).

We chose NDVI as the remote-sensing variable in this study for two reasons despite its limitations in arid environments due to effects of exposed soil, standing dead vegetation, and litter on the spectral response (Richardson and Wiegand 1977, Huete 1988, Gao et al. 2000). First, it is widely used as a relative and indirect indicator of the amount of photosynthetic biomass (Tucker et al. 1979) and second, prior research in a semiarid environment has shown that the choice of vegetation index did not affect modeled output from the BFAST time-series decomposition algorithm (Watts and Laffan 2014). Similarly, we chose MODIS imagery as the NDVI data source over Landsat imagery because recent research at this site indicated that MODIS NDVI was more strongly correlated to biomass measurements due to its higher temporal resolution and thus cleaner temporal signal (i.e., fewer artifacts and data gaps; Maynard et al. 2016). For all 49 subplot locations at each site, we extracted the MODIS NDVI pixel value that each subplot intersected for each image acquisition date. All study sites fell with one or two MODIS pixels, resulting in one or two repeating pixel values across the 49 subplots. At each study site all 49 subplot pixel values were then averaged producing a spatially weighted mean NDVI value per sampling date.

Satellite time-series decomposition

Time-series decomposition was performed using the BFAST algorithm, implemented using the bfast package for R (Verbesselt et al. 2010*a*; version 1.5.7). The BFAST algorithm implements an additive decomposition of a time series into trend, seasonal, and noise components through iteratively fitting a piecewise linear trend and seasonal model. For the time period $t = 1,\ldots, n$, the BFAST model takes the form

$$Y_t = T_t + S_t + \varepsilon_t \tag{1}$$

where Y_t is the observed datum (NDVI for this study) at time t, Y_t is the trend component, S_t is the seasonal component, and ε_t represents the remainder.

The BFAST algorithm is designed to detect and characterize abrupt changes (i.e., breaks) within both the trend and seasonal components. The algorithm tests for the presence of abrupt changes in the data prior to estimating the seasonal and trend components using an ordinary least squares (OLS) residuals-based moving sums (MOSUMs) test (Zeileis and Kleiber 2005). If a significant change is detected at a given α, the optimal number and position of breakpoints within the time series are returned based on the method of Bai and Perron (2003). The magnitude and direction of breaks are calculated from the intercept and slope of the trend component model and can occur at different times in the trend and seasonal components (Verbesselt et al. 2010*a, b*).

The BFAST model uses a numeric bandwidth scalar parameter (*h* value) to determine potential number of breaks that can be detected within a time series by controlling the minimum segment size between breaks (Verbesselt et al. 2010*b*). The *h* value affects the trend component piece-wise linear model. We set the *h* value at 0.15 based on the 12-yr time series and on our knowledge of the life history characteristics of the vegetation, which allowed the time series to be divided into a maximum of six trend segments, separated by five breaks, maintaining a minimum of approximately 2 yr between subsequent breaks. BFAST models were run using a harmonic seasonal model, which is considered to be most adapted to natural vegetation phenological change detection (Verbesselt et al. 2010*b*).

Assessment of BFAST breaks

We compared changes in field-estimated biomass from 2000 to 2012 with BFAST trend and seasonal breaks for the same period to quantify the ability of BFAST to detect shifts in photosynthetic biomass. Trend break dates were compared with changes in total biomass between successive field campaigns while breaks in the seasonal component were evaluated relative to change in the proportion of total biomass by functional group. Trend and seasonal breaks from the BFAST algorithm were classified as successes or failures and seasonal break success was further distinguished by plant functional group.

Differences in sampling frequencies for MODIS and field campaigns to estimate biomass required we establish rules to select the biomass sample interval (and associated change in biomass) used to classify trend breaks as successes or failures. The selection process involved sequential criteria. We first identified the biomass sample interval closest to the BFAST break date. We then assessed whether the median date for the biomass sample period (representing the end of the biomass change interval) occurred within the 95% CI surrounding the BFAST break. If it fell outside of the 95% CI, the break was classified as a "temporal mismatch" (further described below). If it fell within the 95% CI, we assessed whether the change in biomass coincided with the direction of change indicated by the BFAST break (increasing or decreasing). If it did, the break was classified as a success; if it did not, it was classified as a failure. There was one exception to this rule set made for increasing BFAST breaks that occurred in late March, a time for initial growth in several herbaceous species (D. M. Browning et al., *submitted manuscript*). The February biomass sample period represents decreases in biomass from the following fall; therefore, in the three cases of late March trend breaks, we compared break dates to the spring (May) biomass sample interval.

A similar process was used to identify the biomass sample interval for comparison with seasonal breaks. Success for seasonal breaks was defined as the case in which the 95% confident interval overlapped changes in the proportion of total biomass (>0.10) for one or more plant functional groups. Successful seasonal breaks were designated further to identify the functional group with the largest increase or decrease in biomass contributing to the shift in the seasonal signal in NDVI. Failure was assigned to those seasonal breaks that did not correspond to perceivable changes in functional group contributions to total biomass. Similarly, "temporal mismatch" was assigned to seasonal breaks that experienced shifts in functional group contribution to biomass outside the 95% confidence interval.

Results

Trend breaks as indicators of changes in biomass

There were 45 trend breaks across all sites between 2002 and 2012 (Fig. 2) and each was assigned to one of three categories. Fifty-one percent (23/45) of trend breaks were classified as successes, 22% (10/45) as failures, and the 27% (12/45) as temporal mismatches. Eleven of the 12 trend breaks classified as mismatches occurred between 28 July 2006 and 29 August 2006 in response to record-breaking rainfall in 2006. In these 11 cases, CIs were narrow (mean of 81 d) relative to the 90- or 120-d intervals for biomass sampling. Fall season biomass sampling is conducted in mid September to early October as part of the long-term study of net primary production (Peters et al. 2012). We therefore grouped the 11 increasing temporal mismatch breaks in 2006 with successes as field-verified breaks in results that follow.

Changes in field-estimated biomass for successful BFAST breaks revealed patterns in NDVI across vegetation zones. Grass-dominated sites in upland and playa zones were more dynamic with more increasing breaks characterized by maximum change in biomass values and greater variation about the mean (Table 1, Fig. 3). Mesquite-dominated sites demonstrated higher variability than other shrubland sites and is likely in response to 2006 increases in biomass driven by the response of annual grasses at sites in those vegetation zones. The upland grassland site at IBPE experienced an increasing break 12 July 2006 that coincided with a 213.2 g/m^2 change (Fig. 4B) and the mesquite-dominated site NORT experienced a 26 July 2006 increasing break coinciding with a 215.7 g/m^2 change, Fig. 4C. Decreasing breaks at creosote-dominated sites were marked by larger magnitude changes in mean biomass (-74.9 g/m^2) than for increasing breaks (19.2 g/m^2). Mesquite-dominated sites exhibited the highest magnitude changes in biomass associated with decreasing breaks (-247.0 g/m^2; Table 1).

Twenty-two percent (10/45) of trend breaks were classified as failures. Nine of the 10 failures were decreasing breaks and eight of these occurred in 2009, 2011, and 2012. Of the 10 breaks classified as failures three occurred on upland and four on playa grassland sites. Three break failures occurred at the SMAL playa grassland site (Fig. 4A) and failures at upland grassland sites occurred at IBPE (Fig. 4B in 2012), BASN (Appendix S1: Fig. S5A in 2009), and SUMM (Appendix S1: Fig. S5B in 2011).

Patterns in long-term trend in the context of rainfall

Sites experienced between two to four breaks in the long-term trend between 2000 and 2012 with general patterns of synchrony relative to periods of high rainfall and asynchrony relative to periods of low to no rainfall (Fig. 2A). There was a general pattern across nine of 15 sites of significant increase in NDVI coinciding with the first rainfall in 2004 following the 2000–2003 drought period. The nine sites included five of six grassland sites, all three creosote shrubland sites and one of three mesquite dune shrubland sites. There was an even more pronounced synchronous pattern of breaks in the trend that reflected increases in NDVI occurring in 2006 following record-breaking rainfall in 2006 (hereafter "2006 increase"). Thirteen sites experienced this marked increase in NDVI; the only two sites that did not experience the 2006 increase in NDVI were two creosote shrubland sites that experienced a previous increase in 2004.

Fig. 2. (A) Monthly rainfall occurring at 15 long-term research sites from January 2000 through December 2012. Temporal distribution of breaks in the trend derived from Breaks for Additive Season and Trend (BFAST) analysis of 16-d composite Moderate Resolution Imaging Spectroradiometer (MODIS) Normalized Difference Vegetation Index (NDVI; at 250-m resolution). Breaks denote significant deviations in the NDVI compared with the model fitted to the long-term trend component of the time series and are displayed in green (significant increase in NDVI) and orange (significant decrease in NDVI). Up-facing triangles denote an increasing break and down-pointing triangles denote a decreasing break. Solid triangles without interior symbols were classified as successes. Triangles with a black interior signify breaks that were classified as failures; those with white interior triangles signify breaks classified as successes with temporal mismatch. See classification details in *Methods*. (B) BFAST trend breaks displayed atop the proportion of maximum total biomass for each site over the 13-yr period with increasing and decreasing breaks denoted with blue and red triangles, respectively. [Color figure can be viewed at wileyonlinelibrary.com]

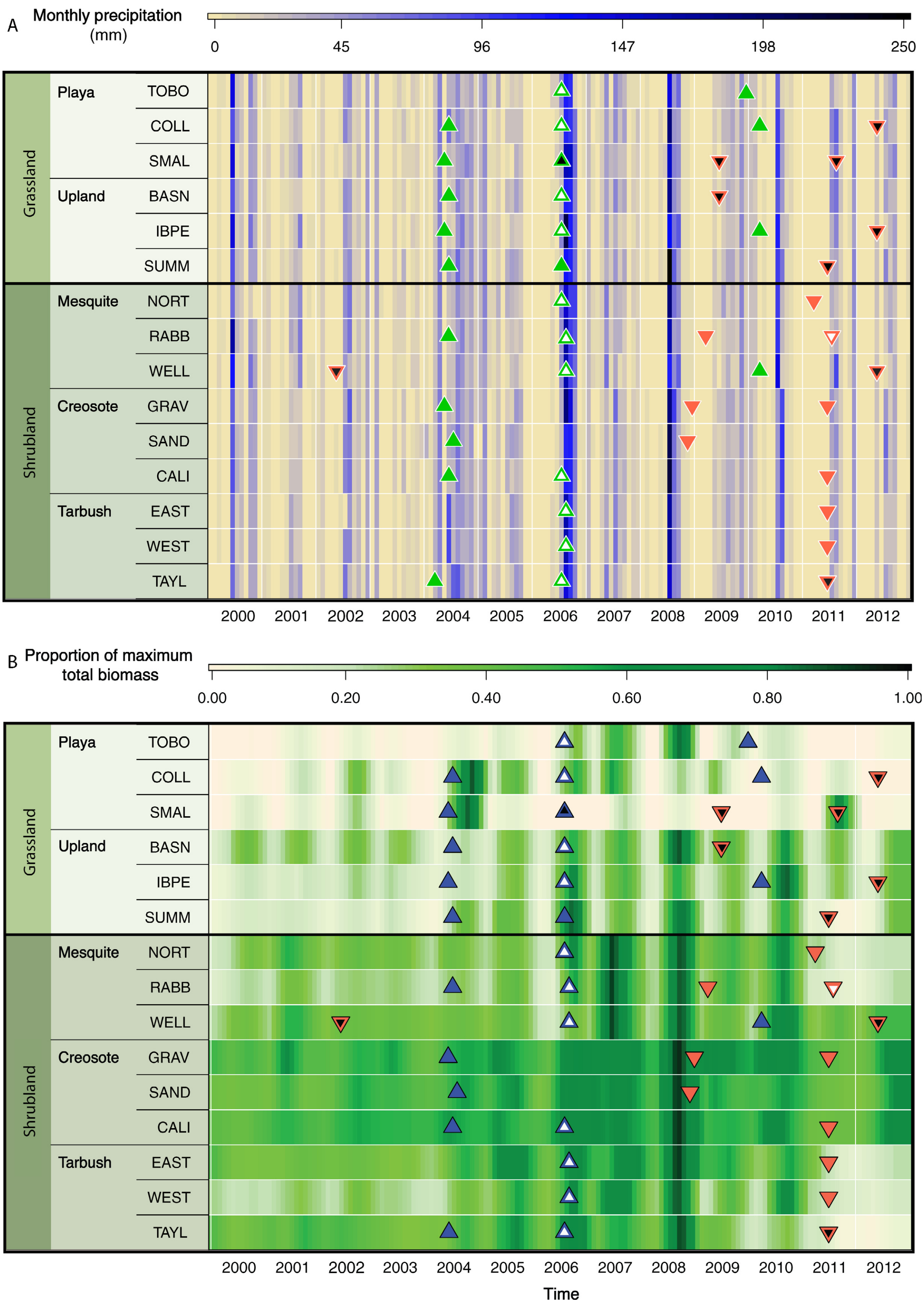

A
Monthly precipitation (mm)
0
45
96
147
198
250
Grassland
Playa
TOBO
COLL
SMAL
Upland
BASN
IBPE
SUMM
Shrubland
Mesquite
NORT
RABB
WELL
Creosote
GRAV
SAND
CALI
Tarbush
EAST
WEST
TAYL
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012
B
Proportion of maximum total biomass
0.00
0.20
0.40
0.60
0.80
1.00
Grassland
Playa
TOBO
COLL
SMAL
Upland
BASN
IBPE
SUMM
Shrubland
Mesquite
NORT
RABB
WELL
Creosote
GRAV
SAND
CALI
Tarbush
EAST
WEST
TAYL
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012
Time

Table 1. Summary statistics for 34 BFAST breaks in the trend that were classified as successes with field-estimated plant biomass at 15 long-term study sites.

Zone	Increasing breaks		Decreasing breaks	
	Area (g/m^2)	No. breaks	Area (g/m^2)	No. breaks
Upland	112.3 ± 132.1	8		0
Playa	124.2 ± 93.6	5		0
Mesquite	133.2 ± 85.8	5	−247.0 ± 122.1	2
Creosote	19.2 ± 9.2	4	−74.9 ± 84.7	4
Tarbush	67.7 ± 45.6	4	−17.6 ± 13.1	2

Notes: There are three study sites in each zone. Area is presented as mean ± SD.

Patterns in the NDVI trend encompassed cases of synchrony and asynchrony ranging from low to high variability in timing of breaks across sites. Timing of trend breaks that reflected decreases in NDVI coinciding with drought conditions in 2009 and 2011–2012 (Fig. 1B) were more variable and less synchronous across sites. Notable dry conditions occurred both in 2009 following record-breaking high rainfall in 2008 as well as from October 2010 to July 2011 of little or no recorded rainfall. The drought period in 2011 also spanned a record-breaking hard freeze in February 2011 (Hardiman 2011). Two of six grassland sites (one playa and one upland) experienced decreasing breaks in the trend in 2009 while seven of nine shrubland sites (two mesquite, two creosote, three tarbush) experienced breaks reflecting decreasing NDVI in 2011, with six of those seven breaks occurring between 10 June 2011 and 12 July 2011 (Fig. 2).

The prevailing pattern in the NDVI trend from 2000 through 2012 was that of relatively fast biological response to rainfall following drought conditions in 2004 and/or 2006, resulting in highly synchronous positive breaks across sites. These trends were followed by subsequent decreases in NDVI trend between 2009 and 2012 with the onset of drier conditions and more variable timing of negative breaks across sites (Fig. 2). Functional group contributions to total biomass lent insight to breaks in the long-term trend. The six of 11 increasing trend breaks in 2006 coincided with changes in annual grasses while the remaining five reflected changes in biomass for perennial grasses. Subsequently high proportions of maximum total biomass that were most prominent in 2008 at shrubland sites (Figs. 2B, 4C, E) were largely due to a strong perennial grass response to a sequence of wet years reported by Peters et al. (2012). The decreasing breaks that occurred between 2009 and 2012 coincided with decreases in biomass among all functional groups although decreases in biomass of grass, annual, and forb species (hereafter "herbaceous") were generally steeper.

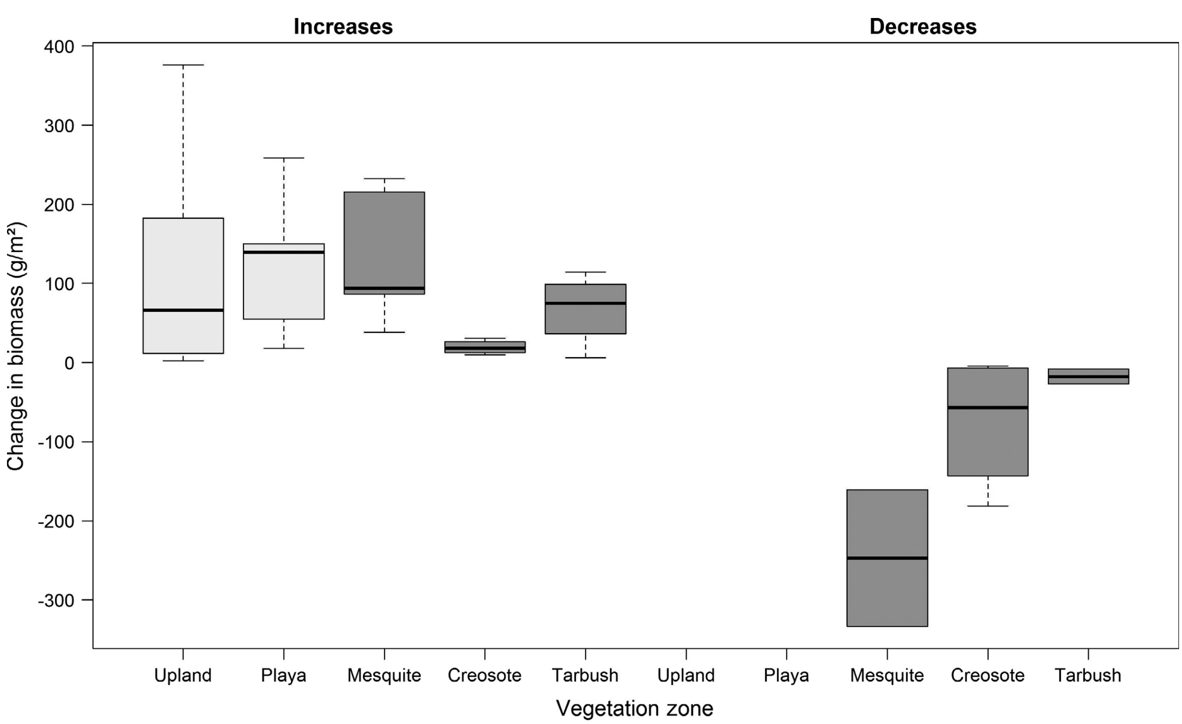


Fig. 3. Box plots for mean change in field-estimated plant biomass (g/m^2) for 34 successful BFAST breaks in the long-term trend. Biomass is estimated at 15 long-term study sites distributed three per each of five vegetation zones. Boxes represent the interquartile range, the mid line is this the median, and whiskers correspond to the minimum and maximum values. Dark gray boxes correspond to shrub-dominated sites and light gray boxes correspond to grass-dominated sites.

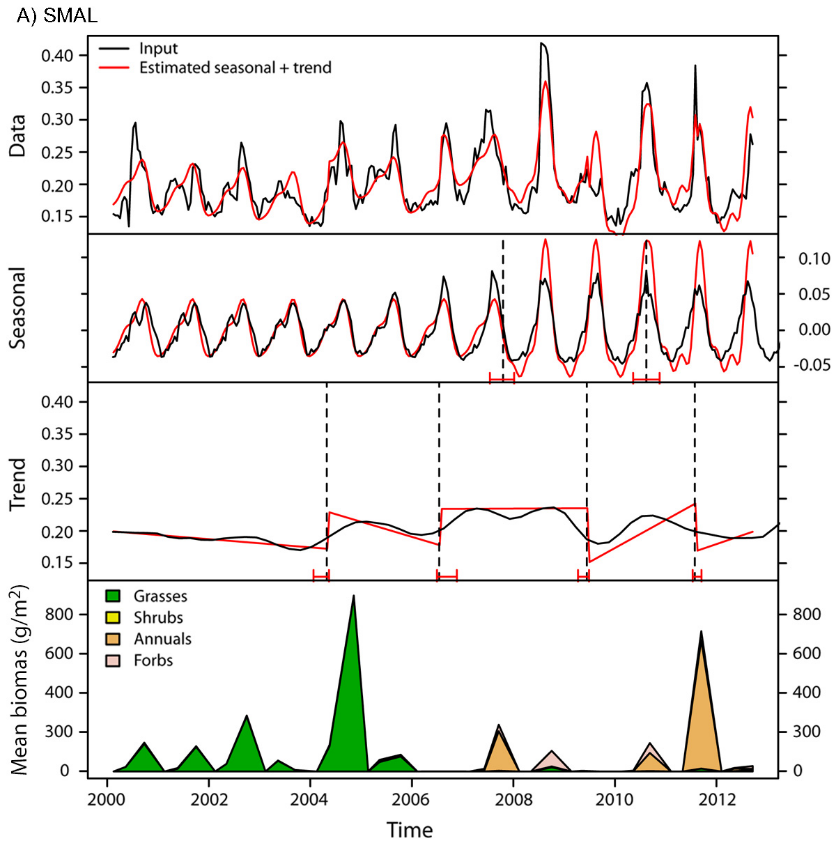


FIG. 4. BFAST output from MODIS NDVI data with mean seasonal biomass for five long-term sites, each characterized by different dominant vegetation in southern New Mexico. Panel (A) is a grass-dominated dry lake bed; (B) is an upland perennial grassland site dominated by *Bouteloua eriopoda* (black grama); (C) is a shrubland dominated by the deciduous shrub *Prosopis glandulosa* (mesquite); (D) is dominated by the evergreen shrub *Larrea tridentata* (creostote); and (E) is dominated by the deciduous shrub *Flourensia cernua* (tarbush). Biomass values were not scaled to a common *y*-axis extent to prevent loss of information.

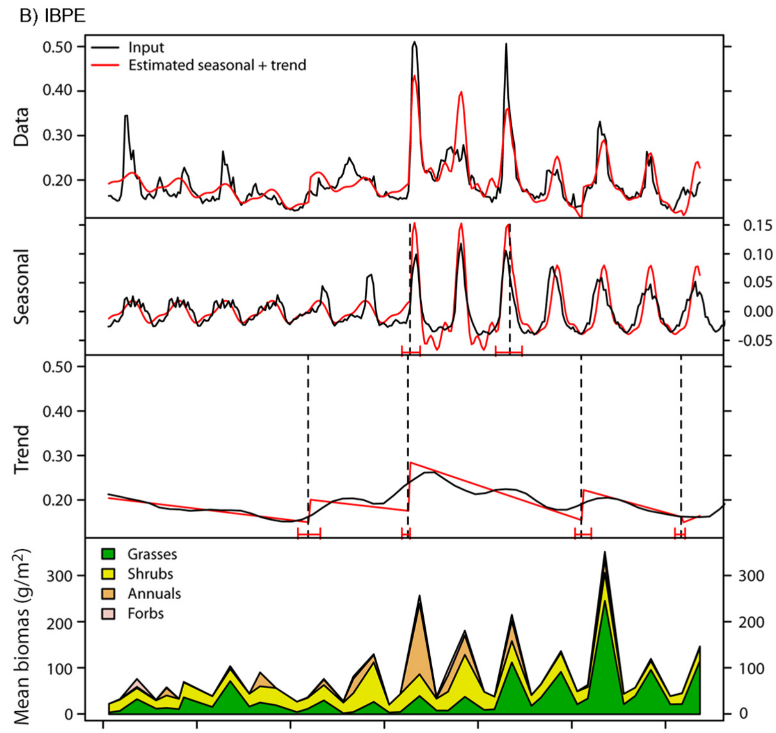
Seasonal breaks as indicators of shifts in phenology

Functional group contributions to biomass elucidated seasonal breaks corresponding to changes in the periodicity of NDVI spectral response. Plant functional group contributions to total biomass revealed that 16 of 19 seasonal breaks coincided with changes in herbaceous biomass that included annual and perennial grasses and forbs. There were two cases of temporal mismatch for seasonal breaks and three failures (Fig. 5). We identified five classes of change for the 16 seasonal trends classified as "successes" that characterize observed shifts in biomass: increase in annuals or forbs (8/16), increase in perennial grass (2/16), increase in all herbaceous functional groups (1/16), decrease or collapse of annuals or forbs (1/16), and collapse of perennial grasses (4/16) (Fig. 5). Given the prominence of change in grass, annual, and forb functional groups, we display classifications in relation to the proportion of maximum herbaceous biomass at each site over the study period and interpolated the three annual measurements to monthly estimates (Fig. 5).

Patterns driven by changes in herbaceous group biomass emerged across sites. Increases in annuals were most widespread at grasslands sites (BASN, IBPE, SUMM, and SMAL, Figs. 4A,B, 5) with increases occurring at three of nine shrubland sites (Fig. 5). Increases in perennial grasses were the second most common seasonal break pattern occurring at grasslands IBPE (Fig. 4B) and TOBO (Appendix S1: Fig. S2A). One mesquite site (NORT) saw increases in perennial grasses coincidently with increases in annuals or forbs in 2007 (NORT, Fig. 4C). Several sites experienced a subsequent collapse in annuals or forbs or collapse in perennial grasses (NORT and RABB, Figs. 4C, 5 and Appendix S1: Fig. S1A).

DISCUSSION

Image-based analytical methods for identifying vegetation changes have potential to greatly benefit dryland research and management by providing spatially explicit indicators of change across broad extents at time steps commensurate with the ecological processes driving them (Browning et al. 2015). This study assessed long-term and seasonal vegetation change metrics derived from satellite imagery with independent field-measured biomass and found success in 78% and 84% of cases



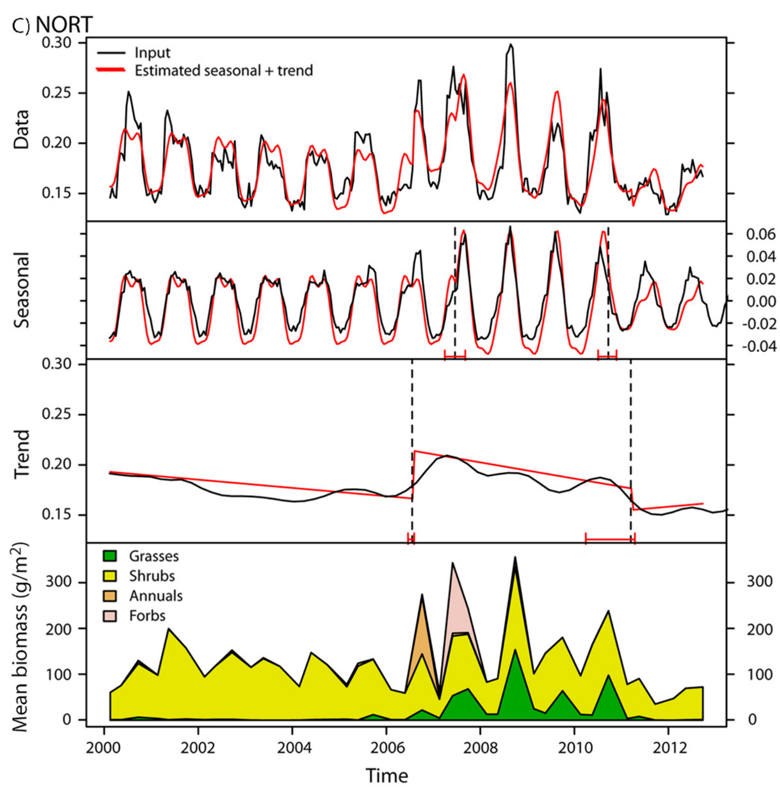


FIG. 4. Continued.

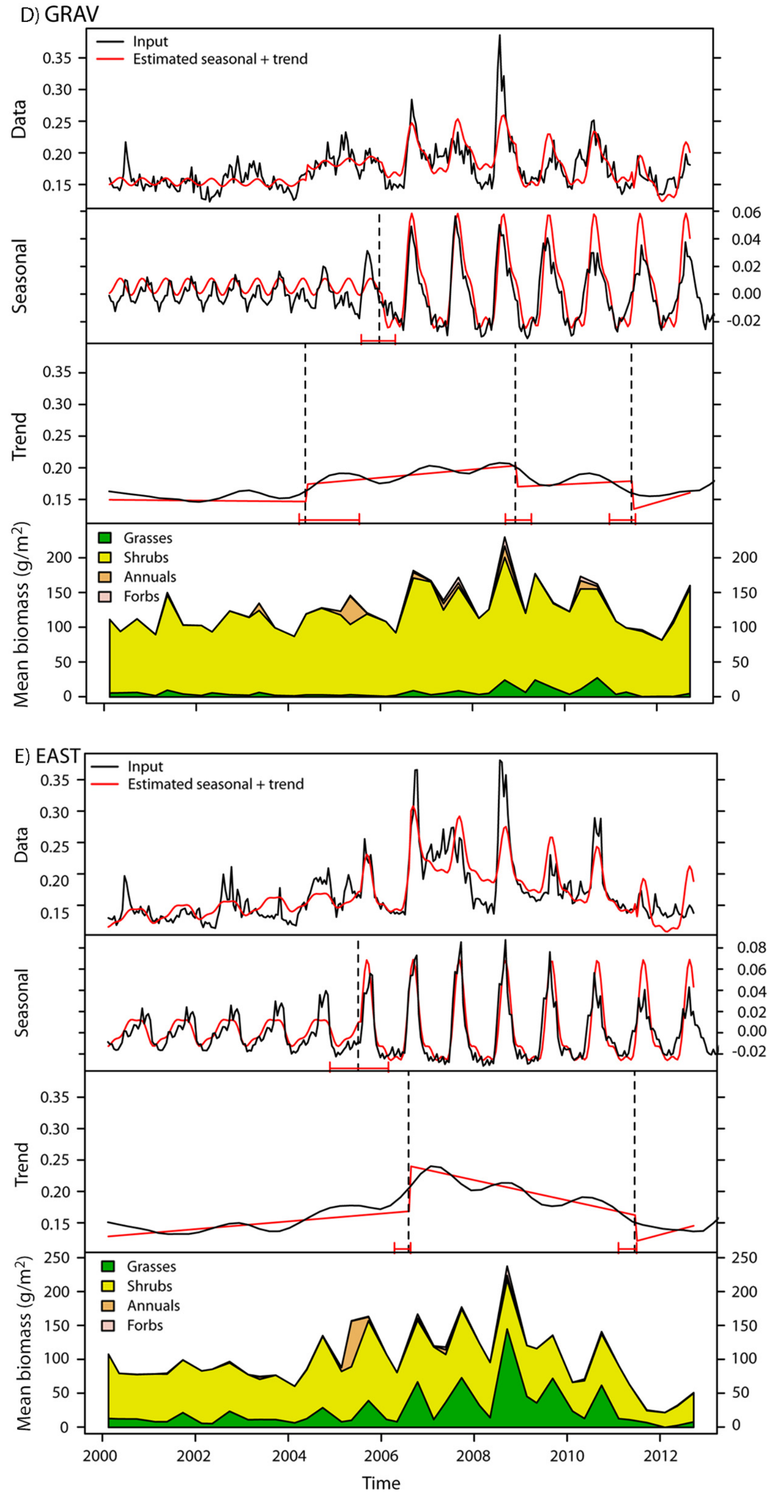


FIG. 4. Continued.

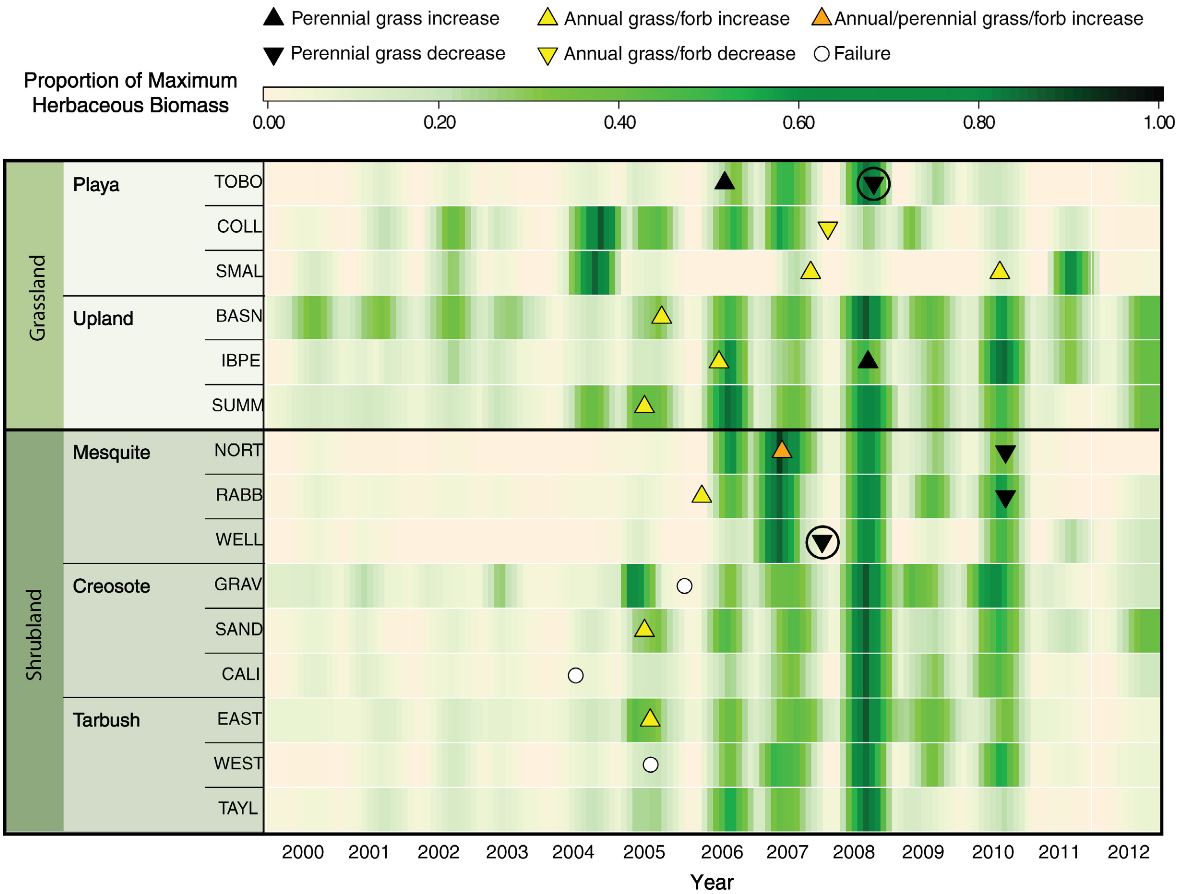


FIG. 5. Temporal distribution of seasonal breaks derived from BFAST analysis of 250-m MODIS NDVI at 15 long-term sites displayed atop the proportion of maximum herbaceous (perennial and annual grasses and forbs) biomass for each site over the 13-yr period. Breaks denote significant deviations in the NDVI compared with the model fitted to the seasonal model component of the time series. Symbols are color coded by the plant functional group that were associated with the shift in the seasonal model. Black circles surrounding symbols indicate the seasonal break was classified as "temporal mismatch." See *Methods* for more details. [Color figure can be viewed at wileyonlinelibrary.com]

relative to the long-term trends and seasonal cycles in land surface phenology, respectively. In addition, metrics associated with long-term trend and seasonal components of the image time series confirmed previously described vegetation changes derived from field estimates of net primary and litter production (Peters et al. 2012, 2014). In the following sections, we discuss patterns in functional group contributions to long-term vegetation dynamics in the context of temperature and rainfall events that coincided with breaks in the NDVI trend and seasonal patterns. We then describe methodological strengths and limitations of BFAST as an image-based change detection method for assessing ecologically meaningful turning points in vegetation.

Functional group contributions to long-term trends in greenness

Greater than 77% of the trend breaks in the MODIS NDVI time series identified turning points (i.e., increasing or decreasing BFAST breaks) in plant biomass in this arid ecosystem, thus supporting our prediction that BFAST trend breaks would coincide with large net increases or decreases in overall plant biomass. The ability to identify trend and seasonal breaks in the image time series provided added insight regarding the timing of known transitions (e.g., influx of *Sporobolus flexosus* grass at mesquite-dominated sites coinciding with maximum biomass in September 2008; Peters et al. 2012) and the occurrence of previously undocumented shifts (e.g., the transition from perennial to annual grasses at the SMAL playa site).

The high level of success and synchrony with positive trend breaks associated with high rainfall can be explained as the response of plants adapted to water-limited environments (Lehouerou 1984). In contrast, greater variability or higher asynchrony in the timing of negative breaks during the subsequent dry periods between 2009 and 2012 could be caused by differential susceptibility to detrimental effects of drought between deep-rooted C_3 shrubs and more shallow-rooted C_4 grasses (Kemp 1983, Gibbens and Lenz 2001). Decreasing trend breaks that occurred at grassland sites BASN and SMAL in 2009 reflected declines in annual grass biomass. Conversely, decreasing trend breaks in 2011 across six of nine shrubland sites were due to the collapse of annual and perennial grass biomass accompanied by decreases in shrub biomass, most likely in response to a period without rainfall from October 2010 to July 2011 and hard-freezing temperatures in February 2011. This combination of drought and extreme low temperature affected shrubs and herbaceous plants differently. Differences in phenology (e.g., evergreen C_3 shrub *Larrea tridentata* vs. C_4 warm season grasses) and growth form expressed as structural damage sustained by woody but not herbaceous plants (D. M. Browning, *unpublished data*).

Differences in species composition and richness at the 15 sites in this study offer interpretation of functional group contributions to vegetation change metrics derived from MODIS NDVI. Across the five vegetation zones, grass-dominated sites were most dynamic and exhibited highly variable increases in biomass over these 13 years. Shrub-dominated sites, generally, did not demonstrate the same degree of increase in biomass for increasing breaks; however, mesquite-dominated sites did experience changes in biomass more similar to grass sites than to other shrub sites. This similarity is due by the fact that the increases and decreases in biomass at mesquite sites were largely driven by perennial grass biomass. High variation and large ranges in change in biomass across vegetation zones precludes the ability to define a minimum change in biomass needed to yield a BFAST trend break. While we note that such insight would be highly valuable for land management decision-making it requires additional research.

Functional group contributions to seasonal vegetation dynamics

The combination of BFAST trend and seasonal breaks captured vegetation dynamics between 2000 and 2012, a period that encompassed above-average rainfall conditions preceded and followed by drought conditions. Successful trend breaks reflected responses across all plant functional groups (i.e., herbaceous and shrub species) while seasonal breaks were driven by responses of annual and perennial grasses and forbs. This finding has implications for monitoring plant community composition and phenology through more ecologically based interpretations of remote sensing time series. It could also help in the development of techniques for interpreting infrequently collected field data and separating vegetation changes related to management activities from those related to climatic variability.

In this water-limited environment, BFAST trend breaks more effectively captured boom and bust cycles in herbaceous biomass than increases in shrub biomass. This may be due to differences in how growth occurs in herbaceous and shrub species. In response to wet conditions that favor grass establishment and production (Peters 2000), grass patches tend to expand laterally into plant interspaces whereas shrubs respond to these conditions to increase canopy leaf area rather than expansion in ground cover (Peters 2002, Peters et al. 2010, Browning et al. 2012). Conversely, under dry conditions deep-rooted shrubs such as *Prosopis glandulosa* have been shown to be more resilient to drought periods than grasses (Browning et al. 2012, Gherardi and Sala 2015*b*). Overall, shrub biomass within grass-dominated areas between 2000 and 2012 was more stable than herbaceous landscape components.

BFAST is likely better suited to capture decreasing shrub biomass due to die-off (e.g., Allen and Breshears 1998, Breshears et al. 2005) or disturbance (e.g., Verbesselt et al. 2012) than increases in shrub biomass that occur as slower processes requiring a longer time series (Browning et al. 2008, 2012). Land surface phenology captures the composite spectral response of plant functional groups present. As such, it is worth noting that large increases or decreases in biomass in one plant functional group have the potential to yield both seasonal and trend breaks if the change in biomass shifts the frequency and phase in NDVI. In such cases, a shift in functional group dominance can yield both seasonal breaks derived from the cyclical component of the time series NDVI signal and trend breaks if the change in biomass is sufficiently large (e.g., 2007 increasing trend break at IBPE, Fig. 4B).

The capability of BFAST seasonal breaks to identify discernible shifts in the periodicity of NDVI is valuable in systems such as ours where plant functional groups or species contrast in their responsiveness to fluctuations in environmental conditions such as rainfall or temperature (Sherry et al. 2007, Cook et al. 2012, Gherardi and Sala 2015*a*, *b*). For landscapes in this study, water is the limited resource and high temperatures increase evaporative losses to plants in late spring and early summer (Wainwright 2006). Plant communities featured in this study comprise a mixture of growth forms that differ in physiognomy and life history traits (e.g., photosynthetic pathway and phenology) that manifest as differential responses to environmental events and conditions. For example, annual grasses respond most quickly to favorable rainfall conditions while perennial grasses respond faster than shrubs (Kemp 1983). As shown here, where functional group phenological responses are understood, BFAST seasonal breaks can capture shifts in relative abundance among plant functional groups.

Methodological considerations and limitations of BFAST

BFAST has been widely used to identify time series breaks in studies ranging from local to regional to global spatial extents (de Jong et al. 2011, 2012, Horion et al. 2016). Despite its widespread use, the BFAST algorithm has been most commonly applied over large study areas, with model validation performed on trend breaks using a variety of geospatial data layers including very high spatial resolution imagery (DeVries et al. 2015), aerial imagery (Lambert et al. 2015), and data products derived from satellite imagery (e.g., MOD14A2 fire product), as well as ocular field assessments (Watts and Laffan 2014). Few studies have evaluated BFAST trend and seasonal breaks using independent quantitative field data although DeVries et al. (2016) is one recent exception.

Results from this study represent a first-of-its-kind evaluation linking BFAST trend and seasonal breaks to long-term field-based measurements of plant biomass quantified by plant functional type. The BFAST algorithm performed well to identify ecologically meaningful changes in total biomass and in functional group contribution to biomass. However, the algorithm also resulted in a few cases where big changes in biomass occurred with no trend break and cases of trend breaks for which there was no discernible change in biomass. Additionally, successful seasonal breaks in two cases did not appear to coincide with changes in functional group contributions to biomass, but rather signified ecologically relevant increases from zero plant biomass (e.g., seasonal breaks in 2007 and 2010 at SMAL reflected a net increase from zero biomass and one of the breaks denoting a shift from perennial to annual grass dominance).

Three factors may explain our observed discrepancies between BFAST outputs and field-estimated biomass: (1) NDVI as a spectral index, (2) mismatches in temporal and spatial resolution, and (3) the *h* value parameter in the BFAST model. First, NDVI is a spectral index and robust proxy to capture vegetation greenness or photosynthetic vigor (e.g., Tucker et al. 1985). Yet, because it is an index, there is no "ground truth" for NDVI. Even though, it has been shown to be an effective proxy for biomass and net primary production as a biophysical parameter commonly linked to remote sensing data products with relevance to ecosystem function and landscape monitoring (Scanlon et al. 2002, Wylie et al. 2012).

Second, all studies comparing data that differ in frequency and granularity involve cases of mismatch. In our case, we used field measurements of aboveground biomass to assess the performance of BFAST breaks as indicators of vegetation change. Biomass data were collected as part of a study designed to characterize long-term patterns in net primary productivity (Huenneke et al. 2002). Field data collected within 49 1 × 1-m quadrats at sites sampled three times a year were not designed to test outcomes from satellite image products with 250-m spatial resolution and 16-d temporal resolution. However, by using 95% confidence intervals around the timing of the image breaks to account for temporal uncertainty, we could identify coincident patterns between biomass change and image-based vegetation change dates.

Differences in the sample frequency of the MODIS sensor and field data collection imposed time lags on clear assessment of some BFAST breaks. The effects of these time lags were most pronounced during periods of elevated rainfall where the temporal response of herbaceous vegetation was rapid, producing high magnitude positive breaks in the NDVI trend with narrow CIs around the timing of each break. Our established ruleset resulted in "temporal mismatches" for breaks with narrow CIs when compared to the 3–4 month biomass sampling interval. However, visual interpretation of the changes in NDVI and biomass showed a high level of correspondence between the temporal increases and decreases of the field and satellite time series. Consequently, the responsiveness of vegetation to environmental conditions demonstrated in this study indicates data collected on a more frequent basis may improve accuracy assessment efforts.

With respect to spatial resolution, prior work in this system showed that the grid sampling scheme for estimating biomass employed at these study sites effectively characterized the spatial variability present within corresponding 250-m MODIS pixels (Maynard et al. 2016). Patterns in vegetation heterogeneity at shrub- and grass-dominated sites are considerably <30 m and the temporal consistency of MODIS imagery made it more suitable for time series analysis than finer-resolution satellites such as Landsat with more temporal data gaps. There are opportunities for bridging the gaps in spatial and temporal resolution that exist between long-term studies and those based on satellite image data products. Data streams now exist that may be more commensurate with processes acting at playa grassland sites such as phenocams, repeat ground photographs, and high spatial resolution imagery from drones (Browning et al. 2015, Brown et al. 2016, Cunliffe et al. 2016).

Third, the single parameter required to run the BFAST model, the *h* value, influences the number of breaks that can occur by specifying the amount of data or time interval between breaks. Smaller *h* values allow for a larger number of breaks to be identified in the piecewise regression model that characterizes long-term trends, but the number of breaks (up to the maximum the time series can accommodate) is determined by the regression model. Watts and Laffan (2014) examined the effect of the *h* value in determining the number of potential breaks in a MODIS time series from a semiarid region in New South Wales and Queensland, Australia and found that while the *h* value influences time series decompositions, a single optimal value applicable across widely variable landscapes could not be identified. In future efforts, we suggest evaluating the temporal distribution of trend and seasonal breaks generated using a range of *h* values as a guide for *h* value selection.

Management implications

The ability to identify ecologically meaningful breaks (i.e., turning points) in image time series using BFAST and its spatially explicit outputs offer several advantages over field measurements or modeling techniques that require field-based data: (1) it is less costly than field observations and easily reformulated as new data become available, (2) it allows for broader spatial extents to be studied and as such can capture greater variability in the land surface, and (3) it can identify "hotspots" in space and time that can be used to inform land management decisions to remove stressors (e.g., livestock), target monitoring efforts, or inform study design to determine optimal sampling periods or ideal locations for sampling. Some field information is needed for interpreting BFAST outputs, but data needs for interpreting image products are lower than those for detecting landscape change using field-based research and monitoring methods in heterogeneous landscapes.

The demonstrated effectiveness of BFAST breaks to identify ecological turning points provides opportunities for the method to bolster ongoing natural resource monitoring programs (e.g., Herrick et al. 2010, Taylor et al. 2012). This study offers evidence that BFAST yields ecologically meaningful breaks at the arid JRN site, which occurs at the low end for the annual amplitude in NDVI of 0.1 recommended by Verbesselt et al. (2010*a*). Multitemporal remote sensing methods like BFAST offer the potential for research and monitoring programs to put traditionally infrequent field measurements in the context of long-term patterns and seasonal cycles. For example, livestock seasons of use and stocking rates on U.S. federal lands are typically determined based on field observations of rangeland (or landscape) condition and available forage assessed at intervals corresponding to the term of a grazing permit (5–10 yr) or long enough for management changes or activities to have an effect on plant communities (BLM 2001). Interpretation of changes in condition between sampling events in this type of monitoring is challenging due to the lack of data that track the fluctuations in monitoring indicators over time. Alternatively, analysis of the frequency of trend breaks in NDVI or other spectral indices over time could identify highly dynamic or sensitive parts of a landscape that could be targeted for additional monitoring effort. BFAST offers real-time monitoring capabilities to further assist with focused field reconnaissance efforts or drought mitigation strategies (Verbesselt et al. 2012). To expand on the idea of differential resilience or susceptibility to drought, future research is needed to investigate the potential for BFAST breaks as an indicator of site stability based on the frequency and magnitude of breaks over time. Remote sensing analytical tools like BFAST that leverage image time series to capture and characterize vegetation change offer the opportunity to not only augment existing monitoring efforts, but expand the spatial and temporal scales of landscape monitoring.

Future research could expand the utility of BFAST for management applications by exploring more fully cases in which seasonal breaks capture shifts in abundance of plant functional groups and where seasonal breaks fall short. A quantitative assessment of *h* values on the consistency in timing and the temporal uncertainty of trend breaks could lessen limitations associated with subjective selection of this single BFAST model parameter. Remote sensing tools and techniques like BFAST can be most effectively implemented once their accuracy, performance, and limitations of the algorithms are examined using the best available data that continue to evolve. Such was our motivation here.

Acknowledgments

Funding for long-term field data collection was provided by the National Science Foundation to the Jornada Basin Long Term Ecological Research Program through New Mexico State University (DEB-1235828) and USDA-ARS CRIS Project # 3050-11210-007-00D. Support for D. M. Browning, J. W. Karl, and D. C. Peters was from appropriated funding to the USDA-ARS Rangeland Management Research Unit, Jornada Experimental Range. Funding for J. J. Maynard was from the USDI Bureau of Land Management's Assessment, Inventory and Monitoring Program. R. Wu and D. James assisted with creating Fig. 2 and D. Morin assisted with edits to Fig. 4 and Appendix S1. M. Buenemann provided constructive comments on the manuscript as did two anonymous reviewers. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. Mention of a proprietary product does not constitute a guarantee or warranty of the products by the U.S. Government or the authors and does not imply its approval to the exclusion of other products that may be suitable.

Literature Cited

Allen, C., and D. D. Breshears. 1998. Drought-induced shift of a forest-woodland ecotone: rapid landscape response to climate variation. Proceedings of the National Academy of Sciences USA 95:14839–14842.

Bai, J., and P. Perron. 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18:1–22.

Bestelmeyer, B. T., et al. 2011. Analysis of abrupt transitions in ecological systems. Ecosphere 2(12):1–26.

BLM, Bureau of Land Management. 2001. Rangeland health standards. Bureau of Land Management, Washington, D.C., USA.

Brandt, M., C. Mbow, A. A. Diouf, A. Verger, C. Samimi, and R. Fensholt. 2015. Ground- and satellite-based evidence of the biophysical mechanisms behind the greening Sahel. Global Change Biology 21:1610–1620.

Breshears, D. D., et al. 2005. Regional vegetation die-off in response to global-change-type drought. Proceedings of the National Academy of Sciences USA 102:15144–15148.

Brown, T. B., et al. 2016. Using phenocams to monitor our changing Earth: toward a global phenocam network. Frontiers in Ecology and the Environment 14:84–93.

Browning, D. M., T. M. Crimmins, S. Spiegal, D. K. James, M. A. Crimmins, and M. R. Levi. S*ubmitted*. Long-term patterns reveal phenological guilds in a water-limited ecosystem. Ecosphere.

Browning, D. M., S. R. Archer, G. P. Asner, M. P. McClaran, and C. A. Wessman. 2008. Woody plants in grasslands: post-encroachment dynamics. Ecological Applications 18:928–944.

Browning, D. M., M. C. Duniway, A. S. Laliberte, and A. Rango. 2012. Hierarchical analysis of vegetation dynamics over 71 years: soil-rainfall interactions in a Chihuahuan desert ecosystem. Ecological Applications 22:909–926.

Browning, D. M., A. Rango, J. W. Karl, C. M. Laney, E. R. Vivoni, and C. E. Tweedie. 2015. Emerging technological and cultural shifts advancing drylands research and management. Frontiers in Ecology and the Environment 13:52–60.

Browning, D. M., and C. M. Steele. 2013. Vegetation index differencing for broad-scale assessment of productivity under prolonged drought and sequential high rainfall conditions. Remote Sensing 5:327–341.

Bulloch, H. E. J., and R. E. Neher. 1980. Soil survey of Dona Ana County Area, New Mexico. USDA-SCS, Washington, D.C., USA.

Carpenter, S. R., et al. 2011. Early warnings of regime shifts: a whole-ecosystem experiment. Science 332:1079–1082.

Cook, B. I., J. E. Smerdon, R. Seager, and S. Coats. 2014. Global warming and 21st century drying. Climate Dynamics 43:2607–2627.

Cook, B. I., E. M. Wolkovich, and C. Parmesan. 2012. Divergent responses to spring and winter warming drive community level flowering trends. Proceedings of the National Academy of Sciences USA 109:9000–9005.

Cunliffe, A. M., R. E. Brazier, and K. Anderson. 2016. Ultra-fine grain landscape-scale quantification of dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. Remote Sensing of Environment 183: 129–143.

de Jong, R., S. de Bruin, A. de Wit, M. E. Schaepmann, and D. L. Dent. 2011. Analysis of monotonic greening and browning trends from global NDVI time-series. Remote Sensing of Environment 115:692–702.

de Jong, R., J. Verbesselt, M. E. Schaepman, and S. de Bruin. 2012. Trend changes in global greening and browning: contribution of short-term trends to longer-term change. Global Change Biology 18:642–655.

de Jong, R., J. Verbesselt, A. Zeileis, and M. E. Schaepman. 2013. Shifts in global vegetation activity trends. Remote Sensing 5:1117–1133.

DeVries, B., A. K. Pratihast, J. Verbesselt, L. Kooistra, and M. Herold. 2016. Characterizing forest change using community-based monitoring data and Landsat time series. PLoS ONE 11:e0147121. https://doi.org/10.1371/journal.pone.0147121

DeVries, B., J. Verbesselt, L. Kooistra, and M. Herold. 2015. Robust monitoring of small-scale forest disturbances in a tropical montane forest using Landsat time series. Remote Sensing of Environment 161:107–121.

Gao, X., A. R. Huete, W. G. Ni, and T. Miura. 2000. Optical-biophysical relationships of vegetation spectra without background contamination. Remote Sensing of Environment 74:609–620.

Gherardi, L. A., and O. E. Sala. 2015*a*. Enhanced interannual precipitation variability increases plant functional diversity that in turn ameliorates negative impact on productivity. Ecology Letters 18:1293–1300.

Gherardi, L. A., and O. E. Sala. 2015*b*. Enhanced precipitation variability decreases grass- and increases shrub-productivity. Proceedings of the National Academy of Sciences USA 112:12735–12740.

Gibbens, R. P., and J. M. Lenz. 2001. Root systems of some Chihuahuan Desert plants. Journal of Arid Environments 49:221–263.

Hardiman, M. 2011. Intense cold wave of February 2011. National Weather Service, El Paso, Texas, USA.

Herrick, J. E., V. C. Lessard, K. E. Spaeth, P. L. Shaver, R. S. Dayton, D. A. Pyke, L. Jolley, and J. J. Goebel. 2010. National ecosystem assessments supported by scientific and local knowledge. Frontiers in Ecology and the Environment 8:403–408.

Herrick, J. E., et al. 2013. The global Land-Potential Knowledge System (LandPKS): supporting evidence-based, site-specific land use and management through cloud computing, mobile applications, and crowdsourcing. Journal of Soil and Water Conservation 68:5A–12A.

Horion, S., A. V. Prishchepov, J. Verbesselt, K. D. Beurs, T. Tagesson, and R. Fensholt. 2016. Revealing turning points in ecosystem functioning over the Northern Eurasian agricultural frontier. Global Change Biology 22:2801–2817.

Huenneke, L. F., J. P. Anderson, M. Remmenga, and W. H. Schlesinger. 2002. Desertification alters patterns of aboveground net primary production in Chihuahuan ecosystems. Global Change Biology 8:247–264.

Huete, A. R. 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment 25:295–309.

Huete, A., K. Didan, T. Miura, E. P. Rodriguez, X. Gao, and L. G. Ferreira. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment 83:195–213.

Hufkens, K., T. F. Keenan, L. B. Flanagan, R. L. Scott, C. J. Bernacchi, E. Joo, N. A. Brunsell, J. Verfaillie, and A. D. Richardson. 2016. Productivity of North American grasslands is increased under future climate scenarios despite increasing aridity. Nature Climate Change 6(7):710–714.

Karl, J. W., J. E. Herrick, and D. M. Browning. 2012. A strategy for rangeland management based on best available knowledge and information. Rangeland Ecology & Management 65: 638–646.

Kemp, P. R. 1983. Phenological patterns of Chihuahuan desert plants in relation to timing of water availability. Journal of Ecology 71:427–436.

Lambert, J., J. P. Denux, J. Verbesselt, G. Balent, and V. Cheret. 2015. Detecting clear-cuts and decreases in forest vitality using MODIS NDVI time series. Remote Sensing 7:3588–3612.

Lehouerou, H. N. 1984. Rain use efficiency—a unifying concept in aridland ecology. Journal of Arid Environments 7:213–247.

Maynard, J. J., J. W. Karl, and D. M. Browning. 2016. Effect of spatial image support in detecting long-term vegetation change from satellite time series. Landscape Ecology 9:2045–2062.

Mattiuzzi, M. 2015. MODIS: Acquisition and Processing of MODIS Products: R package version 0.10-11.

Morisette, J. T., et al. 2009. Tracking the rhythm of the seasons in the face of global change: phenological research in the 21st century. Frontiers in Ecology and the Environment 7:253–260.

Overpeck, J., and B. Udall. 2010. Dry times ahead. Science 328:1642–1643.

Peters, D. P. C. 2000. Climatic variation and simulated patterns in seedling establishment of two dominant grasses at a semi-arid-arid grassland ecotone. Journal of Vegetation Science 11:493–504.

Peters, D. P. C. 2002. Plant species dominance at a grassland-shrubland ecotone: an individual-based gap dynamics model of herbaceous and woody species. Ecological Modelling 152:5–32.

Peters, D. P. C., B. T. Bestelmeyer, and M. G. Turner. 2007. Cross–scale interactions and changing pattern–process relationships: consequences for system dynamics. Ecosystems 10:790–796.

Peters, D. P. C., J. E. Herrick, H. C. Monger, and H. T. Huang. 2010. Soil–vegetation–climate interactions in arid landscapes: effects of the North American monsoon on grass recruitment. Journal of Arid Environments 74:618–623.

Peters, D. C., J. Yao, D. M. Browning, and A. Rango. 2014. Mechanisms of grass response in grasslands and shrublands during dry or wet periods. Oecologia 174:1323–1334.

Peters, D. P. C., J. Yao, O. E. Sala, and J. P. Anderson. 2012. Directional climate change and potential reversal of desertification in arid and semiarid ecosystems. Global Change Biology 18:151–163.

Richardson, A. J., and C. L. Wiegand. 1977. Distinguishing vegetation from soil background information. Photogrammetric Engineering and Remote Sensing 43:1541–1552.

Scanlon, T. M., J. D. Albertson, K. K. Caylor, and C. A. Williams. 2002. Determining land surface fractional cover from NDVI and rainfall time series for a savanna ecosystem. Remote Sensing of Environment 82:376–388.

Sheppard, P. R., A. C. Comrie, G. D. Packin, K. Angersbach, and M. K. Hughes. 2002. The climate of the U.S. Southwest. Climate Research 21:219–238.

Sherry, R. A., X. H. Zhou, S. L. Gu, J. A. Arnone, D. S. Schimel, P. S. Verburg, L. L. Wallace, and Y. Q. Luo. 2007. Divergence of reproductive phenology under climate warming. Proceedings of the National Academy of Sciences USA 104:198–202.

Snyder, K. A., and S. L. Tartowski. 2006. Multi-scale temporal variation in water availability: implications for vegetation dynamics in arid and semi-arid ecosystems. Journal of Arid Environments 65:219–234.

Taylor, J., G. Toevs, J. Karl, M. Bobo, M. Karl, S. Miller, and C. Spurrier. 2012. AIM-monitoring: a component of the BLM assessment, inventory, and monitoring strategy. *In* BLM, U.S. Department of the Interior, editor. BLM National Operations Center, Denver, Colorado, USA.

Tucker, C. J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment 8:127–150.

Tucker, C. J., C. L. Vanpraet, M. J. Sharman, and G. Vanittersum. 1985. Satellite remote sensing of total herbaceous biomass production in the Senegalese Sahel—1980–1984. Remote Sensing of Environment 17:233–249.

USDA-NRCS. 2010. Ecological site information system. National Resource Conservation Service, Lincoln, Nebraska, New Mexico, USA.

Verbesselt, J., R. Hyndman, G. Newnham, and D. Culvenor. 2010*a*. Detecting trend and seasonal changes in satellite time series. Remote Sensing of Environment 114:106–115.

Verbesselt, J., R. Hyndman, A. Zeileis, and D. Culvenor. 2010*b*. Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. Remote Sensing of Environment 114:2970–2980.

Verbesselt, J., A. Zeileis, and M. Herold. 2012. Near real-time disturbance detection using satellite image time series. Remote Sensing of Environment 123:98–108.

Wainwright, J. 2006. Climate and climatological variations in the Jornada Basin. Pages 44–80 *in* K. M. Havstad, L. F. Huennecke, and W. H. Schlesinger, editors. Structure and function of a Chihuahuan desert ecosystem. The Jornada Basin long-term ecological research site. Oxford University Press, Oxford, UK.

Watts, L. M., and S. W. Laffan. 2014. Effectiveness of the BFAST algorithm for detecting vegetation response patterns in a semi-arid region. Remote Sensing of Environment 154:234–245.

Wolkovich, E. M., and E. E. Cleland. 2011. The phenology of plant invasions: a community ecology perspective. Frontiers in Ecology and the Environment 9:287–294.

Woodcock, C. E., et al. 2008. Free access to Landsat imagery. Science 320:1011.

Wylie, B. K., S. P. Boyte, and D. J. Major. 2012. Ecosystem performance monitoring of rangelands by integrating modeling and remote sensing. Rangeland Ecology & Management 65:241–252.

Zeileis, A., and C. Kleiber. 2005. Validating multiple structural change models—a case study. Journal of Applied Econometrics 20:685–690.

Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.1561/full

Data Availability

Data associated with this paper are available as follows: R files and NDVI data on GitHub: https://doi.org/10.5281/zenodo.438715

Plant biomass data are available from the LTER Data Portal: https://doi.org/10.6073/pasta/6479586914e6a732381f46d16f173c45