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Understanding the effect of fire on vegetation composition and gross primary production in a semi-arid shrubland ecosystem using the Ecosystem Demography (EDv2.2) model

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Abstract. Wildfire incidents in sagebrush (*Artemisia* spp.) dominated semi-arid ecosystems in the western United States have risen dramatically in the last few decades. Severe wildfires often lead to the loss of native sagebrush communities and change the biogeochemical conditions which make it difficult for sagebrush to regenerate. Invasion of cheatgrass (*Bromus tectorum*) accentuates the problem by making the ecosystem more susceptible to frequent burns. Managers have implemented several techniques to cope with the cheatgrass-fire cycle, ranging from controlling undesirable fire effects by removing fuel loads either mechanically or via prescribed burns, to seeding the fire-affected areas with shrubs and native perennial forbs. There have been a number of studies at local scales to understand the direct impacts of wildfire on vegetation, however there is a larger gap in understanding these impacts at broad spatial and temporal scales. This need highlights the importance of global dynamic vegetation models (DGVMs) and remote sensing. In this study, we explored the influence of fire on vegetation composition and gross primary production (GPP) in the sagebrush ecosystem using the Ecosystem Demography (EDv2.2) model, a dynamic vegetation model. We selected Reynold Creek Experimental Watershed (RCEW) to run our simulation study, which represents sagebrush dominated ecosystems in the northern Great Basin. We ran point-based simulations at four existing flux-tower sites in the study area for a total 150 years after turning on the fire module in the 25th year. Results suggest dominance of shrub in a non-fire scenario, however under the fire scenario we observed contrasting phases of high and low shrub and C3 grass growth. Regional model simulations showed a gradual decline in gross primary production (GPP) for fire-introduced areas through the initial couple of years instead of killing all the vegetation in the affected area in the first year itself. We also compared the results from EDv2.2 with satellite data for the areas in RCEW affected by the 2015 Soda Fire. We observed a good spatial agreement between modeled GPP and a Landsat image-derived index for the study area with moderate to marginally strong correlations at the pixel level between maps of post-fire recovery GPP and the vegetation response observed in a post-fire Landsat image. This study contributes in understanding the application of ecosystem models to investigate temporal dynamics of vegetation under alternative fire regimes and the spatial behavior of post-fire ecosystem restoration.

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1 Introduction

The number and intensity of wildfires in the sagebrush-steppe of the semi-arid Great Basin, western US have increased dramatically (Keane et al., 2008). Studies have shown that sagebrush (*Artemisia* spp.) has declined significantly across the Great Basin due to fire and other disturbances (Knick et al., 2003; Pilliod et al., 2017; Rigge et al., 2019; Schroeder et al., 2004). Low stature makes sagebrush less adapted in morphological terms to survive fires as most of the flammable fuels are close to the ground (Hood and Miller, 2007; McArthur and Stevens, 2004; Welch and Criddle, 2003). In addition, ongoing research indicates that sagebrush regeneration is complicated by changes in climate, long germination and growth times, and seed dispersal (Chambers, 2000; Shriver et al., 2018; Walton et al., 1986). Even though fire is often recognized as a natural ecosystem process, it reduces woody shrub biomass while increasing herbaceous biomass (Ellsworth et al., 2016). Invasion of non-native cheatgrass (*Bromus tectorum*) alters the competitive balance between woody and herbaceous plants, and also makes the ecosystem more susceptible to frequent and larger fires (Baker, 2006; Building et al., 2013; Whisenant, 1990). A recent study has shown that this cheatgrass-fire cycle has resulted in more than one-third of the Great Basin having been invaded by cheatgrass Bradley et al. (2018), which represents an enormous community shift with potentially large yet unknown effects on ecosystem function at a regional scale (Bradley et al., 2006; Bradley, 2010; Fusco et al., 2019).

Land managers and scientists have identified potential techniques to cope with the problems related to the altered fire regime in the Great Basin, ranging from controlling fire incidents with removing fuel loads either mechanically or using prescribed burns, to seeding the burned areas with shrubs and native perennial forbs. There have been a number of studies (e.g., Diamond et al., 2012; Ellsworth et al., 2016; Miller et al., 2013; Murphy et al., 2013) at the local scale to understand fire impacts, with many studies suggesting fire suppression as a technique to preserve the sagebrush ecosystem. However, there is a gap in understanding the influence at broader spatial scales. Remote sensing studies provide contemporary insights of ecosystem changes at broad spatial scales (e.g., Bradley et al., 2018). However, longer temporal-scale studies in the context of future climate scenarios are needed to better understand fire effects on shrub dominated ecosystems like sagebrush-steppe (Knutson et al., 2014; Nelson et al., 2014).

One method to consider long time scales in the effects of fire on sagebrush ecosystems is to utilize dynamic global vegetation models (DGVMs) (Lenihan et al., 2007; Li et al., 2012). A DGVM can be placed anywhere along the continuum of individual-based to area-based models (Fisher et al., 2010; Smith et al., 2001). Individual-based models (IBMs) represent vegetation at the individual plant level incorporating complex community processes like growth, mortality, recruitment, and disturbances. Area-based models, on the other hand, represent plant communities with area-averaged representation making them more efficient for broad scale applications (Bond-Lamberty et al., 2015; Fisher et al., 2010; Smith et al., 2001).

Ecosystem Demography (EDv2.2) is a DGVM originally developed in 2001 (Moorcroft et al., 2001). EDv2.2 is a cohort-based model that lies in between these two extremes, where individual plants with similar properties, in terms of size, age, and function, are grouped together to reduce the computational cost while retaining most of the dynamics of IBMs (Fisher et al., 2010). EDv2.2 is composed of a series of gridded cells, which experience meteorological forcing from corresponding gridded data or from a coupled atmospheric model (Medvigy, 2006). It captures both vertical and horizontal distributions of vegetation

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structure and compositional heterogeneity compared to area-based models (Kim et al., 2012; Moorcroft et al., 2001; Moorcroft, 2003; Sellers et al., 1992).

While EDv2.2 was originally developed for a tropical forest ecosystem, it has since been updated for broader use (Medvigy et al., 2009), including to understand fire behavior under different probable scenarios in tree dominated ecosystems (Trugman et al., 2016; Zhang et al., 2015). EDv2.2 has a fire subroutine which evaluates conditions leading to potential fire ignition and quantifies fire disturbance effects on vegetation. A detailed description of the EDv2.2 model structure including its fire subroutine is available in earlier publications about the model (Longo et al., 2019; Moorcroft et al., 2001; Medvigy et al., 2009). In this model, fire ignition probability is local in origin but can spread into adjacent areas given favorable conditions for fire. All plants in a burnt patch are killed while carbon and nitrogen are transferred into the below-ground module (Moorcroft et al., 2001). Users can choose from two separate stochastic mechanisms defining fire ignition conditions in the model. Availability of enough fuel (aboveground biomass) is the first necessary condition common to both mechanisms. The second necessary condition could be set up to be either the total soil water content within a designated depth or the accumulated precipitation for the last 12 months. The fire severity parameter (defined between 0 to 1) in the subroutine determines the level of fire-related disturbance depending upon available fuel. Fire in EDv2.2 affects the vegetation mortality rate, which is a function of cohort height for a given plant function type (PFT). New burnt patches are created every year when the minimum area necessary to generate a new patch is available through the loss of affected cohorts.

In this study, we used the version of EDv2.2 with shrub PFT (Pandit et al., 2019) to understand the effect of fire on a shrubland ecosystem in the Reynolds Creek Experimental Watershed (RCEW), Great Basin, USA. We explored the dynamics of shrub and C3 grass gross primary production (GPP) under alternative fire scenarios for four different sites (point-based analysis) in the study area, and also investigated model generated post-fire shrubland recovery patterns against observed Landsat image-derived Normalized Difference Vegetation Index (NDVI) (Wylie et al., 2003; Running et al., 2004) covering the entire RCEW area (regional-based analysis).

2 Methods

2.1 Study area

We ran the EDv2.2 model at the Reynold Creek Experimental Watershed (RCEW), located in the Northern Great Basin region of the western United States (Fig. 1) The RCEW is operated by the USDA Agricultural Research Service and is also a Critical Zone Observatory (CZO) which is approximately 240 km^2 with elevation ranging from about 900 to 2200 m. With an increase in elevation, there is an increase in mean annual precipitation and a decrease in mean annual temperature (Flerchinger et al., 2019; Renwick et al., 2019). Higher elevations in southern areas of the watershed are dominated by quaking aspen (*Populus termuloides*), Douglas fir (*Psuedotsuga menziesii*), and western juniper (*Juniperus occidentalis*) (Seyfried et al., 2000). Lower elevations are primarily covered with Wyoming big sagebrush (*Artemisia tridentate* ssp. *wyomingensis*), low sagebrush (*Artemisia arbuscula*), rabbitbrush (*Ericameria nauseosa*) and bitterbrush (*Pushia tridentate*). Perennial herbs like bluebunch wheatgrass (*Pseudoroegneria spicata*), needle and thread (*Hesperostipa comata*), western wheatgrass (*Pascopyrum smithii*),

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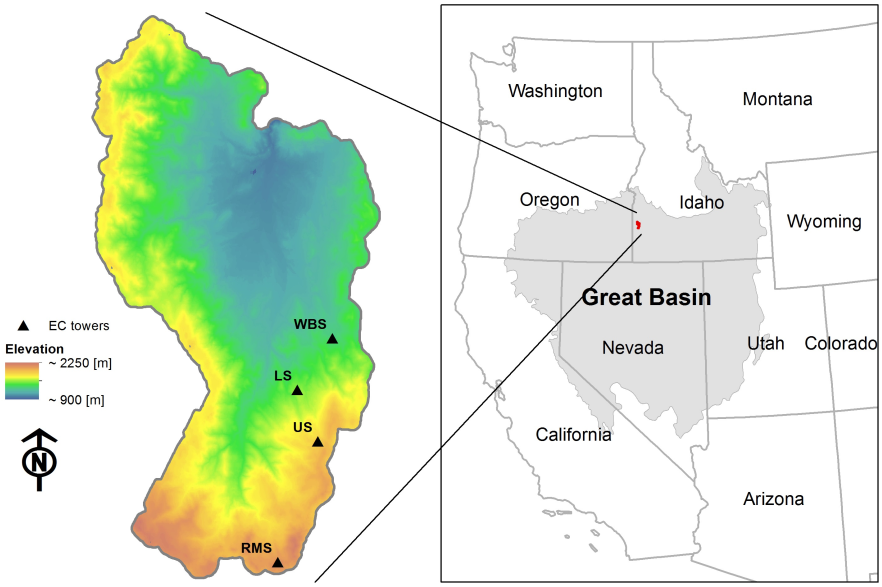

Figure 1. Location of the four EC flux tower sites within the Reynolds Creek Experimental Watershed (RCEW) study area. The inset map shows the location of RCEW within the Northern Great Basin (LCC, 2019).

tapertip hawksbeard (*Crepis acuminata*), and yarrow (*Achillea millefolium*) are also present (Pyke et al., 2015). The 2015 Soda Fire burned over 1,000 km^2 in southeast Oregon and southwest Idaho, including approximately 32% of RCEW in its northern parts (Fig. 2). Collaborative efforts between federal, state and private agencies have been applied to assess risk and devise a plan to implement treatments to stabilize burned areas, promote recovery of native plant communities, increase perennial grasses, and reduce invasive annual species (BLM, 2016).

We used EDv2.2 to run both point-based and regional (all of RCEW) analyses. For the point-based runs, we used four 200 m x 200 m polygons centered at four eddy covariance (EC) tower sites in RCEW to represent the tower footprints. The four sites include: Wyoming Big Sagebrush (WBS), Lower sheep (LS), Upper Sheep (US), and Reynolds Mountain Sagebrush (RMS) (Table 1). Wyoming big sagebrush (*Artemisia tridentata* ssp. *Wyomingensis*) is the dominant shrub at the WBS site with perennial grasses like bluebunch wheatgrass (*Pseudoroegneria spicata*), squirreltail (*Elymus elymoides*), and Sandberg bluegrass (/textitPoa secunda). The dominant shrub at the LS site is low sagebrush (*Artemisia arbuscula*) along with Sandberg bluegrass, squirreltail (*Elymus elymoides*), and Idaho fescue (*Fescue idahoensis*). Mountain big sagebrush (*Artemisia tridentata* ssp. *Vaseyana*) is the common shrub cover at the US and RMS sites, where there is also a strong presence of forbs including longleaf phlox (*Phlox longifolia*), pale agoseris (*Agoseris glauca*), and silvery lupine (*Lupinus argentius*) (Flerchinger et al., 2019). For the regional runs, we used grids of 1 km resolution covering the entire RCEW area.

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Table 1. Description of EC sites used in the point-based analysis.

Site	Ameriflux ID	Location	Elevation [m]	Mean annual precipitation [mm]	Mean annual temperature [°C]
WBS	US-Rws	43.1675, -116.7132	1425	290	8.9
LS	US-Rls	43.1439, -116.7356	1608	333	8.4
US	US-Rwf	43.1207, -116.7231	1878	505	6.5
RMS	US-Rms	43.0645, -116.7486	2111	800	5.4

2.2 Meteorological forcing data

We used outputs from high resolution climate reanalysis obtained from the Weather Research and Forecast (WRF) model (Skamarock et al., 2008) to obtain meteorological forcing data as presented in Pandit et al., (2019) (Table 2). These WRF outputs correspond to data from different heights above the ground surface. Wind speeds refer to 10 m above ground, temperature and specific humidity refer to 2 m above ground, downward shortwave radiation, long-wave radiation, surface pressure and accumulated precipitation refer to the ground surface (Flores et al., 2016). Grid size and time interval of the data are 1 km and 1 hr, respectively. We partitioned shortwave radiation into direct and diffuse, visible and near-infrared components as summarized by Weiss and Norman (1985).

Table 2. Meteorological data from the WRF model used for simulation. Adapted from Pandit et al., (2019)

Variable description	Name	Unit
2-m temperature	T2	K
Surface pressure	PSFC	Pa
Accumulated precipitation	RAINNC	mm
Terrain height	HGT	m
10-m u wind (zonal) component	U10	$\mathrm{ms^{-1}}$
10-m v wind (meridional) component	V10	$\mathrm{ms^{-1}}$
2-m specific humidity	Q2	$\mathrm{kgkg^{-1}}$
Downward longwave flux at ground surface	GLW	$\mathrm{Wm^{-2}}$
Downward shortwave flux at ground surface	SWDOWN	$\mathrm{Wm^{-2}}$

2.3 Point-based simulation

We ran point-based simulations at four EC tower sites in RCEW to understand the temporal dynamics of PFTs for alternative fire conditions. We initialized ecosystem conditions using representative existing vegetation conditions with equal densities (0.25 plants $\mathrm{m^{-2}}$) of shrubs and grasses as PFTs. The shrub density was based on field studies in the area (Glenn et al., 2017).

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For the shrubs, we used a PFT especially developed for sagebrush in the study area based on our previous work (Pandit et al., 2019) whereas for the grasses, we used the temperate C3 grass PFT which is the closest match from among available PFTs in EDv2.2. We assumed that this existing temperate grass PFT in the model would represent common perennial grass species in the study area. We tried to minimize interannual climate variability by calculating mean monthly precipitation from thirty years of WRF data (1988-2017), then selecting the year 2012 as the year that most closely matched the 30-year mean precipitation record. All four sites were run for an initial 25 years, after which each site was run with three different scenarios: (i) no fire, (ii) low fire severity, and (iii) high fire severity, for the next 125 years. Fire severity parameter in the model which specifies intensity of disturbance from fire can range from 0 to 1, where we applied 0.5 and 0.9 values for low and high severity fires, respectively. We observed GPP trends of shrub and grass PFTs for these three scenarios at all four EC sites, and compared results with GPP data from the sites (Fellows et al., 2017).

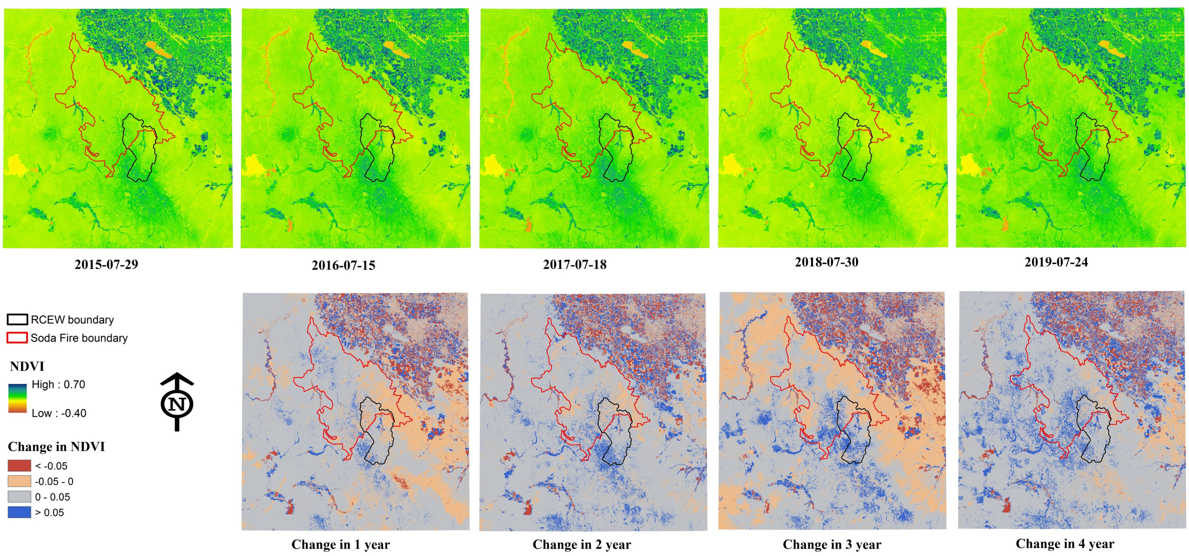

Figure 2. NDVI maps derived from Landsat images acquired in July of each year from 2015 (Soda Fire burn year) to 2019 (top row), and change in NDVI each year post-fire (bottom row).

2.4 Region-based simulation

We performed region-based simulations to explore post-fire vegetation recovery for the entire RCEW area. In this case, we initialized EDv2.2 with a bare-earth scenario from 1990 and ran it for the following 25 years, similar to the point analysis. For this analysis, we used meteorological data from the years corresponding with the simulation years, except for 2018 and 2019 when WRF data were not available. For these two years, we imputed WRF data from other years which closely resembled monthly total precipitation with the observations (NOAA, 2019). To compare vegetation dynamics in the burnt area with the unburnt area, we introduced fire into that portion of RCEW which burned in 2015 as part of the Soda Fire, and the remaining portion of the watershed without fire. The fire severity parameter in the model was kept at high level (0.9) to relate with the severity observed in the Soda Fire. We ran the model with these conditions for the next 4 years (2015 to 2019). This allowed us to observe changes in GPP between burned and unburned areas across time and space.

We compared the results from EDv2.2 based regional simulations to NDVI values derived from Landsat 8 images. Specifically, NDVI maps from selected dates (Fig. 2) were compared with the EDv2.2 GPP outputs from same dates for the respective years. NDVI maps for all years were clipped and resampled to match the spatial coverage and grid resolution ($1\ \mathrm{km}$) of the EDv2.2 simulation, before making comparisons.

3 Results

3.1 GPP for alternate fire conditions

GPP trends for the shrub and C3 grass PFTs were about similar for the LS, WBS and US sites and slightly different for the RMS site located at the highest elevation (Fig. 3). Without fire, shrubs eventually dominated to comprise the entirety of GPP persisting through the end of the simulation period. GPP for C3 grass was high during the initial years, but decreased rapidly after about 2-3 years of simulation, while shrub GPP increased gradually and became more dominant than grass after 10-15 years. Between 30 and 40 years, shrub GPP peaked, C3 grass GPP completely disappeared, and GPP reached an approximate equilibrium at or slightly above 0.3 $\mathrm{kgCm^{-2}yr^{-1}}$ for the three lower elevation sites (LS, US, WBS) and 5.0-5.5 $\mathrm{kgCm^{-2}yr^{-1}}$ for the highest elevation site (RMS).We did not observe any growth of conifer PFTs throughout the simulation period, even for the no fire scenario.

Upon introduction of simulated fire in the model after 25 years, shrub GPP declined abruptly and C3 grass GPP increased dramatically in all four study sites. However, around 25 years after fire is introduced, shrubs initiate a recovery and maintain a gradual increase until reaching a peak in 50-75 years; at the same time C3 grass GPP gradually decreased to a minimal level. Among four sites, LS site showed the longest time for shrub recovery while the RMS site recovered the quickest. Disturbance rates from fire spiked in the first couple of years when fire was introduced and later stabilized to closely follow the trend of shrub GPP, suggesting the highest disturbance rate at the peak of shrub GPP leading to decline of shrub GPP afterwards. A similar cycle was observed for the remainder of the simulation years. In most of the cases, we observed the peaks of total GPP catching up well with total GPP from the no fire scenario (at a cycle of about 60-75 years), and C3 grass GPP dominates the overall shape of total GPP in the post-fire years.

We identified some differences between low and high fire severity conditions, even though the general trend of GPP dynamics was similar for both. Compared to the low fire severity scenario, high fire severity simulations suggested lower peaks of shrub GPP, despite having approximately equal (or even higher for some) levels of total GPP due to higher levels of grass GPP. The LS and RMS sites showed a broader range of stability for peak shrub GPP (65 years after fire at LS and 50-85 years after fire at RMS) with high fire severity. We compared average annual GPP from EDv2.2 for different scenarios (at an equilibrium state for no fire condition and at the peak level for fire conditions) with the observed GPP from EC flux tower sites from 2015,

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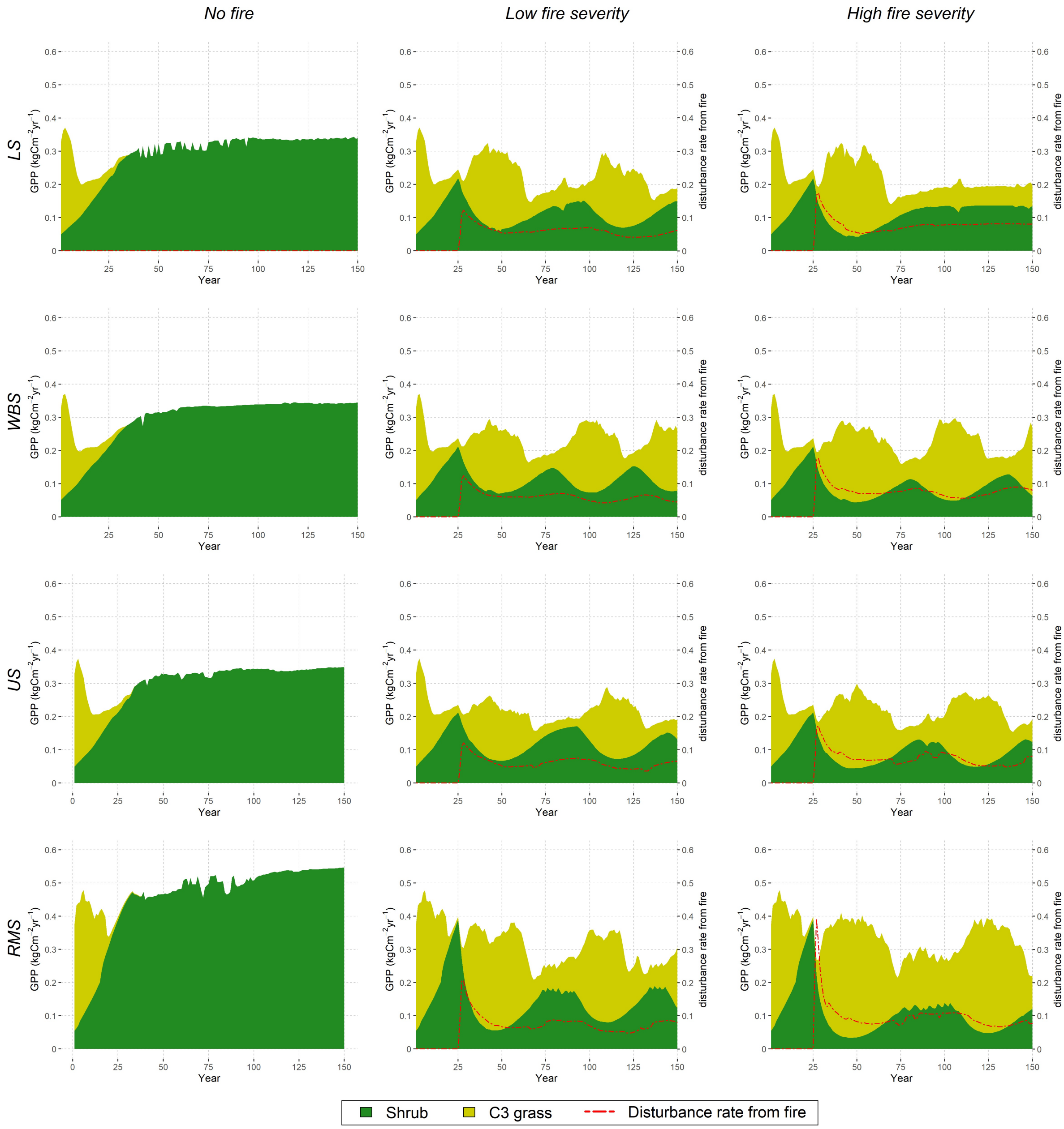

Figure 3. Mean annual trends in shrub, grass (temperate C3 grass) and total GPP (kgCm^{-2}yr^{-1}) simulated at four EC flux tower sites (LS, WBS, US, and RMS). Figures in the left column represents the trend in the no fire condition, the middle column the low fire severity condition, and the right column the high fire severity condition. For the model runs with fire conditions, fire was introduced in the 25th year of simulation. The red dashed line is scaled by the secondary y-axis (right), which shows mean fire disturbance rate for the simulation years.

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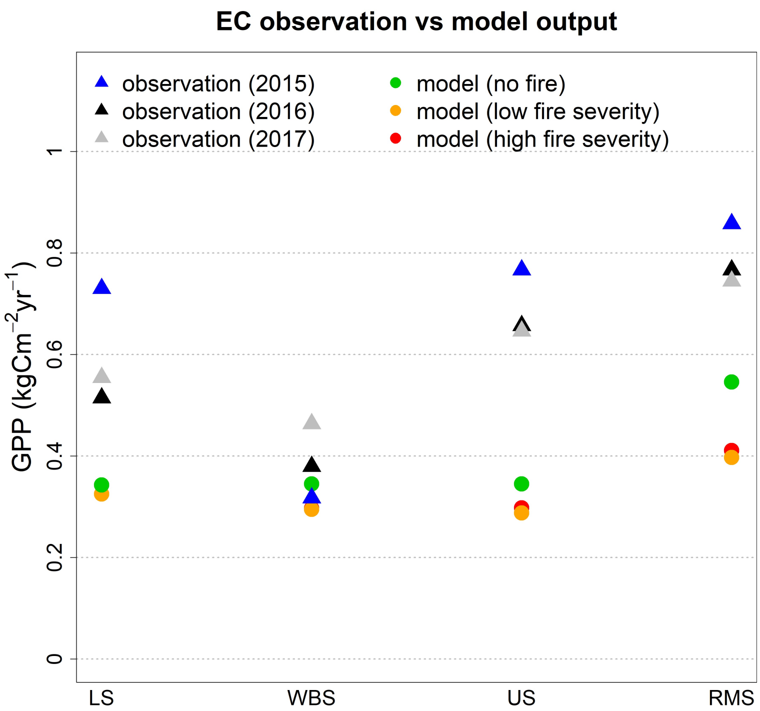

Figure 4. Comparison of simulated average annual GPP from EDv2.2 for alternate fire scenarios (no fire, low fire severity, and high fire severity) with observations (from 2015, 2016, 2017) from all four EC tower sites.

165 2016, and 2017 for all four sites (Fig. 4). EDv2.2 underpredicted GPP for all sites, except for the WBS site which was close to observation.

3.2 Comparison of modeled post-fire GPP with NDVI

Introduction of fire in the northern portion of the study area to the EDv2.2 simulation resulted in observable loss and recovery of GPP in the burned area. Modeled loss of GPP in the fire-affected area is a gradual process spanning several years following fire (Fig. 5). The first year after the fire showed evidence of some disturbance, however the impact was most evident only during the second (2017) and third years (2018) after fire, based on changes between pre- and post-fire GPP output (Fig. 5). The spatial variation in fire-induced disturbance suggests close association with elevation (Fig. 1), which largely influences the precipitation pattern in the study area. A hint of recovery in GPP for the fire-affected area is seen only after the fourth year (2019), even though GPP in the burnt area still lags behind the unburnt areas.

Modeled spatial patterns of GPP for pre-fire conditions in 2015 resembled observed NDVI patterns derived from Landsat 8 imagery for that same year (Fig. 5 and 6), along with some notable geographic differences. The simulated model output from

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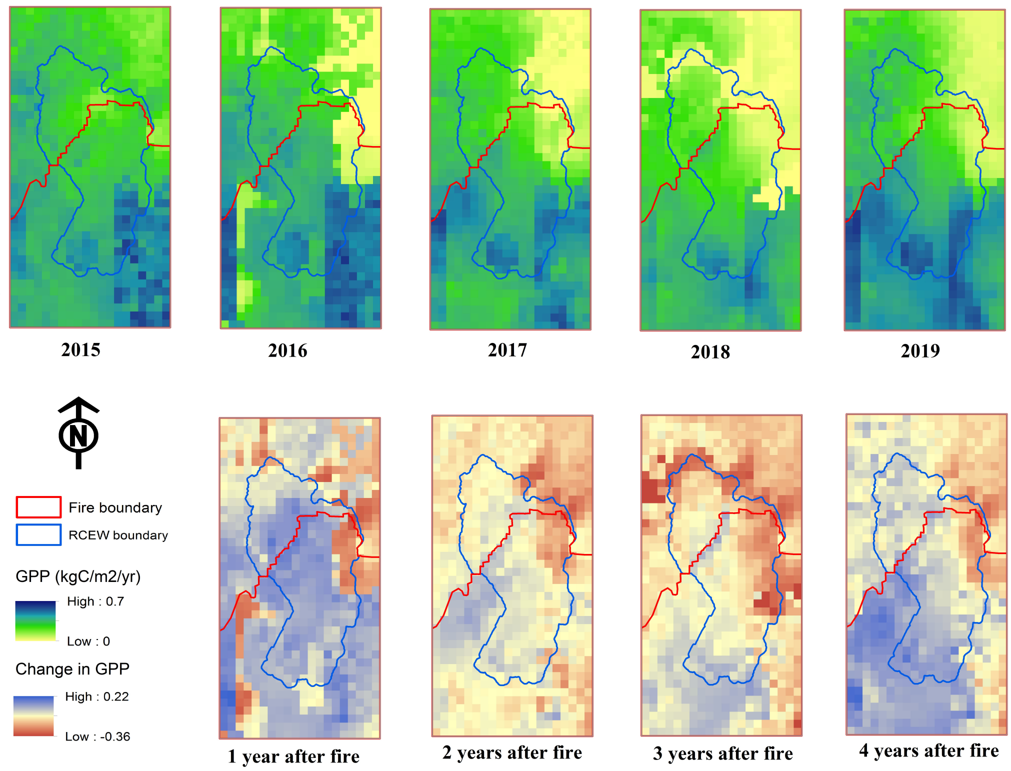

Figure 5. Snapshots of total GPP ($kgCm^{-2}yr^{-1}$) for July 29th, July 15th, July 18th, July 30th, and July 24th respectively for 2015, 2016, 2017, 2018, and 2019 compared to NDVI (Fig. 6) from the same dates. The starting year (2015) shows the pre-fire condition in the 25th year of spin-up, and the 4 subsequent years represent annual conditions after fire. Maps in the bottom show change in GPP every subsequent year after the fire incident compared to the pre-fire condition in 2015.

Table 3. Pearson's correlation coefficient calculated between modeled GPP and NDVI for burnt, unburnt, and whole area.

Year	Burnt area		Unburnt area		Whole area	
	Number of grids (n)	Pearson's correlation coefficient (r)	Number of grids (n)	Pearson's correlation coefficient (r)	Number of grids (n)	Pearson's correlation coefficient (r)
2015	336	0.489*	464	0.212*	800	0.427*
2016	336	0.487*	464	0.228*	800	0.440*
2017	336	0.566*	464	0.380*	800	0.566*
2018	336	0.404*	464	0.551*	800	0.638*
2019	336	0.480*	464	0.500*	800	0.598*

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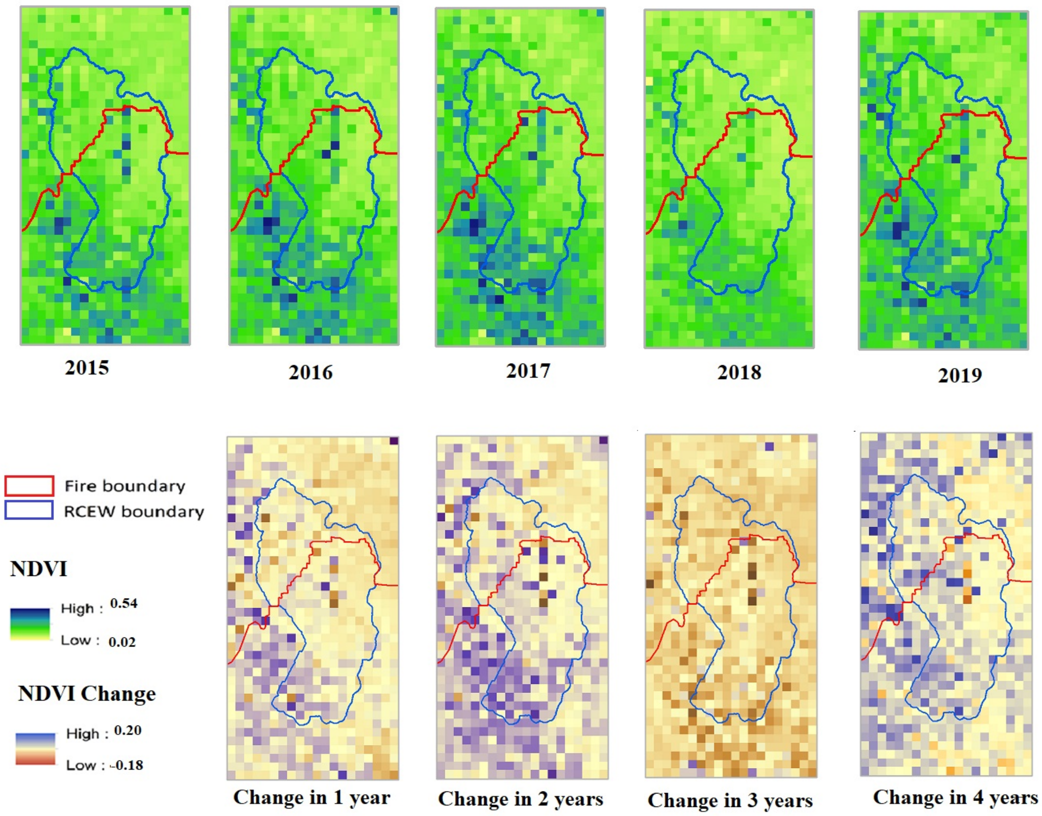

Figure 6. NDVI from Landsat images for pre-fire (2015) and post-fire years (top maps), and NDVI change every subsequent years after the fire incident compared to pre-fire NDVI (bottom maps). Landsat images were dated July 29th, July 15th, July 18th, July 30th, and July 24th respectively for 2015, 2015, 2017, 2018, and 2019.

EDv2.2 uniquely predicted higher GPP at some northwestern and southeastern areas in comparison to the rest of the study area, while NDVI clearly depicted higher values for a swath of the southern portion of study area that extends towards the northwest.

In contrast to a gradual decline in GPP predicted by the EDv2.2 simulations after fire, as expected we observed fire effects captured rather quickly by NDVI in Landsat images. However, the severity of damage shown by NDVI maps is rather subtle compared to the strong disturbance patterns in the model outputs. There was a clear reduction in NDVI values in the fire-affected area during the year immediately after fire, but by the second year, differences in NDVI between fire and non-fire areas were largely imperceptible. We calculated Pearson's correlation to further explore the association between modeled GPP and NDVI. We observed weak to moderate correlations for different areas (Table 3 and Fig. S1 in the supplement). In general, correlations were moderate for the burnt areas and moderately strong for the whole area (Table 3). Correlations for the unburnt areas were moderately weak for different years of data. Lower correlations for unburnt areas in the beginning years (2015 and

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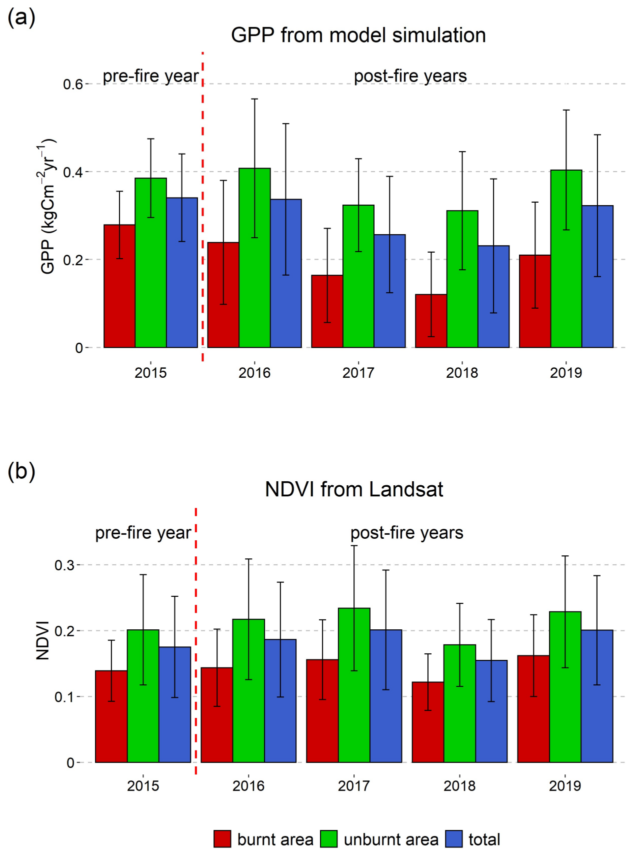

Figure 7. Average GPP from EDv2.2 and NDVI from Landsat calculated for all the burnt, unburnt, and total grids for annual July snapshot maps from 2015 to 2019 (a-b). Error bars in the figure represent ± one standard deviation.

2016) could be because of higher variation in vegetation productivity in these areas and because simulated GPP has not yet reached an equilibrium.

When mean NDVI and GPP values (from the EDv2.2 simulation) were plotted for the entire burnt area, unburnt area, and whole area, there was moderate year-to-year agreement among the two sources in terms of immediate fire effects, with agreement primarily limited to immediate burnt area reductions in productivity relative to unburnt areas during the first three years post-fire (Fig. 7a-b). While there was more pronounced annual variation in predicted GPP for all types of areas, we observed less variation for NDVI, with 2018 showing the lowest vegetation growth for both type of measures. GPP in bunt areas continued to decrease until the third year post-fire (2018) and hinted towards recovery in the fourth year. In the pre-fire condition (2015), the fire-affected region had 27% less GPP than non-fire affected areas, but this gap increased to 41%, 49%, and 61% in the first (2016), second (2017) and third year (2018) post-fire, respectively. This deficit was reduced to 48% in the fourth year (2019) after fire as post-fire recovery seemed to start. Although mean NDVI values in the burnt area increased

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slightly during the first and second year post-fire when looked in absolute numbers, however there was slight decline in relative terms with unburnt area. In the pre-fire condition (2015), NDVI values for burnt area was about 31% less than unburnt area, and this difference increased to about 34% in the first year post-fire. From the second year onward this deficit started to shrink until it finally reached 29%, which is lower than the pre-fire level in the fourth year post-fire (2019). When modeled GPP suggested some recovery only in the fourth year after fire, NDVI from Landsat showed complete recovery and some gain by that time.

4 Discussion

In general, the modeled shrub and grass dynamics are similar to those documented in the literature. With a sustained absence of fire or other disturbance, shrub cover and biomass can dominate over herbaceous species in shrub-steppe ecosystems (Bukowski and Baker, 2013; Cleary et al., 2010; West and Young, 2000), although the complete disappearance of the grass component suggested by our models is unlikely without the influence of other stressors (e.g., livestock grazing).

Thus, this latter dynamic suggests a need for further refinements in PFT development within the EDv2.2 framework, particularly for the C3 grass which we used to represent perennial grasses in the study area. Nevertheless, the EDv2.2 model captures the prevailing trend in ecosystem response to fire, giving it credibility and potential utility as a planning tool. Our modeled fire effects in these ecosystems are also mostly corroborated by the literature. Most sagebrush species are easily top-killed by fire, do not resprout, and have poor seed viability and dispersal capacity; thus, species of big sagebrush typically require several decades or more to recover to mature conditions post-fire (Baker, 2006; Lesica et al., 2007; Shinneman and McIlroy, 2016). If fire becomes too frequent, shrubs may be prevented from reestablishing, especially in the presence of fire-adapted, nonnative, annual grasses (Brooks et al., 2004). However, even in the presence of nonnative plants, field-based observations suggest that with enough time between fires, shrubs may gradually recovery as nonnative herbaceous species dominance declines (Rew and Johnson, 2010; Shinneman and Baker, 2009).

Despite the interannual variability evident in the observed flux tower data, the poor comparisons for the higher elevation sites US and RMS than the lower elevation sites could be explained by the fact that the shrub parameters we used were mainly developed and calibrated for the lower sites (Pandit et al., 2019), and thus may not have accounted for local variability. Higher ecosystem productivity and quick post-fire recovery at the RMS site compared to the other three sites can be associated with higher productivity, higher precipitation and lower temperature, as suggested by previous studies (Keane et al., 2008; Nelson et al., 2014; Shriver et al., 2018).

With the introduction of fire, even though we observed drastic change in PFT composition, total GPP barely dipped for about 5 years post-fire. Recovery of NDVI in the burnt area in the second year post-fire could be mainly because of perennial grasses and shrubs. Grasses (perennial) could be growing in the second year post-fire when conditions were favorable for their growth. The seasonality of the fire also affects how quickly perennial grass grow back, as a late summer or early fall fire would cause less damage to these grasses (White et al., 2008; Wright and Klemmedson, 1965). This prompt recovery of grass vegetation in the ecosystem was probably not well captured by the EDv2.2 with the default PFT parameters based on a temperate C3 grass.

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Spatial pattern of disturbance and recovery of GPP from the EDv2.2 model was fairly consistent with NDVI from respective years. As expected, fire disturbance phenomena in the EDv2.2 model could not truly represent the true circumstances in the affected area, even though we tried to parameterize the fire severity to match the real scenario. The fire disturbance function in the model did not burn the entire area at once; it rather selected grids randomly that would meet the potential fire criteria and kill the vegetation. Forkel et al. (2019) also found DGVMs underestimating burned area compared to satellite-derived responses. In addition, this process was gradual and spread over the subsequent years, therefore we saw the most obvious differences between burnt and unburnt areas only at the end of the second year (2017) postfire. Li et al. (2012) found a similar pattern predicted by CLM-DGVM in burnt areas while testing different fire parameters (Levis et al., 2004; Thonicke et al., 2001) in the model, showing annual variability in burnt area that was at maximum only in the fifth year post-fire. Updating of fire and PFT related parameters along with functional structures about fire-vegetation interactions in the model could better predict burnt areas and vegetation recovery.

Our GPP outputs from spin-up simulations by EDv2.2 in a bare-earth scenario was largely influenced by meteorological forcing data. Our use of modeled meteorological data from the WRF model may be an additional source of error. A final layer of uncertainty rests with the use of NDVI as a proxy for GPP. Properly interpreted, NDVI is an indicator of green vegetation cover, not GPP (Sellers, 1987), and likely is responding more strongly to new green grass regrowth stimulated by the fire, than to the shrub component that is the larger contributor to GPP in this ecosystem. This is likely contributing to the moderately strong correlations between GPP and NDVI (Table 3 and Appendix 1).

5 Conclusions

In this study, we explored fire-induced alterations to GPP in a dryland shrub ecosystem, in terms of shrub and C3 grass PFT. Under the no fire condition, shrubs were dominant and C3 grasses disappeared while approaching an equilibrium state of pure shrubs. Simulation results from the WBS site matched well with observations, whereas model results from the remaining three sites underestimated observed GPP data from flux towers. With the introduction of fire, we saw a decline in shrubs and a simultaneous rise in C3 grasses for approximately 3 to 4 decades of time, followed by slow recovery of shrubs at the expense of grasses. Regional simulation of GPP with EDv2.2 showed continued reduction in GPP for several years post-fire, which only started to increase again with increasing shrub prevalence by the fourth year post-fire. These modeled GPP trends moderately correlate to what actual GPP trends may be, as indicated by the post-fire NDVI response observed from four years of post-fire Landsat imagery.

This study documents an application of EDv2.2 to understand vegetation productivity trends in a semi-arid shrubland ecosystem under alternate fire scenarios at the point scale and evaluating the spatiotemporal trend of fire disturbance and vegetation recovery at the regional scale. We could reduce uncertainties in comparing model outputs with EC tower observation and satellite-derived products by improving fire and vegetation parameters and by applying observed meteorological data.

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Code and data availability. The original EDv2.2 is available on the GitHub repository at https://github.com/EDmodel/ED2 (ED2 Model Development Team, 2014, last access: 05 November, 2019). EDv2.2 with shrub PFT parameters used in this study is available at https://doi.org/10.5281/zenodo.3461233 (Pandit, 2019a, last access: 16 December, 2019), and input data are available at http://doi.org/10.5281/zenodo.3592261 (Pandit, 2019b, last access: 23 December, 2019).

Author contributions. KP led the model runs and manuscript preparation with significant contributions from all co-authors. KP, HD, ATH, NFG, ANF and DJS conceived the idea and contributed to the research design.

Competing interests. The authors declare that they have no conflict of interest.

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