FINAL REPORT

Title: Modeling long-term effects of fuel treatments on fuel loads and fire regimes in the Great Basin

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List of Abbreviations

BLM – Bureau of Land Management
CZO - Critical Zone Observatory
DBH - Diameter at breast height
DGVM - Dynamic global vegetation models
DOD – Department of Defense
EC - Eddy covariance
ED - Ecosystem Demography model
EOS - End of season
GPP - Gross primary production
LS – Low sagebrush EC site
MAD - mean absolute deviation
MBS - Mountain big sagebrush EC site
MODIS - Moderate Resolution Imaging Spectroradiometer
NDVI - Normalized difference vegetation index
NEE – Net ecosystem exchange
NSF - National Science Foundation
PEST - Parameter Estimation and Uncertainty Analysis
PFT - Plant functional type
RCEW - Reynolds Creek Experimental Watershed
RMSE - Root Mean Square Error
SA - Sensitivity analysis
SLA - Specific leaf area
SOS - Start of season
US – Upper Sheep EC site
USDA-ARS - United States Department of Agriculture Research Service

Keywords

Gross primary production (GPP), Ecosystem Demography model (EDv2.2), parameter estimation, uncertainty analysis, sagebrush shrubland, plant functional type, fire, eddy covariance tower, remote sensing, dynamic global vegetation model (DGVM), Reynolds Creek Experimental Watershed (RCEW), Idaho

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Abstract

The principal motivation for this study is that sagebrush-steppe ecosystems are undergoing significant state changes, and land managers are challenged with optimizing their resources for both short- and long-term use. Yet, limited knowledge is available regarding how the sagebrush-steppe will respond to environmental changes related to precipitation and temperature regimes, and disturbance such as fire. Furthermore, there is a lack of understanding on how fuels reduction and other fuel management activities will impact these ecosystems over the long-term. We addressed these challenges by adapting and testing a vegetation dynamics model, the Ecosystem Demography v2.2 model (EDv2.2), for the sagebrush-steppe. Vegetation dynamics models can provide estimations of ecosystem productivity in their natural and disturbance states, and thus serve as a tool to understand and predict potential changes in various processes and properties of vegetation communities. Yet, there is no vegetation dynamics model that is well-developed for the sagebrush-steppe, and thus significant effort is needed to test EDv2.2 for its application. As part of our efforts to develop the EDv2.2 model into a useful tool for the sagebrush-steppe, we developed a sagebrush plant functional type (PFT) as part of this study, and then performed sensitivity analyses, model calibration, and finally model evaluation. Furthermore, we developed several model scenarios under natural (undisturbed) and disturbed (fire) environments. We compared our model outputs with ground-based data (field and eddy covariance) and remote sensing observations. The results of our project include a sagebrush PFT that can be used in both future EDv2.2 modeling efforts and other vegetation dynamic models. Our results from the model sensitivity analysis indicate that specific leaf area (SLA), stomatal slope (STO_S), cuticular conductance (CUT_C), and carboxylase rate constant (VM0) are sensitive parameters to vegetation productivity in the model (based on gross primary production, GPP), and future modeling efforts will benefit from both lab and field studies of these parameters and sensitivity analyses. Through calibration, we found that the EDv2.2 model estimates of GPP were modeled well at our lowest elevation field site in Reynolds Creek Experimental Watershed (RCEW), which is dominated by Wyoming big sagebrush. On the contrary, we found poorer results at higher elevation site shrub sites. These sites are characterized by either low sagebrush or mountain big sagebrush, and have more forb cover than the low elevation site. In this project we also implemented the fire model in EDv2.2 to explore how shrub and C3 grasses respond to fire by analyzing post-fire GPP. We ran both point and regional model runs with fire introduced. In most fire scenarios, fire substantially reduced shrub GPP and it took several decades for shrub GPP to return to pre-fire conditions. Grass GPP responded more quickly in post-fire conditions. While these processes are representative of what other studies have found, significant efforts to improve the fire processes in EDv2.2 are needed. For example, nuances associated with the fire subroutine in the model (running periodic fire events versus instantaneous fires and fire intensity) will need to be expanded. Another significant contribution to our knowledge gap is that additional PFTs to represent the sagebrush-steppe (e.g. annual grasses such cheatgrass) are needed for EDv2.2. Regardless, this project made significant advances in PFT development and model testing. Moreover, the EDv2.2 provides a useful framework to conceptualize vegetation dynamics, project future conditions, and consider fire as a disturbance. With additional parameterizations, PFTs, and fire routines, EDv2.2 will evolve as a tool for which to better understand future ecosystem dynamics of the sagebrush-steppe.

1 Objectives

The objectives of this project were to address how vegetation responds to precipitation and temperature regimes and fire in the sagebrush-steppe, and to assess long-term implications for productivity (as measured by gross primary production, GPP). An overarching objective was to test the applicability of a vegetation dynamic model (Ecosystem Demography model, V2.2) for application to the sagebrush-steppe to help address these questions. This objective led to extensive development, calibration, and testing of the EDv2.2 model. As such, a significant investment of time and effort in EDv2.2 resulted in filling a large knowledge gap for future studies to build upon and utilize in scenario modeling that should prove valuable to management of rangelands and conservation of dryland ecosystems.

The objectives in the original proposal were to address the following questions: 1) How will fuels shift over the next 20 years with predicted changes in temperature, moisture, invasive species, and fire regimes?; 2) How does vegetation respond (e.g., growth, production, structure, species composition) in the years after fuel treatments and post-fire seedings; and what are the implications for long-term, repeated maintenance of fuels in these areas?; and 3) What are the attributes of climate variability that fuels treatments are most sensitive to? These objectives were met in the context of the model calibration and scenario runs using GPP; however additional work is needed to more fully answer these questions. For example, we estimated GPP over 20 years optimizing plant functional type (PFT) parameters and comparing to MODIS remote sensing GPP (Q1). We also developed model scenarios of fire / no fire and ran the EDv2.2 model for 65 years to understand differences in shrub and grass GPP responses (Q2). We did not directly address Q3 due to efforts spent towards model development, however we addressed this question through model runs of seasonal/yearly GPP responses to precipitation. Further information on the above is presented below.

2 Background

Dryland ecosystems, such as the vast grasslands, shrublands, and woodlands of the Great Basin, are vulnerable to broad scale changes in fuels and fire regimes as a result of invasive species, changing precipitation and temperature patterns, and other perturbations. Climate warming is already modifying the structure and function of dryland ecosystems, causing shifts in phenology and in some cases altering species distributions to higher latitudes and altitudes (Backlund et al., 2008; Bradley, 2009). Moreover, changing fire regimes (Balch et al., 2013) and invasive species (Bradley and Mustard, 2005) exert major controls on climate-biome patterns (Backlund et al., 2008). In the semiarid Great Basin, native shrubs are being replaced by non-native, annual plants (e.g. *Bromus tectorum*, 'cheatgrass'), manifesting in the "grass-fire cycle" (D'Antonio & Vitousek, 1992; Pilliod et al., 2017). As a result, fire has not only become the dominant disturbance process in these systems but, by interacting with climate change, altered fire and fuel dynamics are creating further vulnerability for "catastrophic regime shifts" at biome-scales (Reisner et al., 2013; Bradley et al., 2018).

To address the changing fire regimes in the Great Basin, management agencies are using fuel reduction and seeding treatments to modify the amount, structure, and continuity of flammable vegetation to reduce fire occurrence and intensity, and risks posed by wildfire. However, ecological impacts and long-term effectiveness of fuel reduction and seeding treatments are poorly understood, especially at broad spatial and temporal scales. This knowledge gap gives rise to the need to develop foundational tools that can be used to further understand dynamics associated with management practices.

Ecosystem dynamic models have the potential to help answer how ecosystems may respond to changes in climate as well as management treatments at scales useful for long-term planning. However, while ecosystem dynamic models have been widely used to project ecosystem characteristics over time and space (Dietze et al., 2014; Fisher et al., 2018), these models have also been associated with high levels of uncertainty and questions regarding their applicability to distinct and often complex ecosystems at large scales (Kwon et al., 2008). The latter is especially true in sagebrush ecosystems which are often spatially heterogeneous and shaped by complex dynamics over time. To address this knowledge gap, we conducted extensive development, calibration, and testing of the Ecosystem Demography (EDv2.2) model.

Ecosystem Demography (EDv2.2) is a process-based ecosystem dynamic model that approximates the behavior of ensembles of size and age-structured individual plants to capture sub-grid level ecosystem heterogeneity using partial differential equations (Medvigy et al., 2009; Moorcroft et al., 2001). EDv2.2 is the most recent version of ED-2, and specific details can be found in Longo et al. (2019). The ED model was originally developed to study tropical ecosystems with trees as a primary component, but it has since been modified and applied to several different ecosystem types, including boreal forests (Trugman et al., 2016) and temperate forests (Antonarakis et al., 2014; Medvigy et al., 2009; Medvigy et al., 2013). However, its application to semi-arid shrubland ecosystems had not been explored (prior to this study) and importantly, it lacked a shrub Plant Function Type (PFT) for these ecosystems. Thus, we developed and parameterized a sagebrush PFT for EDv2.2 and used it to estimate gross primary production (GPP) for the sagebrush ecosystem in the Reynolds Creek Experimental Watershed (RCEW), Idaho, USA. GPP is the rate at which solar energy is captured in plants during photosynthesis (per unit area per unit time), and effectively represents "the capacity of ecosystems to produce flammable biomass" (Parisien et al., 2012). We then used this model to explore fire dynamics and future scenarios of the ecosystem. Since EDv2.2 has not been applied to shrublands, evaluating the performance of the model before performing any analysis related to fire was necessary. Placing this study in the RCEW was opportune, as it is one of the few dryland sites in the western US in which there are eddy covariance (EC) towers along an environmental gradient. The EC data are important for comparing and interpreting the EDv2.2 results. Thus, in this study we contributed significant effort towards model evaluation, and specifically on: I) defining a shrub PFT, II) performing a sensitivity analysis, III) performing model calibration, and IV) comparing results of model simulations with eddy covariance tower, field, and remote sensing data from the study area.

3 Materials and Methods

3.1 Study area

The study area is the Reynolds Creek Experimental Watershed (RCEW), a National Science Foundation (NSF) Critical Zone Observatory (CZO), monitored by the USDA Agricultural Research Service (ARS) since 1960 (Figure 1). RCEW is approximately 240 m^2 and has an elevation gradient of 900-2200 m. With increasing elevation, the mean annual precipitation increases and temperature decreases (Flerchinger et al., 2019; Renwick et al., 2019), typically enhancing both GPP and ecosystem heterogeneity. Additional environmental characteristics of RCEW can be found in Seyfried et al. (2018). In this study, we used four eddy covariance (EC) towers located at different elevations in RCEW (WBS, LS, US, MBS, Figure 1, Table 1). The dominant vegetation cover of each site is different species of sagebrush (*Artemisia* spp.) including Wyoming big sagebrush (*Artemisia tridentata* ssp. *wyomingensis*; WBS site), low sagebrush (*Artemisia arbuscula*; LS site) and mountain big sagebrush (*Artemisia tridentata* ssp. *vaseyana*; US and MBS site). Other vegetation at the WBS site includes green rabbitbrush (*Chrysothamnus viscidiflorus*), spineless horsebrush (*Tetradymia canescens*), cheatgrass and perennial graminoids including bluebunch wheatgrass (*Pseudoroegneria spicata*), squirreltail (*Elymus elymoides*), and Sandberg bluegrass (*Poa secunda*). The LS site includes predominantly Sandberg bluegrass, squirreltail, and Idaho fescue (*Fescue idahoensis*). A prescribed fire (roughly 0.26 km^2) was conducted in the US site in fall 2007 and vegetation in this plot is recovering. Other vegetation types in US include mountain snowberry (*Symphoricarpos oreophilus*), green rabbitbrush and juvenile mountain big sagebrush. Mountain snowberry is also a common shrub in the MBS site. Cheatgrass is less abundant at both LS and MBS compared to the WBS site, however at LS and MBS there is a strong presence of forbs including longleaf phlox (*Phlox longifolia*), pale agoseris (*Agoseris glauca*), and silvery lupine (*Lupinus argenteus*). A full description of each of these sites is presented in (Flerchinger et al., 2019).

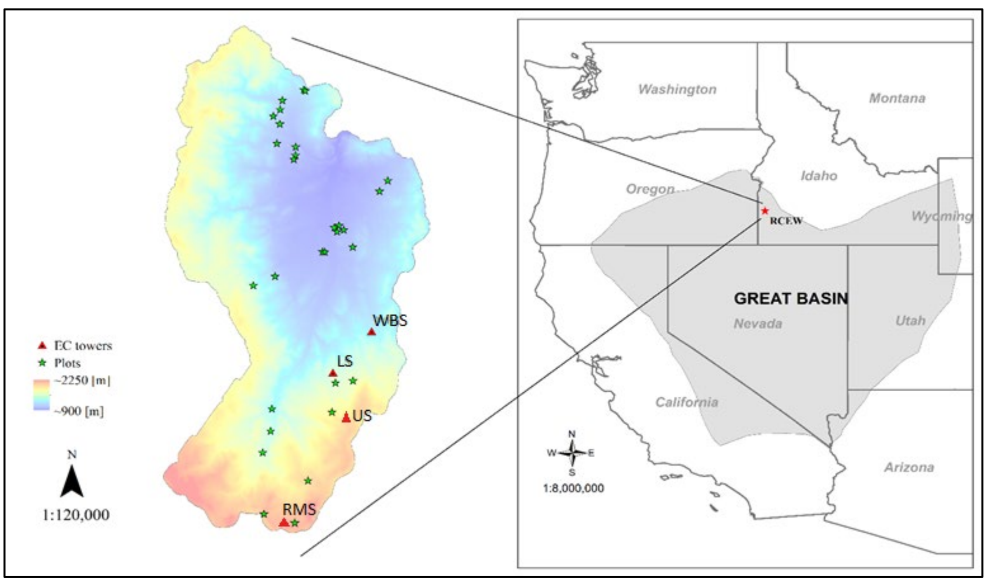

Figure 15. Location of EC towers in Reynolds Creek Experimental Watershed, Idaho.

Table 1. Site descriptions of the four eddy covariance sites, WS, LS, US, MBS.

Site	Elevation [m]	Dominant vegetation cover	Mean annual precipitation [mm]	Mean annual temperature [°C]	Data availability (water year)
WBS	1187.9	Wyoming big sagebrush	292	9.4	2014-2016
LS	1618.4	Low sagebrush	333	8.6	2015-2016
US	1808	Mountain big sagebrush	505	6.5	2014-2016
MBS	2113	Mountain big sagebrush	800	5.6	2014-2016

3.2 Model evaluation

We developed a sagebrush PFT in EDv2.2 and constrained uncertainties through optimization of selected PFT parameters. To accomplish this, we employed a three-tiered approach. First, we parameterized the sagebrush PFT, by fitting allometric relationships for sagebrush using field-collected data, information from existing sagebrush literature, and borrowing parameters from other land models. EDv2.2 was originally developed for tropical forests, and thus typically specifies allometric relationships in terms of diameter at breast height (DBH). However, this length-scale variable has limited application to shrubs of the sagebrush-steppe ecosystem, which rarely exceed 1.5 m in height. Thus, we developed a substitute length-scale variable for DBH that effectively corresponds to shrub volume. We synthesized existing data from a previously-funded JFSP project "*Quantifying and predicting fuels and the effects of reduction treatments along successional and invasion gradients in sagebrush habitats*" and a NASA project "*Scalable Vegetation Structure for Ecosystem Modeling in the Western US*" to develop the substitute length-scale variable. We found a strong fit (r^2=0.71) of estimating DBH by approximating it with the cube root of shrub volume, which was calculated using crown area (characterized as an ellipse and approximated with semimajor and semi-minor axis lengths) and height. The results of this step were recently published by Pandit et al. (2019a), in the first primary publication produced for this project (see Appendix B). Cube root of volume, height, and plant density information from the above-mentioned data were used to initialize the ecosystem conditions in the model. The model then spins up the dynamics of the shrub cohorts within patches based on the availability of light and nutrients, where each individual plant cohort grows per the allometric equations.

To identify the most influential parameters in GPP predictions, we used a sensitivity analysis (SA) and identified the most-sensitive parameters. We implemented a local SA method based on the sensitivity index (SI) developed by Hoffman and Miller (1983) and also a global SA based on the Morris method (Morris, 1991). Selection of parameters were based on their relevance to the daily GPP process. The main goal of the SA was to reduce the uncertainty of the model by excluding non-influential parameters from the model calibration processes (section 3.4).

To improve upon and assess model performance, we optimized the most sensitive parameters using an exhausting search method and also a mathematical method offered by the PEST++ (Parameter Estimation and Uncertainty Analysis) package (White et al., 2019). In both calibration methods the initial values of parameters and their range comes from expert knowledge or borrowed from other dynamic global vegetation models (DGVMs) or literature (Pandit et al., 2019a). Hourly meteorological forcing variables for the years 1988-2017 were based on high resolution (1 km^2) reanalysis data obtained from the Weather Research and Forecast (WRF) model recently developed for portions of western US (Flores et al., 2016). The filling and partitioning of NEE into GPP and respiration is described in Fellows et al. (2017).

Model evaluation was based on comparing the simulated GPP using EDv2.2 and GPP estimated from EC towers and from the MODIS sensor (Running et al., 2004). The spatial and temporal resolutions of the MODIS data (MYD17A2H006 GPP product) are 500 m and 8 days, respectively. We acknowledge uncertainties in the MODIS GPP dataset since it is observational across coarse spatial scales and its application to dryland ecosystems challenging. For model evaluation purposes we excluded the US site due to a prescribed fire in 2007 (section 3.1) which may have changed the vegetation composition and cover of the site (this is an area of potential further evaluation with the model). Both R^2 and Root Mean Square Error (RMSE) were used to compare the data. Since the EC tower data are temporally limited (Table 1), a meaningful time series analysis is challenging. Thus, for long term model evaluation we compare the start of season (SOS) and end of season (EOS) and trends retrieved from calibrated model simulations and MODIS GPP for the 2000-2017 time period. For both phenology and trend analysis, we aggregated the daily simulated and MODIS GPP into monthly values based on the maximum composition approach (Forkel et al., 2015a; Holben, 1986). Additional details of the above methods are provided in Pandit et al. (2019a) and Dashti et al. (in review).

3.3 Fire runs

After completing the model evaluation steps, we implemented fire scenarios at both point and regional scales. Fire in EDv2.2 affects the vegetation mortality rate which is a function of cohort height for a given PFT type. Fire ignition in the model depends upon both enough fuel (aboveground biomass) availability and upon meeting a soil dryness threshold. We set up fire intensity parameters at a high level which produces higher fire severity depending upon available fuel. See Longo et al. (2019), for additional details of the fire model in EDv2.2. For point-based fire simulations, all four sites were run for an initial 25 years with a ‘no fire’ condition to allow the model to reach equilibrium. We used inventory data collected in the field to initialize the model (Pandit et al., 2019a). We then introduced fire in year 25 at all sites (by turning on the fire routine in EDv2.2) and then ran the model for the next 40 years. As a comparison, we also ran the model for the next 40 years without fire. We observed GPP trends of shrub and grass PFTs, as an indicator of relative fuel production, before and after the introduction of fire among these sites. As a separate analysis, for the regional simulation, we initialized the model with a bare-earth scenario from 1990 and ran it for the following 25 years (similar to the point analysis). To explore post-fire vegetation dynamics with EDv2.2, we introduced fire in the area of RCEW that burned in 2015 as part of the Soda Fire, and we left the remaining portion of the watershed unburned. We ran the model with these conditions for the next 4 years (i.e., 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 the normalized difference vegetation index (NDVI) values derived from Landsat 8 images. NDVI can be correlated to several vegetation characteristics or parameters (e.g., leaf area index, green biomass), and it can be used to derive estimates of fuel moisture, classify fuel types, or help produce wildfire risk assessments (e.g., Burgan et al., 1998; Keane et al., 2001). Specifically, we selected July 15th of each year from 2015 to 2019 to calculate NDVI and compared those with EDv2.2 outputs from July 15th of the same years.

4 Results and Discussion

4.1 Model evaluation

Our sensitivity analyses using both the SI and Morris methods showed that the EDv2.2 model exhibited reasonable behavior by being the most sensitive to parameters that are directly used in calculating GPP. Details of the parameters included in the sensitivity analyses are provided in Pandit et al. (2019a) and Dashti (2019). Specific leaf area (SLA), stomatal slope (STO_S), cuticular conductance (CUT_C), and carboxylase rate constant (VM0) showed the highest individual influence (μ*) and the highest potential non-linearity and/or parameter interaction (σ) among all parameters (Figure 2). All four parameters indicated as influential are indeed used in the photosynthesis sub-model of EDv2.2 which is directly related to GPP (further discussion in Dashti, 2019). The other eight parameters are clustered at the lower left of the figures below, indicating that EDv2.2 is less sensitive to them in simulating GPP.

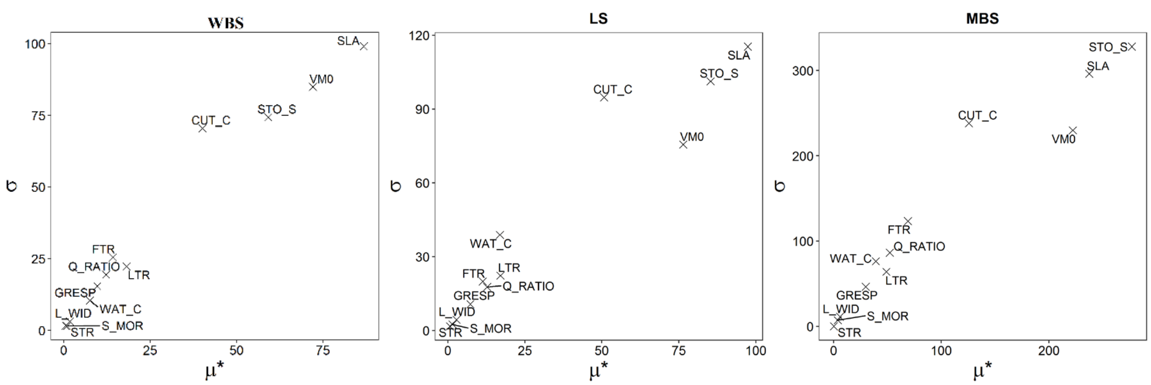

Figure 16. Sensitivity analysis based on Morris for WBS, LS, and MBS, μ* and σ are the mean and standard deviation. At all three sites, SLA, STO_S, CUT_C, and VM0 are identified based on this analysis as the most important parameters to estimate GPP.

Table 2 shows the four best estimated parameter values and corresponding standard deviation and confidence intervals using the PEST++ method. Table 3 shows the calibration/validation R^2 and RMSE between simulated and estimated GPP from EDv2.2 and the EC towers, respectively. We exclude MBS (the highest elevation site) from Table 3 because the EDv2.2 calibration process performed poorly in this site (more details below and in Dashti, 2019). In general using both the exhaustive search calibration method (results not shown here but can be found in Pandit et al., 2019a) and PEST++, the performance of EDv2.2 in capturing GPP degrades in higher elevation sites in the study area where the vegetation production (i.e. GPP) is also higher. Figure 3 shows the observed vs. EC tower GPP values for the WBS site, which performed the best in EDv2.2 in terms of photosynthesis capacity.

Table 2. PEST++ results for SLA, STO_S, CUT_C, and VM0 and their uncertainty.

Parameter	WBS		LS		MBS	
	Best	STDV (upper bound; lower bound)	Best	STDV (upper bound; lower bound)	Best	STDV (upper bound; lower bound)
Specific leaf area [m^2kg^{-1}] (SLA)	6.14	0.03 (6.04;6.18)	7.50	0.47 (6.55;8.45)	2.82	3.25 (-3.67;9.32)
Carboxylase rate constant [$\mu molm^{-2}s^{-1}$] (VM0)	24.50	0.21 (24.06;24.93)	19.45	0.48 (18.48;20.43)	7.44	2.04 (3.33;11.51)
Stomatal slope (STO_S)	13.97	0.03 (13.90;14.05)	9.85	0.53 (8.77;10.92)	7.82	1.98 (3.83;11.76)
Cuticular conductance [$\mu molm^{-2}s^{-1}$] (CUT-C)	999.51	112.184 (775.143;1223.88)	1000	462.68 (74.62;1925.37)	1000	267.44 (465.121;1534.89)
Number of model runs	166	---	56	----		

Table 3. Calibration and validation results for EDv2.2 for WS and LS sites.

Site	Calibration		Validation	
	R2 (daily; monthly)	RMSE (daily; monthly)	R2 (daily; monthly)	RMSE (daily; monthly)
WBS	0.56; 0.81	0.22; 0.18	0.34; 0.60	0.44; 0.38
LS	0.72; 0.85	0.29; 0.24	0.44; 0.62	0.47; 0.39

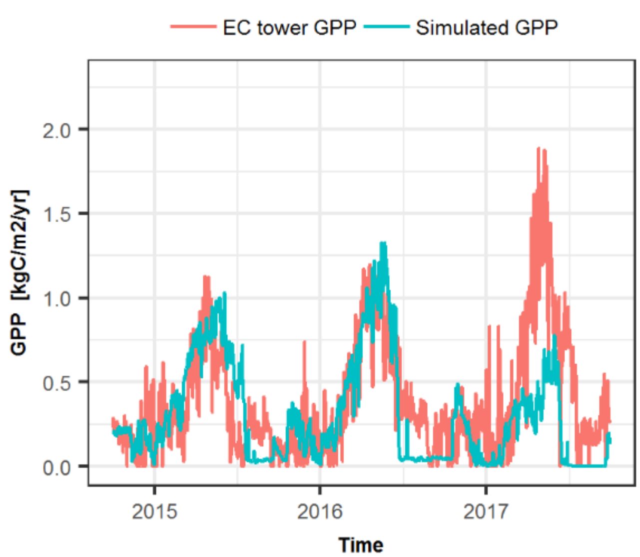

Figure 17. Model simulations vs. tower observation for WBS.

The model's generally poor performance in higher production sites/years, as indicated in Tables 2 and 3 and Figure 3 (i.e., 2017), can be explained by several factors. One is the lack of ecosystem heterogeneity representation in the EDv2.2 model. As elevation increases at RCEW, the heterogeneity of the ecosystem also increases (Flerchinger et al., 2019). For example, the presence of forbs at MBS is noteworthy and can contribute up to 50% to the carbon budget (Flerchinger et al., 2010). Thus, the lack of forbs and other PFTs common in drylands in EDv2.2 may partly explain the poor performance of the model in capturing GPP at higher elevation sites. The EDv2.2 model structure may also play an important role in its poor performance at high production sites and years. For example, Flerchinger et al. (2019) found that the timing of complete snowmelt is a strong control on GPP at the MBS site. The snowmelt process is not included in EDv2.2. Plant hydraulic traits control the water potential within the leaf which itself regulates processes such as photosynthesis and leaf shedding (Xu et al., 2016). In EDv2.2, an empirical method has been employed to represent plant hydraulic processes. For example, photosynthesis is regulated as a function of root water supply (Medvigy et al., 2009). Recent advances in mechanistic representation of water hydraulics in EDv2.2 for tropical forests may be adopted for drylands with future examination.

Due to better performance of EDv2.2 at the WBS site, we restricted our time series analysis to this site. Visually there is good agreement between MODIS and EDv2.2 estimated phenometrics (i.e., SOS and EOS; the start and end dates for a phenological phase or event, defined here using estimated GPP values) (Figure 4). However, the mean absolute deviation (MAD) of the SOS and EOS is 18.6 and 25.2 days, respectively. We should note that, in this study, we did not perform an interannual analysis of the changes in phenometrics.

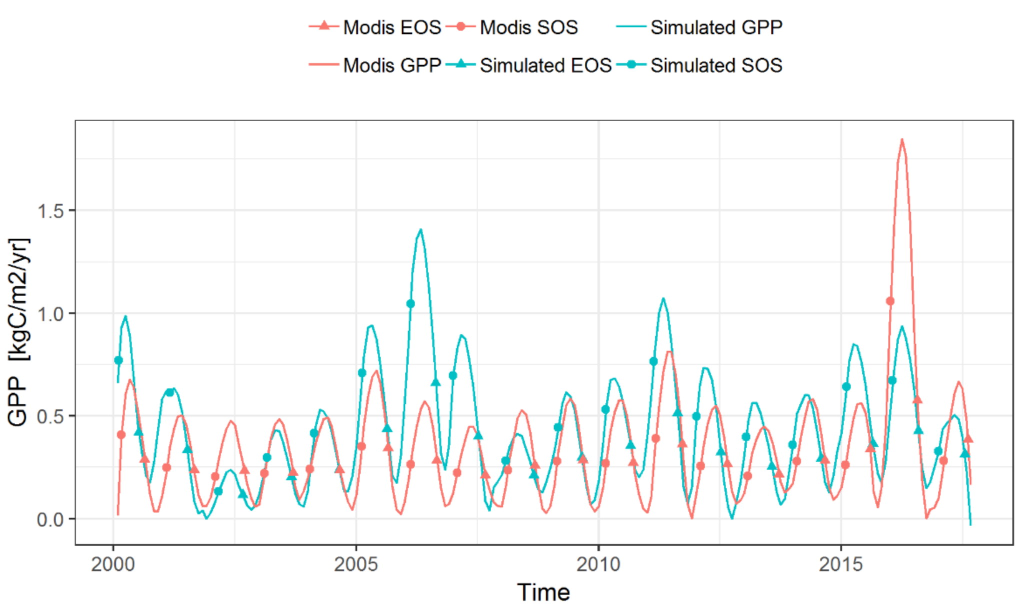

Figure 18. Phenometrics estimated from MODIS GPP and simulated GPP using EDv2.2.

The results of the interannual trend analysis are shown in Figure 5. There is general agreement between MODIS and EDv2.2 during greening events, specifically in years 2011 and 2016. We also calculated the seasonal and trend components of precipitation for the WBS site (2000-2017) (Figure 6). The precipitation trend increases in years 2006, 2011 and 2016. This increase in precipitation leads to an increase in GPP in both the model and MODIS for years 2011 and 2016. The model also captured the greening in 2006, however this greening occurs in the MODIS data in the year 2005. There is a significant difference in the intensity of browning events. For example, between 2000 and 2004 MODIS shows no significant trend in GPP, however during this time period, EDv2.2 GPP shows significant browning. In general, the browning and greening events are more intensified in EDv2.2 simulations than in the MODIS GPP. Comparing seasonal components shows a similar pattern except for the year 2016 where GPP was higher when EDv2.2 shows no increase in seasonal GPP. Thus, our main conclusion is that at lower elevations, precipitation drives the general trend of the GPP which is captured by both MODIS and EDv2.2; however, the model generally exaggerates this trend in comparison to MODIS observations. An increase in precipitation in 2016 resulted in large peak greening event in that year. The model did not capture this peak and thus underestimated the subsequent browning.

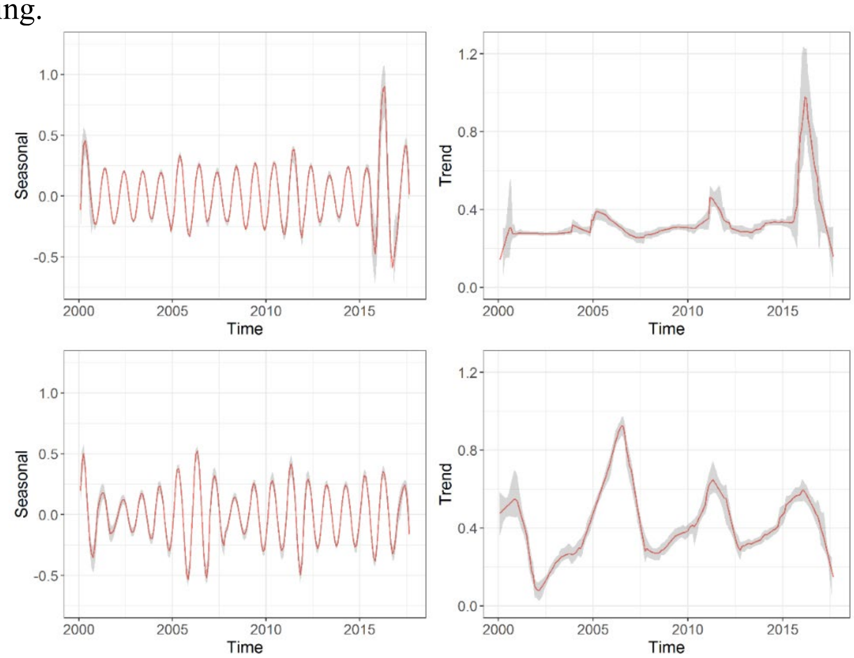

Figure 19.Estimated seasonal and trend components for MODIS (top row) and EDv2.2 GPP (bottom row) for years 2000-2017.

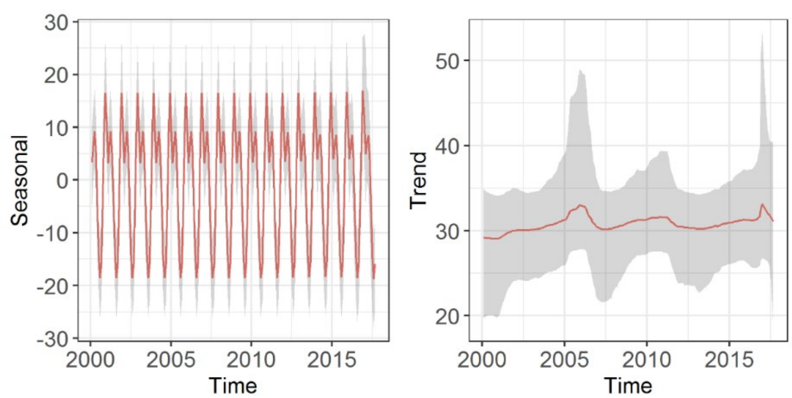

Figure 20. Precipitation seasonal and trend components and their confidence interval for WS site (2000-2017). The precipitation data comes from WRF model (section 2.1).

The difference between estimated phenometrics derived from MODIS versus EDv2.2 may be due to a combination of uncertainty in remote sensing data, the EDv2.2 model structure, and methods used. In this study we used MODIS GPP for the time series analysis. Analyses using Normalized Difference Vegetation Index (NDVI) and a newly developed vegetation index (NIRv = NDVI ×NIR; Badgley et al., 2017), led to different results than the MODIS GPP (results not presented here). Thus, which remote sensing dataset to use for this type of phenological study remains an open question. The cold-deciduous phenology sub-routine in EDv2.2 is based on changes in temperature (Botta et al., 2000), through which modeled vegetation drops their leaves. However, the actual phenology of sagebrush is more complicated. Sagebrush is a semi-deciduous plant that maintains a sizeable proportion of its leaves (persistent leaves) during cold season (Evans and Black, 1993; Williams et al., 1997). A recent method was developed to account for better representation of sagebrush phenology in DGVMs (Renwick et al., 2019); however, such methods still require empirical thresholds (e.g. percent of persistent leaves), some of which will likely differ significantly along elevation gradients, successional gradients, or among sagebrush species. In general, mechanistic modeling of phenology for any PFT is a challenging task (e.g., Forkel et al., 2015b; Migliavacca et al., 2012; Richardson et al., 2013).

Our results showed that at lower elevations, the general decadal trend in GPP is coincident with the general trend of precipitation. This finding is consistent with an extensive analysis of the WBS site by Flerchinger et al. (2019) and other similar sites (Yan et al., 2019). However, the greening-browning events are generally exaggerated by the EDv2.2 model. Since precipitation is the main driver of vegetation productivity and it shows more stability in trends (Figure 6), we conclude that EDv2.2 overestimates greening-browning events due to a model structural problem. EDv2.2 shows oversensitivity to the precipitation at the WBS site; small changes in precipitation led to sharp changes in GPP trend. The WBS site is constantly under water stress (Flerchinger et al., 2019). A key ecosystem process that mitigates such stress is changing of plant community composition in response to interannual variation in precipitation (La Pierre and Smith, 2015; Wilcox et al., 2015). However, because the representation of dryland plant communities in EDv2.2 is currently limited, this structural oversimplification likely leads to increased sensitivity of the model to precipitation variability. Thus, one potential solution to increase the representation of ecosystem heterogeneity in dryland ecosystems, primarily by adding more PFTs (e.g., forb plant communities).

4.2 Fire runs

The ability of fire to influence spatial and temporal patterns of GPP over time is also apparent from our initial EDv2.2 modeling results. In the point-based analysis without fire, shrubs eventually dominated over time to comprise the entirety of GPP, persisting through the end of the simulation period (Figure 7). Although GPP for C3 grasses was high during initial years, it 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, grass GPP completely disappeared, and GPP reached approximate equilibrium at or slightly above 0.3 kgC m^{-2} yr^{-1} for the three lower elevation sites (LS, US, WBS) and at ~4.5-5.0 kgC m^{-2} yr^{-1} for the highest elevation site (MBS). Based on these results (i.e., complete dominance of shrubs over grasses), additional development of both PFTs and the fire subroutine are needed to make EDv2.2 more applicable to the sagebrush-steppe.

Upon introduction of simulated fire to the point-based models after 25 years (Figure 7), shrub GPP declined abruptly and C3 grass GPP increased dramatically, and disparately low and high GPP values were maintained for the shrub and grass PFTs, respectively, for much of the remaining fire years. However, around 25 years after fire is introduced, shrubs initiate and maintain a gradual increase in GPP. This slow and delayed recovery of shrubs in post-fire environments is consistent with field studies in the northern Great Basin (Shriver et al., 2019). Despite the dynamic changes in vegetation composition, the change in total GPP after fire was abrupt but negligible in magnitude, and recovery to pre-fire levels was achieved within ~7-15 years at all four sites. However, this result may not be typical for Great Basin shrublands where precipitation is variable and unpredictable, and possibly getting worse (Knutson et al., 2014; Shriver et al., 2018)

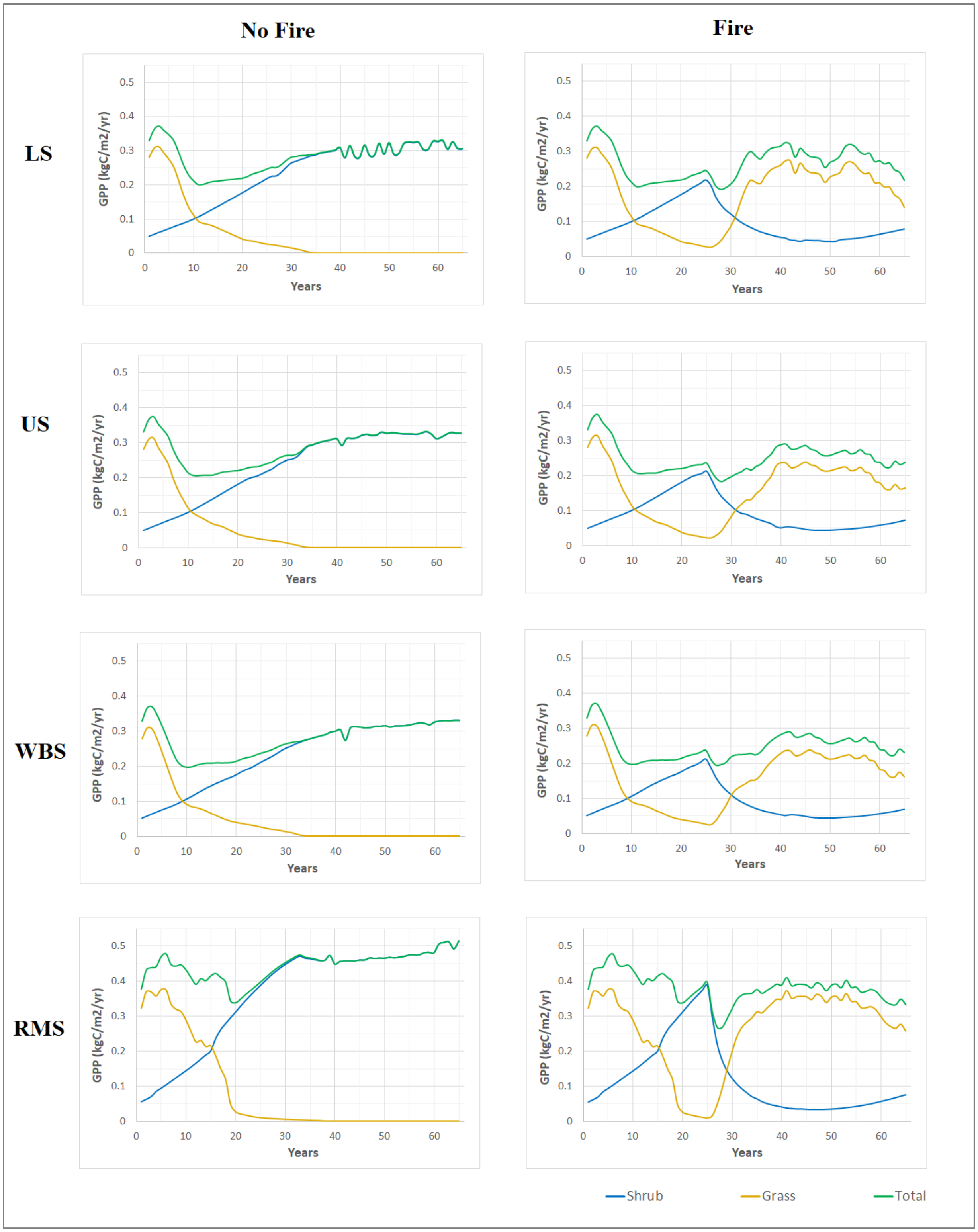

Figure 21.Mean annual trends in shrub, grass (temperate C3 grass) and total GPP (kgC m-2 yr-1) simulated at four EC flux tower sites. Left figures represent trend in no fire condition whereas right side figures show trend with fire condition, when fire was introduced.

For the regional fire analysis, modeled spatial patterns of GPP for pre-fire conditions in 2015 resemble observed NDVI patterns derived from Landsat 8 imagery for that same year (Figures 8 & 9), but some geographic differences between predicted GPP and observed NDVI patterns are notable. The simulated model output from EDv2.2 uniquely predicted higher GPP at some northwestern and southeastern areas in comparison to the rest of the study area, whereas NDVI clearly depicted higher values for a swath of the southern portion of study area that extends towards the northwest.

Introduction of fire in the northern portion of the study area (i.e., matching the extent of the 2015 Soda Fire) to the EDv2.2 simulation resulted in observable loss and recovery of GPP in the burned area. Loss of GPP in the fire-affected area relative to the rest of the study area was most evident during the second year after fire (2017), based on changes between pre- and post-fire GPP output (Figure 8). Recovery in the fire-affected area began during the third year, and by the fourth year (2019) the spatial pattern of GPP was similar to the pre-fire year (2015). However, when compared at the pixel level with pre-fire conditions, the 2019 GPP values suggest slower growth on average in the fire-affected area compared to the unburned portion of the study area.

Changes in GPP after fire predicted by the EDv2.2 simulations are more gradual than rates captured by NDVI in Landsat images. There was a clear reduction in NDVI values in the Soda 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. Unlike the apparent similarities in spatial patterns between EDv2.2 simulated GPP and Landsat derived NDVI maps for certain years (particularly 2015 and 2019), we did not observe strong relationships between these two variables via pixel-level comparisons (maximum $R^2 = 0.13$ for GPP-NDVI comparisons across all years for fire-affected, no-fire, and entire study area).

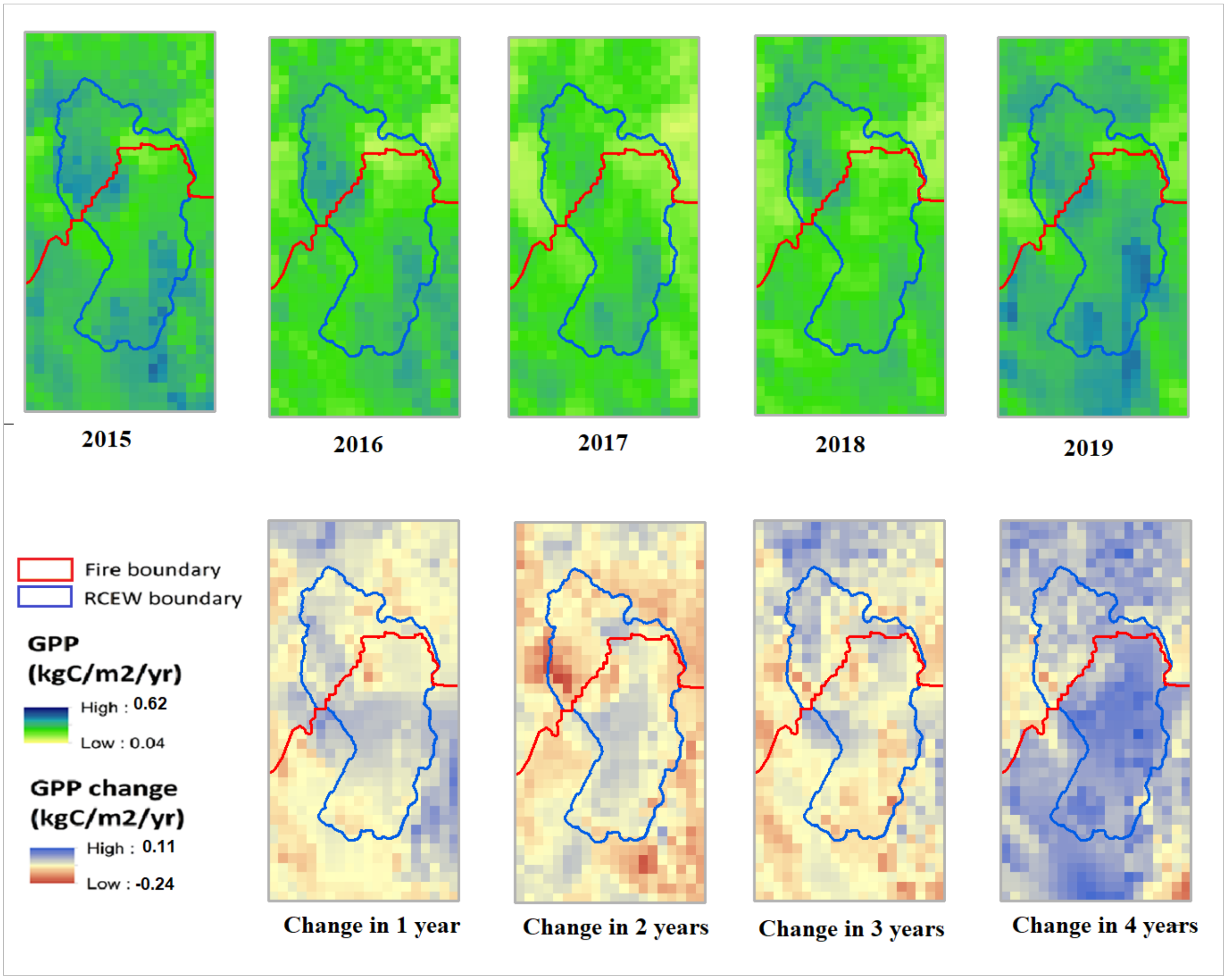

Figure 22. Snapshots (from July 15 of each year) of total simulated GPP (kgC/m2/yr) for different years; starting year in the 25th year (2015), and 4 subsequent years after fire. Maps in the bottom show change in GPP every subsequent year after the fire incident compared to the pre-fire condition in 2015. Blue boundary represents the RCEW and the area north of the red boundary represents the area affected by the fire in 2015.

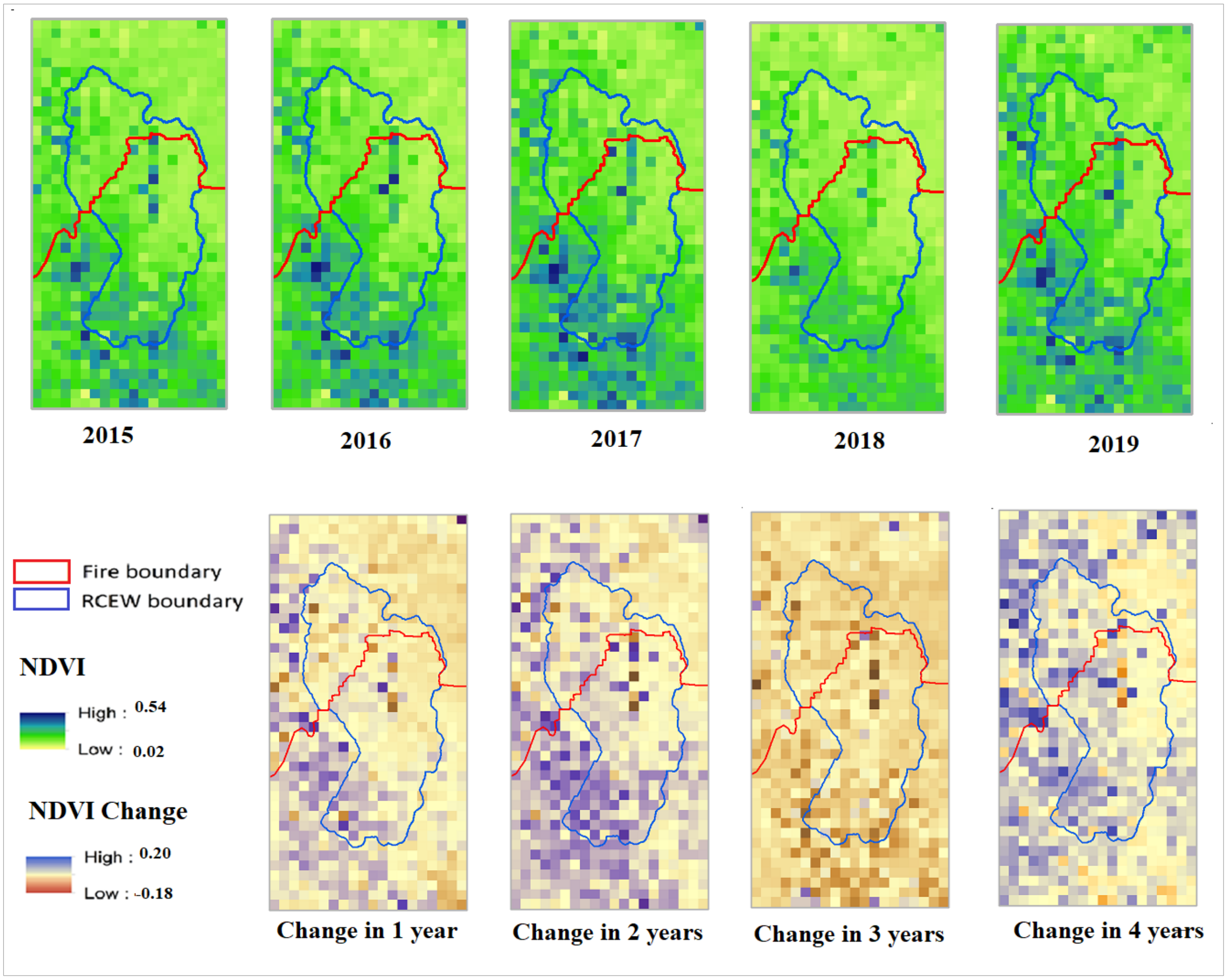

Figure 23. NDVI from Landsat images for pre-fire (2015) and post-fire years (top maps), and change in NDVI after every subsequent years after fire incident compared to pre-fire NDVI (bottom maps). Landsat images were dated July 29th, July 15th, July 18th, July 30.

When average values of NDVI and GPP (from the EDv2.2 simulation) are plotted for the entire fire-affected area, no-fire area, and total study area, there is still poor year-to-year agreement among the two sources in terms of immediate fire effects, with only occasional agreement in the direction or magnitude among post-fire changes in productivity in burned areas relative to unburned areas (Figure 10). However, simulated GPP also ignored the extensive post-fire seeding events that occurred across the burned area that could influence perceived outcomes.

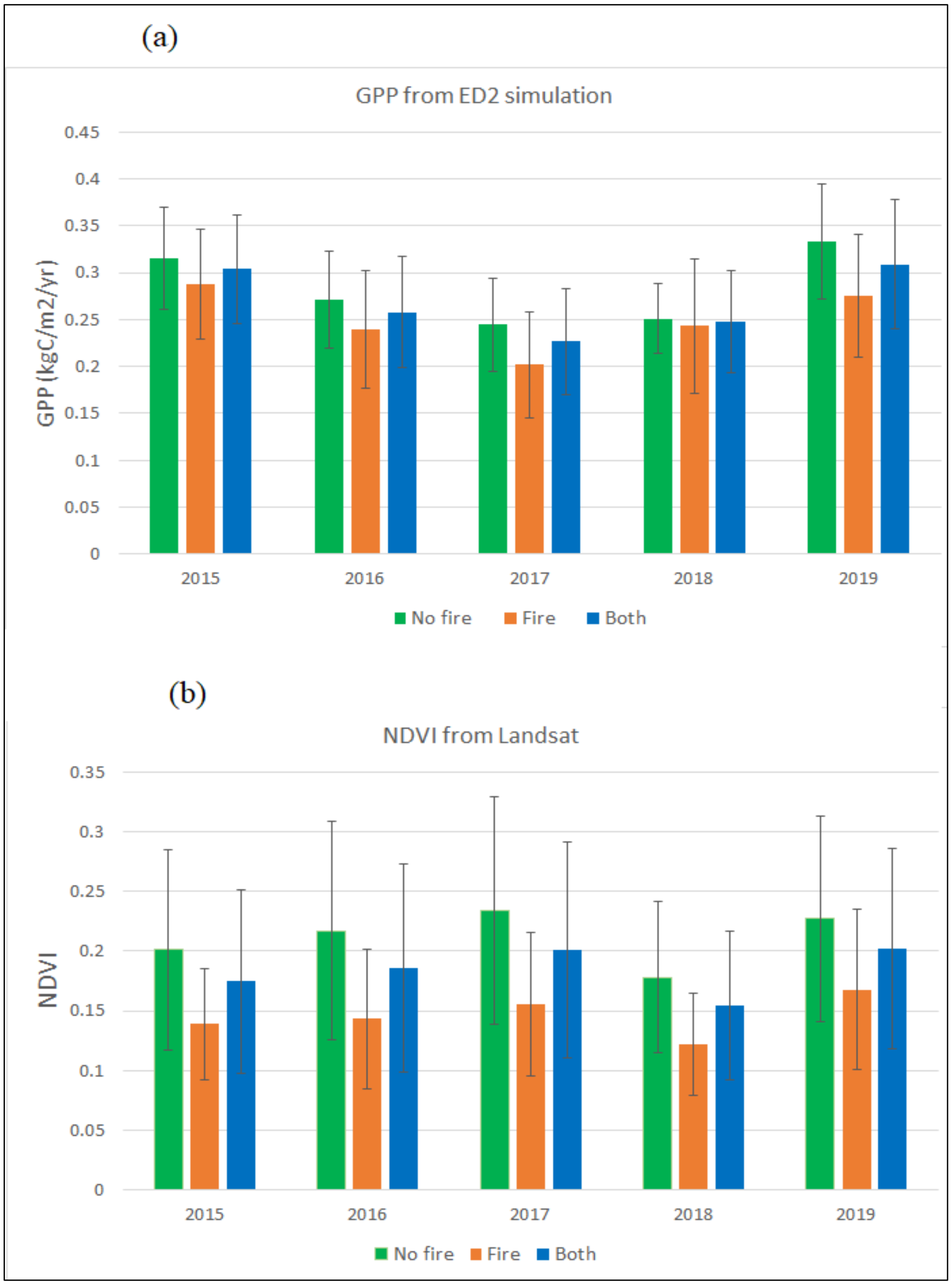

Figure 24. Average GPP from EDv2.2 (a) and average NDVI from Landsat (b) calculated for all the fire affected, non-fire, and total grids for snapshot maps from the studied years. Exact dates of the analyzed maps are as stated above. Error bars represent ± one standard deviation of GPP (a) and NDVI (b).

In general, these modeled 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), although the complete disappearance of the grass component suggested by our point-based 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. With the introduction of fire in the point-based analyses, we observed drastic changes in modeled PFT composition; however, there was only a small decrease in total GPP that occurred over a ~5 year period after fire, primarily as a result of the immediate regrowth of the C3 grass PFT, followed by the gradually recovery of the shrub PFT. 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 from few to several decades or more to recover to mature shrub conditions after fire (e.g. 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 fire events, shrubs may have potential for gradual recovery as dominance by nonnative herbaceous species declines (Rew and Johnson, 2010; Shinneman and Baker, 2009). The capacity of the EDv2.2 model to capture these prevailing trends in dryland ecosystem responses to fire gives it credibility and suggests potential future utility as a planning tool.

In the regional analysis, recovery of NDVI shown in the fire-affected area in the second year after fire is likely from growth of perennial grasses in areas where growing conditions were favorable. The (likely) post-fire recovery of perennial grasses in the ecosystem reflected by NDVI was not well captured by EDv2.2 using default parameters for the temperate C3 grass PFT. Moreover, disturbance and recovery patterns of vegetation biomass from regional EDv2.2 model outputs were not consistent with NDVI from the same years. The fire disturbance phenomenon in the EDv2.2 model could not truly represent the circumstances in the affected area, in part due to the challenges of parameterizing fire severity accurately. For example, although we initiated fire disturbance in the model, the entire area was not burned at once; rather grids were selected randomly to meet the potential fire criteria and kill the vegetation. 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 et al. 1987), and likely is responding more strongly to new green grass regrowth stimulated by the fire, than to the shrub component (that is generally the larger contributor to GPP in this ecosystem). Due to these limitations, we did not find strong relationships between the EDv2.2 derived GPP and Landsat derived NDVI for either year-wise spatial maps (Figures 8 and 9) or when assessed using direct grid-wise comparisons (scatter plots and correlation results shown in Pandit et al., in prep.).

5 Conclusions and Implications for Management / Policy and Future Research

Our work was focused on implementing EDv2.2 as a platform to answer questions such as how sagebrush-steppe vegetation responds to shifts in climate and fire. We used a combination of field data, remote sensing, literature, and expert opinion through formal and informal meetings with the BLM, USDA-ARS, DOD (at the Mountain Home Air Force Base), and Idaho Army National Guard (at the Orchard Combat Training Center). Results of this study led to multiple technical advancements that are or will be published as peer-review journal articles, datasets, and conference presentations. While the learning curve is steep for the EDv2.2 model, there are significant opportunities to explore meaningful scenarios for the sagebrush-steppe. However, with further advancements we expect that the EDv2.2. model framework could eventually contribute to more effective near- and mid-term management planning, especially to test the effects of climate variability and specific management actions on flammable biomass production in rangeland ecosystems.

From a technical perspective, we found that in general, the heterogeneity of the sagebrush-steppe plays an important role in modeling. For example, EDv2.2 was most capable of capturing key ecosystem processes, such as photosynthesis capacity and activity, in lower elevations of our study area landscape that typically have less ecosystem heterogeneity. Currently there is limited ability to represent ecosystem heterogeneity in EDv2.2 (and in many other DGVMs), which often leads to underestimation of ecosystem production, and this may be especially problematic in higher elevations of our study area where vegetation production is higher due to more favorable temperatures and precipitation. Thus, defining additional PFTs, such as forbs, may better represent the heterogeneity in these higher elevation shrublands. Nonetheless, considering that vast expanses of sagebrush-steppe in the Great Basin occupy lower elevations, the developed model in this study may be of great value for scientific, resource management, and policy-making communities.

In this study, we also demonstrated the potential of EDv2.2 to simulate the effects of fire, by implementing wildfire at point and regional scales. Introducing fire into the model led to drastic changes in vegetation composition and associated productivity, generally consistent with our understanding of fire-vegetation interactions in drylands. Although additional work will be required to more accurately capture the finer-scale spatiotemporal dynamics of fire-vegetation interactions, our modestly successful implementation of a disturbance scenario suggest several exciting possibilities from a management/policy perspective. First, fire is only one of several types of vegetation manipulations (known as *events*) that can be modeled in EDv.2.2. Currently EDv2.2 is capable of handling multiple events, such as fertilizing, planting, irrigation, pesticide application, and harvesting. Many of these events could be designed to simulate the effects of fuel treatments in sagebrush rangelands. Second, introducing decision-making scenarios that incorporate events in EDv2.2 can be done through use of a simple text file that may be modified or adapted to produce alternative scenarios. For instance, Figure 11 shows an example of introducing fire, the ability to design alternative fire occurrence and severity settings, and the ability to turn off or on additional anthropogenic disturbances. Such scenario testing can be used to better understand interactions between fire and vegetation in dryland ecosystems, as EDv2.2 provides a useful framework to conceptualize vegetation dynamics, project future conditions, and consider the effects of management and disturbance. Although EDv2.2 simulates stochastic processes, it is useful to investigate the conditions (e.g. soil moisture, fuels etc.) under which vegetation for given locations are most likely to be affected by disturbance, as well subsequent trends and patterns of ecosystems change or recovery.

```
!---------------------------------------------------------------------------------------!
!      The following parameters adjust the fire disturbance in the model.               !
! INCLUDE_FIRE   -- Which threshold to use for fires.                                   !
!                   0.  No fires;                                                       !
!                   1.  (deprecated) Fire will be triggered with enough biomass and     !
!                       integrated ground water depth less than a threshold.  Based on  !
!                       ED-1, the threshold assumes that the soil is 1 m, so deeper     !
!                       soils will need to be much drier to allow fires to happen and   !
!                       often  will never allow fires.                                  !
!                   2.  Fire will be triggered with enough biomass and the total soil   !
!                       water at the top 75 cm falls below a threshold.                 !
!                   3.  Fire will be triggered with enough biomass and accumulated      !
!                       water deficit exceeds the threshold given by SM_FIRE times.     !
!                       the total precipitation of the past 12 months.  This method     !
!                       does not directly depend on soil texture.                       !
! FIRE_PARAMETER -- If fire happens, this will control the intensity of the disturbance !
!                   given the amount of fuel (currently the total above-ground          !
!                   biomass).                                                           !
! SM_FIRE        -- This is used only when INCLUDE_FIRE = 2 or 3, and it has different  !
!                   meanings.  The sign here matters.                                   !
!                   When INCLUDE_FIRE = 2:                                              !
!                      >= 0. - Minimum relative soil moisture above dry air of the top  !
!                              1m that will prevent fires to happen.                    !
!                      <  0. - Minimum mean soil moisture potential in MPa of the top   !
!                              1m that will prevent fires to happen.  The dry air soil  !
!                              potential is defined as -3.1 MPa, so make sure SM_FIRE   !
!                              is greater than this value.                              !
!                   When INCLUDE_FIRE = 3, values between 0 and 2 are allowed.  This is !
!                   the minimum water deficit relative to the total rainfall, over the  !
!                   past 12 months, to trigger fires.                                   !
!---------------------------------------------------------------------------------------!
NL%INCLUDE_FIRE    = 0
NL%FIRE_PARAMETER  = 0.5
NL%SM_FIRE         = 0.07
!---------------------------------------------------------------------------------------!



!---------------------------------------------------------------------------------------!
!  IANTH_DISTURB -- This flag controls whether to include anthropogenic disturbances    !
!                   such as land clearing, abandonment, and logging.                    !
!                   0.  no anthropogenic disturbance.                                   !
!                   1.  use anthropogenic disturbance dataset.                          !
!---------------------------------------------------------------------------------------!
NL%IANTH_DISTURB   = 0
!---------------------------------------------------------------------------------------!
```
Figure 25. A snapshot of EDv2.2 model inputs for introducing fire and disturbance.

Finally, we also found a few key knowledge gaps that need to be addressed in future applications of the model. EDv2.2 is developed for forest ecosystems, thus processes such as plant hydraulics are not well adapted for shrublands. Future work could build on recent advances in combining EDv2.2 with land surface models such as CLM-ED (Fisher et al., 2015), which will help to mechanistically account for land surface processes. Moreover, although we have suggested in this report that developing herbaceous PFTs for forbs may be necessary for effective modelling of higher elevation shrublands, this is not a trivial endeavor. This is due in part to the heavy dependence of EDv2.2 on defining allometric equations for plants (e.g. between stem diameter and biomass) to properly parametrize PFTs, which is challenging for herbaceous plants. Furthermore, land surface processes such as snowmelt are also highly influential in sagebrush steppe ecosystems. The potential to couple a land surface model with EDv2.2 (e.g. CLM-ED; Fisher et al., 2015) to link such system processes has not been explored for drylands. Finally, although EDv2.2 can provide insight on natural outcomes of management decisions, it can't directly address social consequences. To our knowledge EDv2.2 has never been actively integrated with adaptive management frameworks. For example, land use/land cover models could be coupled with EDv2.2 for depicting long term trajectories of human-ecosystem interactions.

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Appendix A

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Appendix B

Articles in peer-reviewed journals

Pandit, K., Dashti, H., Glenn, N.F., Flores, A.N., Maguire, K.C., Shinneman, D.J., Flerchinger, G.N., Fellows, A.W., 2019, Developing and optimizing shrub parameters representing sagebrush (Artemisia spp.) ecosystems in the Northern Great Basin using the Ecosystem Demography (EDv2.2) model, Geoscientific Model Development, 12, 4585–4601, https://doi.org/10.5194/gmd-12-4585-2019.

Dashti, H., Pandit, K., Glenn, N.F., Graaf, M.A., Flores, L., Ilangakoon, N., Ustin, S., Shinneman, D.J., Hudak, A.T., Flerchinger, G., Fellows, A.W., Performance of Ecosystem Demography model (ED.v2.2) in simulating photosynthesis capacity and activity along an elevation gradient in a dryland study site, in review, Journal of Advances in Modeling Earth Systems.

Pandit, K., Hudak, A.T., Dashti, H., Glenn, N.F., Flores, L., Shinneman, D.J., Understanding the influence of fire on vegetation composition and biomass using the Ecosystem Demography (EDv2.2) model in a semi-arid shrubland ecosystem, in prep

Pandit, K., Hudak, A. T., Dashti, H., Glenn., N. F., Flores, A. N., Shinneman, D. J., Estimating biomass with Ecosystem Demography (EDv2.2) model for Juniper dominated ecosystem in the Great Basin region of Western United States, in prep.

Doctoral thesis

Dashti, H., 2019, Characterizing dryland ecosystems using remote sensing and dynamic global vegetation modeling, PhD Geosciences Dissertation, Boise State University, in review, submitted to Boise State University Graduate College.

Presentations

- Pandit, K., Dashti, H, Glenn, N., Flores, A., Shinneman, D.J. and Hudak, A. 2019. *Understanding the uncertainties in estimating post-fire recovery of biomass using the Ecosystem Demography (EDv2.2) model.* Lightening talk at Ecological Forecasting Initiative Conference, May 13-15, D. C.
- Pandit, K., Dashti, H, Glenn, N., Flores, A., Shinneman, D.J. and Hudak, A. 2019. *Modeling vegetation composition and biomass of the sagebrush ecosystem in the Reynolds Creek Experimental Watershed (RCEW) for different CO2 and fire conditions, using the Ecosystem Demography (EDv2.2) Model.* Paper presented at Land Model and Biogeochemistry Working Group Meetings. National Center for Atmospheric Research. February 11-13, Boulder, CO.
- Pandit, K., Dasthi, H, Glenn, N., Flores, A.N., Shinneman, D.J., and Hudak, A.T. 2018. Assessing the dynamics of the sagebrush ecosystem under different conditions of vegetation, ambient CO2, and fire. Poster presented at 2018 AGU Fall Meeting, December 10-14, Washington DC.
- Pandit, K., Dashti, H, Glenn, N., Flores, A.N., Maguire, K., and Shinneman, D.J. 2018. Assessing the response of sagebrush ecosystem to initial ecosystem and altered climate

conditions. Paper presented at 9th Annual Northwest Climate Conference. October 9-11, Boise, ID.

- Pandit, K., Dasthi, H, Glenn, N., Flores, A.N., Maguire, K., and Shinneman, D.J. 2018. *Application of Ecosystem Demography (ED2) model to quantify sagebrush-steppe ecosystem in Western US*. Paper presented at Annual Ecosystem Demography meeting. January 16-17, 2018, Notre Dame, IN.
- Pandit, K., Glenn, N., Flores, A.N., Maguire, K., Shinneman, D.J., and Dasthi, H. 2017. *Estimating sagebrush biomass growth in Great Basin using Ecosystem Demography model.* Morley Nelson Snake River Birds of Prey National Conservation Area Science Working Group Annual Symposium. October, 30, 2017. Boise, ID.

Workshops

- ED Model Development Workshop for USFS WWETAC in Boise on 8-9 August 2018. We hosted a meeting at Boise State University to discuss ED modeling applications for management. The following attended: USFS (Andy Hudak, Becky Kerns, Matt Reeves), USGS (Doug Shinneman, Stephen Boyt), Oregon State (Yueyang Jiang (post-doc)), Colorado State (Steven Filippelli (research associate)), Boise State (Lejo Flores, Nancy Glenn, Karun Pandit (post-doc) and the following students: Hamid Dashti, Katie Murenbeeld, Jake Graham, Juan Ordonez, Monica Vermillion, Nayani Ilangakoon). The outcomes of the meeting included a) the need for a juniper and C3 grass PFT for precise prediction of vegetation dynamics using ED; b) exploring the use of remote sensing based products (data and map) already available for the study area to validate the results from ED; c) potential research on incorporating remote sensing to initialize ecosystem state to reduce uncertainties in prediction form ED; and d) challenges in distinguishing different grass communities (annual vs perennial) in ED outcomes, and possible solutions with the use of unique grass phenological cycles.

- USFS/NASA Workshop, 2019. We hosted a Breakout Session on May 2, 2019 on Vegetation Structure & Biomass at the USFS/NASA Workshop in Salt Lake City. There were approximately 30 participants from USFS, NASA, and universities. Outcomes of the workshop were opportunities and barriers/gaps on remote sensing and field data for fires and fuels modeling and management by USFS.

Appendix C

This project produced Ecosystem Demography (EDv2.2) model output. In order to run the EDv2.2. model, model initialization and input data were needed. These data include vegetation data such as for modeling cohorts and patches and climate data. The vegetation data include shrub species, cover, height and associated data for the Reynolds Creek Experimental Watershed and have been previously published and publicly shared via the Oak Ridge National Laboratory Distributed Active Archive Center (see Glenn et al., 2017). The climate data include a 30-year climate dataset which is publicly available via the Boise State University ScholarWorks archive (see Flores et al., 2016). Metadata of all other data used for model initialization and running the model have been drafted and submitted for feedback with the USDA Forest Service Research Data Archive (https://www.fs.usda.gov/rds/archive/) with the intent to archive the metadata with the USDA Forest Service and have the data available via ScholarWorks, GitHub, and/or the associated journal website. The model initialization and runs are documented in their respective manuscripts (Pandit et al., 2019a and Dashti et al., in review). Additional model runs will be documented in a manuscript that is in prep (Pandit et al., in prep). Modified source codes for EDv2.2 are publicly available (see Pandit et al., 2019b).

To compare model outputs, we used flux tower and remote sensing data that are publicly available. The flux tower data are published and publicly available via the Boise State University ScholarWorks archive (see Fellows et al., 2017). The Landsat 8 and MODIS MYD17A2H06 remote sensing data used in the project are publicly available via the US Geological Survey, and specifically for MODIS see Running et al., 2015.

The original Ecosystem Demography (ED2) model was developed by Moorcroft et al., 2001 and Medvigy et al., 2009, and team, which is available at github (https://github.com/EDmodel/ED2).