Dr. Kirsten Thonicke
Associate Editor
Biogeosciences

Dear Dr. Thonicke,
Thank you very much for your comments on our manuscript. All your comments, along with reviewers' comments were very helpful for us in reshaping and revising this manuscript. We tried our best to revisit the manuscript. Following are responses to your comments/questions on the manuscript. As you understand, this is our preliminary work on fire using EDv.2.2 based on shrubs in dryland ecosystem. We will appreciate your further suggestions/comments on this revision.

Best regards,
Karun Pandit

Regarding your response to reviewer #1, please

1. include your response to the comment on line L156-157 in the manuscript.
We added some texts on L273-277 to clarify this comment.

2. make sure you not only add biomass to your figures, but also add the interpretation of those results (GPP change vs. biomass change after) in the manuscript text (reviewer comment to "L169-170: why". You need to thoroughly explain why GPP is reduced over several years after fire and explain it with the model assumptions and model algorithm/equations. This is unusual outcome compared to observations that see a quick GPP recovery after fire.
We added sentences about fire model behavior in the EDv2.2 in lines L84 ("Area of burnt …") and L90 ("New burnt patches …"). We also added sentences in L291-292 and L301-303 to discuss about the gradual increase in fire damage, and also provided reference (L 305-309) from similar other works that suggest gradual decrease in GPP for initial few years before the vegetation recovery.
We also added two figures to address this concern; one showing temporal pattern of AGB (we can see that AGB is directly related to fire damage in the model) for shrub and C3 PFTs (Fig. A1) in the appendix, and other showing spatial pattern of each PFTs showing post-fire damage and recovery (Fig. A2). We observe C3 grass recovery in three years after fire while shrub GPP is still declining.

Response to Reviewer 2
1. Please add sentences on the conclusion and discussion points of this study in the abstract and check if you have answered (conclusions) and discussed the objectives of your manuscript in the respective sections.
We added texts at L320-321 to compare our results with the research objective.

2. Make sure that you address all reviewer comments regarding model description, methods and statistics used in the analysis of model results. The effect of fire on shrub GPP needs to be plausibly described. If you have benchmarked your model already in a previous publication then please cite the outcome in the GPP evaluation.
We tried to address most of reviewers comments. We have cited and rephrased texts at L284-286 to show results from previous study.

3. your response to the comment referring to L153: I think your response misses the point raised by the reviewer. Your response explain the general fire ecology in the shrub ecosystem under study, but you need to make sure you explain the curves displaying fire and GPP in your model results. Please check again this point in your model and model analysis and make sure the simulated pattern are sufficiently explained in the manscript.
We added some text at L191-194 to state that fire damage is directly related to AGB and is also in some way aligned with GPP. We added AGB figure (Fig. A1) at the appendix, to show the trend in AGB for each fire and no fire conditions, and to show corresponding fire damage at the given time.

4. your response to comment regarding L158: when adding this aspect to your manuscript, please consider the time scales of your simulation study and make sure the stability definition is not flawed by discussing seasonal pattern.
Thank you for your comment. We removed the term 'stability' as it was a little off-track from our results. We rephrased the sentences at L203-206 to highlight that the difference were more evident for total AGB than GPP, and the fire return interval was longer for some of the sites.

Response to interactive comment on "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" by Karun Pandit et al.

Reviewer 1

Overview:

This study uses a dynamic vegetation model to quantify the impact of fire on GPP in a shrub community. The model is somewhat able to represent observed patterns in vegetation and GPP dynamics after fire. However, I find the manuscript to be somewhat immature, with pieces of the methods section in the introduction, unsatisfying basic description of model parts which are relevant for this study, missing information in figures etc. and especially a lack of a clear science question or hypotheses to be tested. While I agree that it is worthwhile to improve shrub representation in DGVMs and how these interact with fire, I don't have the feeling the present study takes advantage of the DGVM to ask questions beyond what is known regarding basic impact of fire on sagebrush communities.

Thank you for the comments. We moved the model description from the introduction to methods, rephrased our objective, and tried to state our hypothesis with more clarity. We have also reworked on some of the figures to provide clarity on them

We agree there is more work to be done to understand fire in sagebrush communities with EDv2.2 and other DGVMs. However, there is a knowledge gap in understanding the uncertainties of EDv2.2 in assessing the impact of fire on shrub dominated semi-arid ecosystems like the Great Basin region. The aim of this study is to document the potential usefulness and errors in modeling fire behavior with EDv2.2 as a first step in further developing the model for shrublands. Findings from this study has a potential to contribute to substantial utility beyond academic exercise to track shrubland carbon and productivity dynamics at broader scales, as sagebrush is found throughout Western United States and Southwest Canada. Results from our study would also be valuable given this widespread ecosystem is threatened by fire and invasive grasses. Our study could be a preliminary step in that process, to make EDv2.2 a model that can address global changes via dynamics in semiarid shrublands.

We have revised our introduction section and added relevant references to emphasize the importance of this study. In addition, we added texts in the conclusion to re-emphasize these issues and the potential for EDv2.2 to address them with further PFT parameters and fire module refinement.

We have rewritten our science question more precisely as given in the final paragraph of introduction section as given in L65-71.

Comments

Line 51-71: why would you want to describe the model in this detail in the introduction? This section clearly needs to be moved to the methods. It also needs to be expanded so that one can get a basic idea what the model does, what the fire model does, what happens with the vegetation when a fire occurs etc.

Thank you for your comments. We have moved the major portion of model description from the introduction to the methods and provided additional information on the fire module in a subsection of the Methods at L74-99. We also provided reference to original EDv2.2 model papers that discuss in detail about the model.

L72-78: Why are you only interested in the effect of fire on GPP, as this is probably the variable where you expect least change through time as vegetation generally is replaced or regrows. In the abstract you mention changes in fire frequency, but you don't follow up on this in your objectives and analysis performed. Probably changes in fire frequency might have an impact, possibly on (soil) carbon, or impact vegetation competition through feedback through the N-cycle, etc. To be clear, I don't say you have to do other analysis, but after reading the manuscript I still wonder why you focused on GPP and no on other aspects of the system which be as relevant.

We used GPP as it is often a direct output of process-based vegetation models. EDv2.2 calculates GPP based maximum photosynthesis using the Farquhar model (Farquhar et al.,1980). In addition, GPP estimates correspond well with remote sensing derived products like NDVI (normalized difference vegetation index), LAI (Leaf area index) and fAPAR (fraction of photosynthetically active radiation absorbed by the vegetation). While we limited our study to GPP, future studies could compare EDv2.2 outputs with remote sensing observations such as net ecosystem production (NEP), leaf area index (LAI), or above ground biomass (AGB). We compared two different levels of fire severity against control (no-fire) scenario at point levels to explore the dynamics of vegetation through the patterns in GPP. The EDv2.2 model could be simulated with alternate N effects including its effect on photosynthesis and decomposition. However, in this analysis we were not focused in the Nitrogen cycle.

Even though we were not able to redo the analysis with AGB, we tried to add a figure (Fig. A1) showing trend of AGB for different fire and no-fire scenarios. We included reference to AGB along with GPP results at the results section (L184-186; L191-194; L197-199; L201-205)

L 83: Can you give the range in mean temperature and precipitation?

We have added texts to provide these information about the study area at L105-106.

L105: indicate which reanalysis data was used for downscaling using WRF.

We used "North American Regional Reanalysis" to downscale WRF data. We have added text L131 and reference to make this clear.

L121: Does this mean you don't perform a spinup? How does this work with the N-cycle (which you seem to model, based on what you say in the introduction).

We used existing vegetation state with both shrub and C3 grass to initialize the point-based simulations. We ran the simulation for 25 years to get the vegetation and other ecosystem conditions such as Nitrogen and soil carbon. However, as suggested in this study we were not focused on assessing N-cycle.

L142: Trends doesn't seem to be the right term, temporal dynamics in GPP? There should exist some literature on vegetation dynamics after fire for these vegetation communities so that you can have an indication whether your simulations capture vegetation dynamics.

We rephrased the term as temporal dynamics in GPP (L139). There are a number of studies assessing GPP recovery and vegetation dynamics after fire. Such studies suggest change in ecosystem carbon exchange from source to sink after fire. These studies show considerable variability in the number of years required to return GPP to pre-fire conditions. Another threat to these ecosystems is that many do not recover and become dominated by exotic annual grass communities that are highly fire prone. We have cited studies related to sagebrush-steppe post-fire recovery, as a comparison to our results (L267; L279-283). We have highlighted the need for further development of the C3 grass PFTs to better reflect annual grass dynamics in the conclusion section (L331-333).

L156-157: You don't explain what the driver in the model for this lower GPP with increasing shrub cover is.

The main driver behind this dynamic of GPP for two PFTs can be described in terms of secondary succession and competition. In the initial years after fire, there are favorable growing conditions for grasses to grow quickly and produce high GPP. As shrubs start to recover, competition increases, shade is increased and belowground root completion is also higher. These factors reduce the growth of grass thus causing a net loss in total GPP, even with the increase in shrub GPP. We have added texts on L273-277 to further clarify this comment.

L163-164: why didn't you use actual reanalysis forcing so that you can compare interannual variability. Like that one could also assess model performance in figure 4.

We agree that it would be possible to assess model output by comparing results with EC towers if we used respective years of forcing data. However, as the primary intent of this study was to explore the temporal GPP dynamics for two PFTs with fire disturbance as the driving factor, we used an average annual meteorological forcing data and thus minimized interannual variability from weather data. In our previous study on model performance (Pandit et al., 2019), we had applied actual yearly forcing data to perform model validation.

L169-170: why? E.g. a fire will burn a shrub immediately, so why would GPP be lowest a couple of years after the fire. When reading this, one wants to know why this happens. Maybe put biomass and GPP for each pft though time in a time series plot or so.

Most vegetation models with fire modules kill plants at different times, which may not correspond to real circumstances. The grids that are not killed (disturbed) in a given year could have higher probability of being killed in the later years as the fuel load (AGB) increases. Fire damage is also affected largely with the lack of soil moisture in later years. In this analysis we turned on the fire module for post-fire years, which resulted in such a pattern. Our comparative analysis between fire and no-fire scenario (regional analysis) shows how the disturbance from fire is in effect until few years after fire.

We added sentences about fire model behavior in the EDv2.2 in lines L84 ("Area of burnt …") and L90 ("New burnt patches …"). We also added sentences in L291-292 and L301-303 to discuss about the gradual increase in fire damage, and also provided reference (L 305-309) from similar other works that suggest gradual decrease in GPP for initial few years before the vegetation recovery.

We also added two figures to address this concern; one showing temporal pattern of AGB (we can see that AGB is directly related to fire damage in the model) for shrub and C3 PFTs (Fig. A1) in the appendix, and other showing spatial pattern of each PFTs showing post-fire damage and recovery (Fig. A2). We observe C3 grass recovery in three years after fire while shrub GPP is still declining.

L179-180: I am sorry, but I barely see any difference in delta NDVI between the burned and unburned areas. This is not very convincing, and it almost seems as if there is more of signal from the interannual variability in NDVI due to climate variability then a real fire signal. This entire analysis is a bit shaky; e.g. why do you take GPP for one single day instead of the mean of the month, which should be more representative of hence compare better with NDVI? And possible show the modelled delta GPP between a run with and without fire, instead of comparing between years, so that you only have the fire signal in your simulation results (now one cannot know what is the impact of climate and what is the impact of fire). It would also have taken the mean/median NDVI for multiple images to avoid impact of individual images (especially now that so much Landsat imagery is available).

We agree that the NDVI maps did not capture equivalent fire damage as suggested by the model and we have adjusted this sentence accordingly. In addition, in a semi-arid system like this where moisture limitation is a major driving factor, climate signals could be strong enough to dilute the effects of fire.

We used MODIS derived GPP instead of Landsat NDVI in the revised analysis. In this analysis, instead of making comparison for a given date (a single day), we have made comparisons for July (mean GPP for the month), as described at L173-175.

In addition, we also ran spatial simulation for a control, ie. no fire condition for the current fire affected area as given in L155-157. This helped us show the model behavior more clearly for damage and recovery caused by the fire.

L212-214: Would have been nice to see a comparison between the model and vegetation dynamics though time as given in the literature.

We have tried to address this comparison in the discussion such as in L267; L279-283.

L 235: I don't understand what you want to say with this sentence.

We apologize for inconvenience. Our intention here was to illustrate results from other studies, where fire-related damage behaved differently compared to satellite observations. As stated earlier, damage defined by these models may lag by a few years depending on biomass and soil moisture conditions.

As stated in previous comment, we have added few sentences as in lines L84, L90, L291-292, L301-303 to discuss about the gradual increase in fire damage in model and provide related reference on similar results.

L234: what do you mean with "annual variability"? I think the discussion needs some work to be more focused and understandable.

Thank you for your suggestion. We tried to suggest annual variability between different years of observed data, so we tried to rephrase it to make it more clear in L284.

Figure 1: include lon-lat and scale to have an idea how big your study area is.

Thank you for your suggestion. We included lat-lon in one of the maps in study area, which should probably help understand the scope of the study area.

Figure 2: include lon-lat and scale to have an idea how big your study area is. Indicate what that blob of high NDVI to the northeast is, as it is somewhat distracting.

We did not include Figure 2 in this analysis as we did not use NDVI for comparison.

Figure 3: first sentence of the caption is confusing, shrub, grass and total GPP? Is Grass GPP put on top of shrub GPP?

Yes, we put grass GPP on top of shrub GPP. Both are stacked and represent a total GPP. We have tried to make this clear in the figure caption.

Reviewer 2

General Comments:

In this study Pandit et al. aim to understand the effect of fire on vegetation composition and primary production in sagebrush semi-arid ecosystem using a newly developed shrub implementation (Pandit et al., 2019) embedded within EDv2.2. I commend the authors for their addition of a shrub PFT into a DGVM and their work towards better representation of vegetation dynamics in semi-arid systems. The aims of the study were:

Aim 1: understand the effect of fire on vegetation composition.

Aim 2: understand the effect of fire on primary production.

I have a number of major concerns with respect to this submission. (1) as reviewer 1 pointed out, simulations run to examine how fire affects modelled GPP and compare this with satellite derived NDVI lack a "fire-off" control which uses the same initialisation random seeds, therefore the presented results cannot at this point be attributed to fire effects. These effects could also be due to climate forcing. This lack of control greatly reduces the ability to associate modelled changes in GPP with fire and thus many of the stated results. (2) There is a lack of formal statistical testing on the effect of fire on modelled GPP and fire on NDVI values resulting in a heavy reliance on apparent visual changes being taken as results. I find it necessary that the authors carry out proper significance testing, such testing will greatly improve the manuscript quality.

While the study does attempt to address relevant aims I do not believe they have reached them. There are no concrete conclusions reached in the abstract or discussion which would contribute to understanding the effects of fire on vegetation composition or productivity in semi-arid shrubland systems. Overall this manuscript seems to be more like a model development study than a biogeosciences study.

Thank you for the comments. As per your suggestion and reviewer 1's suggestion, we also performed a control simulation (no fire scenario) as given in L154-158. This led us to do a two-way comparison; (i) of EDv2.2 predicted GPP between control (no-fire) and fire scenario, and (ii) between true scenario simulation (including burnt and unburnt areas) from the model and MODIS derived GPP. We could not perform t-test due to major difference in means between model predicted GPP and MODIS derived GPP.

We changed our research questions (L65-71) and subsequent sections as suggested by reviewer #1 for further clarity.

Specific Comments:

The shrub implementation used by Pandit et al. has already been published in geoscientific model development in 2019, as such I have not gone into detail on the validity of this implementation. Given that the stated aims of the study are to investigate fire effects I found that the lack of proper description of fire in the model greatly impeded my ability to assess the results. Fire apparently affects mortality which is influenced by height (line 69) and on line 124 the two fire severity parameter values used are presented. I am clueless as to how this all works, how fire is distributed across patches, how the shrub implementation influences the probability of mortality, how grasses are treated with respect to fire mortality, and what is fueling fire. I have no idea what the red line in Fig. 3 (disturbance rate from fire) is showing me.

As per your comment and reviewer 1's comment we added texts and a couple of equations under the methods (L74-99) to elaborate on the model itself and the fire module. We tried to summarize the fire related damage. We also included a description of the important parameters that would be influential in causing severe damage and potential recovery for shrub and grasses. The red line in the Fig 3 represents the amount of damage (proportion of grids burnt every year) resulting from fire. It is defined by the available fuel and user selected fire intensity parameter. Available fuel includes all aboveground biomass including grass biomass as given in Equation 1 in L94.

The bulk of new methods presented appear to have already passed peer review and are presumably valid. Fig. 1 is almost identical to Fig. 1 in Pandit et al. (2019), Table 2 appears to be identical, and large sections of text are very similar to the 2019 paper which is fine for a methods section.

Thank you for your comments. The table has been slightly adjusted. In our previous paper (Pandit et al., 2019), from the same study area, we used only two EC tower sites to validate our model. The previous study was more about calibration of model using newly derived PFT parameters. In this study, we are only focused on exploring the effect of fire on vegetation dynamics, at extended temporal and spatial scales.

With regard to modelled GPP, GPP appears to be about 50% too low (Fig. 4) apart from at one site, this large discrepancy makes me question whether the approach used is appropriate to understand the effect of fire on GPP. Perhaps I have missed it but the authors only appear to mention this apparent large underestimation on lines 165 and 251 with no further discussion. Please put numbers to this, e.g. GPP at RMS with low fire severity is 50% lower than the observed mean for the 2015-2017 time period. Also the authors should explain why they think the model can appropriately investigate the effect of fire on modelled GPP in spite of these generally rather large underestimations at the plot level.

We have tried to discuss this issue further in the manuscript in objectives, results and discussion. We rephrased objective L65-66 to specify that we used parameters from previous study. At L207-208 we rephrased words on comparing EDv2.2 performance. We also touched upon this issue in the discussion at L284-289. However, our objective in this study is to understand the effect of fire on vegetation recovery/composition and on primary production. We performed our model validation for shrub parameters in our previous study (Pandit et al., 2019), where we benchmarked our model using two EC tower points (LS and WBS sites), which are at the lower elevation, with reasonable fidelity. Results from RMS and US which were not benchmarked are far off from the observation. In our another study which is in review (Dashti et al, in review), we found elevation to be a major factor behind poor model performance for the other sites. Our primary focus in this work was towards understanding the effect of fire by exploring the fire module in the EDv2.2 model by running simulation for different alternate fire scenarios. Our assumption here was we could infer such comparisons using a fairly adapted EDv2.2 model for shrubland based on our previous study.

A major concern with regard to the simulations run to produce Fig. 5, as reviewer 1 pointed out, there is no control simulation run for this area with fire turned off which uses the same initialisation random seeds, therefore the presented results cannot be attributed to fire effects. This lack of control precludes associating modelled changes in GPP with fire and thus many of the stated results, e.g. lines 170-174.

As stated above we performed a fire/no-fire simulation for a portion of study area (Fig. 4 and Fig. A2) to explore effect of fire against a control (no-fire) simulation (L154-157).

It is puzzling why the authors chose to compare modelled GPP with NDVI. A much better comparison would have been to compare modelled GPP with satellite derived GPP. Indeed, some of the r-squared values from the supplement are very low (Rˆ2=0.044944, 2015 unburnt). I am not an expert in satellite derived products but MODIS products appear to be available at the same resolution as simulation runs for the time period. If these data are available simulated GPP should be compared to satellite derived GPP and a control “no-fire” run included.

Thank you for your suggestion. In our revised manuscript, we have compared our model outputs with MODIS GPP information (L157-158). As suggested by reviewer #1, we used monthly mean GPP values from July of each year (from 2015 to 2019) EDv2.2 and MODIS for comparison (L173-175). In addition, we also provided PFT-wise mean change in GPP through years for fire and no-fire areas. We clearly observed higher GPP growth for C3 grass in third and fourth years after fire (both in mean values, Fig6 and spatial maps, Fig A2), while shrub recovery was not evident yet.

Overall, a great deal of work needs to be done by the authors in order to allow proper assessment of whether the results are sufficient to support the interpretations. Given the shown response, or lack thereof, of GPP to fire at the plot level (Fig. 3) and the above

mentioned lack of control I remain to be convinced that the changes in GPP presented in Fig. 5 are the result of fire. The lower panel plots in Fig. 5 do not show any clear difference between GPP change in fire vs non-fire areas. In general I would suggest the use of statistical methods to test whether there is a statistically significant difference in GPP between fire and non-fire sites, this would remove the need for eyeballing the results and the need for words such as "suggests" (L172), "hint" (L172), "resembled" (L175), "subtle" (L180). Statistical methods should also be applied to the NDVI changes (NDVI change fire vs no-fire areas) as well as the comparison of GPP change and NDVI change (%change GPP no fire vs %change NDIV no fire) (%change GPP fire areas vs %change NDIV fire areas). I see no signal in the NDVI values which would delineate fire vs no fire areas but proper method can resolve that. Adding a similar satellite derived GPP comparison to modelled GPP, using appropriate statistical methods, would greatly help the authors better make their case.

We observed considerable effects of fire at the plot level as seen in Figure 3. As stated above, we have provided further details on the EDv2.2 fire module. We applied average annual meteorological data to remove interannual climate variability, which would otherwise be a major driving factor in GPP simulation. As we kept every other thing constant, and only changed fire parameters, we state that the results in our point simulation are from the fire.

We used similar parameterization, as with point simulation, to run the spatial simulation (Figure 5). However, we used actual annual meteorological data that allowed us to compare with respective years of satellite derived data. Instead of NDVI from Landsat in our previous version, we used GPP from MODIS to make better comparisons. Still there was little, evidence of fire damage observed in the first year after fire. We have tried to explain this in our discussion section the possible conditions that may lead to such situation, including rapid recovery of vegetation (by annual or perennial herbs) as suggested by previous few studies.

As stated above, we also ran a control simulation with no-fire scenario to observe and compare between fire and no-fire conditions. We used MODIS GPP instead of Landsat NDVI for better comparisons.

Minor comments:

L13 + L148 – how do you explain shrub dominance and lack of conifer growth in the absence of fire, shouldn't there be conifer growth in the area which would potentially replace shrubs?

We did not include conifer growth in this study since many of these locations do not have conifers. Moreover, future studies could improve conifer PFTs for local conditions to include in the simulations. We will expand on this in the discussion section.

L15 GPP already written out on L10

Thank you. We corrected it.

L21: how are you investigating spatial dynamics? Can fire spread between grid-cells? Perhaps make it more clear what you mean by "spatial behaviour of post-fire ecosystem restoration".

We rephrased the sentence. In this model, although the fire ignition is local it can spread into adjacent patches given favorable conditions such as fuel availability and moisture content. This behavior in interaction with other factors like climate and topography would influence post-fire ecosystem restoration.

L34: citep(Bradley 2018)

We corrected it.

L69: a much better description of fire is needed as commented above.

As stated above, we have tried to elaborate further on fire module in the EDv2.2 model.

L99: backslash — (/textitPoa secunda).

Thank you. We will correct it.

L112: table 2. It looks identical to Pandit et al., (2019), not adapted. Perhaps I'm mistaken.

We have made minor changes in this table from the original one.

L147: Off by a decimal place? — 5.0-5.5 kgCm−2yr−1

Thank you for the comment. We changed it to 0.55 kgCm-2yr-1.

L153: it's not clear to me how this fire disturbance works or what the red line is showing. I dont see disturbance following GPP that closely. Why is disturbance highest when shrub GPP is highest rather than when grass GPP is highest? What is fueling the fire? Grass should add a great deal of fuel to the fire yet disturbance is highest when shrub GPP is highest. How often are fires happening?

We agree that grass may lead to more fuel continuity and hence more frequent and larger fires. However, the fire return intervals may not perfectly align with the most fire-prone fuel conditions. In our model simulations, the disturbance is mainly related to aboveground biomass, so it tends to follow GPP (and more so with AGB). We updated some texts to state what red line is showing and how it is related to biomass. It appears that under the current model parameterization and structural composition, the shrub GPP has more impact on fuel availability compared to grass, because of the woody nature of the PFT compared to grass and higher biomass storage rates. It looks like the mean fire return interval is somewhat close in length and aligns with peak biomass. Future work on PFT parameterization and fire module would improve the results.

Fire here is an ongoing process after the 25th year. So, the fire related damage will increase when there is available fuel and it will reduce when there is no fuel (aboveground biomass). If we compare this trend as a fire return interval, we can compare this with studies showing fire return periods ranging from 35 years to 435 years for different type of sagebrush ecosystems.

L158: At LS, why does high fire severity lead to a more stable shrub proportion of GPP? L162: How do you define stability?

We removed the term ‘stability’ and showed how high fire severity could actually keep AGB at lower level and for some sites increase fire return interval (as described above).

L170: the GPP change 1 year after fire looks to be about the same for the entire study area. why would the biggest change in GPP come two to three years after fire? It’s hard to tell whether the changes in GPP are the result of fire or climate.

As described above, disturbance due to fire in the model behaves as a continued process instead of one-time effect. So, there could be spatial growth in fire from one grid to another depending upon fuel and moisture condition. A grid cell not meeting a threshold to get burnt could be burnt next year with slight increase in biomass. In addition, we should definitely take into consideration the effect of climate into these damages. Our updated analysis comparing GPP between fire and no fire scenario, supports the idea that the result should be mostly the result of fire.

Table 3: what are the * behind every Pearson number supposed to indicate?

They mean significant.

L205: Cite the literature you are referring to.

Thank you.

L212: Cite the literature you are referring to.

Thank you.

L246: “larger contributor to GPP in this ecosystem” citation needed.

Thank you.

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

Karun Pandit[1], Hamid Dashti[2], Andrew T. Hudak[3], Nancy F. Glenn[1], Alejandro N. Flores[1], and Douglas J. Shinneman[4]

[1]Department of Geosciences, Boise State University, 1910 University Dr, Boise, ID 83725-1535, USA
[2]School of Natural Resources and Environment, University of Arizona
[3]US Forest Service, Forest Sciences Laboratory, 1221 South Main Street Moscow, ID, 83843, USA
[4]United States Geological Survey, Forest and Rangeland Ecosystem Science Center, 970 Lusk St., Boise, ID 83706, USA

Correspondence: Karun Pandit (karunpandit@gmail.com)

Abstract. ~~Wildfire incidents~~ Wildfires in sagebrush (*Artemisia* spp.) dominated semi-arid ecosystems in the western United States have ~~risen dramatically in~~ increased dramatically in frequency and severity 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~~ an intensively monitored sagebrush-dominated ecosystem 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~~ shrubs in a non-fire scenario, however under the fire scenario we observed contrasting phases of high and low shrub density and C3 grass growth. Regional model simulations showed a gradual decline in ~~gross primary production (GPP)~~ 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~~ satellite-derived GPP estimates for the areas in RCEW ~~affected by the~~ burned by a wildfire in 2015 ~~Soda Fire~~(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~~ moderate pixel-level correlations between maps of post-fire recovery ~~GPP and the vegetation response observed in a post-fire Landsat image~~EDv2.2 GPP and MODIS derived GPP. This study contributes ~~in~~ to understanding the application of ecosys-

tem models to investigate temporal dynamics of vegetation under alternative fire regimes and ~~the spatial behavior of~~ post-fire ecosystem restoration.

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)~~(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). DGVMs are now increasingly intertwined with land surface models in ways that facilitate the integrated simulation of changes in vegetation community composition and surface water, energy, and biogeochemical cycles in response to changes in climate, land use, and fire regimes. Fisher and Koven (2020) provide a review of the increasingly sophisticated treatment of land surface processes in global land models, highlighting in particular the complex ways that vegetation influences fluxes and stores of water, energy, and carbon within these models. In the last two decades, fire sub-models in various DGVMs have evolved through time from simple statistical methods to more complicated approaches with induced ignition and process-based spread and intensity (Thonicke et al., 2001, 2010; Knorr et al., 2016).

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~~ seeks to balance the fidelity of process representation in individual-based models with the computational efficiency of area-based models, wherein 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). Because of this balance between process fidelity and computational burden, demography-based models are becoming increasingly popular versions of DGVMs within global land models (Fisher et al., 2017). While EDv2.2 ~~is~~ 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).

In this study, we used Ecosystem Demography model (EDv2.2) with a recently developed plant functional type (PFT) parameterization of shrubs (Pandit et al., 2019) with the objective to examine model-derived effects of fire on a shrubland ecosystem in the Reynolds Creek Experimental Watershed (RCEW). We developed and ran a two-step numerical experiment to accomplish this. First, we explored the projected gross primary production (GPP) of a sagebrush-steppe ecosystem (in terms of shrub and C3 grass PFTs) in EDv2.2 for two different fire disturbance scenarios and a no-fire or control scenario (performed at point-level). Second, we compared the model-simulated spatiotemporal variability of GPP to a remotely sensed estimate of GPP (Wylie et al., 2003; Running et al., 2004) prior to and after a 2015 fire that burned a portion of the RCEW study area.

2 Methods

2.1 Ecosystem Demography (EDv2.2) model

EDv2.2 is a process-based dynamic vegetation model which takes cohorts (a group of individuals with similar properties) as the smallest units of simulation. It 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 structure and compositional heterogeneity ~~compared to~~ better than most of the 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 ~~(?Moorcroft et al., 2001; Medvigy et al., 2009).~~

(Longo et al., 2019b; Moorcroft et al., 2001; Medvigy et al., 2009). Here we present a brief summary of the fire subroutine.

In this model, fire ignition probability is ~~local~~ based on soil dryness which is local (within-gap) in origin but can spread into adjacent areas given favorable conditions for fire. All plants in a burnt patch are killed while part of carbon and nitrogen are transferred into the below-ground module (Moorcroft et al., 2001). Area of burnt patches within grids can increase linearly through years as a function of aboveground biomass (AGB). Users can choose ~~from two separate stochastic mechanisms defining fire ignition conditions~~ one of the two stochastic methods that define fire ignition in the model. Availability of enough fuel (~~aboveground biomass~~AGB) is the first necessary condition common to both ~~mechanisms~~of these methods. 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. Disturbance rate from fire (λ^{FR}_{μ,μ_0}) for a patch u (given by supscript u) is given by the following equation (Eq. 1) as originally defined by Moorcroft et al. (2001) and later revisited by Longo et al. (2019b).

~~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)~~

$$\lambda^{FR}_{\mu,\mu_0} = I\sum_{u=1}^{N_p}\sum_{k=1}^{N_{T_u}}\left\{\left[C_{ul_k} + F_{AG_{uk}}\left(C_{u\sigma_k} + C_{uh_k}\right)\right]\gamma_u\alpha_u\right\} \tag{1}$$

where N_p is number of patch, N_{T_u} is number of cohort in patch u, γ_u is binary ignition function which is defined as given in equation 2 below, α_u is relative ara of patch, I is fire intensity, $F_{AG_{uk}}$ is fraction of tissue aboveground, C_{ul_k} is leaf biomass, $C_{u\sigma_k}$ is sapwood biomass and C_{uh_k} is structural biomass.

3 ~~Methods~~

$$\gamma_u = \begin{cases} 1, & \text{if } \left(\frac{1}{|Z_{Fr}|}\int_{Z_{Fr}}^{0}\nu_g dz\right) < \nu_{Fr} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where, Z_{Fr} is the maximum soil depth considered and ν_{Fr} is an average soil moisture below ignition Z is the depth.

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~~. The watershed is approximately 240 km^2 in area 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). Mean annual temperature ranges from 5 to 10 °C and mean annual precipitation range from 250 to 1100 mm in the watershed. Because of the strong orographic gradient in temperature in the watershed, most precipitation at lower elevations falls as rain, whereas precipitation at higher elevations is dominated by snow. 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*), 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~~ region (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~~*Poa 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~~ discretized the watershed into a 1 km ~~resolution covering the entire RCEW area~~rectangular grid covering the entirety of the watershed, consistent with the resolution of the meteorological forcings input to the model described below.

2.2 Meteorological forcing data

~~We used outputs from high resolution climate reanalysis obtained from~~ Meteorological forcing data input to the EDv2.2 model consisted of output from a long-term run of the Weather Research and Forecast

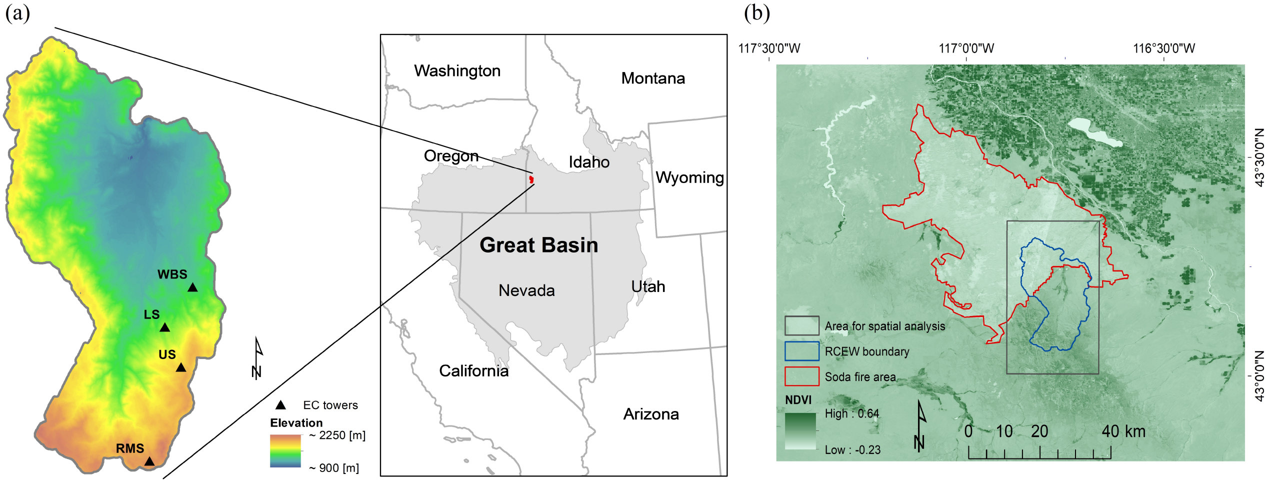

Figure 1. (a) Location of the four EC flux tower sites within the Reynolds Creek Experimental Watershed (RCEW) study area. The inset map shows the location of RCEW within the Northern Great Basin (LCC, 2019). (b) Map showing area affected by Soda Fire, 2015 (red polygon), boundary of RCEW (blue boundary), and rectangle covering RCEW (black polygon) used to run regional EDv2.2 simulation. Normalized Difference Vegetation Index, NDVI (Landsat image, August, 2015) map in the background shows the disturbance from fire in the Soda Fire area.

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

(WRF) model (Skamarock et al., 2008)~~to obtain meteorological forcing data as presented in Pandit et al., (2019) (~~, which was used to dynamically downscale data from the North American Regional Reanalysis (National Centers for Environmental Prediction, National Weather Service, NOAA, U.S. Department of Commerce, 2005) to a spatial resolution of 1 km (Pandit et al., 2019) (Table 2). ~~These~~ WRF outputs correspond to ~~data from different heights above the ground surface. Wind speeds refer to 10 above ground,~~ atmospheric outputs at a standard height of 2 m for temperature and specific humidity~~refer to 2 above ground, downward shortwave radiation,~~ , 10 m for wind speed and direction, and the ground surface for downward shortwave and 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~~ , and precipitation (Flores et al., 2016). The temporal resolution of the WRF data is 1 ~~and~~ hr and it is available for the period from October 1~~, respectively.~~ , 1986 to September 30, 2018. 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~~ Long-term simulation at point scale

We ran point-based simulations at four EC tower sites in RCEW to understand the long-term 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). 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. In the fire scenario simulations, we ran the model with active fire for these later 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).

~~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~~ Short-term simulation at regional scale

We performed ~~region-based simulations to explore post-fire vegetation recovery for the entire RCEW area. In this case~~regional (watershed) scale simulations to perform comparisons between across simulations for fire/no-fire conditions, between model simulations and satellite-derived estimates of ecosystem productivity. First, we compared the fire caused vegetation disturbance and recovery at the regional scale by allowing EDv2.2 to run with both fire and no-fire (control) conditions. Second, we compared the model predicted GPP (for both burnt and unburnt areas in the region) with the MODIS derived GPP from the study area. To perform these simulations, 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~~these model runs, 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 ran fire and no-fire model simulations for a region inside RCEW which was actually affected by the Soda Fire in 2015. For fire scenario, we activated fire subroutine in the model from 2015 and ran it until 2019. In this run, we adopted a high fire severity (0.9) to relate closely with the severity observed in the Soda Fire. For the no-fire (control) scenario, we allowed the model to continue without fire until 2019. We compared difference between fire and no-fire simulations for each year.

For the next experiment, we tried to run the EDv2.2 in the way that would represent the true circumstances for the entire study area. To perform this, we introduced fire (with same parameter as above) only into that portion of RCEW which actually burned in 2015 ~~as part of the Soda Fire, and~~ and simulated 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~~ purpose of this experiment was to compare the predictions from EDv2.2 (for burnt and unburnt areas) with that derived from MODIS images. The unburnt area in this simulation would work as a benchmark for comparisons and to offset for annual variations. Like before, we ran the model with these conditions for the next ~~4~~ 5 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~~ We produced GPP from MODIS Gross Primary Production CONUS datasets (Robinson et al., 2018), using Google Earth Engine. Mean of all available MODIS images for the month of July of each year was calculated, clipped and resampled to match the spatial coverage and grid resolution (1 km) of the EDv2.2 simulation, before making comparisons with mean monthly GPP of July from the model.

3 Results

3.1 Long-term GPP ~~for alternate fire conditions~~prediction at point scale

~~GPP trends for the~~ Temporal dynamics of the GPPs for shrub and C3 grass PFTs were about similar for the LS, WBS and US sites ~~and~~ while slightly different for the RMS site ~~located at the highest~~ (Fig. 2), which is located at higher elevation (Fig. ~~3~~1).

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~~ at about 0.55 $\mathrm{kgCm^{-2}yr^{-1}}$ for the highest elevation site (RMS). We observe that during its initial rapid growth phase (Fig. 2), some portion of the total above ground biomass (AGB) is also covered by C3 grass (Fig. A1), which in the later years got completely wiped out by shrub AGB. 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~~ activation of fire module after 25 years of simulation, shrub GPP declined abruptly and C3 grass GPP increased dramatically in all four study sites. However, around 25 years after fire ~~is introduced~~activation, shrubs initiate a recovery and maintain a gradual increase until reaching a peak in 50-75 years; at the same time ~~C3~~ C_3 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~~We observed lower overall GPP during the years when shrub GPP was at the peak, since at this time C3 grass productivity was at the minimum. Disturbance rates from fire spiked in the first couple of years when fire was first introduced and later stabilized to closely follow the trend of shrub ~~GPP~~AGB (Fig. A1), suggesting the highest disturbance rate at the peak of shrub ~~GPP~~ AGB leading to decline of shrub GPP (and shrub AGB) 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~~ . For most of the sites, while shrub GPP remains lower compared to no fire scenario C_3 in the post-fire years, grass GPP dominates the overall shape of total GPP~~in the post-fire years~~. However, if we look into the cycles of total AGB after fire, they match well with the trend of shrub AGB which in turn influence the approximate fire return interval (with maximum fire disturbance rate in about 50-75 years) in the ecosystem.

We identified some differences between low and high fire severity conditions, even though the general ~~trend~~ temporal pattern 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~~ We can see clear difference in total AGB (Fig. A1) with lower peaks for high fire severity conditions for all four sites. With high fire severity, we observe longer fire return intervals for 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~~ (about 60 years for both LS and RMS) compared to the lower fire severity condition (>100 years for LS and >75 years for RMS). 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, 2016, and 2017 for all four sites (Fig. ~~4~~3). EDv2.2 underpredicted GPP for all sites, ~~except for the WBS site which was close to observation~~with the lowest error for WBS site (≈12%) and the highest error for US site (≈ 100%) for no fire scenario.

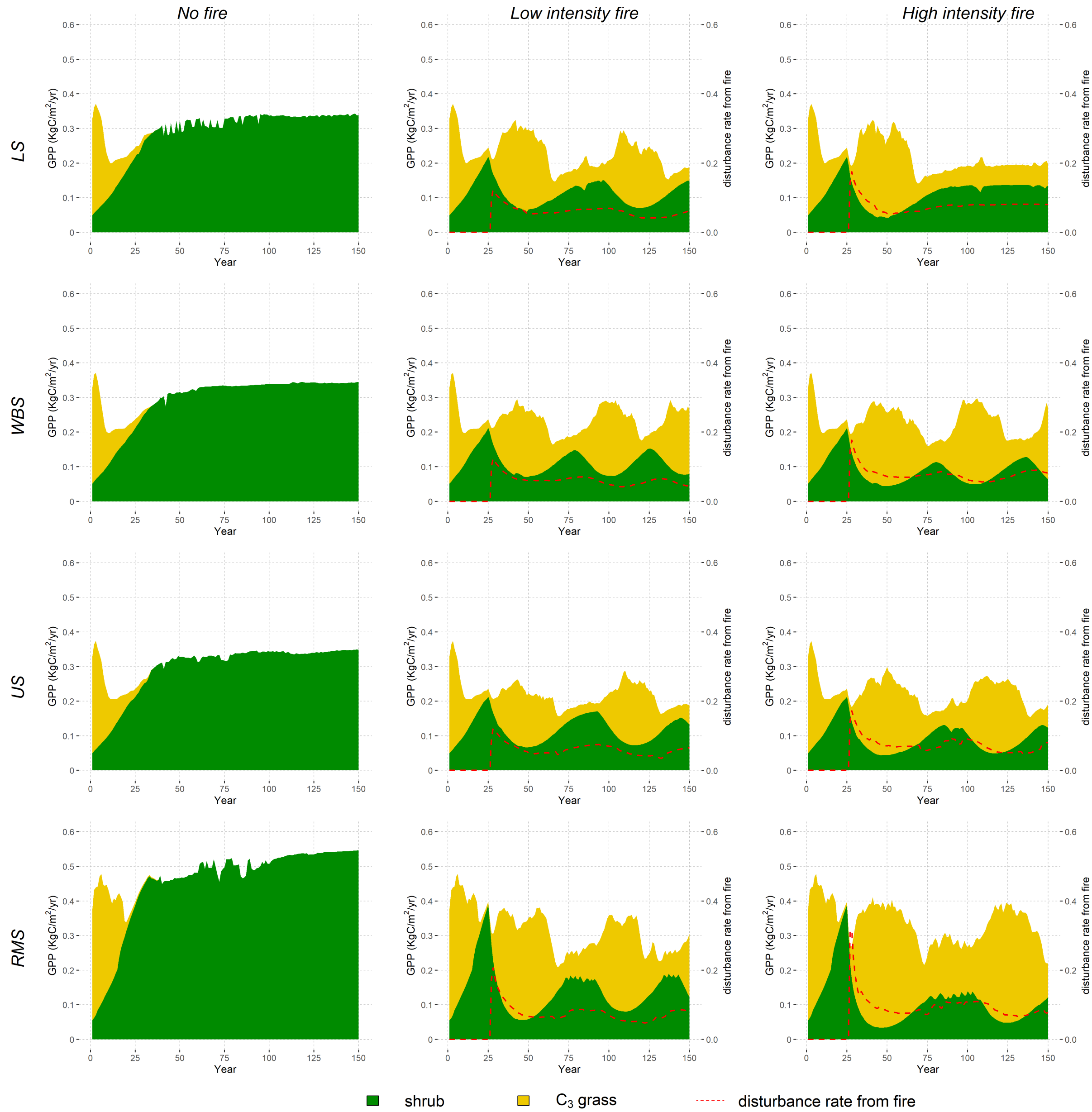

Figure 2. Mean annual trends in shrub, C_3 grass (temperate ~~C3~~ C_3 grass) and total GPP ($\mathrm{kgCm^{-2}yr^{-1}}$) (shrub and C_3 grass GPP showed in stack) simulated at four EC flux tower sites (LS, WBS, US, and RMS). Figures in the left column represents the trend in the no fire condition, the 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.

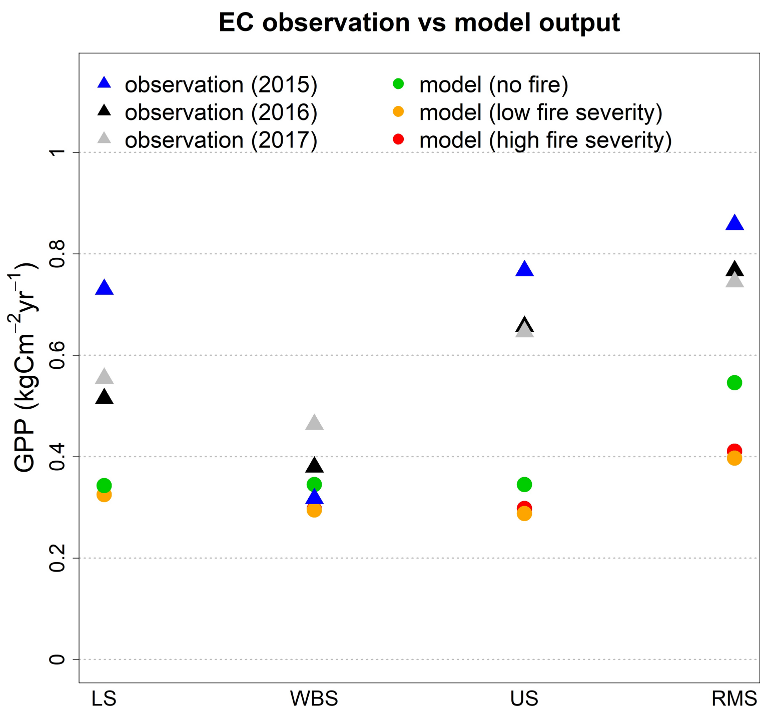

Figure 3. Comparison of simulated average annual GPP from EDv2.2 for alternate fire scenarios (no fire, low fire severity, and high fire severity) with observations (from 2015, 2016, 2017) from all four EC tower sites.

3.2 ~~Comparison of modeled post-fire GPP with NDVI~~Short-term GPP prediction at regional scale

3.2.1 EDv2.2 GPP for fire and no-fire scenarios

We observed annual variation in GPP predictions for both fire and no-fire scenarios (Fig. 4). Annual variation of GPP in no-fire model simulation could be mostly attributed to annual climatic variations. Despite the climatic influence, we can clearly observe the difference between fire and no-fire GPP outputs, especially from 2017 to 2019. High GPP areas at the southwestern regions in no-fire simulations are almost missing from the fire simulations. The difference maps in the bottom row of Figure 4 clearly show the differences among two scenarios. For the first year after fire, there is very low loss in GPP and doesn't show clear spatial pattern. In the second year, loss of GPP from fire is clearly increased, at least in some parts (western region), and shows a clear spatial pattern. From the third year, loss of GPP intensifies in certain locations while most of other areas remain similar. In the fourth year, the intensity of loss even gets worse in certain areas, and we can also see certain pockets with positive GPPs, meaning some recovery for limited areas.

We observed obvious difference in EDv2.2 prediction of GPP for shrub PFT and C3 grass PFT for post-fire years (Fig. A1). Since shrub PFT covers major portion of the overall GPP, the later is highly influenced by the pattern of shrub PFT. While

Table 3. Pearson's correlation coefficient calculated between modeled GPP and ~~NDVI~~ MODIS GPP 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~~0.58*	464	~~0.212~~0.40*	800	~~0.427~~0.50*
2016	336	~~0.487~~0.63*	464	~~0.228~~0.46*	800	~~0.440~~0.55*
2017	336	~~0.566~~0.57*	464	~~0.380~~0.50*	800	~~0.566~~0.63*
2018	336	~~0.404~~0.52*	464	~~0.551~~0.49*	800	~~0.638~~0.63*
2019	336	~~0.480~~0.54*	464	~~0.500~~0.55*	800	~~0.598~~0.66*

shrub GPP is gradually decreasing in through these years after fire, in contrast, C_3 grass starts to recover by third year after initial loss in the first and second year (Fig. A1). The pockets of slight increase in GPP seen in overall GPP (Fig. 4) appears to be the effect of this C_3 grass recovery. These results are in agreement with our results from point-scale fire simulations.

3.2.2 EDv2.2 GPP and MODIS GPP

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 ~~.~~ (Fig. 5). 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~~ has close association with elevation (Fig. 1), which largely influences the precipitation pattern in the study area. ~~A hint of recovery~~ 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~~ When we compared 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~~ (2015) EDv2.2 ~~uniquely predicted higher GPP at some northwestern and southeastern areas in comparison to the rest of the~~ GPP prediction with MODIS GPP, we found that there is an under-prediction across 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~~ with major differences towards southern region (higher elevation areas) of the study area (Fig. 6). The results corroborates with our understanding from point-based results where we found better predictions for lower elevation study points compared to those at higher elevations. We can observe a clear

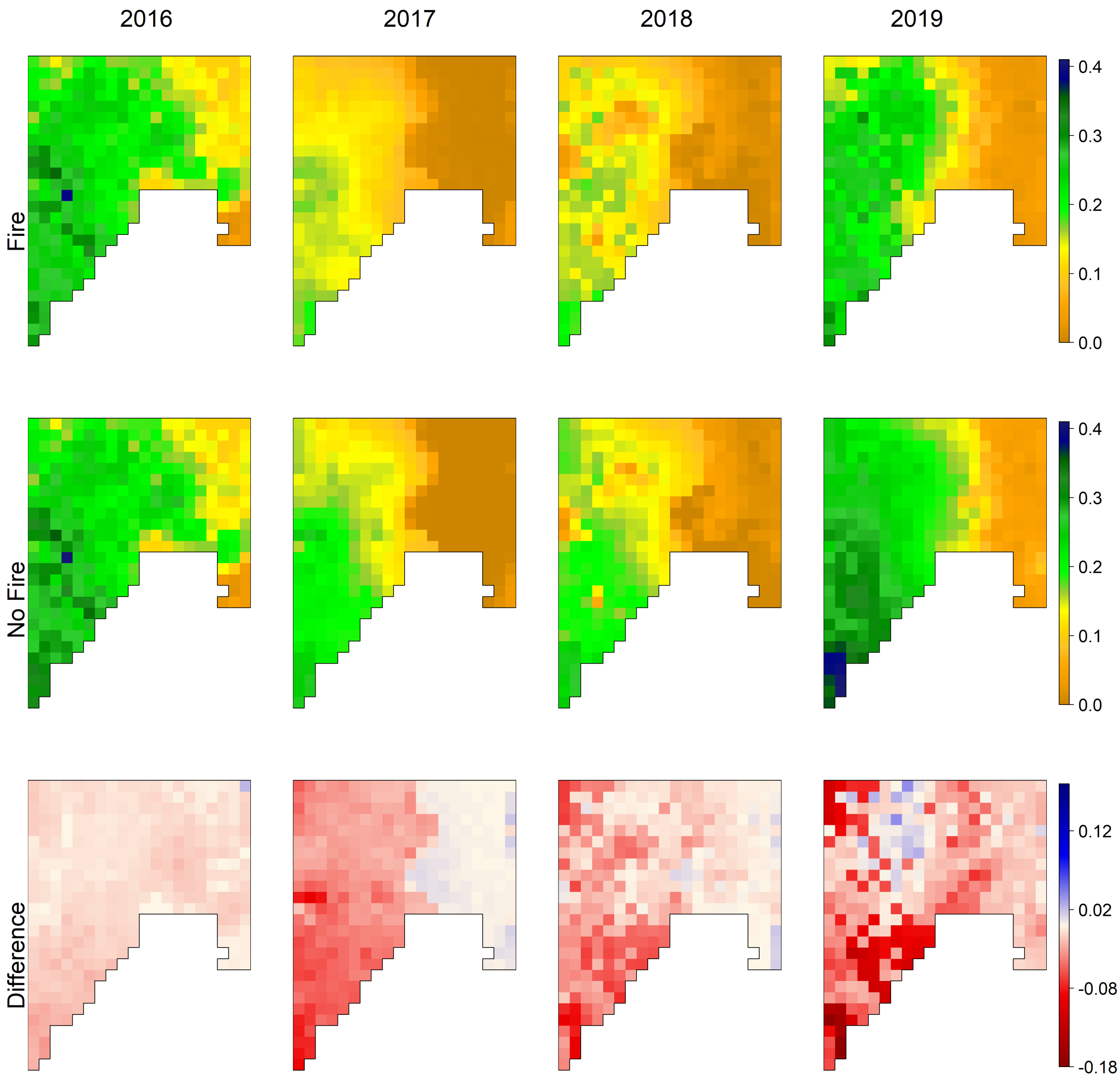

Figure 4. ~~Snapshots of total~~ EDv2.2 predicted mean monthly GPP (kgCm^{-2}yr^{-1}) for the month July~~29th~~, ~~July 15th, July 18th, July 30th, and July 24th respectively for 2015, 2016, 2017, 2018, and 2019 compared to NDVI (Fig. 6)~~ showing outputs from the ~~same dates. The starting year~~ model with fire (~~2015~~upper row)~~shows the pre-fire condition in the 25th year of spin-up~~, without fire (middle row) and difference between two scenario for 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~~ 2016 to ~~the pre-fire condition in 2015.~~2019 (representing post-fire years after Soda Fire)

reduction in 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~~

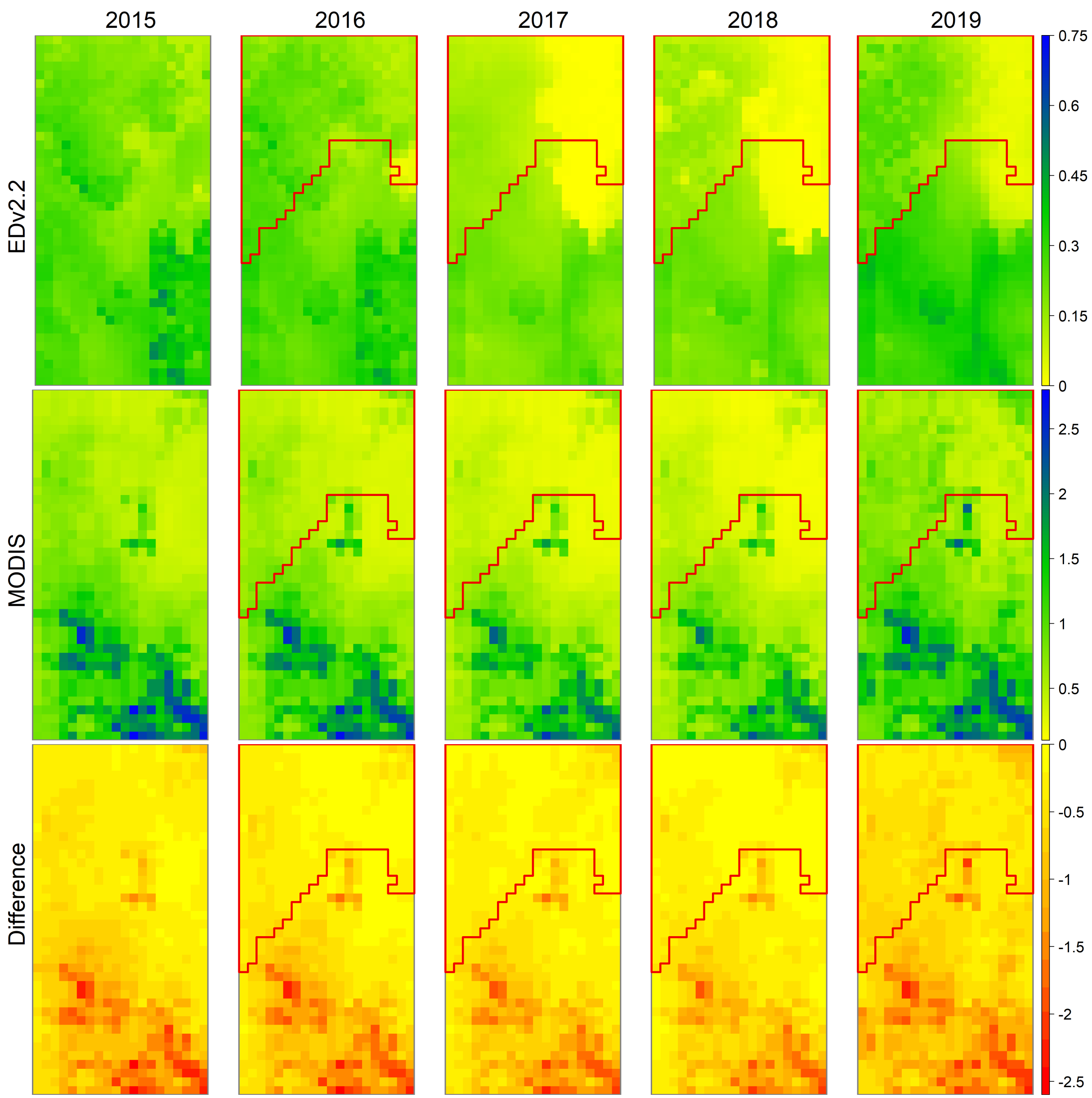

Figure 5. ~~NDVI from Landsat images~~ Mean monthly GPP ($kgCm^{-2}yr^{-1}$) for the month of July for entire study area for the pre-fire (2015) and post-fire (2016 to 2019) years, predicted from EDv2.2 (~~top maps~~top-row), derived from MODIS (middle-row) and ~~NDVI change every subsequent years after~~ the ~~fire incident compared to pre-fire NDVI~~ difference between two sources (~~bottom maps~~bottom-row). ~~Landsat images were dated July 29th, July 15th, July 18th, July 30th, and July 24th respectively for 2015, 2015, 2017, 2018, and 2019.~~Area surrounded by red polygon represents the area burnt by Soda Fire.

~~fire, but by the second year, differences in NDVI between fire and non-fire areas were largely imperceptible.~~ GPP within fire affected region only second year after fire (2017) with signs of recovery in 2019. On the other hand, we could see only a slight reduction in MODIS derived GPP, particularly for the years 2017 and 2018, for the burnt areas, in the post-fire years. By the year 2019, we could observe a good recovery for MODIS GPP.

We calculated Pearson's correlation to further explore the association between modeled GPP and ~~NDVI~~MODIS GPP. 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 yearsof data~~A2). For the entire area and for unburnt area the trend is such that correlation is increasing through the years. Lower correlations for unburnt areas in the beginning years (2015 and 2016) could be because of higher variation in vegetation productivity in these areas and because simulated GPP has not yet reached an equilibrium. On the other hand, correlation for burnt area slightly increases after fire and drops back again, revealing more homogeneity and close comparisons immediately after fire.

~~When mean NDVI and GPP values (~~

When mean GPP values from the EDv2.2 simulation ~~)~~ and MODIS 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).~~ GPP for the entire area. There was clear under-prediction of GPP with EDv2.2 compared to that from MODIS, in general. 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~~ not much difference GPP between burnt and unburnt areas for EDv2.2 in the pre-fire condition, where as there was already a huge difference between these areas for MODIS GPP. For EDv2.2 GPP

EDv.2.2 GPP in burnt areas started to reduce significantly in the second year after fire (2017), continued to remain low until 2018 and showed some recovery in the fourth year. ~~In the pre-fire condition (2015), the fire-affected region had 27~~For the modeled GPP, the burnt region had 20% less GPP than ~~non-fire affected areas~~ unburnt areas in the pre-fire year (2015), but this gap ~~increased to 41%, 49~~changed to 22%, 53%, and ~~61% in~~ 50% , and 44% through the first (2016), second (2017)~~and third year~~ , third (2018)~~post-fire, respectively. This deficit was reduced to 48% in the fourthyear~~ , and fourth(2019) ~~after fire as~~ post-fire ~~recovery seemed to start. Although mean NDVI values in the burnt area increased 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~~ years, respectively (Table A1). Though there was not much variation observed with MODIS GPP when looked at absolute numbers but as we looked into percent difference in GPP between burnt and unburnt areas, we noticed slight change in this gap through the years. Pre-fire (2015) ~~, NDVI values for burnt area was about 31%less than unburnt area, and this difference increased to about 34%in the firstyear~~ gap between burnt and unburnt areas for MODIS GPP was 50%, which increased slightly to 55%, 61%, 62% through first, second and third post-fire ~~. From the second year onward this deficit started~~

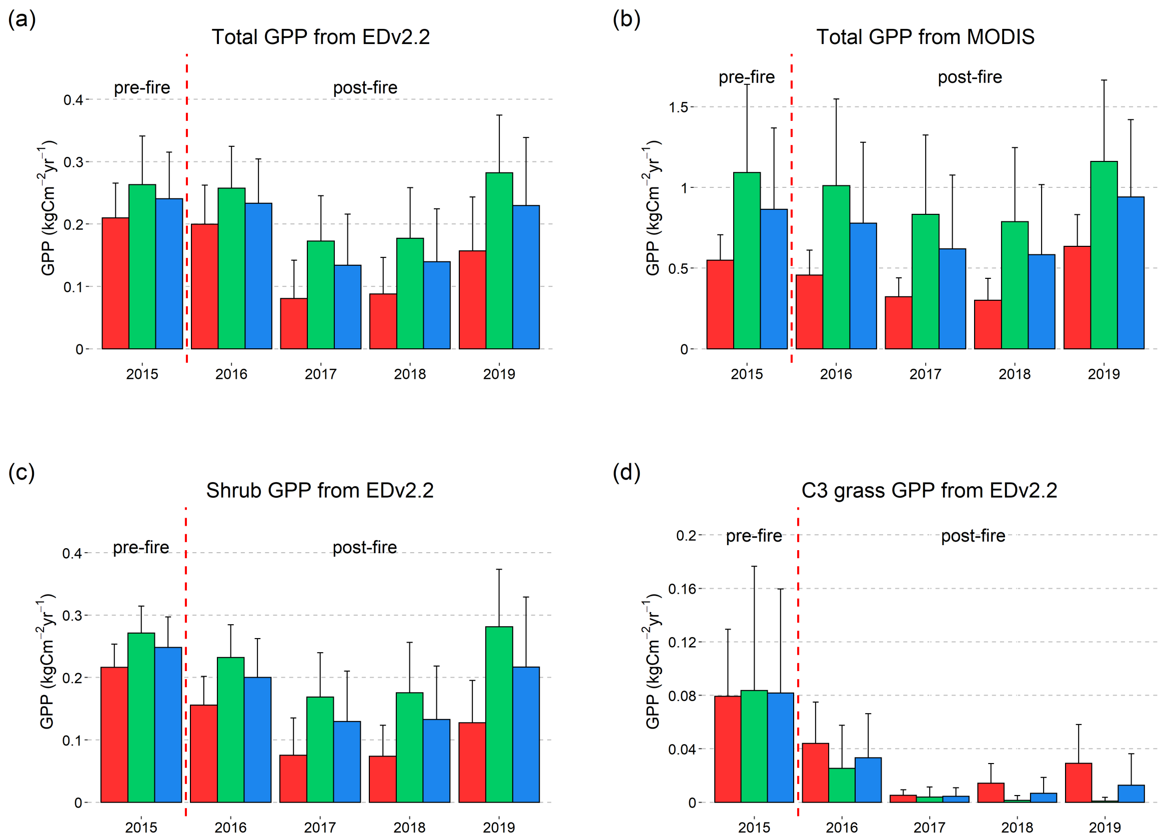

Figure 6. Average GPP from EDv2.2 and ~~NDVI~~ MODIS from Landsat calculated for all the burnt, unburnt, and total grids for annual July snapshot maps from 2015 to 2019 (a-b). Error bars in the figure represent ± one standard deviation.

~~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~~ years rspectively, before reducing this gap to 45% in the year 2019.

Modeled GPP for shrub followed the pattern of total GPP showing considerable loss in GPP in post fire years. One difference with the total GPP, was observed during the fourth year after fire, ~~NDVI from Landsat showed complete recoveryand some gain by that time~~when the shrub had not started recovery. In contrast, we observed different effects on C3 grass GPP. The GPP for C3 grass in burnt areas were slightly higher than unburnt areas immediately after fire in 2016 and showed upward growth trends until 2019. Although, the percent of C3 grass is very low in total GPP, some recovery seen in total GPP in 2019 is mostly contributed by the C3 grass growth.

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 ~~.~~ in terms of the vegetation loss, PFT competition and recovery. Variation in growth and productivity for C3 grass and shrub after fire disturbance can be understood as their role during different stages of secondary succession. Being an early successional PFT, C3 grass grows quickly and produces high GPP by making most out of the favorable growing conditions following the disturbance as shown by Moorcroft et al. (2001). As shrubs start to recover, competition increases at both above and below ground levels for light, water and nutrients reducing the growth of grass thus causing a net loss in total GPP despite an increase in shrub GPP. 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~~ recover 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~~GPP as evident from the flux tower observation, 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 (LS and WBS sites) with reasonable agreement (Pandit et al., 2019), and thus may not have accounted for ~~local~~ regional 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~~ shown in 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~~ model predicted GPP for burnt areas for about 4 years post-fire. ~~Recovery of NDVI in the burnt area in the second year~~ An increased reduction in GPP in burnt areas until third year after fire introduction could be the result of fire behavior in the EDv2.2 model (Longo et al., 2019a), where there is a linear increase in burnt area through years given the availability of fuel. There was some recovery observed in the GPP in the fourth year after fire which was mostly because of the increase in C3 grass GPP. Absence of major reduction in MODIS GPP in the burnt area in the post-fire years could be mainly because of perennial grasses and shrubs. Grasses (perennial) could be growing in the second year post-fire when conditions ~~were~~ are 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.

~~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~~ 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~~ until the end of the ~~second year (2017~~third year (2018) postfire. ~~Li et al. (2012) found a~~ Zou et al. (2019) in their study on Region-specific Ecosystem Feedback Fire (RESFire) model with Community Earth System Model also found a decline in GPP until second year after fire with a recovery in about eight years. Li et al. (2012) also found 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. These findings based on a regional application of a fire module developed explicitly for global applications of a DGVM suggest that future effort is needed to develop more realistic treatments of fire when models like EDv2.2 are applied over smaller regions.

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).~~ While making these comparisons, we need to understand that there are also sources of uncertainty associated with MODIS derived GPP (Robinson et al., 2018).

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. Results show that fire model in EDv2.2 capture long-term vegetation dynamics fairly well while fire model behavior resulted in mismatch at short-term predictions when compared with MODIS GPP. 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~~ some increase in C3 grass GPP 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~~ GPP response observed from four years of post-fire ~~Landsat~~ MODIS 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~~ provides spatiotemporal trends in vegetation disturbance due to fire disturbance and ~~vegetation~~ subsequent recovery at the regional scale. We could reduce uncertainties in comparing model outputs with EC tower observation and satellite-derived products by improving representation of fire and vegetation ~~parameters and by applying observed meteorological~~ characteristics and through a more detailed accounting of the errors in input forcing data.

Appendix A

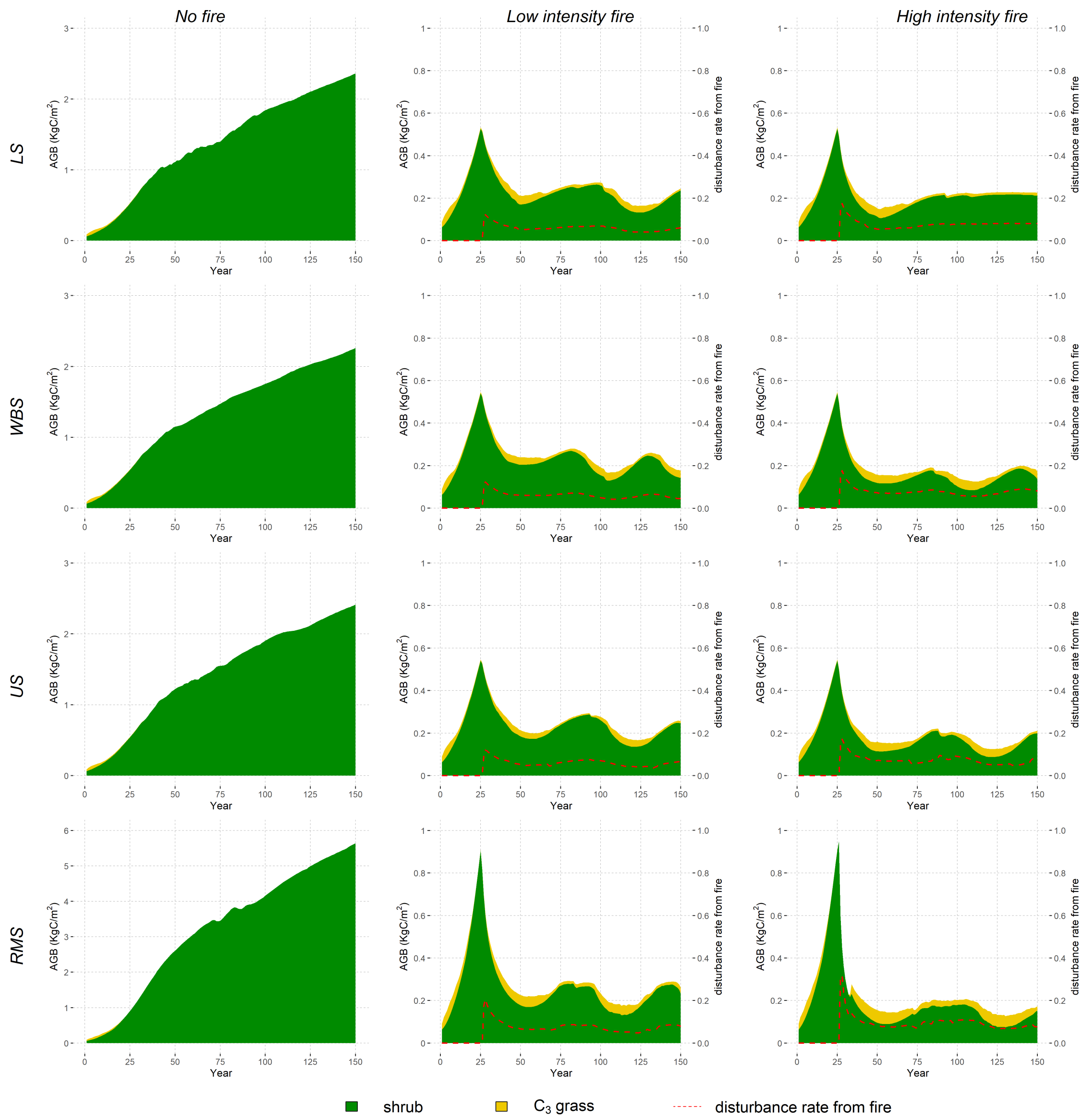

Figure A1. Mean annual trends in shrub, C_3 grass (temperate C_3 grass) and total AGB ($\mathrm{kgCm^{-2}}$) (shrub and C_3 grass AGB showed in stack) simulated at four EC flux tower sites (LS, WBS, US, and RMS). Figures in the left column represents the trend in the no fire condition, the middle column 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.

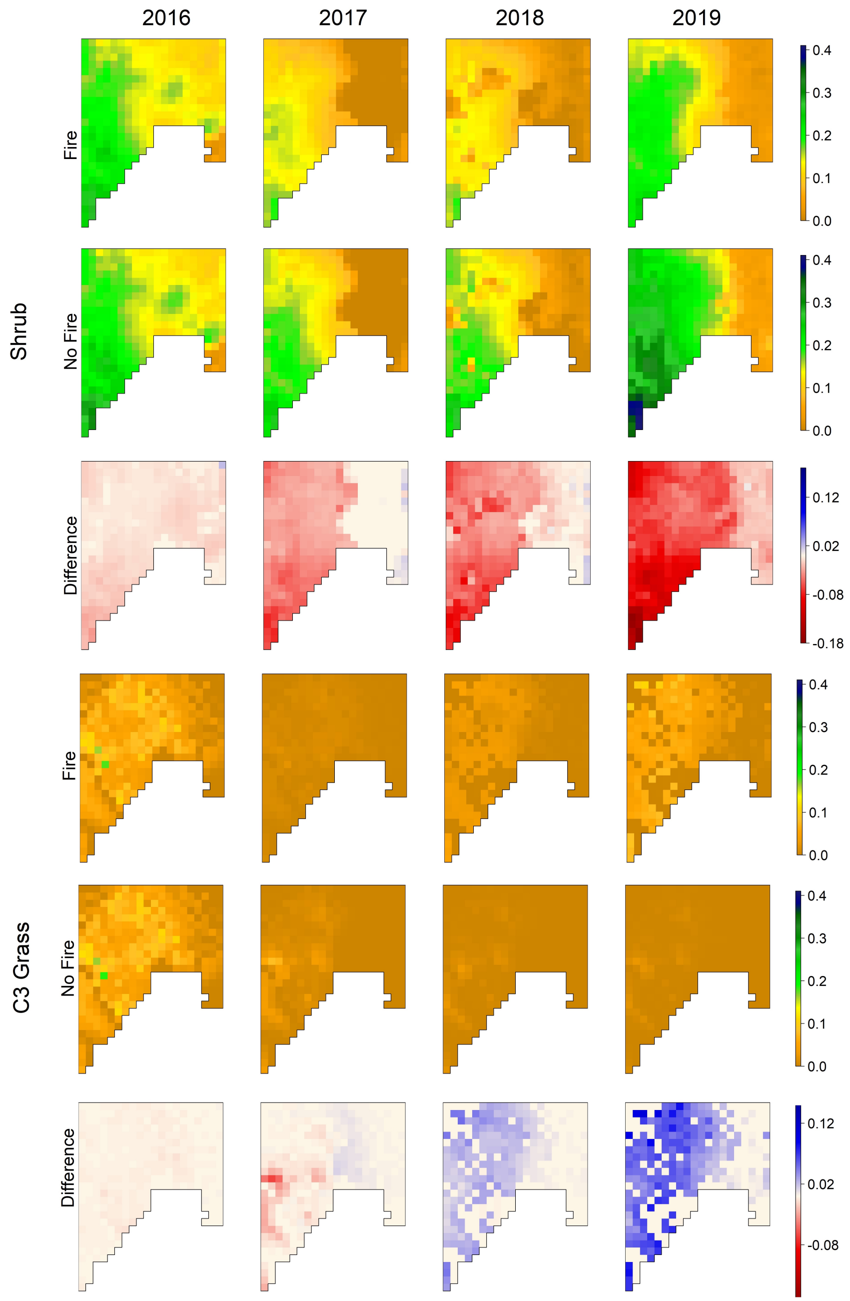

Figure A2. Mean monthly GPP ($kgCm^{-2}yr^{-1}$) for the month July of every year . The starting year (2015) shows the pre-fire condition in the 25th year of spin-up, and the 4 subsequent years represent annual conditions after fire. Maps in the bottom show change in GPP every subsequent year after the fire incident compared to the pre-fire condition in 2015.

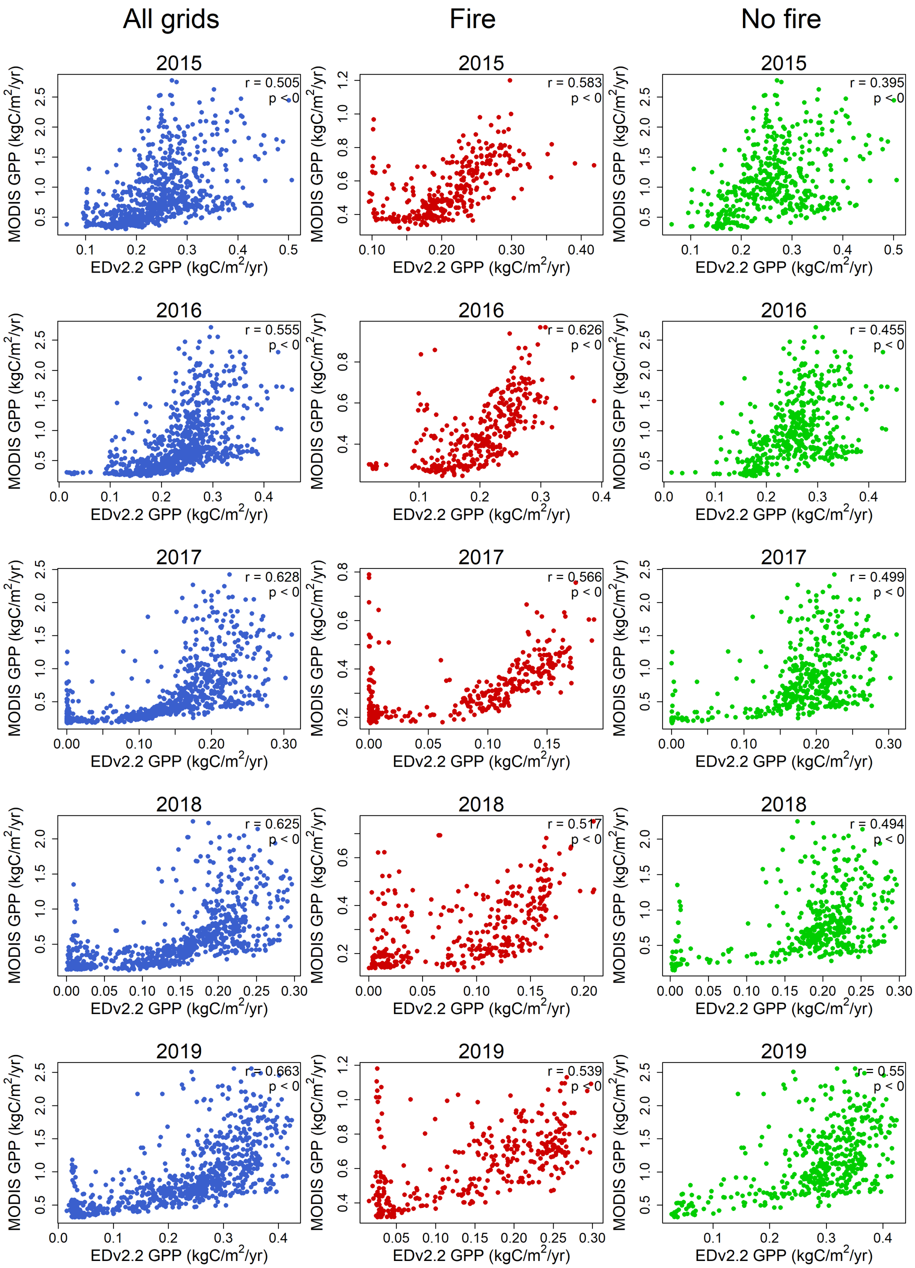

Figure A3. Mean monthly GPP ($kgCm^{-2}yr^{-1}$) for the month July of every year . The starting year (2015) shows the pre-fire condition in the 25th year of spin-up, and the 4 subsequent years represent annual conditions after fire. Maps in the bottom show change in GPP every subsequent year after the fire incident compared to the pre-fire condition in 2015.

Table A1. Percent difference of GPP between burnt and unburnt areas ((GPP in unburnt area - GPP in burnt area)/GPP in unburnt area) for pre-fire and post-fire years.

Year	MODIS GPP	EDv2.2 GPP (total)	EDv2.2 shrub GPP	EDv2.2 C3 grass GPP
2015	0.50	0.20	0.20	0.05
2016	0.55	0.22	0.33	-0.74
2017	0.61	0.53	0.55	-0.35
2018	0.62	0.50	0.58	-8.71
2019	0.45	0.44	0.55	-34.32

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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