Anonymous Referee #1Received and published: 6 June 2019

We would like to thank the referee for the valuable comments. We have prepared a point to point response to the comments and will incorporate the changes in the revised manuscript.

Overall assessment. The current manuscript presents new research regarding the long-term assessment of fire danger based on hydrological data. Overall, it is an interesting study and the manuscript itself is well written. There are some points that could be improved, as highlighted in the following. Minor comments:

Section 2.1: In its current form, this section would be more suited to a technical report document, rather than to a scientific publication. I would appreciate it if the authors revised their text, avoiding the bullet-style format.

We have revised the text, avoiding the bullet-style format:

For the purpose of this study, four input data sets were used (Figure 1). First, monthly VPD (panel a) was generated from the AIRS near surface air temperature (Tmean) and relative humidity (RH) Version 6 (Aumann et al., 2003; Goldberg et al., 2003). Please refer to (Behrangi et al., 2016) for the formulation based on monthly air temperature (Tmean) and dewpoint temperature (Tdmean) as well as the reliability of this formulation for monthly VPD derivation. The data are in 0.5 degree spatial resolution and available since September 2002. The second input to the model was monthly surface soil moisture data (panel b) were produced at the NASA Goddard Space Flight Center (GSFC) using the Catchment Land Surface Model (CLSM) (a physically based land surface model) and assimilated ground and space-based meteorological observations (Houborg et al., 2012; Reager et al., 2015; Tapley et al., 2004; Zaitchik et al., 2008). The SSM data are available since April 2004 and in 0.25 degree spatial resolution. The third dataset was Global Fire Emissions Database version 4 (GFED-4s) provided wildfire burned area, generated at 0.25 degree spatial resolution. GFED-4s is primarily derived from MODIS from 2001 to present and is reported as fraction of a cell burned for a given month (van der Werf et al., 2017). GFED data are available since 1997. Panel c shows GFED burned area in August 2010 while panel e shows long-term August burned area in sq km. As shown, wildfires occurs all around the CONUS in August. The amount of area burned however is considerably larger in the Western United such as in Northern Rockies, North West, Rocky

Mountain and Northern California. Finally, in this study, we have excluded agricultural fires by masking out agricultural regions as classified by the 2011 National Landcover Database (panel d) (NLCD 2011) (Homer et al., 2015).

L115: Is there any reference that could be used for supporting the statement that GACCs exhibit similar fire weather types?

Here are two publications that support the statement that GACCs are geopolitical boundaries that represent similar fire-weather types and are used to allocate fire management resources across the contiguous United States.

Finco, M. Monitoring Trends and Burn Severity (MTBS): Monitoring Wildfire Activity for the Past Quarter Century Using Landsat Data. 2012, 7.

Abatzoglou, J. T.; Kolden, C. A. Relationships between Climate and Macroscale Area Burned in the Western United States. Int. J. Wildland Fire 2013, 22 (7), 1003. https://doi.org/10.1071/WF13019.

Table 1: Discussion of results should be removed from the legend of the Table, which should only provide information about the data presented.

The discussion of results was removed from Table 1 legend. Here is the updated legend:

Table 1. Overall model performance and separate influence of individual hydrologic variables. We use Nash-Sutcliffe coefficients to describe the combined Soil Moisture (SSM) and Vapor Pressure Deficit (VPD) simulation performance (ES), the climatology performance (EC) and the individual predictor performance (ES,VPD ES,ssm) vs the observations.

L219-222: Some references on the different behavior of different vegetation types would enhance the statement made here.

We have added some references on the different behavior of vegetation types:

For example, in the Northern Rockies, it is roughly half evergreen forest and half herbaceous (Figure 1); evergreen forest typically need to be dried to sustain combustion (high VPD in the month prior), while herbaceous communities typically need wet conditions months prior to grow fuels (high SSM 2 months prior) (Littell et al., 2009; Stavros et al., 2014a).

Littell, J. S., McKenzie, D., Peterson, D. L. and Westerling, A. L.: Climate and wildfire area burned in western U.S. ecoprovinces, 1916–2003, Ecol. Appl., 19(4), 1003–1021, doi:10.1890/07-1183.1, 2009.

Stavros, E. N., Abatzoglou, J., Larkin, N. K., McKenzie, D. and Steel, E. A.: Climate and very large wildland fires in the contiguous western USA, Int. J. Wildland Fire, 23(7), 899, doi:10.1071/WF13169, 2014a.

L229-236: This paragraph is mostly a repetition from the Introduction. I believe it does not add anything to the discussion and could be thus removed.

We have removed this paragraph from the manuscript.

Technical remarks L56: "far away" . Changed
L70: "Behrangi et al. (2016)" Changed
L85: "hypothesis" Changed
Fig.1: Please, annotate the different panels of the figure (a, b, c, ..)

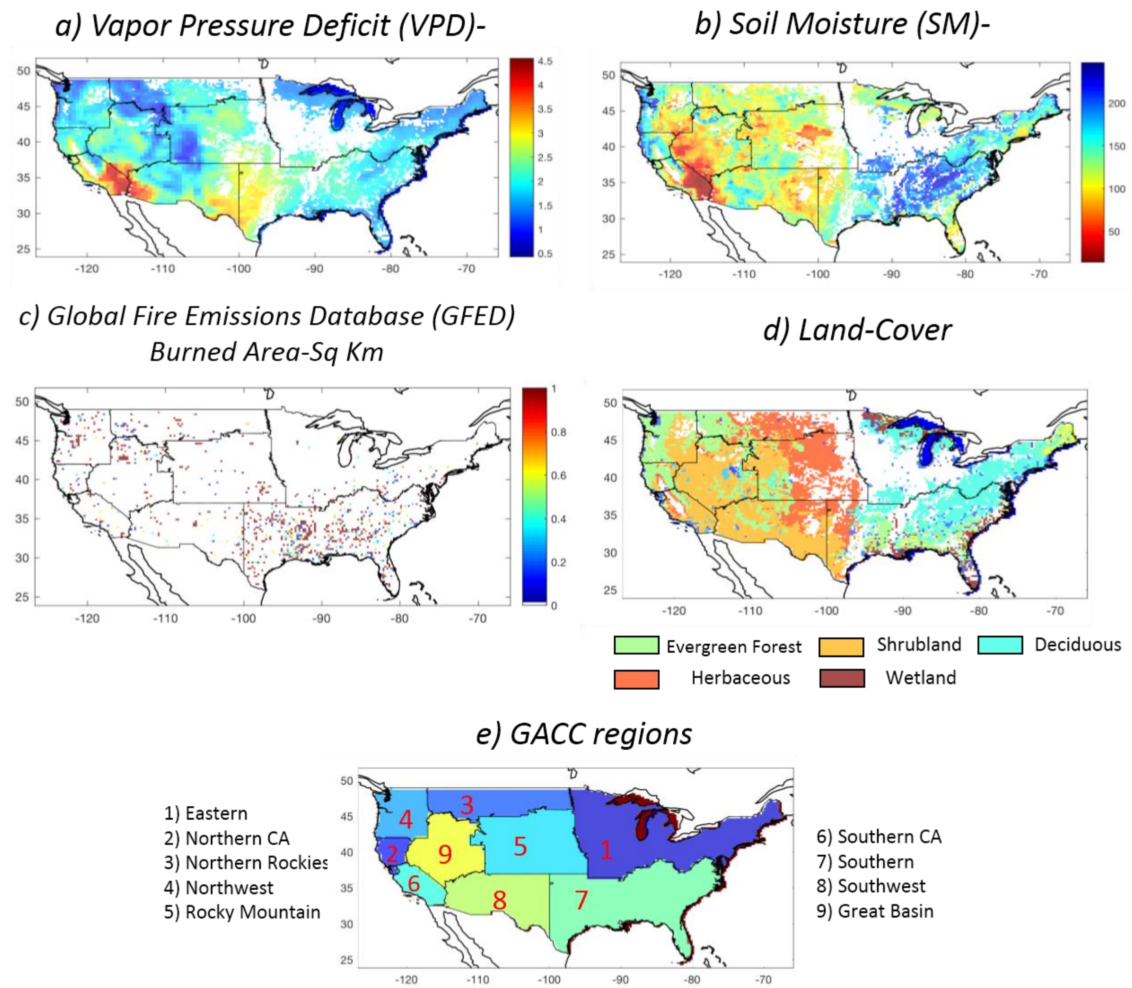


Figure 1: Snapshot of August 2010 of the datasets used in relation to the Geographic Area Coordination Centers (GACCs).

Equations: Please, number all the equations present in the manuscript.

We have numbered the equations. Here is the list of the numbered equations:

$E_w = \sum_{j=1}^{12} E_j * FAB_j$ (1)

$E_j = 1 - \frac{\sum_{i=1}^{n}(AB_{obs,i} - AB_S)^2}{\sum_{i=1}^{n}(AB_{obs,i} - AB_C)^2}$ (2)

$AB_s = AB_C + AB_A$ (3), $where$

$AB_A = a + b * (VPD_A) + c * (SM_A)$ if $E_j > 0$

$AB_A = 0$ if $E_j \leq 0$

Section "Results" is not numbered. Same for "Discussion and Conclusions".

Section "Results" will be third and section "Discussion and Conclusions" will be fourth section.

L166: "evergreen vegetation". L172,175:"herbaceous vegetation". L184: "worst" instead of "least". Changed all

Matin Rahnamay

We would like to thank Dr. Matin Rahnamay for his valuable comments. We have prepared a point to point response to the comments and will incorporate the changes in the revised manuscript.

The manuscript "Satellite Hydrology Observations as Operational Indicators of Forecasted Fire Danger across the Contiguous United States" by Farahmand et al. investigates the potential for employing remotely sensed hydrologic observations for predicting burned area. The manuscript specifically proposes a monthly burned area model, which employs soil moisture data and vapor pressure deficit with different lag time. The manuscript is very interesting to read and well written. I have a few minor comments as follows:

Minor Comments:
Please clarify the output of the proposed model in the abstract. Although improvement in predicting the wildfire burned area is discussed in the abstract, the goal of the modeling framework is not clear. Please be more specific about the burned area model in the abstract.

In the abstract, we have clarified the output of the model which is wildfire burned area. The output is highlighted in red.

Traditional methods for assessing fire danger often depend on meteorological forecasts, which have reduced reliability after ~10 days. Recent studies have demonstrated long lead-time correlations between pre-fire-season hydrological variables such as soil moisture and later fire occurrence or area burned, yet no potential value of these relationships for operational forecasting have not been studied. Here, we use soil moisture data refined by remote sensing observations of terrestrial water storage from NASA's GRACE mission and vapor pressure deficit from NASA's AIRS mission to generate monthly predictions of fire burned area at scales commensurate with regional management. We test the viability of predictors within nine US Geographic Area Coordination Centers (GACCs) using regression models specific to each GACC. Results show that the model framework improves interannual wildfire burned area prediction relative to climatology for all GACCs. This demonstrates the importance of hydrological information to extend operational forecast ability into the months preceding wildfire activity.

- In section 2.1, three datasets are presented. However, in line 89, the authors mentioned that four datasets are used as input. The numbering in this section can cause confusion.

We have eliminated the numbering which cause confusion. Here is the revised text, which explains four datasets used in this study:

For the purpose of this study, four input data sets were used (Figure 1). First, monthly VPD (panel a) was generated from the AIRS near surface air temperature (Tmean) and relative humidity (RH) Version 6 (Aumann et al., 2003; Goldberg et al., 2003). Please refer to (Behrangi et al., 2016) for the formulation based on monthly air temperature (Tmean) and dewpoint temperature (Tdmean) as well as the reliability of this formulation for monthly VPD derivation. The data are in 0.5 degree spatial resolution and available since September 2002. The second input to the model was monthly surface soil moisture data (panel b) were produced at the NASA Goddard Space Flight Center (GSFC) using the Catchment Land Surface Model (CLSM) (a physically based land surface model) and assimilated ground and space-based meteorological observations (Houborg et al., 2012; Reager et al., 2015; Tapley et al., 2004; Zaitchik et al., 2008). The SSM data are available since April 2004 and in 0.25 degree spatial resolution. The third dataset was Global Fire Emissions Database version 4 (GFED-4s) provided wildfire burned area, generated at 0.25 degree spatial resolution. GFED-4s is primarily derived from

MODIS from 2001 to present and is reported as fraction of a cell burned for a given month (van der Werf et al., 2017). GFED data are available since 1997. Panel c shows GFED burned area in August 2010 while panel e shows long-term August burned area in sq km. As shown, wildfires occurs all around the CONUS in August. The amount of area burned however is considerably larger in the Western United such as in Northern Rockies, North West, Rocky Mountain and Northern California. Finally, in this study, we have excluded agricultural fires by masking out agricultural regions as classified by the 2011 National Landcover Database (panel d) (NLCD 2011) (Homer et al., 2015).

- Please specify the spatial resolution of the soil moisture data in section 2.1.

The spatial resolution of soil moisture data is 0.25 degree (Houborg et al., 2012; Zaitchik et al., 2008)

Houborg, R., Rodell, M., Li, B., Reichle, R. and Zaitchik, B. F.: Drought indicators based on model-assimilated Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage observations: GRACE-BASED DROUGHT INDICATORS, Water Resour. Res., 48(7), doi:10.1029/2011WR011291, 2012.

Zaitchik, B. F., Rodell, M. and Reichle, R. H.: Assimilation of GRACE Terrestrial Water Storage Data into a Land Surface Model: Results for the Mississippi River Basin, J. Hydrometeorol., 9(3), 535–548, doi:10.1175/2007JHM951.1, 2008.

- Since monthly VPD is in 0.5-degree spatial resolution, please clarify the downscaling method or cite related references. It is not clear to me how linear interpolation is employed for this purpose.

For downscaling AIRS 0.5 degree spatial resolution to 0.25 degree spatial resolution, we have used the linear interpolation “interp2” function in Matlab. Vq = interp2(X,Y,V,Xq,Yq) returns interpolated values of a function of two variables at specific query points using linear interpolation. The results always pass through the original sampling of the function. X and Y contain the coordinates of the original 0.5 degree AIRS sample points. V contains the corresponding function values of AIRS data at each sample point. Xq and Yq contain the coordinates of the desired 0.25 degree points.

- The lagged VPC-SSM combination for each GACC is selected according to a Weighted Nash-Sutcliffe efficiency (NSE). I think the approach needs to be further clarified in the methodology section. In line 127, the authors mentioned “lagged model”, which can cause confusion. Are the authors referring to models with lagged input as the “lagged model”?

We agree about that the “lagged model” term could cause confusion. Here is the updated text:
Each GACC uses the “best” prior monthly VPD-SSM combination for all months. The “best” model was identified for each GACC by selecting the model with the lagged input that represents highest Weighted Nash-Sutcliffe efficiency (E_w).

- Following my previous comment, why the combination selection is performed according to the weighted NSE for all months, and each month is not considered separately for selection? This way, each month and each GACC will have a different variable combination.

This is a great suggestion. However, that would have created 108 (9 GACCs*12 months) models. While mathematically it is feasible to build such models, this approach would assume total random nature of wildfire burned area and danger prediction. However, numerous studies have indicated that wildfire danger and burned area prediction is not random and depend on the ecosystem type. As cited in the manuscript, previous research indicates that Fuel limited systems typically rely on pre-fire season conditions to grow fuels that carry fire, thus influencing the total burned area. On the other hand, Flammability-limited systems typically need to be dried to sustain combustion (Littell et al., 2009; Stavros et al., 2014a; Swetnam and Betancourt, 1998). The motivation of our study was to develop models that could predict wildfire burned area based on prior month hydrologic conditions. Our results are comparable with previous findings. For example, in the Northern Rockies, it is roughly half evergreen forest and half herbaceous (Figure 1); evergreen forest typically need to be dried to sustain combustion (high VPD in the month prior), while herbaceous communities typically need wet conditions months prior to grow fuels (high SSM 2 months prior). Similarly, in the Northwest it is roughly half evergreen (high VPD two months prior) and half shrub (high SSM three months prior). The Rocky Mountains are mostly herbaceous and shrubland (high SSM three months prior) but has some evergreen (high VPD one month prior). In Northern California, landcover is mostly evergreen (high VPD one month prior) with some shrub (high soil moisture two months prior).

Technical Comments:- Please define acronyms USFS.
USFS stands for United States Forest Service

in line 36.- Figure 2, 3, and 4, please align the axis labels.-

Here are the updated figures:

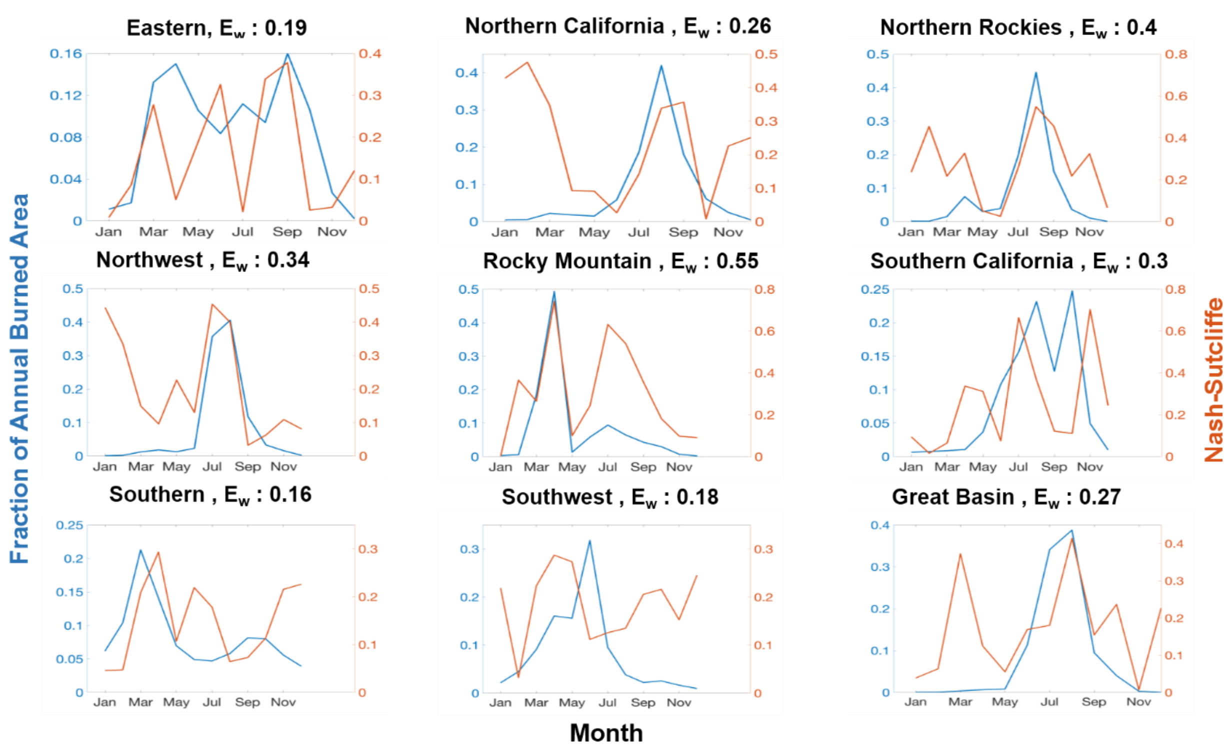


Figure 2

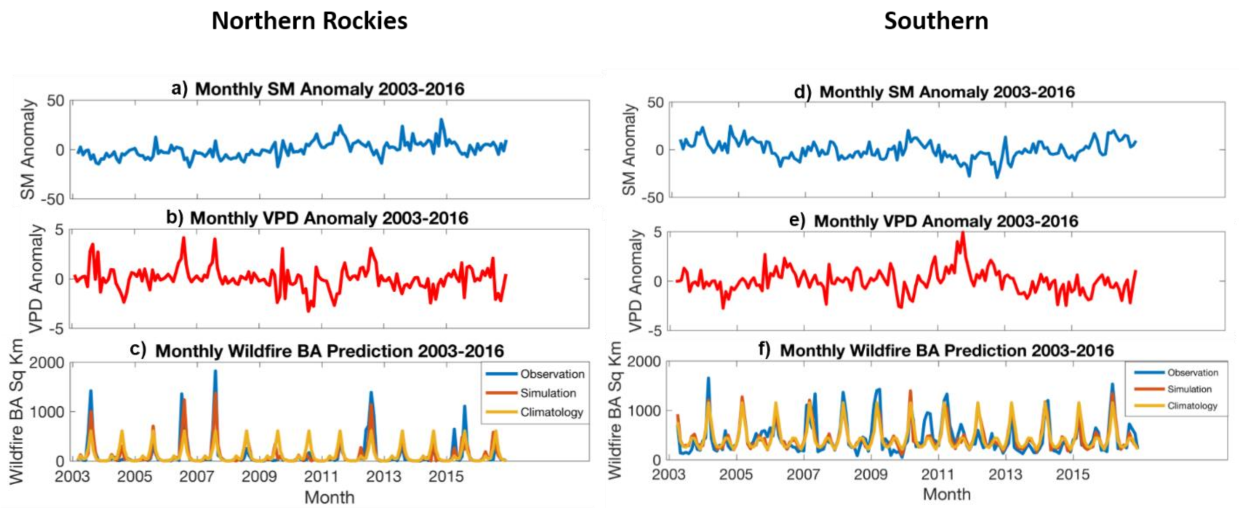


Figure 3

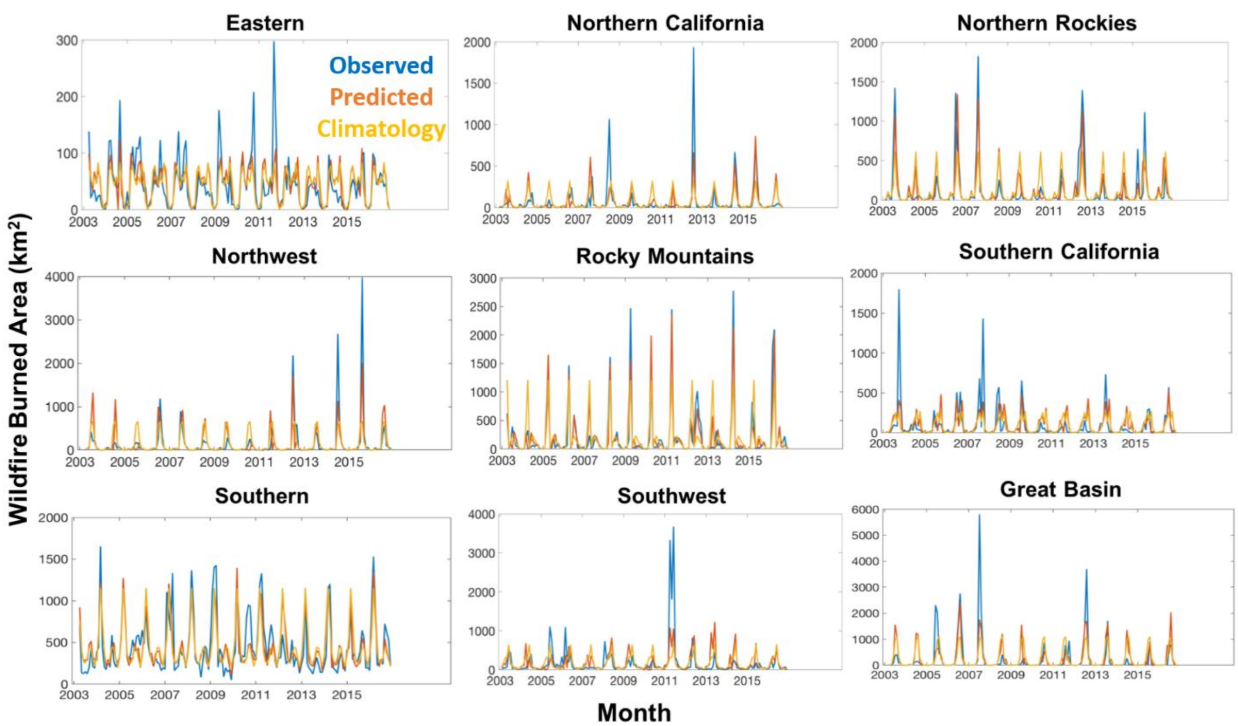


Figure 4

Figure 2, Is the orange line the NSE value for the best model?- Yes, the orange line in NSE for best model. Here is the updated caption for figure 2:

Figure 2. Best model selection based on the monthly Nash-Sutcliffe for each GACC. The blue line shows variable peak fire month by mean annual area

burned (FAB) and the orange line shows the monthly Nash-Sutcliffe of best model for each GACC showing variable peak fire month. The weighted Nash-Sutcliffe (*Ew*) is calculated using the different combinations of VPD and SSM. The best model was selected based on highest *Ew*, which demonstrates the relative strength of the different models by GACC.

Please number the equations.-

$E_w = \sum_{j=1}^{12} E_j \, * \, FAB_j$ (1)

$E_j = 1 - \frac{\sum_{i=1}^{n}(AB_{obs,i} - AB_s)^2}{\sum_{i=1}^{n}(AB_{obs,i} - AB_C)^2}$ (2)

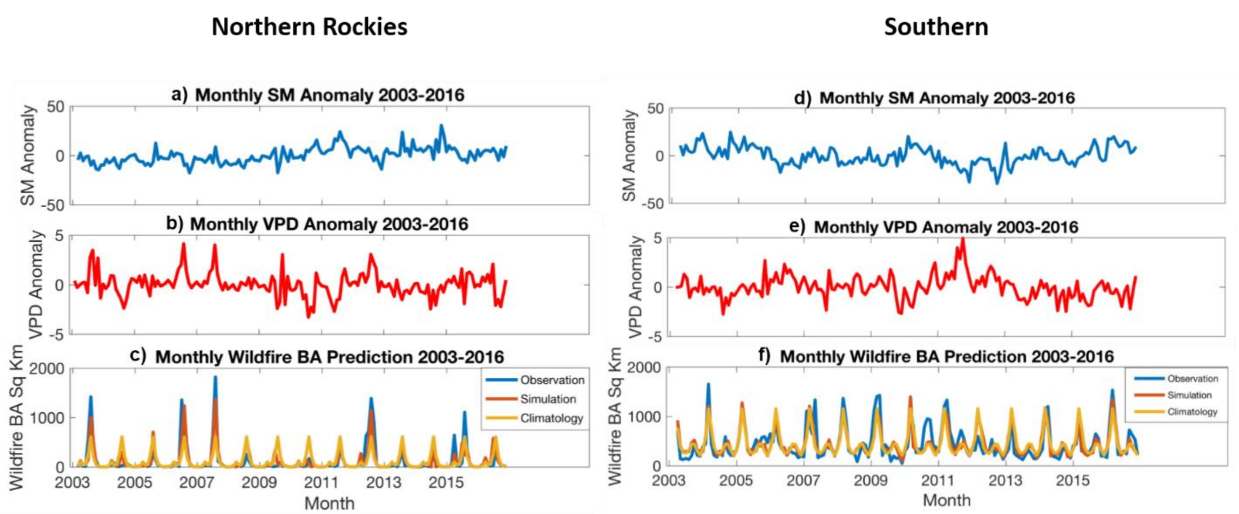
$AB_s = AB_C + AB_A$ (3), $where$

$AB_A = a + b \, * \, (VPD_A) + c \, * \, (SM_A)$ if $E_j > 0$

$AB_A = 0$ if $E_j \leq 0$

Figure 3, please label each subplot and specify which subplot is for which GACC.-

We have updated figure 3:



Line 279, I didn't find Table 2. This was a typo. The text will be changed to Table 1

Anonymous Referee #2

We would like to thank the referee for the valuable comments. We have prepared a point to point response to the comments and will incorporate the changes in the revised manuscript.

**General comments:
This manuscript aims to predict monthly fire danger across the United States at the scale of the Geographic Area Coordination Centers (GACC), using the preceding vapor pressure deficit (VPD) from AIRS satellite mission and assimilated soil moisture as two predictors. Overall it is a very interesting topic and can provide valuable information for fire management planning. The results showed that the prediction of monthly area burned worked better than using the long term monthly mean climatology of fire activities. However, a more meaningful test or evaluation of the forecasting capability would be to quantify if the approach can capture various categories of fire danger, especially considering there are already quite a few forecasting models available as mentioned in the Introduction.

The goal of this study was not to compete with all other wildfire forecasting models. This study was intended to demonstrate the capabilities of satellite hydrologic data to predict long lead monthly wildfire burned area at spatial and temporal scales commensurate with regional and global fire management decision-making. While previous studies look at long lead wildfire danger forecasting (Parks et al., 2014; Shabbar et al., 2011; Westerling et al., 2002; Xiao and Zhuang, 2007), this study is the first one that demonstrates the potential of satellite hydrologic variables of soil moisture and vapor pressure deficit to forecast monthly wildfire burned area. Here is part of the introduction that mentions this:

A number of previous studies have demonstrated relationships between fire and hydrological indicators (Parks et al., 2014; Shabbar et al., 2011; Westerling et al., 2002; Xiao and Zhuang, 2007). Vapor pressure deficit (VPD), specifically has been shown as an indicator of fire danger (Abatzoglou and Williams, 2016; Seager et al., 2015; Williams et al., 2014) and is considered a viable proxy for evapotranspiration demand and plant water stress during drought (Behrangi et al., 2015; Weiss et al., 2012). VPD is defined as the amount of moisture in the air compared to amount of moisture the air can hold. (Behrangi et al., 2016) shows that VPD in monthly time-scales has the advantage in capturing onsets of meteorological droughts earlier than other variables such as precipitation. This advantage could be helpful in developing fire-danger forecast models. More recently, a study using model-assimilated observations of terrestrial water storage from NASA's GRACE mission to asses pre-fire-season surface soil moisture conditions (January-April) demonstrated skill in predicting both the number of fires and fire burned area in the following May-April period (Jensen et al., 2017).

The goal of this work is to investigate the utility of remotely sensed hydrology observations for predicting fire danger, defined as the amount of area likely to burn given an ignition, at spatial and temporal scales commensurate with regional and global fire management decision-making. Specifically, the objective is to investigate the utility of remotely sensed satellite-observed vapor pressure deficit (VPD) from NASA's AIRS mission and surface soil moisture (SSM) from a numerical data-assimilation of terrestrial water storage from NASA's GRACE mission as indicators for predicting monthly fire danger across the United States from 2002 until 2016 at the scale of the Geographic Area Coordination Centers (GACC) (Figure 1). To meet the objective, we test the hypotheses that burned area varies monthly as a function of previous months' water availability in the soil (SSM) and evaporative demand (i.e., previous months' VPD).

In terms of the evaluation metrics, we have evaluated each of our nine models with the climatology using NSE (or R2 in this case) metric which is widely used in fire literature.

Although VPD and SSM had been shown highly correlated with fire activities from other studies and for sure these two need to be included, I think it would still be necessary to explore other variables such as temperature and have a rigorous variable selection.

We appreciate this suggestion. While it is certainly true that a number of variables are critical in wildfire danger, we would like to point out that this study was solely aimed to forecast fire danger using satellite hydrologic information. Among satellite hydrologic variables, we selected GRACE-assimilated SSM since Jensen et al., 2017 showed that pre-season GRACE-assimilated SSM product is highly correlated with wildfire burned area in the fire season. The reason we selected satellite-based AIRS VPD was because several studies have shown that VPD is better correlated to wildfire danger compared to other variables such as temperature or relative humidity (Williams et al., 2019; Seager et al., 2015; Williams et al., 2014). VPD is an attractive hydrologic variable that incorporates both properties of relative humidity and temperature. While other variables could be used to forecast wildfire danger, the results of our model indicates that the combination of SSM and VPD has improved wildfire danger forecasting significantly (Please refer to Table 1). The NSE for all GACCs show significant improvement compared to the NSE of the climatology.

Seager, R., Hooks, A., Williams, A. P., Cook, B., Nakamura, J. and Henderson, N.: Climatology, variability, and trends in the U.S. Vapor pressure deficit, an important fire-related meteorological quantity, J. Appl. Meteorol. Climatol., 54(6), 1121–1141, doi:10.1175/JAMC-D-14-0321.1, 2015.

Williams, A. P., Seager, R., Macalady, A. K., Berkelhammer, M., Crimmins, M. A., Swetnam, T. W., Trugman, A. T., Buenning, N., Noone, D., Mcdowell, N. G., Hryniw, N., Mora, C. I. and Rahn, T.: Correlations between components of the water balance and burned area reveal new insights for predicting forest fire area in the southwest United States, Int. J. Wildland Fire, 24(1), 14–26, 2014.

Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., & Lettenmaier, D. P., Observed impacts of anthropogenic climate change on wildfire in California, Earth's Future, 2019.

For the model assessment, I think some standard statistics such as R2 between observed and predicted monthly burned areas would be helpful.

In this paper, we have used Nash-Sutcliffe (NSE) for assessing the performance of model. In linear regression-based models, Nash-Sutcliffe is equivalent to R2 and is calculated as:

$$E_j = 1 - \frac{\sum_{i=1}^{n}\left(AB_{obs,i} - AB_{s,i}\right)^2}{\sum_{i=1}^{n}\left(AB_{obs,i} - AB_C\right)^2}$$

where n is total number of observations, $AB_{obs,i}$ is observed area burned in month j and $AB_{S,i}$ is the model simulated area burned for month j, and AB_C is the mean area burned in month j over the climatological record

** Other specific comments are listed below.1. Introduction can be a bit more thorough, especially with regard to the fire management need, such as how forecasting of fire danger is helpful for fire prevention and suppression, and what is the preferred lead time?

In the following paragraphs, we have explicitly talked about how forecasting of fire danger is helpful for fire prevention and suppression, and what is the preferred lead time. Please see the highlighted area. The preferred lead time is months since well-accepted short-term (weekly to 10 days) fire danger forecast are available. The purpose of monthly fire danger forecast allocate fire management resources across jurisdictional boundaries (e.g., state or national) when local response capabilities are exhausted.

Fires are a key disturbance globally, acting as a catalyst for terrestrial ecosystem change and contributing significantly to both carbon emissions (Page et al., 2002) and changes in surface albedo (Randerson et al., 2006). Furthermore, the socioeconomic impact of fires includes human casualties as well as approximately $21b loss in property from 1995-2015 (USD 2015; NatCatSERVICE, accessed October 2017). Several studies have shown that in the Western US, fires have demonstrated a positive trend in annual area burned that will likely continue into the future (Littell et al., 2010; Stavros et al., 2014b). In response to increasing annual area burned and detrimental losses, the US Forest Service has increased funding for active fire management from 16 to 52% of their total budget that would have otherwise been spent on land management and research (USFS, 2015) . These increased costs translate directly to increased United States Forest Service (USFS) information needs because any intra-or interannual early warning helps decrease the cost of preparing for, managing, and, when necessary, suppressing fires that occur.

The severe consequences of wildfires motivate the need for capabilities to map fire potential on timescales ranging from days to months. Operational fire management agencies rely on two primary sources of information to predict fire danger: meteorological forecasts and expert judgment (e.g. https://www.predictiveservices.nifc.gov/outlooks/outlooks.htm; accessed 28 November 20). Fire danger forecasts are generally reported in the form of qualitative categories (e.g. normal, below-normal and above-normal). Such categories are used by the US National Interagency Fire Center (NIFC) to allocate fire management resources across jurisdictional boundaries (e.g., state or national) when local response capabilities are exhausted. These qualitative metrics are derived from many information layers including fire danger indices. Fire danger indices (e.g., the US National Fire Danger Rating System – NFDRS; Bradshaw et al., 1983) typically use meteorological input (Abatzoglou & Brown, 2012; Holden & Jolly, 2011) that is sometimes not available with the long-lead time needed for regional, transboundary fire management planning.

Gridded meteorological data often have several limitations. The data are interpolated between weather stations (Daly et al., 2008), or developed by combing spatial and temporal attributes of different climate data and validated with weather stations (Abatzoglou, 2013; Abatzoglou and Brown, 2012), or provided from meteorological reanalysis, i.e., numerical weather prediction models that assimilate weather station data (Kalnay et al., 1996; Roads et al., 1999). These weather stations are sometimes far removed from the location of interest, and are not always good estimates of local climate, especially in complex topography. Moreover, forecasts beyond 10 days for a given landscape location have low skill (Bauer et al., 2015). The mentioned limitations of current operational fire danger systems result in the need for additional information that could help improve predictions of fire danger at monthly intervals and to help allocate resources across the country as the active fire season progresses and resources become strained. This added information could result in less subjective and more accurate fire danger forecasts for larger areas and for timescales of a month or longer.

2. Fire danger (Line 78) was defined as amount of area likely to burn given an ignition. The GFED burned area dataset, however, represented the actual area burned, which included the contribution of both ignition probability and fire spread once ignited. Please clarify.

As you have correctly pointed out, GFED is a burned area dataset which represents the fire burned area. As stated in the manuscript, there are numerous studies that have looked at forecasting fire burned area using climatic or hydrologic information without separating ignition probability and the fire spread once ignited (Parks et al., 2014; Westerling et al., 2002; Xiao and Zhuang, 2007). This research work was based on the concept of these studies that predict wildfire burned area directly using prior hydrologic conditions. The burned area forecast model could be integrated with other models such as ignition probability and fire spread models. To avoid confusion, we have eliminated the phrase "given an ignition".

Parks, S. A., Parisien, M.-A., Miller, C. and Dobrowski, S. Z.: Fire Activity and Severity in the Western US Vary along Proxy Gradients Representing Fuel Amount and Fuel Moisture, edited by M. Germino, PLoS ONE, 9(6), e99699, doi:10.1371/journal.pone.0099699, 2014.

Westerling, A. L., Gershunov, A., Cayan, D. R. and Barnett, T. P.: Long lead statistical forecasts of area burned in western U.S. wildfires by ecosystem province, Int. J. Wildland Fire, 11(4), 257, doi:10.1071/WF02009, 2002.

Xiao, J. and Zhuang, Q.: Drought effects on large fire activity in Canadian and Alaskan forests, Environ. Res. Lett., 2(4), 044003, doi:10.1088/1748-9326/2/4/044003, 2007.

3. What land cover product was used (e.g. in Figure 1)? For GFED Burned Area map, it doesn't look like the unit is in sq km as the color bar shows 0-1. Also, I think it would be helpful to show a map of long term mean August burned area from GFED.

As pointed in line 107, the 2011 National Landcover Database (NLCD 2011) (Homer et al., 2015) was used in the study.

Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N., Wickham, J. and Megown, K.: Completion of the 2011 National Land Cover Database for the conterminous United States–representing a decade of land cover change information, Photogramm. Eng. Remote Sens., 81(5), 345–354, 2015.

The GFED unit is in sq km. Since most fires in a given month cover a small portion of each 0.25 degree cell, we used 0-1 scale bar so that the spatial distribution of fires can be seen. Here is the map of long-term mean August burned area which will be added to the manuscript in Figure 1:

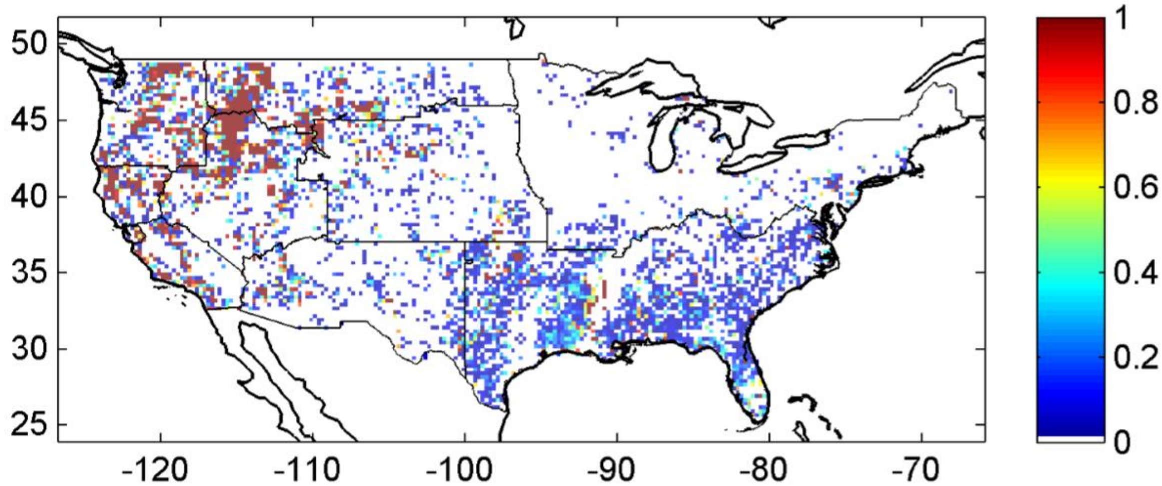


Figure 1 addition: Long term August GFED Burned Area

As shown, wildfires occurs all around the CONUS in August. The amount of area burned however is considerably larger in the Western United such as Northern Rockies, North West, Rocky Mountain and Northern California

4. How the regression models were built needs clarification. For example, for each month and each GACC, each sample is a 0.25 deg grid cell? Please list the sample size for each GACC.

Yes. Each sample is a 0.25 degree grid cell. Here is a table of number of non-agriculture grids per each GACC:

GACC	Eastern	Northern CA	Northern Rockies	Northwest	Rocky Mountain	Southern CA	Southern	Southwest	Great Basin
Number of Pixels	1564	255	898	694	1415	351	2106	1358	1161

Also, we have calculated the mean number of burned grid cells for each GACC and each month:

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Eastern	7.36	13.93	71.93	116.71	72.71	70.29	85.07	76.93	59.86	34.29	20.43	3.07
Northern CA	6.50	9.57	17.36	20.36	17.57	19.43	21.07	23.00	20.50	30.86	31.79	11.36
Northern Rockies	3.14	2.64	19.21	68.36	63.07	18.43	45.57	71.36	73.21	76.43	42.64	2.21
Northwest	5.21	9.07	21.36	38.71	46.07	27.36	53.14	66.29	58.00	104.86	88.71	12.00
Rocky Mountain	10.43	15.71	110.36	136.00	42.00	43.00	58.71	52.43	73.29	43.86	19.14	6.86
Southern CA	8.93	13.36	17.93	17.36	22.64	26.71	28.36	26.57	22.86	25.36	22.29	10.79
Southern	331.21	457.79	778.21	576.93	376.79	428.29	413.71	442.86	512.14	552.21	385.64	258.86
Southwest	35.14	49.00	75.93	60.29	59.43	69.57	57.29	47.43	57.00	63.00	48.14	28.14
Great Basin	2.50	4.21	18.43	28.79	26.21	34.14	61.50	69.07	64.50	48.00	20.50	3.07

5. Some of terms described in Line 134-136 are not consistent with those shown in the Equation (Line 133), e.g., Xobs vs. ABobs.

Each GACC uses the “best” prior monthly VPD-SSM combination for all months. The “best” model was identified for each GACC by selecting the model with the lagged input that represents highest Weighted Nash-Sutcliffe efficiency (E_w):

$$E_w = \sum_{j=1}^{12} E_j \; * \; FAB_j \quad (1)$$

where FAB_j is the mean historical fraction of annual area burned in month j, and E_j is the Nash-Sutcliffe (E) for any given month (j). E_j (Nash and Sutcliffe, 1970) is a metric that measures the skill of the model against the skill of the long term mean value (i.e. persistence), defined as:

$$E_j = 1 - \frac{\sum_{i=1}^{n}\left(AB_{obs,i} - AB_{s,i}\right)^2}{\sum_{i=1}^{n}\left(AB_{obs,i} - AB_C\right)^2} \quad (2)$$

where n is total number of observations, $AB_{obs,i}$ is observed area burned in month j and $AB_{S,i}$ is the model simulated area burned for month j, and AB_C is the mean area burned in month j over the climatological record. E can range between 0 and 1. E of zero shows that the model performance is as good as the mean of observations over the entire record. If E exceeds 0, the model preforms better than the mean of observations and if E falls below zero, the mean of observations is a better predictor than the model simulations. An E of 1 represents the perfect prediction by the model.

6. Would it make more sense to summarize the forecasting skill over the fire season rather than whole year?

Over the past decades, there has been a significant changes in the intensity, duration, timing of fire regimes due to climate change, which is likely to worsen over the next decades (Dale et al., 2001; Flannigan et al., 2000). Although most wildfire danger forecasting focus only on the fire season, we decided to develop models that predict fire danger all year round. Year round wildfire occurrence would also help USFS and NIFC stakeholder better prepare, manage and suppress fires that occur.

Dale, V. H., Joyce, L. A., McNulty, S., Neilson, R. P., Ayres, M. P., Flannigan, M. D., ... & Simberloff, D. (2001). Climate change and forest disturbances: climate change can affect forests by altering the frequency, intensity, duration, and timing of fire, drought, introduced species, insect and pathogen outbreaks, hurricanes, windstorms, ice storms, or landslides. BioScience, 51(9), 723-734.

Flannigan, M. D., Stocks, B. J., & Wotton, B. M. (2000). Climate change and forest fires. Science of the total environment, 262(3), 221-229.

7. Figure 3: it is hard to see the association between SM, VPD, anomalies and burned areas, I'd suggest use single column

We appreciate the comment. We believe that a single column graph would not convey the information appropriately given the three different scales (SM, VPD and Burned Area) and five different time series. We have however modified the graph. We believe that the modified would better convey the necessary information to the audience.

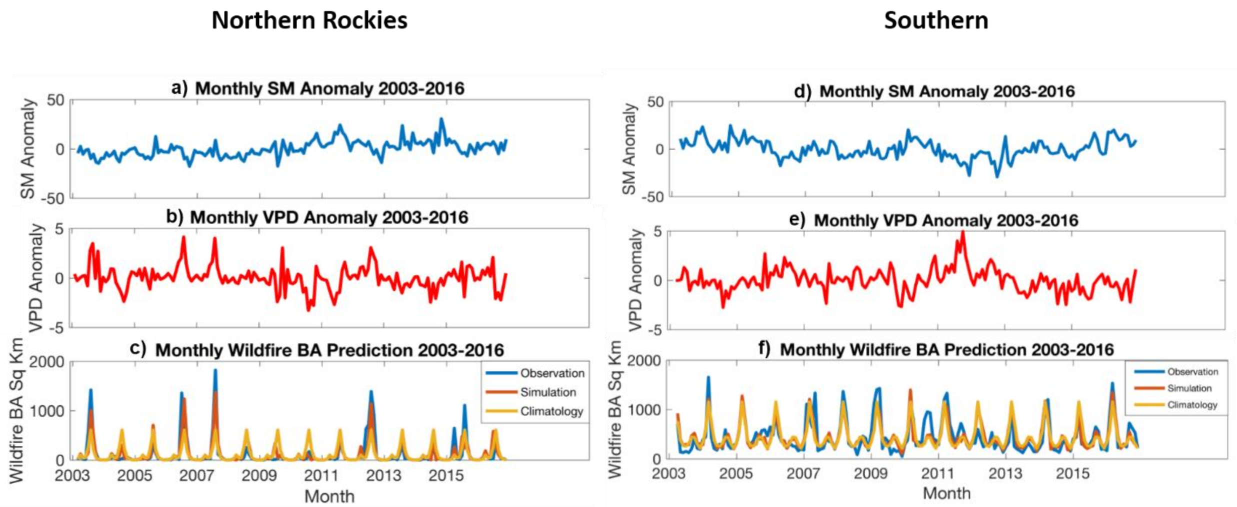


Figure 3

Satellite Hydrology Observations as Operational Indicators of Forecasted Fire Danger across the Contiguous United States

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Keywords: wildfire; vapor pressure deficit (VPD); soil moisture; prediction; GRACE; AIRS

Abstract

Traditional methods for assessing fire danger often depend on meteorological forecasts, which have reduced reliability after ~10 days. Recent studies have demonstrated long lead-time correlations between pre-fire-season hydrological variables such as soil moisture and later fire occurrence or area burned, yet no potential value of these relationships for operational forecasting have not been studied. Here, we use soil moisture data refined by remote sensing observations of terrestrial water storage from NASA's GRACE mission and vapor pressure deficit from NASA's AIRS mission to generate monthly predictions of fire danger at scales commensurate with regional management. We test the viability of predictors within nine US Geographic Area Coordination Centers (GACCs) using regression models specific to each GACC. Results show that the model framework improves interannual wildfire burned area prediction relative to climatology for all GACCs. This demonstrates the importance of hydrological information to extend operational forecast ability into the months preceding wildfire activity.

1. Introduction

Fires are a key disturbance globally, acting as a catalyst for terrestrial ecosystem change and contributing significantly to both carbon emissions (Page et al., 2002) and changes in surface albedo (Randerson et al., 2006). Furthermore, the socioeconomic impact of fires includes human casualties as well as approximately $21b loss in property from 1995-2015 (USD 2015; NatCatSERVICE, accessed October 2017). Several studies have shown that in the Western US, fires have demonstrated a positive trend in annual area burned that will likely continue into the future (Littell et al., 2010; Stavros et al., 2014b). In response to increasing annual area burned and detrimental losses, the US Forest Service has increased funding for active fire management from 16 to 52% of their total budget that would have otherwise been spent on land management and research (USFS, 2015) . These increased costs translate directly to increased USFS (United States

Forest Service) information needs because any intra-or interannual early warning helps decrease the cost of preparing for, managing, and, when necessary, suppressing fires that occur.

The severe consequences of wildfires motivate the need for capabilities to map fire potential on timescales ranging from days to months. Operational fire management agencies rely on two primary sources of information to predict fire danger: meteorological forecasts and expert judgment (e.g. https://www.predictiveservices.nifc.gov/outlooks/outlooks.htm; accessed 28 November 20). Fire danger forecasts are generally reported in the form of qualitative categories (e.g. normal, below-normal and above-normal). Such categories are used by the US National Interagency Fire Center (NIFC) to allocate fire management resources across jurisdictional boundaries (e.g., state or national) when local response capabilities are exhausted. These qualitative metrics are derived from many information layers including fire danger indices.

Fire danger indices (e.g., the US National Fire Danger Rating System – NFDRS; Bradshaw et al., 1983) typically use meteorological input (Abatzoglou & Brown, 2012; Holden & Jolly, 2011) that is sometimes not available with the long-lead time needed for regional, transboundary fire management planning. Gridded meteorological data often have several limitations. The data are interpolated between weather stations (Daly et al., 2008), or developed by combing spatial and temporal attributes of different climate data and validated with weather stations (Abatzoglou, 2013; Abatzoglou and Brown, 2012), or provided from meteorological reanalysis, i.e., numerical weather prediction models that assimilate weather station data (Kalnay et al., 1996; Roads et al., 1999). These weather stations are sometimes far away from the location of interest, and are not always good estimates of local climate, especially in complex topography. Moreover, forecasts beyond 10 days for a given landscape location have low skill (Bauer et al., 2015). The mentioned limitations of current operational fire danger systems result in the need for additional information that could help improve predictions of fire danger at monthly intervals and to help allocate resources across the country as the active fire season progresses and resources become strained. This added information could result in less subjective and more accurate fire danger forecasts for larger areas and for timescales of a month or longer.

A number of previous studies have demonstrated relationships between fire and hydrological indicators (Parks et al., 2014; Shabbar et al., 2011; Westerling et al., 2002; Xiao and Zhuang, 2007). Vapor pressure deficit (VPD), specifically has been shown as an indicator of fire danger (Abatzoglou and Williams, 2016; Seager et al., 2015; Williams et al., 2014) and is considered a viable proxy for evapotranspiration demand and plant water stress during drought (Behrangi et al., 2016; Weiss et al., 2012). VPD is defined as the amount of moisture in the air compared to amount of moisture the air can hold. (Behrangi et al., 2016) shows that VPD in monthly time-scales has the advantage in capturing onsets of meteorological droughts earlier than other variables such as precipitation. This advantage could be helpful in developing fire-danger forecast models. More recently, a study using model-assimilated observations of terrestrial water storage from NASA's GRACE mission to asses pre-fire-season surface soil moisture conditions (January-April) demonstrated skill in predicting both the number of fires and fire burned area in the following May-April period (Jensen et al., 2017).

The goal of this work is to investigate the utility of remotely sensed hydrology observations for predicting fire danger, defined as the amount of area likely to burn, at spatial and temporal scales commensurate with regional and global fire management decision-making. Specifically, the objective is to investigate the utility of remotely sensed satellite-observed vapor pressure deficit (VPD) from NASA's AIRS mission and surface soil moisture (SSM) from a numerical data-assimilation of terrestrial water storage from NASA's GRACE mission as indicators for predicting monthly fire danger across the United States from 2002 until 2016 at the scale of the Geographic Area Coordination Centers (GACC) (**Figure 1**). To meet the objective, we test the hypothesis that burned area varies monthly as a function of previous months' water availability in the soil (SSM) and evaporative demand (i.e., previous months' VPD).

2. Methods

2.1. Datasets

For the purpose of this study, four input data sets were used (Figure 1). First, monthly VPD (panel a) was generated from the AIRS near surface air temperature (T_{mean}) and relative humidity (RH) Version 6 (Aumann et al., 2003; Goldberg et al., 2003). Please refer to (Behrangi et al., 2016) for the formulation based on monthly air temperature (T_{mean}) and dewpoint temperature (Td_{mean}) as well as the reliability of this formulation for monthly VPD derivation. The data are in 0.5 degree spatial resolution and available since September 2002. The second input to the model was monthly surface soil moisture data (panel b) were produced at the NASA Goddard Space Flight Center (GSFC) using the Catchment Land Surface Model (CLSM) (a physically based land surface model) and assimilated ground and space-based meteorological observations (Houborg et al., 2012; Reager et al., 2015; Tapley et al., 2004; Zaitchik et al., 2008). The SSM data are available since April 2004 and in 0.25 degree spatial resolution. The third dataset was Global Fire Emissions Database version 4 (GFED-4s) provided wildfire burned area, generated at 0.25 degree spatial resolution. GFED-4s is primarily derived from MODIS from 2001 to present and is reported as fraction of a cell burned for a given month (van der Werf et al., 2017). GFED data are available since 1997. Panel c shows GFED burned area in August 2010 while panel e shows long-term August burned area in sq km. As shown, wildfires occurs all around the CONUS in August. The amount of area burned however is considerably larger in the Western United such as in Northern Rockies, North West, Rocky Mountain and Northern California. Finally, in this study, we have excluded agricultural fires by masking out agricultural regions as classified by the 2011 National Landcover Database (panel d) (NLCD 2011) (Homer et al., 2015).

For consistency, all datasets were converted using linear interpolation into monthly, 0.25 degree spatial resolution products that were then used to perform the model training and analysis for the period 2003 through 2016.

2.2. Analysis

GACCs are geopolitical boundaries that represent similar fire-weather types and are used to allocate fire management resources across the contiguous United States (CONUS) (Abatzoglou and Kolden, 2013; Finco et al., 2012) (Figure 1). In this study, we predict anomalous monthly burned area using a linear regression model; a separate model is developed for each GACC and for each month in a climatological sense. All fire events, for a given GACC and a month of the year are selected as a single population for model training. For example, all fires occurring in the Northern Rockies GACC, during the months of February 2004, February 2005, February 2006, etc. through February 2016 are placed into a single population. Each monthly, 0.25 degree fire burned area observation has a matched SSM and VPD observation at the corresponding time and grid location. These sets are then used to train the model, and various time lags are imposed between the independent variables (SSM and VPD) and the dependent variable (burned area) in order to maximize predictive skill.

Each GACC uses the "best" prior VPD-SSM combination for all months. The "best" model was identified for each GACC by selecting the model with the lagged input that represents highest Weighted Nash-Sutcliffe efficiency (E_w):

$$E_w = \sum_{j=1}^{12} E_j * FAB_j \qquad (1)$$

where FAB_j is the mean historical fraction of annual area burned in month j, and E_j is the Nash-Sutcliffe (E) for any given month (j). E_j (Nash and Sutcliffe, 1970) is a metric that measures the skill of the model against the skill of the long term mean value (i.e. persistence), defined as:

$$E_j = 1 - \frac{\sum_{i=1}^{n}\left(AB_{obs,i} - AB_{s,i}\right)^2}{\sum_{i=1}^{n}\left(AB_{obs,i} - AB_C\right)^2} \qquad (2)$$

where n is total number of observations, $AB_{obs,i}$ is observed area burned in month j and $AB_{S,i}$ is the model simulated area burned for month j, and AB_C is the mean area burned in month j over the climatological record. E can range between 0 and 1. E of zero shows that the model performance is as good as the mean of observations over the entire record. If E exceeds 0, the model preforms better than the mean of observations and if E falls below zero, the mean of observations is a better predictor than the model simulations. An E of 1 represents the perfect prediction by the model.

We constructed a forecasting method that would only rely on the model prediction of burned area, as opposed to the burned area climatology, if the model had demonstrated skill for a given month. The estimation of E_w for each GACC and for each monthly model ensures that months with higher predictive skill are assigned a higher weight in the combined time series. Also, months exhibiting higher amount of historical wildfire activity are assigned a higher weight as well.

The model is then defined as follows:

$$AB_s = AB_C + AB_A \quad (3) \quad , where \qquad AB_A = a + b * (VPD_A) + c * (SM_A) \; if \; E_j > 0$$

$$AB_A = 0 \; if \; E_j \leq 0$$

AB_s is the simulated area burned for a given month, AB_c is the climatological area burned or the mean annual area burned by month, VPD_A and SSM_A are the anomalous VPD and SSM in one, two or three months prior to the wildfire month. Different combinations of prior VPD and SSM observations were tested to represent the reliability of a single VPD-SSM model per GACC for the entire year.

Finally, AB_S is compared to AB_C by comparing two Nash-Sutcliffe (E) values of the entire time series. The first E is measured using the 2003-2016 monthly time series of model predictions and observations ($E_{simulated,observation}$). The second E is computed by using 2003-2016 monthly time series of climatology and observations ($E_{climatology,observation}$). If $E_{simulated,observation}$ exceeds $E_{climatology,observation}$, the model has more accuracy compared to the climatology. If $E_{climatology,observation}$ is greater than $E_{simulated,observation}$, then the climatology has more accuracy in forecasting wildfire activity.

3. Results

Figure 2 shows the hydrologic variable combination used to develop the best model of anomaly burned area using the monthly Nash-Sutcliffe (E), the weighted Nash-Sutcliffe (E_w), and the fraction of annual area burned for each month, while Table 1 shows the best variable combination for each GACC. There are some notable patterns, though few without exceptions. For example, Northern California, Northern Rockies and the Northwest all have the same peak month (August) for area burned, while also having significant fractions of evergreen vegetation (Figure 1). Area burned in the Great Basin also peaks in August, however it does not have substantial evergreen landcover, although at this spatial scale we can not determine if that is where fires happen. The models with the highest relative predictive ability throughout the year (denoted by weighted Nash-Sutcliffe) are generally in the GACCs with substantial landcover and dominated by fuel limited systems (herbaceous and shrublands): Great Basin, Southern California, Rocky Mountains, Northwest, Northern Rockies; however, the Southwest also has heavy herbaceous vegetation, but has relative low predictability throughout the year. Similarly, the Northern Rockies, Northwest, Rocky Mountains and Great Basin all have high predictability in their peak burned area month and are all substantially covered by herbaceous vegetation, but the Southwest does not. One pattern that is robust is that the Great Basin, the Southwest, and Southern California all rely on 1-month lead soil moisture in their predictive model and all also have substantial shrubland cover. Notably, the Eastern, Northern Rockies, Rocky Mountains, Southern California and Southern GACCs all have bimodal burned area distributions, but no similar landcover characteristics to explain the pattern.

Figure 3 shows two example cases of model predictions based on hydrological variables. We show results for our best and worst performing GACC in order to capture the range of model skill in different fire climate regions. For our best preforming GACC, the Northern Rockies, we see consistent peaks in between dominant hydrologic variable, VPD and the fire area burned, suggesting the dominant role of VPD in fire burned area prediction for that GACC (Table 1). These strong relationships between hydrology and wildfire occurrence in the Northern Rockies confirms the findings of the previous studies (Littell et al., 2009; Westerling et al., 2011). For our worst performing GACC, the Southern, two hydrologic variables are seemingly much more connected and it is less clear what drives the pattern of monthly area burned.

In order to evaluate the model predictions against the observations, we have calculated two Nash-Sutcliffe coefficients (Table 1). As shown, for all GACCs, the model is forecasting the wildfire activity with higher accuracy than the climatology, but the improvement is variable by GACC. The results reveal that the Rocky Mountains and Northern Rockies GACCs have the best model performance (E of 0.82 and 0.64 respectively), while the Southwest and Southern CA (E of 0.34 and 0.35 respectively) show the least model performance. Similar to the time series of the Eastern and Southern GACCs, the model has not improved the climatology to a great extent. In all other regions, the improvement of the simulated compared to the climatology is substantial. The key difference between overall evaluation metric (E_{S-C}) and the time series is that the time series demonstrate the variability of predictive ability from month to month.

Figure 4 shows the time series of wildfire burned area observation (blue), simulation (red) and climatology (yellow) for nine different GACCs from 2003 through 2016. This figure shows that the performance of the model varies by location and months. In general, the models capture interannual variability for most GACCs. Notably in Figure 4, some months show the simulation has higher agreement to the observations than does the climatology. In the Southern GACCs, model performance is relatively similar to the climatology. In the Southern GACC, both the simulation and climatology indicate close agreement with the observations. In the Northern Rockies and Rocky Mountains show the highest agreement between model and observations in the higher than normal fire years. Specifically, in the Northern Rockies, the model detects expected burned area for the above-than normal fire activity years 2003, 2006, 2007 and 2012; and in the Rocky Mountains GACC, years 2006, 2008, 2009, 2011, 2015 and 2016 show high agreement between simulated and the observations. The model also detects higher than normal fire activity in Northern California years 2012, 2014 and 2015, Northwest years 2006, 2007, 2012, 2014 and 2015, Great basin years 2006, 2007, 2012 and 2013, and Eastern for years 2004, 2012 for Eastern GACC. Lastly, the simulation outperforms the climatology slightly for Southern CA and the Southwest. However, neither model nor the climatology have detected inter-annual fire activity for these regions with high accuracy.

Lastly, the models were built using only either VPD or SSM to determine the relative influence of either variable on burned area within each GAAC (Table 1, $E_{S,VPD}$ and $E_{S,SSM}$). For some of the GAACs, the influence of the variable appears to be associated with the relative fractions of landcover influenced by that variable. For example, in the Northern Rockies, it is roughly half evergreen forest and half herbaceous (Figure 1); evergreen forest typically need to be dried to sustain combustion (high VPD in the month prior), while herbaceous communities typically need wet conditions months prior to grow fuels (high SSM 2 months prior) (Littell et al., 2009; Stavros et al., 2014a). Similarly, in the Northwest it is roughly half evergreen (high VPD two months prior) and half shrub (high SSM three months prior). The Rocky Mountains are mostly herbaceous and shrubland (high SSM three months prior) but has some evergreen (high VPD one month prior). In Northern California, landcover is mostly evergreen (high VPD one month prior) with some shrub (high soil moisture two months prior) The other GAACs have less obvious relationships between landcover and hydrology.

4. Discussion and Conclusion

Wildfire activity results in billions of dollars of losses every year (USD 2015; NatCatSERVICE, accessed October 2017). Forecasting wildfire activity could therefore substantially reduce the damages associated with wildfire burned area. Historical wildfire prediction models have limitations including the mismatch in scale between fire danger models and common application, as well as the unreliability of meteorological data in remote regions. As such, current operational wildfire forecast models for forecasts >10 days are heavily based on subjective expert knowledge to predict expected area burned. Thus, the aim of this study was to predict area burned in different geographic regions (GACCs) of the United States.

There are some notable patterns in predictive model development across GACCs largely driven by landcover fractional cover and mesoscale climate (Table 1). The Great Basin, the Southwest, and Southern California GACCs all have substantial shrubland cover and have the same soil moisture predictor (1-month lead). This could be a function of the shallow rooting of shrubs. This was the only pattern by landcover that was not contradicted by mesoscale climatic influence. For example, the Great Basin, Southern California, Rocky Mountains, Northwest, and Northern Rockies models have the highest predictive ability throughout the year (E_w) and have substantial landcover dominated by fuel-limited systems (grasslands and shrublands). Fuel limited systems typically rely on pre-fire season conditions to grow fuels that carry fire, thus influencing the total burned area (Stavros et al., 2014a; Swetnam and Betancourt, 1998). Although the Southwest also has heavy grasslands, it has a relatively low predictability throughout the year, but is the GACC most influenced by the Southwest Monsoon, which can have variable onset that affects the fire season (Grissino Mayer and Swetnam, 2000). The southwest monsoon also explains why the Northern Rockies, Northwest, Rocky Mountains and Great Basin all have high predictability in their peak burned area month, but the Southwest (also substantially covered by grasslands) does not. Further substantiating the claim that mesoscale climate affects model predictability is the fact that Southern California has a bimodal distribution of fire area burned throughout the year. According to (Jin et al., 2014), there are two different kinds of fire in Southern California (those in the summer driven by hot and dry conditions and those in the fall driven by Santa Ana winds) and each have different climatic conditions explaining the number of fires and burned area.

Beyond climate and landcover, humans play a significant role in the predictability of area burned (Balch et al., 2017). This explains the bimodal fire distributions found in the Eastern, Northern Rockies, Rocky Mountains, and Southern GACCs. Most of the fires in the Eastern and Southern GACCs are prescribed burns, which can happen throughout the year (as denoted by the relatively flat, although slight bimodal distributions of percent annual area burned by month – Table 1). Also, there is a notable decoupling of the relationship between hydrologic variables and burned area (Figure 4) in the Southern GAAC, which has mostly anthropogenic fire starts, as compared to the Northern Rockies, which has mostly lightning caused ignitions when burned area peaks in Fall (Figure 2). This also explains why the simulation performs closely to the climatology (Figure 3), with only minor improvements in Nash-Sutcliffe as compared to other GACCs (Table 1). Notably, the GAACs that have a strong bimodal distribution perform less well than those that don't, however in all GAACs with bimodal distributions (Figure 2), there are substantial crop lands (which were excluded from the analysis) where agricultural burning occurs independent of the hydrologic conditions (Figure 1).

Mesoscale climate (e.g., monsoons) and anthropogenic influence on fire regimes, are likely less direct relationships between hydrologic variables and burned area. Specifically, the GACCs that are more influenced by mesoscale climate (Southern California and the Southwest) and by anthropogenic burning (Southern and Eastern) did not show a clear association between relative influence of the hydrologic variable and the relative fractions of landcover, unlike the Northern Rockies, Northwest, Northern California or Rocky Mountains.

In general, this work demonstrates how lead data on hydrologic variables that can be measured by satellite (i.e., not limited by proximity to in situ infrastructures) can be used to forecast fire danger 1-month before it happens. In all geographic regions, the models improved over normal (Table 1) and demonstrated the ability to capture interannual variability (Figure 2). Future work should consider how these models are developed by landcover type and if there are different models based on how that landcover type is typically managed (e.g., cropland vs. forest).

Acknowledgements

We would like to acknowledge Ed Delgado, at National Interagency Fire Center (NIFC). This research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration (NASA). This research was supported by Jet Propulsion Laboratory research and technological development program in Earth Sciences.

Code/Data availability

The data used for this study is freely available at:
Vapor Pressure Deficit (VPD): https://airs.jpl.nasa.gov/data/get_data
Surface Soil Moisture (SSM): https://nasagrace.unl.edu/
Fire Burned Area: https://www.globalfiredata.org/data.html
Land-cover map: https://www.mrlc.gov/nlcd11_data.php

Author contribution

AF performed the data analysis, developed the model code, and produced the figures. AF wrote the manuscript with major contributions from ENS and further input from all co-authors. All co-authors analyzed the results and contributed to discussions. JTR managed the project schedule and budget.

Competing interests

Alireza Farahmand, E. Natasha Stavros, John T. Reager, Ali Behrangi, James Randerson, and Brad Quayle declare that they have no conflict of interest

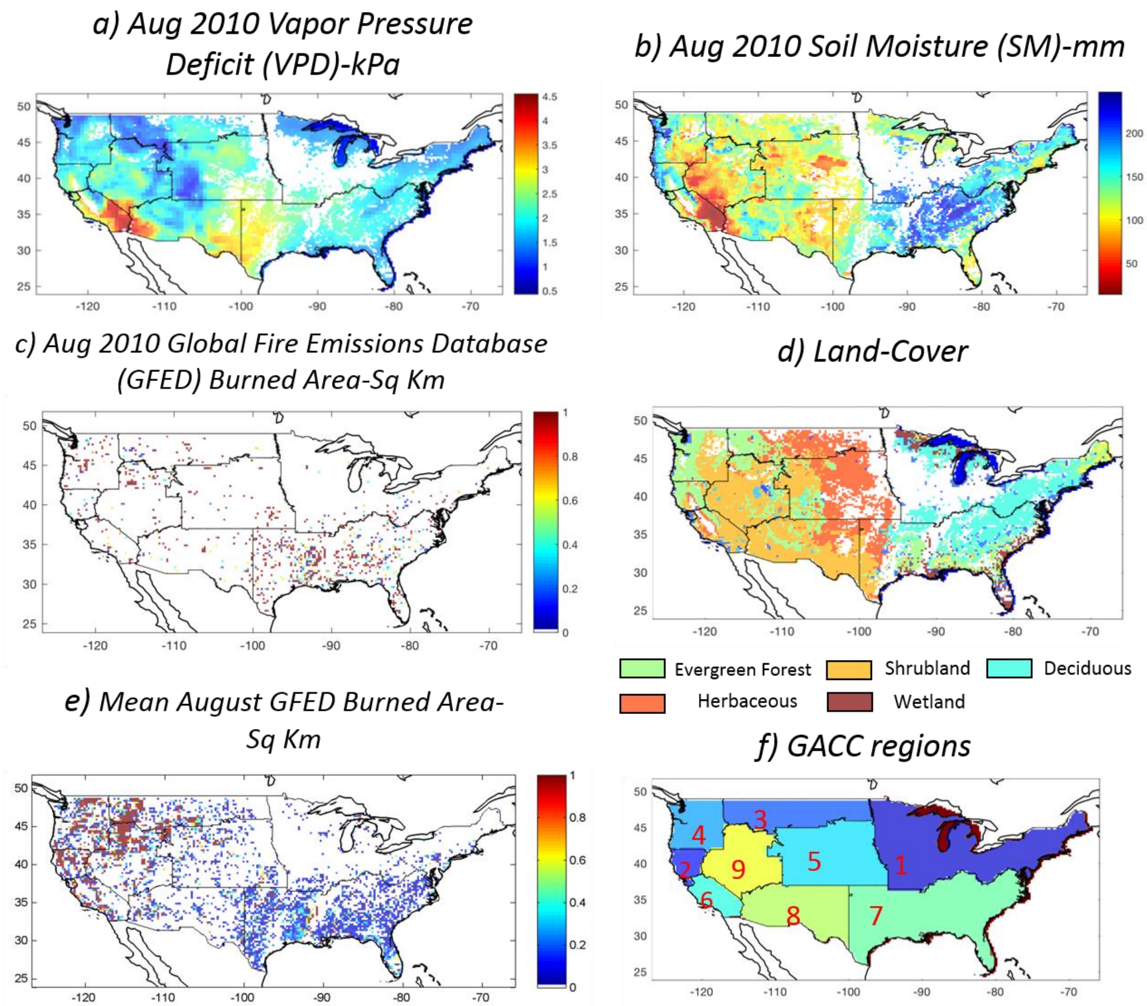

Figure 1: Snapshot of August 2010 of the datasets used in relation to the Geographic Area Coordination Centers (GACCs). Panel e shows long term mean of August GFED Burned Area. GACC regions are: 1) Eastern; 2) Northern CA; 3) Northern Rockies; 4) Northwest; 5) Rocky Mountain; 6) Southern CA; 7) Southern; 8) Southwest; and 9) Great Basin

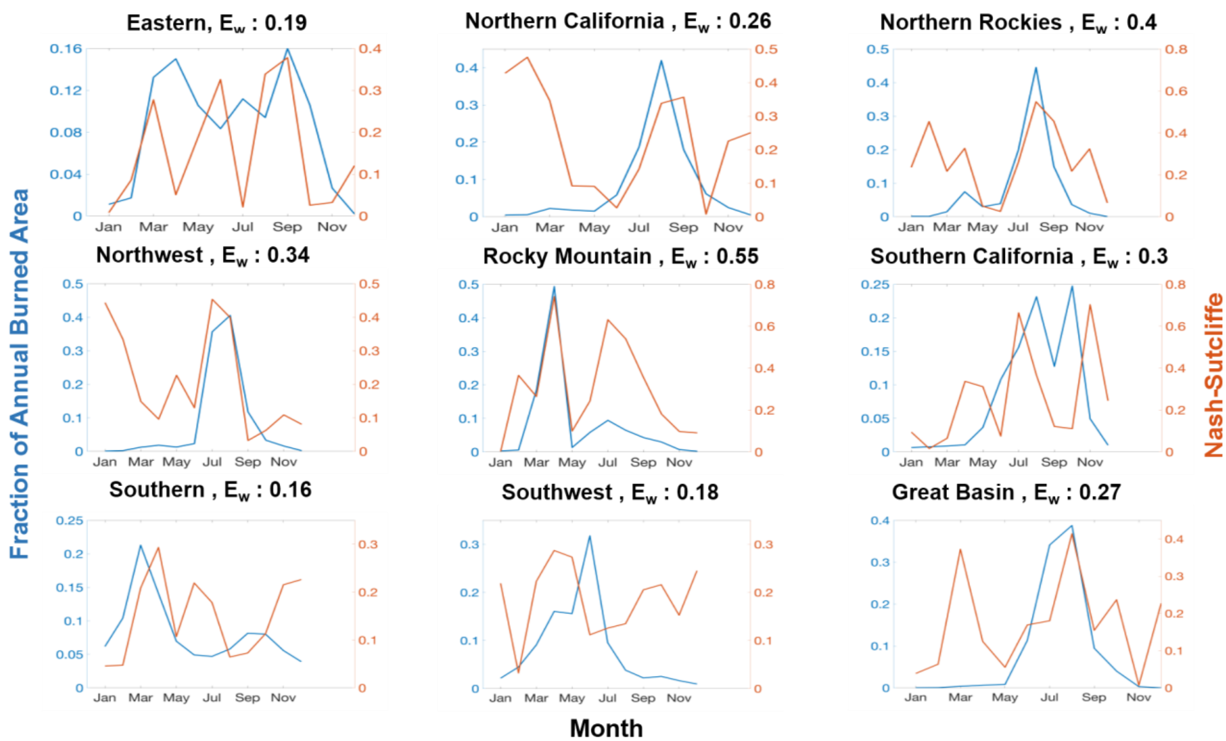

Figure 2. Best model selection based on the monthly Nash-Sutcliffe for each GACC. The blue line shows variable peak fire month by mean annual area burned (FAB) and the orange line shows the monthly Nash-Sutcliffe for each GACC showing variable peak fire month. The weighted Nash- Sutcliffe is calculated using the different combinations of VPD and SSM. The best model was selected based on highest E_w , which demonstrates the relative strength of the different models by GACC.

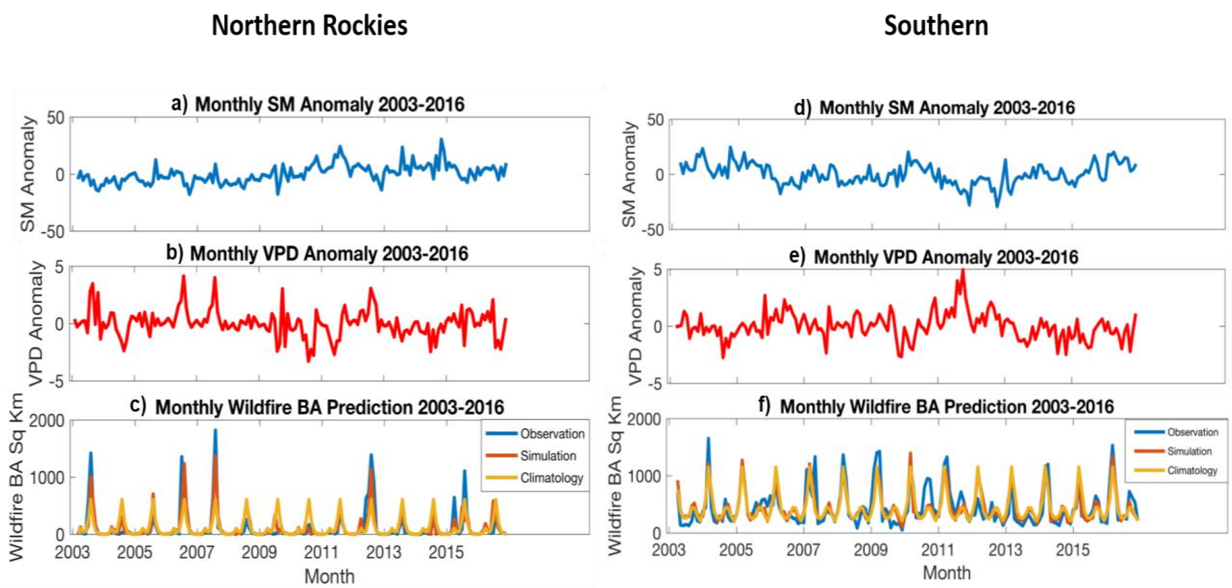

Figure 3. The impact of hydrologic predictors on best and worst performing Geographic Area Coordination Centers (GACCs) models. Monthly time series from 2003 through 2016 show the GACCs with the best (left) and worst (right) coupled response of burned area (bottom) to vapor pressure deficit anomaly (middle) and soil moisture anomaly (top); thus, demonstrating the respective value added of these variables in the modeled burned area ("simulation" in orange) compared to the climatology (yellow) as compared to the observed (blue).

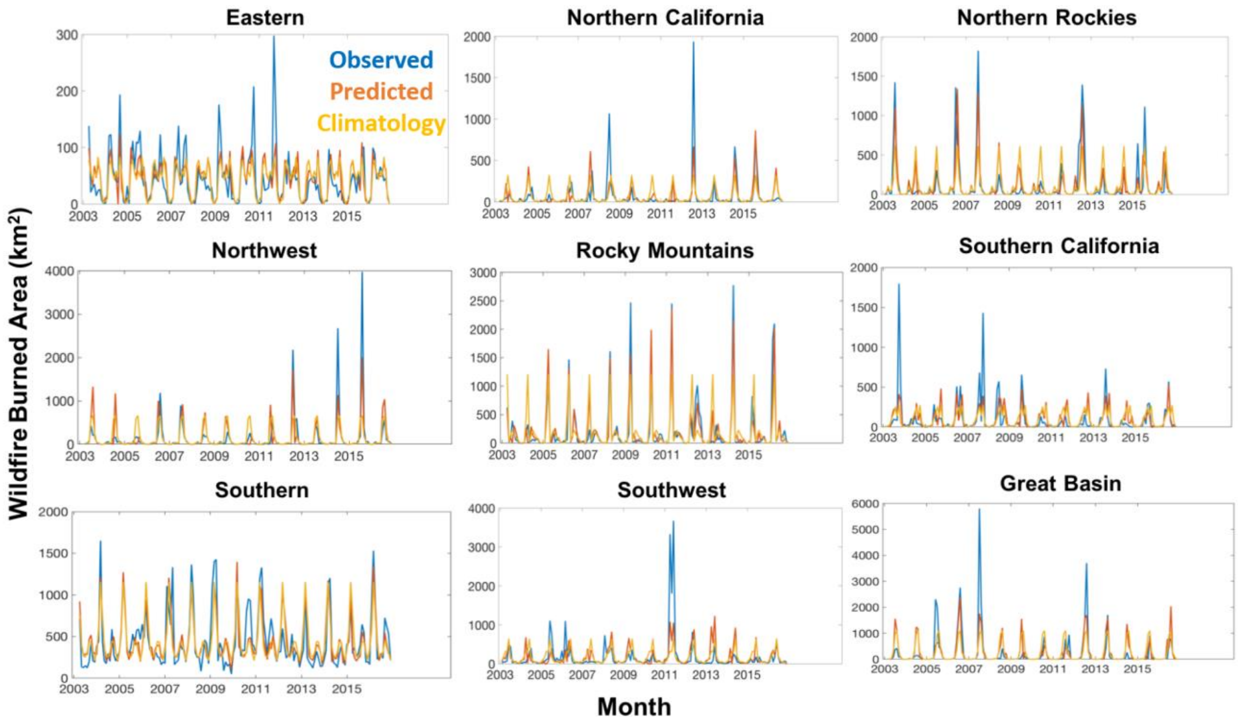

Figure 4. The ability of the regional models to predict (orange) the observed burned area (blue) is improved over the climatology (yellow), which demonstrates the ability to capture interannual variability by Geographic Area Coordination Centers.

GACC	AB_A =	E_S	E_C	$E_S - E_C$	$E_{S,\,VPD}$	$E_{S,\,ssm}$
Eastern	$VPD_{-2} + SSM_{-3}$	0.51	0.37	0.14	0.42	0.42
Northern California	$VPD_{-1} + SSM_{-2}$	0.44	0.22	0.22	0.29	0.33
Northern Rockies	$VPD_{-1} + SSM_{-2}$	0.64	0.38	0.26	0.63	0.39
Northwest	$VPD_{-2} + SSM_{-3}$	0.58	0.28	0.30	0.46	0.42
Rocky Mountains	$VPD_{-1} + SSM_{-3}$	0.82	0.51	0.31	0.64	0.61
Southern California	$VPD_{-1} + SSM_{-1}$	0.35	0.19	0.16	0.25	0.29
Southern	$VPD_{-2} + SSM_{-3}$	0.64	0.57	0.07	0.63	0.59
Southwest	$VPD_{-1} + SSM_{-1}$	0.34	0.16	0.18	0.28	0.23
Great Basin	$VPD_{-2} + SSM_{-1}$	0.47	0.3	0.17	0.43	0.37

Table 1. Overall model performance and separate influence of individual hydrologic variables. We use Nash-Sutcliffe coefficients to describe the combined Soil Moisture (SSM) and Vapor Pressure Deficit (VPD) simulation performance (E_S), the climatology performance (E_C) and the individual predictor performance ($E_{S,VPD}$ $E_{S,ssm}$) vs the observations.

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