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 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, 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. Furthermore, (Behrangi et al., 2016) shows that AIRS 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. While other variables could be investigated for forecasting wildfire danger as well, the results of our model indicate that the combination of SSM and VPD has improved wildfire danger forecasting significantly (Please refer to Table 1). The NSE of the model simulations show significant improvement compared to the NSE of the climatology for all GACCs.

Jensen, D., Reager, J., Zajic, B., Rousseau, N., Rodell, M. and Hinkley, E.: The sensitivity of US wildfire occurrence to pre-season soil moisture conditions across ecosystems, Environ. Res. Lett., doi:10.1088/1748-9326/aa9853, 2017.

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.

Behrangi, A., Fetzer, E. J. and Granger, S. L.: Early detection of drought onset using near surface temperature and humidity observed from space, Int. J. Remote Sens., 37(16), 3911–3923, doi:10.1080/01431161.2016.1204478, 2016.

-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 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 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 study 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.

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 sq km scale bar so that the spatial distribution of most of the fires can be seen in the map. Here is the map of long-term mean August burned area which will be added to the manuscript in Figure 1:

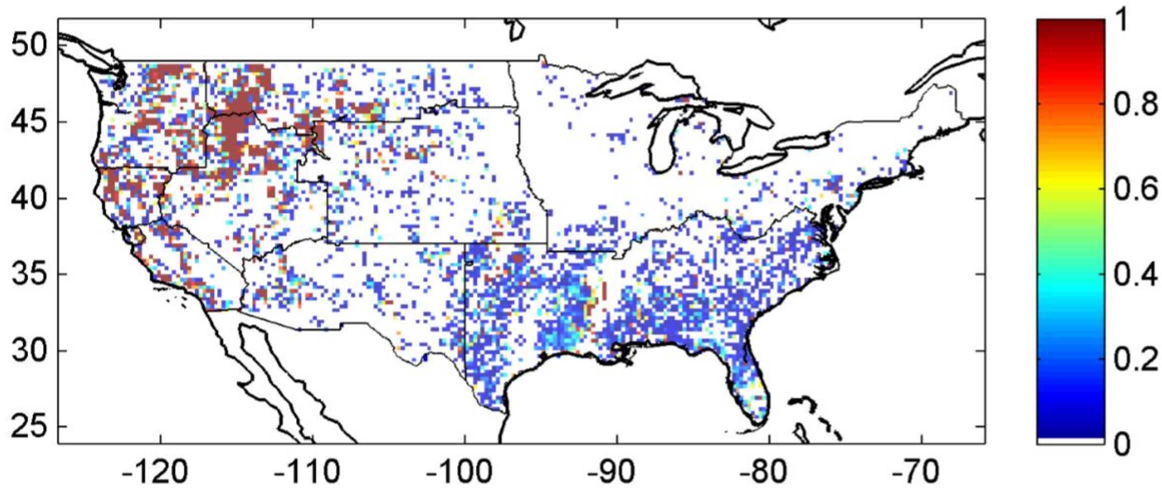

Figure 1 addition: Long term August GFED Burned Area

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 with the 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.

We have revised the 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):

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

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 -∞ 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.

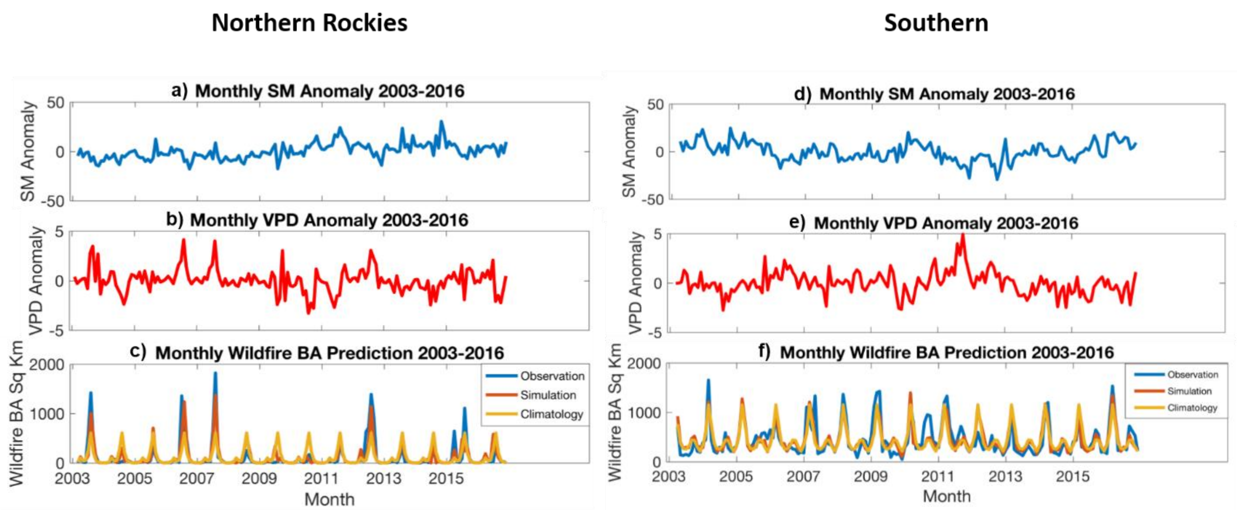

Figure 3