Matin Rahnamay

We would like to thank Dr. Matin Rahnamay Naeini 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 the four datasets used in this study:

For the purpose of this study, four input data sets were used (Figure 1). First, monthly VPD 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 the model was monthly surface soil moisture data, which are 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 (Tapley et al., 2004; Houborg et al., 2012; Reager et al., 2015; Zaitchik et al., 2008). The SSM data are available since April 2004. The third dataset was the Global Fire Emissions Database version 4 (GFED-4s), which provides wildfire burned area 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. Finally, in this study, we have excluded agricultural fires by masking out agricultural regions as classified by the 2011 National Landcover Database (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.

As mentioned in the manuscript:

“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.”

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 landcover 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:

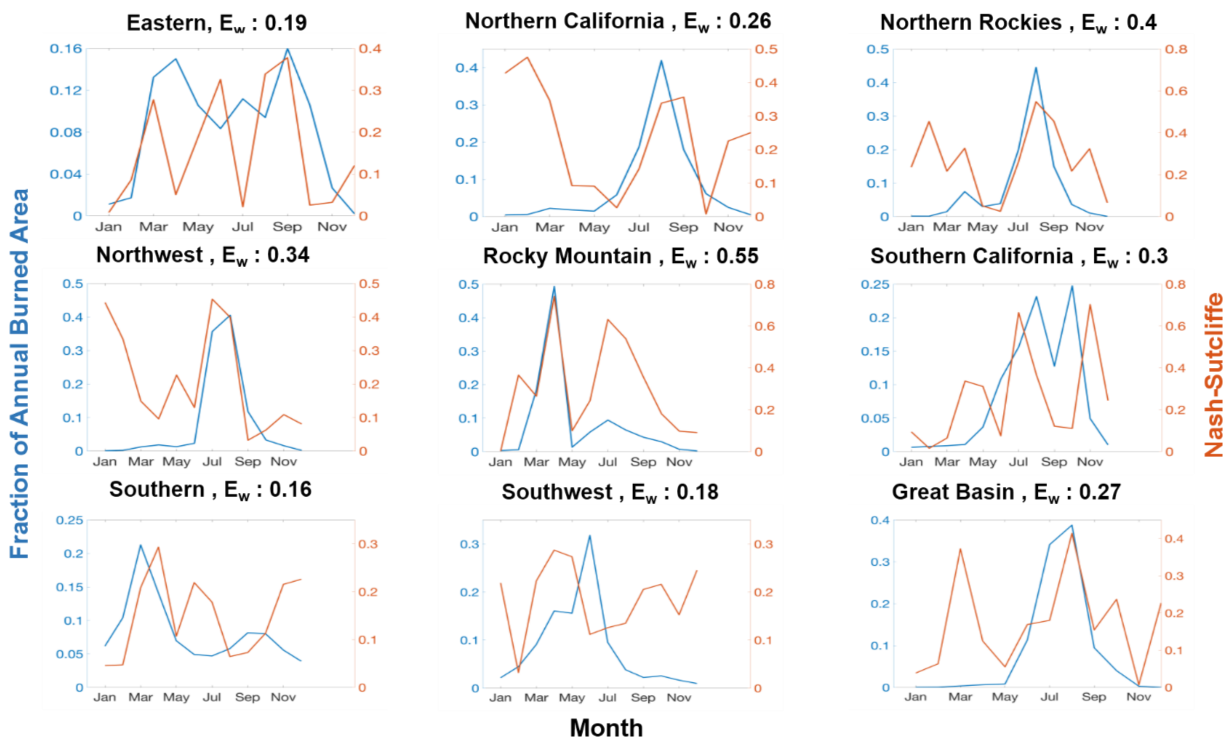


Figure 2

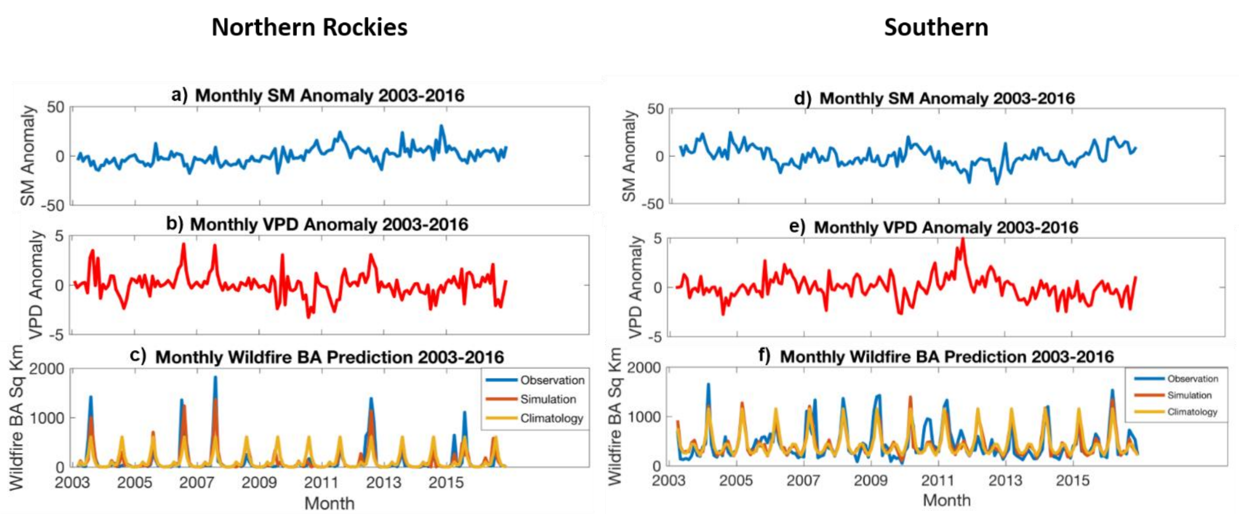


Figure 3

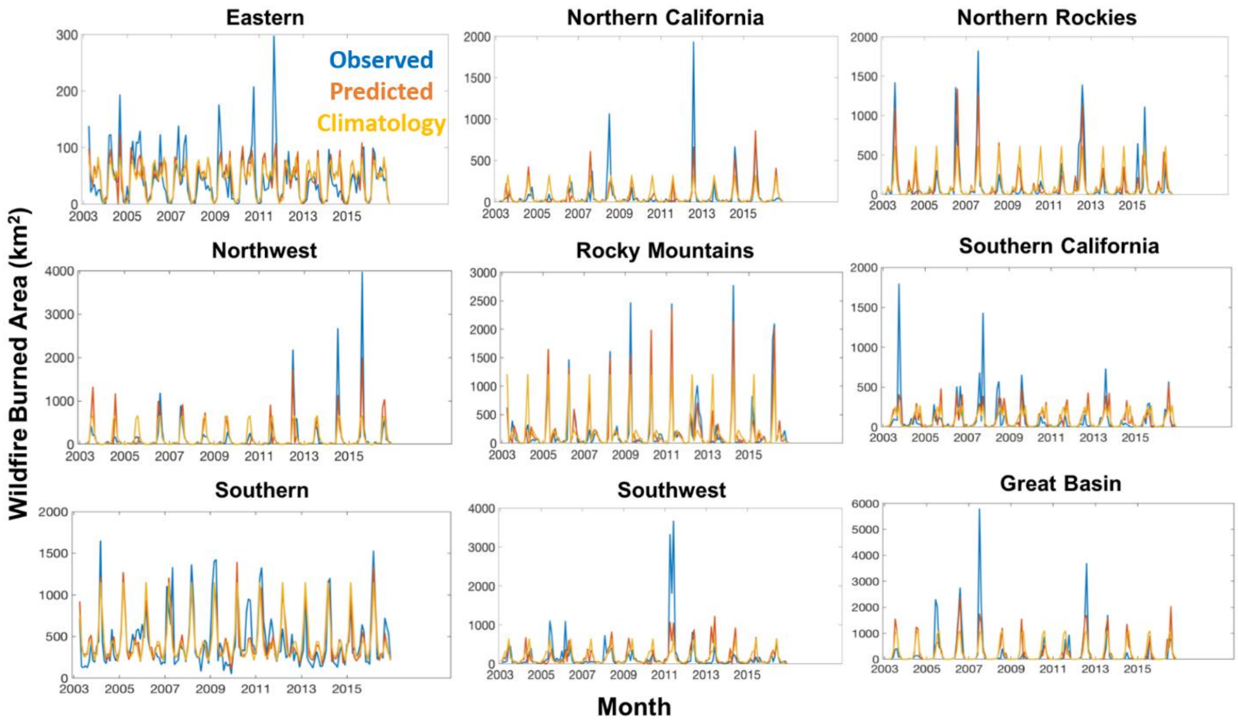


Figure 4

-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.-

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

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

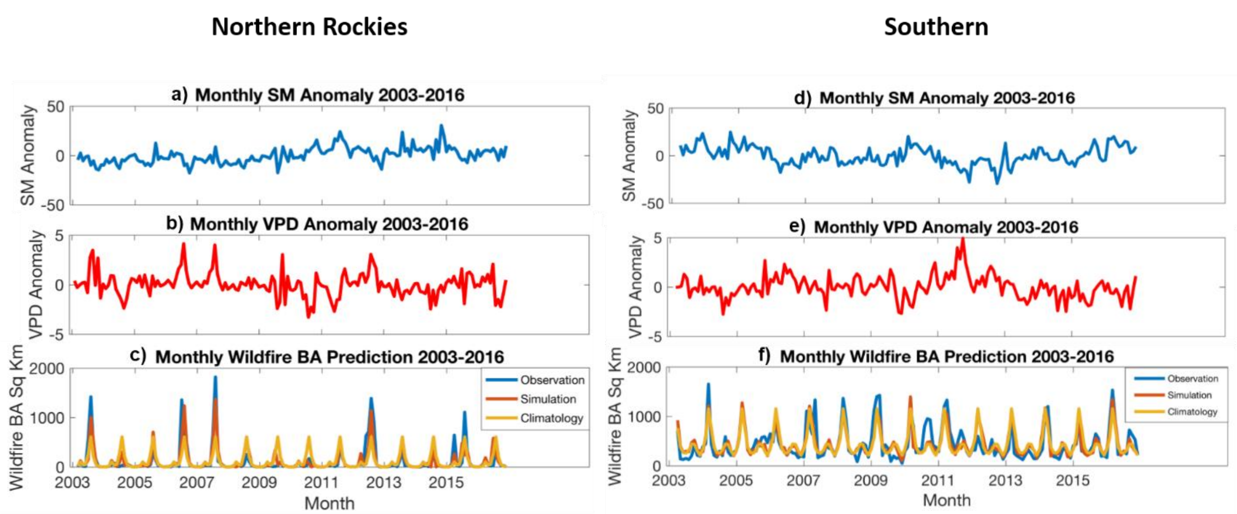
$$AB_s = AB_C + AB_A \quad (3), \quad where$$

$AB_A = a + b * (VPD_A) + c * (SM_A)$ 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