# Interpreting machine learning prediction of fire emissions and comparison with FireMIP process-based models

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8 Abstract. Annual burned areas in the United States have increased twofold during the past decades. With more 9 large fires resulting in more emissions of fine particulate matter, an accurate prediction of fire emissions is critical 10 for quantifying the impacts of fires on air quality, human health, and climate. This study aims to construct a machine learning (ML) model with game-theory interpretation to predict monthly fire emissions over the contiguous US 11 12 and to understand the controlling factors of fire emissions. The optimized ML model is used to diagnose the 13 process-based models in the Fire Modeling Intercomparison Project (FireMIP) to inform future development. 14 Results show promising performance for the ML model, Community Land Model (CLM), and Joint UK Land 15 Environment Simulator-Interactive Fire And Emission Algorithm For Natural Environments (JULES-INFERNO) 16 in reproducing the spatial distributions, seasonality, and interannual variability of fire emissions over CONUS. 17 Regional analysis shows that only the ML model and CLM simulate the realistic interannual variability of fire emissions for most of the subregions (r>0.95 for ML and r=0.14~0.70 for CLM), except for Mediterranean 18 19 California, where all the models perform poorly (r=0.74 for ML and r<0.30 for the FireMIP models). Regarding 20 seasonality, most models capture the peak emission in July over western US. However, all models except for the 21 ML model fail to reproduce the bimodal peaks in July and October over Mediterranean California, which may be 22 explained by the smaller wind speeds of the atmospheric forcing data during Santa Ana wind events and limitations 23 in model parameterizations for capturing the effects of Santa Ana winds on fire activity. Furthermore, most models 24 struggle to capture the spring peak in emissions in southeastern US, probably due to underrepresentation of human 25 effects and the influences of winter dryness on fires in the models. As for extreme events, both the ML model and 26 CLM successfully reproduce the frequency map of extreme emission occurrence but overestimate the number of 27 months with extremely large fire emissions. Comparing the fire PM<sub>2.5</sub> emissions from the ML model with process-28 based fire models highlights their strengths and uncertainties for regional analysis and prediction and provides 29 useful insights on future directions for model improvements.

#### 30 1. Introduction

Large fires have increased across the United States over the past two decades, especially in the western US. While the total area burned in 2020 increased by 51% compared to the 10-year average for 2010-2019, the total number of fires in 2020 is smaller than the 10-year average. This indicates the contribution of larger and more powerful fires to the growing burned areas (NIFC, 2020). Large fires can directly lead to property damages and pose a threat to human lives (Thomas et al., 2017). Meanwhile, fine particulate matter ( $PM_{2.5}$ , particles with an aerodynamic diameter smaller than and equal to 2.5  $\mu$ m) emitted from fires not only have negative impacts on human health but also affect climate and ecosystems (Johnston et al., 2012; Ward et al., 2012; Rap et al., 2013; Kaulfus et al., 2017; Liu et al., 2018; Wang et al., 2018; Stowell et al., 2019). Driven by stronger fire heating and with higher injection height, aerosols emitted from large fires can be transported to broader area and stay in atmosphere longer. Given the increasing trend of fire emissions, fire smokes may become the predominant source of  $PM_{2.5}$  in the US in the future (Yue et al., 2013; Liu et al., 2016; Ford et al., 2018). Thus, an accurate prediction of fire emissions is imperative for investigating the impacts of historical and future fires on air quality, human health, and climate.

44 One of the widely used methods for predicting fire emission is process-based fire parameterization. These 45 process-based models generally employ universal functions depicting non-linear relationships between fires and 46 the input variables and apply the same functions to all grid cells in a model (Pechony and Shindell, 2009; Thonicke 47 et al., 2010). In addition, the parameters of the process-based model are usually determined by empirical or 48 statistical functions, assuming that the same parameters apply to all the regions or regions with limited fire 49 observations (Crevoisier et al., 2007; Parisien et al., 2016). Recently, Zou et al. (2019) developed the Region-50 Specific ecosystem feedback Fire (RESFire) model that includes region- and PFT-specific fire parameterizations in subregions over the globe. Their model shows improved spatial distributions and temporal variations of fire 51 52 activities compared to the CLM fire model. Process-based models are usually included in the dynamic global 53 vegetation models (DGVMs) to simulate fire dynamics, vegetation dynamics, and biogeochemistry driven by 54 atmospheric forcing and socio-economic data (Li et al., 2013; Knorr et al., 2016). Fire emissions, including trace 55 gases and aerosols, are calculated from the simulated fire carbon emissions and the emission factors, with the 56 former computed as the product of the burned area, fuel load, and combustion completeness. The process-based 57 models in DGVM coupled with other components of Earth system models can be used to assess the impacts of 58 environmental factors on fires and the feedback between fire emissions, land processes, and climate (Kloster et al., 59 2010). In 2014, the Fire Model Intercomparison Project (FireMIP) was initiated to compare nine DGVMs that 60 include fire modules to better understand the performances of the global fire models (Rabin et al., 2017). The 61 FireMIP enables comprehensive evaluation and comparison across various process-based models and provides a 62 dataset of long-term fire simulations for regional and global analysis (Li et al., 2019; Hantson et al., 2020).

63 Besides process-based fire models, data-driven statistical models are also commonly used to estimate fire activities using relationships between fires and predictor variables. Multiple linear regression (MLR) is a popular 64 simple statistical method used for fire modeling (Spracklen et al., 2009; Morton et al., 2013; Urbieta et al., 2015; 65 66 Williams et al., 2019). MLR can achieve a good performance, but it fails to capture the non-linear relationships between fires and predictors, and it is sensitive to the collinearity and combinations of predictors (Littell et al., 67 68 2009). Unlike MLR, machine learning (ML) is a novel tool for advancing fire modeling, given its strengths in 69 resolving the complex relationships between the target and predictor variables. Different ML approaches have been 70 used to estimate fire occurrence, burned areas, or emissions at various time scales and spatial scales (Cortez and Morais, 2007; Aldersley et al., 2011; Dillon et al., 2011; Birch et al., 2015; Kane et al., 2015; Coffield et al., 2019; 71 72 Wang and Wang, 2020). Even though ML models generally achieve higher accuracy than simple statistical models, 73 their decision processes are often inscrutable, and hence lack interpretability. The development of explainable ML 74 represents major advances for scientific applications beyond predictions (Gunning, 2017; Arrieta et al., 2020). For 75 example, Wang et al. (2021) used the Extreme Gradient Boosting (XGBoost) algorithm and Shapley Additive explanation (SHAP) to predict wildfire burned area and revealed the relationships between burned areas and 76 77 predictor variables. As process-based and data-driven models have their own advantages and weaknesses, as listed 78 in Table 1, comparing these models and assessing their uncertainties in historical simulations and future projections 79 are important. Yue et al. (2013) applied an MLR and a parameterization method to estimate burned areas in 80 ecoregions of the western US and found that both models explained  $\sim 50\%$  of the variance in the observed burned 81 areas. Although they compared the burned areas estimated by the two methods and quantified their uncertainties in 82 fire projections, both methods are only driven by meteorology while the effects of fuels and human activities are 83 not considered.

84 The FireMIP dataset provides long-term simulations of multiple DGVMs with fire modules, allowing 85 comparisons between process-based and data-driven models, with all models considering all the potential factors 86 influencing fires, including climate, weather, vegetation, and human activities. This study aims to develop an ML model with game theory interpretation for fire emission prediction and to understand controls of fire emissions. 87 88 The ML model and SHAP are then used to reveal the important factors controlling fire emissions and diagnosis the 89 process-based FireMIP models. The ML model predicts the monthly PM<sub>2.5</sub> emissions from fires during 2000-2020 at a spatial resolution of  $0.25^{\circ} \times 0.25^{\circ}$  over the contiguous US (CONUS). It uses the XGBoost algorithm and 90 incorporates various predictors, including local and large-scale meteorology, land surface characteristics, and 91 92 socioeconomic variables, which are common input variables also used by the FireMIP models while some are 93 specifically related to fire activities in CONUS. We acknowledge that different input variables between the ML 94 and FireMIP models might cause additional uncertainty for comparison. This study aims to construct an ML model that predicts fire emissions over CONUS and utilize the ML model and SHAP to reveal the important factors 95 contributing to fire emissions that might not be fully represented in the process-based models. In this context, the 96 97 ML model and FireMIP models are optimized using different data or predictors at various scales, which enables us 98 to use the ML to diagnose the performance of FireMIP models over CONUS through the comparisons of their 99 performances and variable importance from the ML model. We evaluate and compare the predicted fire emissions 100 from the ML and FireMIP models against the GFED fire emission product, focusing on spatial distributions, 101 seasonality, and interannual variability over selected regions in CONUS. Additionally, the ML model and the SHAP importance are used to identify the important drivers of fire emissions in different regions and compare them 102 with the corresponding parameterizations in the process-based models. Lastly, we compare the process-based and 103 104 ML model performances in simulating extremely large fire emissions, including the spatial distributions of 105 frequency and two case studies.

#### 106 2. Data

#### 107 2.1 Fire-induced PM<sub>2.5</sub> emission data

108 Monthly fire PM<sub>2.5</sub> emission data is obtained from the Global Fire Emissions Database (GFED). GFED 109 version 4 provides monthly burned area at 0.25° spatial resolution from 1997 to present, based on a combination of the MODIS burned area product with active fire data from the Tropical Rainfall Measuring Mission (TRMM) 110 111 Visible and Infrared Scanner (VIRS) and Along-Track Scanning Radiometer (ATSR) family of sensors (Giglio et 112 al., 2013). The GFED fire  $PM_{2.5}$  emissions are estimated by combining the burned area boosted by small fire burned area (Randerson et al., 2012) and the emission factors based on Akagi et al. (2011) with a revised version of the 113 114 Carnegie-Ames-Stanford Approach (CASA) biogeochemical model that estimates fuel loads and combustion completeness for each monthly time step (van der Werf et al., 2017). The emission factors are dependent on the 115 116 fire types, including savanna, boreal forest, temperate forest, tropical forest, and agriculture (van der Werf et al., 117 2017). We use the GFED fire  $PM_{2.5}$  emission as the target variable in the machine learning model development and for model evaluation. 118

To reduce spatial heterogeneity and help model learning, we apply the inverse distance weighting (IDW) (Bartier and Keller, 1996; Shepard, 1968) to interpolate the monthly gridded fire  $PM_{2.5}$  emission at  $0.25^{\circ} \times 0.25^{\circ}$ . The IDW method determines the value at a grid cell as the weighted average of the surrounding values within a search distance, with the weights proportional to the inverse of the distance raised to the power value *p*. Here we choose a value of 1 for *p* and a search distance of 35 km for IDW processing. Note that the total fire emitted  $PM_{2.5}$ within a search distance after IDW processing is constrained to be the same as the original data. In this study, we only include grids with more than eight months of fire emissions larger than zero (in a total of 250 months), 126 encompassing 90% of the total fire emissions and ensuring sufficient data for the XGBoost model training. The

127 interpolated fire emission is normalized based on its 21-year mean and standard deviation for each grid to reduce

128 the skewness and improve data symmetry.

### 129 2.2 Predictor variables

We develop an empirical model at  $0.25^{\circ} \times 0.25^{\circ}$  grid resolution driven by various predictor variables at a monthly scale from January 2000 to October 2020. Given the datasets have different spatial resolutions, all the predictor variables are resampled to the spatial resolution of  $0.25^{\circ} \times 0.25^{\circ}$  by linear interpolation. The predictor variables used in the model along with their original spatial and temporal resolutions are included in Table 2. Most variables were also used in Wang et al. (2021) for developing an ML model of fire burned area over the contiguous U.S.

*Local meteorology:* Same as the local meteorological predictors used in Wang et al. (2021), we include monthly 136 data of mean surface temperature, relative humidity (RH) at 2 m, daily precipitation, zonal (U) and meridional (V) 137 138 components of wind at 10 m from the North American Regional Reanalysis (NARR) (Mesinger et al., 2006) and 139 1000-hour dead fuel moisture (FM1000), Energy Release Component (ERC), and vapor pressure deficit (VPD) from the gridMET dataset (Abatzoglou and Kolden, 2013; Coffield et al., 2019). Drought is a natural phenomenon 140 that influences fires through ignition efficiency, fuel availability, and fuel moisture. Thus, we include the monthly 141 142 Standardized Precipitation Evapotranspiration Index (SPEI), a multiscalar drought index based on climatic data 143 (Vicente-Serrano et al., 2010). Given that lightning is one of the major ignition sources of fires and makes up 144 approximately 75% of burned areas in western US (Pyne, 1984; Stephens, 2005), in this study, we add the cloud-145 to-ground (CG) lightning flash density from Severe Weather Data Inventory (SWDI) based on the National 146 Lightning Detection Network (NLDN) (Cummins and Murphy, 2009; NOAA, 2006). The daily number of CG lightning flashes is summarized in  $0.1^{\circ}$  tiles and we aggregate the daily data to monthly scale. 147

Large-scale meteorological patterns: Large-scale meteorological patterns at a synoptic scale have been found to 148 link to large fire events (Crimmins, 2006; Trouet et al., 2009; Zhong et al., 2020; Dong et al., 2021). Furthermore, 149 150 it has been shown that including predictors of large-scale meteorological patterns conducive to wildfires significantly improves the prediction of burned areas over CONUS (Wang et al., 2021). Thus, we follow the 151 152 methods developed by Wang et al. (2021) using the singular value decomposition (SVD) method to construct 153 predictors representing the synoptic patterns driving fire emission variability. Note that the only difference between 154 Wang et al. (2021) and this study is that they used wildfire burned area data and we use fire emissions to construct the SVDs. Three regions where large fires periodically occur are selected for constructing SVDs: Northern 155 California, southern Rocky Mountains, and southeastern US, as defined in Wang et al. (2021). For each region, we 156 157 calculate the daily mean fire PM<sub>2.5</sub> emissions over the region and compute the day-to-day correlations between the 158 regional mean fire PM<sub>2.5</sub> emissions and the five gridded daily meteorological variables (surface temperature, 2meter RH. U-wind and V-wind at 850 hPa, and geopotential height at 500 hPa) for all  $1^{\circ} \times 1^{\circ}$  grid cells within the 159 160 large-scale domain, giving a correlation map for each meteorological variable. The correlation maps are then used to derive the SVD modes representing the large-scale meteorological patterns related to fires. Finally, we compute 161 the monthly standard deviation of the daily SVD time series for the first two SVD modes, representing the month-162 163 to-month variations of synoptic fluctuations and atmospheric instability. The detailed methods and discussions about the SVDs are provided in Wang et al. (2021). Overall, the identified SVDs for the three regions are similar
to the SVDs in Wang et al. (2021) calculated using wildfire burned areas (Figs. S1-3).

*Land-surface properties:* We use the same set of variables in the burned area model that represent the effects of 166 fuel and land surface states on fire emissions, including evapotranspiration (ET), surface soil moisture, land types, 167 and topography (Wang et al., 2021). Monthly mean ET, vegetation fraction, and surface soil moisture are obtained 168 169 from the North American Land Data Assimilation System (NLDAS-2) (Xia et al., 2012). Land cover data of the 170 LAI classification scheme is obtained from the Terra and Aqua combined MODIS Land Cover Climate Modeling Grid (CMG) Version 6 data (Friedl, 2015). Since the land cover data is at yearly intervals from 2001 to 2020, we 171 172 use the land cover data of 2001 for 2000. Topography data of slope and elevation is obtained from Amatulli et al. 173 (2018).

Besides the above-mentioned variables that were also used in Wang et al. (2021), in this study, we consider 174 175 the effect of fuel load on fire emissions, since fuel load is critical to fire emissions through its controls on fuel 176 consumption and burned areas (Parks et al., 2012; Liu and Wimberly, 2015). As there are limited observations of 177 fuel load, we use LAI to approximate the canopy bulk density, which is important crown characteristics to predict 178 crown fire spread, and vegetation fraction to represent the existing amount of vegetation (Keane et al., 2005). LAI 179 is taken from MODerate resolution Imaging Spectroradiometer (MODIS) instruments (Myneni et al., 2015) and vegetation fraction is obtained from the NLDAS-2. As LAI may not fully represent the available biomass, we also 180 include fuel load simulated by Community Land Model (CLM). Monthly fuel load data from 2000 to 2015 is 181 182 obtained from a simulation by CLM version 5 with biogeochemistry and prognostic crop, driven by atmospheric 183 forcing from GSWP3v1 (Lawrence et al., 2019). The fuel load after 2015 is taken from a simulation under the SSP3 184 (shared socioeconomic pathways) scenario. CLM fuel load is validated by comparing with the fuel-measured fuel load from the global fuel consumption database (van der Werf et al., 2017; Van Leeuwen et al., 2014), as shown in 185 186 Fig. S4. The CLM-simulated fuel load is generally consistent with the measured fuel load for different vegetation types across CONUS based on the limited measurements. Additionally, we include normalized fuel load as a 187 predictor to capture the effects of temporal variation of fuel load, as the influence of fuel load on fire emissions is 188 189 mainly attributed to its spatial variation rather than the temporal variation (Lasslop and Kloster, 2015).

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Socioeconomic variables: We use population density and gross domestic product (GDP) per capita to represent human effects on wildfires. The population density data is obtained from the Gridded Population of the World data collection (GPW V4) for the years 2000, 2010, 2015, and 2020, with a spatial resolution of 30 arc-second (CIESIN-Columbia University, 2017). The populations in other years are linearly interpolated between the abovementioned four years. The GDP per capita is taken from a gridded global dataset for 2000-2015 with a spatial resolution of 5 arc minutes (Kummu et al., 2018). For the GDP after 2015, we use the data of 2015.

# 197 **3. Description of fire emission models**

# 198 **3.1 Process-based fire emission models**

The Fire Model Intercomparison Project (FireMIP) includes a set of common fire modeling experiments from nine DGVMs driven by the same forcing data, allowing a better understanding of global fire models (Rabin et al., 2017). The FireMIP dataset provides global gridded burned area fraction and fire emissions, including carbon and 33 species of trace gases and aerosols over 1700-2012. Nine DGVMs with different fire modules are included

in FireMIP, including Community Land Model version 4.5 (CLM4.5) with the CLM5 fire module, Canadian 203 204 Terrestrial Ecosystem Model (CTEM), Jena Scheme for Biosphere-Atmosphere Coupling in Hamburg with Spread and InTensity fire model (JSBACH-SPITFIRE; hereafter referred to as JSBACH), Joint UK Land Environment 205 Simulator with Interactive Fire And Emission Algorithm For Natural Environments (JULES-INFERNO; hereafter 206 207 referred to as JULES), Lund-Potsdam-Jena General Ecosystem Simulator with Global FIRe Model (LPJ-GUESS-GlobFIRM; hereafter referred to as LPJ-Glob), LPJ-GUESS with SIMple FIRE model and Blaze-Induced Land-208 Atmosphere Flux Estimator (LPJ-GUESS-SIMFIRE-BLAZE; hereafter referred to as LPJ-SIM), LPJ-GUESS with 209 210 SPITFIRE model (LPJ-GUESS-SPITFIRE; hereafter referred to as LPJ-SPI), MC2, and Organizing Carbon Hydrology In Dynamic Ecosystems with SPITFIRE model (ORCHIDEE-SPITFIRE; hereafter referred to as 211 ORCHIDEE) (Rabin et al., 2017). 212

The nine DGVMs in FireMIP are driven by the CRU-NCEP v5.3.2 atmospheric forcing data with a spatial 213 resolution of  $0.5^{\circ}$  and a 6-hourly temporal resolution (Wei et al., 2014; Rabin et al., 2017). Other forcing data, 214 including annual global atmospheric CO<sub>2</sub> concentration, land use and land cover, and population density from 1700 215 to 2012 is taken from various data sources (Klein Goldewijk et al., 2010; Hurtt et al., 2011; Le Quéré et al., 2014). 216 Monthly cloud-to-ground lightning frequency with a resolution of  $0.5^{\circ} \times 0.5^{\circ}$  over 1901-2012 is calculated based 217 on the observed relationship between present-day lightning and convective available potential energy (CAPE) 218 219 anomalies (Pfeiffer et al., 2013). Fire emissions in FireMIP are calculated considering the fire carbon emissions and vegetation characteristics based on the plant functional type (PFT) from the FireMIP historical transient control 220 221 run (SF1). SF1 breaks the simulation period into three phases: the spin-up phase in 1700, the transient phase in 222 1701-1900, and the transient phase in 1901-2012 (see the detailed descriptions and model settings in Rabin et al., 2017, Li et al., 2019, and Hantsan et al., 2020). In the 1901-2012 transient phase, the models are driven by time-223 224 varying atmospheric forcing,  $CO_2$  concentration, LULCC, population density, and lightning data. Note that the 225 MC2 and CTEM runs start from 1901 and 1861, while the rest of the models start from 1700. As the spatial 226 resolutions of the FireMIP models are different, the regridded model outputs with  $1^{\circ} \times 1^{\circ}$  resolution obtained from 227 Li et al. (2019) are used to compare with the GFED data and the ML model.

#### 228 3.2 ML-based approach: An eXtreme Gradient Boosting (XGBoost) model

The eXtreme Gradient Boosting (XGBoost) is a decision-tree-based ensemble machine learning method using the gradient boosting approach (Chen and Guestrin, 2016). The XGBoost model builds multiple decision trees that are added subsequently and learn the errors of the previous tree to reduce the loss and obtain the best prediction. Unlike the gradient boosting machine (GBM) that also uses the gradient boosting approach, XGBoost utilizes a more regularized model formalization to prevent over-fitting and improve the computational efficiency. The formula for the prediction at step *t* and grid location *i* can be defined as follows:

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$$\hat{y}_i^t = \sum_{k=1}^t f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i)$$

where  $f_t(x_i)$  is the tree model at step t,  $\hat{y}_i^t$  and  $\hat{y}_i^{(t-1)}$  are the predictions at steps t and t-1, and  $x_i$  are the predictor variables. The parameters of the model  $f_t(x_i)$  are selected by optimizing the objective function that measures how well the model fit the training data:

$$Obj^t = \sum_{i=1}^n L^t + \Omega^t$$

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which is composed of the loss function  $L^t$  and the regularizing term  $\Omega^t$  in each step.  $L_t$  is defined as  $l(y_i, \hat{y}_i^{t-1} + f_t(x_i))$  and  $\Omega^t$  is defined as  $\gamma T + \frac{1}{2}\lambda ||\omega||^2$ , where  $\gamma$  is the regularization term which penalizes the number of leaves in the tree *T* and  $\lambda$  is the regularization term which penalizes  $\omega$ , the weights of different leaves.

We use grid search to choose the set of suitable hyperparameters and achieve the best ML model performance. Grid search is a tuning technique for computing the optimal values of hyperparameters considering a range of numbers with a given increment. The parameter set that yields the best 5-fold cross-validation score is selected as the final set of hyper-parameters. The considered hyper-parameters, their search domains, and the final values are denoted in Table S1.

The 10-fold cross-validation (CV) technique is applied to evaluate the model and avoid overfitting. First, we randomly divide the fire emission dataset (2000-2020 over CONUS) into ten equal-sized splits. Then, we train the model with nine splits of the data and use the trained model to predict fire emissions for the remaining one split. This process is repeated ten times for each split. Finally, the predictions are evaluated by grids and regions using root mean square error (RMSE), correlation coefficient (R), and the index of agreement (IoA). The IoA represents the ratio of the mean square error and the potential error, and the value closer to 1 indicates better agreement.

#### 254 **3.3 Shapley additive explanations (SHAP)**

We utilize the SHAP to identify the relative importance of the predictor variables. SHAP is a novel 255 256 approach to resolve and explain variable importance based on game theory (Lundberg and Lee, 2017). Within the 257 scope of game theory, the goal is a prediction for a single observation. Each predictor variable is referred to as a "player" in this game and contributes to the goal ("payout"). For each predictor, the SHAP variable importance 258 259 measures the marginal contribution considering all possible combinations of the predictor variables. The marginal contribution is calculated by comparing the differences between the model fit  $f_x(S \cup \{i\})$  including the predictor i 260 and another model fit  $f_x(S)$  without predictor i. When there is more than one predictor i, the marginal contribution 261 also depends on the interactions with other predictors. Thus, the calculation repeats considering the whole set of 262 263 the predictors. The final contribution  $\phi_i$  of predictor *i* is the weighted average of all marginal contributions:

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$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|! (F - |S| - 1)!}{F!} [f_x(S \cup \{i\}) - f_x(S)]$$

where *F* is the total number of features, *S* is the subset of predictors from all predictors except for predictor *i*,  $\frac{|S|!(F-|S|-1)!}{F!}$ is the weighting factor counting the number of permutations of the subset *S*.  $f_x(S)$  is the expected output given the predictors subset *S*.  $[f_x(S \cup \{i\}) - f_x(S)]$  is the difference made by predictor *i*.

Compared to the commonly used feature importance, such as gain, or split count, SHAP is more consistent and faithful to the model (Lundberg et al., 2019). More importantly, SHAP provides local importance that measures the variable importance for each sample, while most of the feature importance metrics only have global importance that measures variable contributions limited to the entire dataset. The global importance by SHAP is the average of the absolute SHAP values for each predictor, providing an overall picture of the predominant variables controlling fire emissions in CONUS. The local importance will be used to identify the important predictors for large fire events in the ML model and diagnose the deficiency of the process-based models.

#### 275 **4. Results**

#### 276 4.1 XGBoost model performance and variable importance

Table 3 shows the whole CONUS and regional model performance, including RMSE, IoA, and correlation. 277 278 The model performs well at grid level over CONUS, with an RMSE of 0.16 g/m<sup>2</sup> and an IoA of 0.84. Figure 1a 279 shows the map of correlation between the observed and predicted monthly fire emission time series for each grid 280 over CONUS. Overall, the results indicate the ML model can reproduce the interannual variability of fire emissions at 0.25° resolution over CONUS, with a mean correlation of 0.58 and more than 70% of the grids having 281 282 correlations larger than 0.4. To better assess model performance in different regions, Table 3 summarizes the model performance for several selected regions: (1) western forest area, (2) Mediterranean California, (3) southwestern 283 284 US, and (4) southeastern US (color boxes in Fig. 1a). The regions where fires frequently occur are selected by the similarity of ecoregions, vegetation types, and fire regimes. Figs. 1b-e show the time series of observed and 285 predicted fire  $PM_{2.5}$  emissions averaged over several regions. Generally, the ML model reproduces the interannual 286 variability of fire emissions for the selected regions (r=0.84-0.98). Among these regions, Mediterranean California 287 288 has the smallest correlation coefficient and largest RMSE compared to other regions, which can be explained by 289 the fact that fires in this region interact with multiple factors, including human activity, complex terrain, and Santa 290 Ana winds (Syphard et al., 2008; Yue et al., 2014). The interactions between fires and these factors pose 291 uncertainties and challenges in fire prediction over this region. It is also worth noting that the ML model captures the large fire events in September 2020 in Oregon and California but underestimates the peak values by ~30% 292 293 (Figs. 1b and 1c). In addition, we also test the ML model's ability to provide accurate predictions on unseen data 294 (i.e., generalization) by using data from 2000 to 2019 as a training set and data from 2020 as a testing set. As shown 295 in Fig. S5, the ML model can reproduce the spatial patterns of fire emissions well but underestimates the emissions 296 of the peak in September 2020. The results are within our expectations because the ML model generally fails to 297 make accurate predictions for the data outside of the training domain or has large uncertainties in extrapolation 298 (Tsubaki and Mizoguchi, 2020; Hooker, 2004). Since 2020 features the largest fire emissions in the study period, 299 we conducted another test using 2000-2017 and 2019-2020 to train the ML model and test on the data of 2018. We 300 selected 2018 because 2018 had the largest fires on record before 2020. The ML successfully reproduces the 301 temporal variability of fire emissions (r=0.92) and captures the peak in Aug 2018, as well as the spatial distributions of fire emissions (r=0.52). 302

To improve understanding of the ML prediction, we utilize the SHAP method to quantify the contributions 303 304 of each predictor variable to the prediction and identify the key contributing factors of fire  $PM_{2.5}$  emission. SHAP importance is chosen because it provides not only global importance but also local importance that helps understand 305 306 which variables have larger contributions to specific events or regions. Here, we first demonstrate the global importance that considers all the samples. Fig. 2 shows the 20 most important variables for the model ranked by 307 308 the absolute mean SHAP values. The SHAP value for a feature indicates its contribution to the prediction, so larger absolute mean SHAP values indicate larger contributions to the fire emissions. Among the top 10 variables, seven 309 310 of them are local meteorological variables, indicating local meteorology is the predominant control of fire emissions, as these variables control fire activity directly (Liu and Wimberly, 2015; Abatzoglou et al., 2016; Wang 311 312 et al., 2021). Besides local meteorology, the predictors of large-scale meteorology (SVD1 SElag2 and SVD2 SElag2) are identified as the eighth and tenth important variables, showing that meteorology is not only 313 important at local scale but also at synoptic scale (Trouet et al., 2009; Pollina et al., 2013; Dong et al., 2021). 314 315 Finally, in addition to meteorology, fuel load is identified as the fifth important variable in the model, as fuel load affects emission through controlling burned area and fuel consumption (Seiler and Crutzen, 1980). Considering the 316 317 important variables in different regions, the selected regions in western US (western forest area, Mediterranean California, and southwestern US) generally share the common top 10 variables (Fig. S6). Over western US, 318

predictors controlling fuel dryness and fuel amount, including RH, fuel moisture (FM1000), ERC, vegetation
 fraction, and fuel load, contribute more to fire emissions. On the other hand, large-scale meteorological patterns
 (SVDs\_SElag2) are more important for fire emissions in southeastern US.

As the dominant drivers differ for different temporal scales, we aggregate the monthly SHAP values to 322 323 obtain annual and seasonal time series of SHAP values for each variable. The annual and seasonal time series are 324 the averaged SHAP values over the study period for each year and month, respectively. Fig. S7 shows the mean 325 SHAP values at seasonal and interannual time scale for the whole CONUS. Considering both the mean SHAP 326 and larger correlations (r > 0.5) between the annual/seasonal time series of SHAP and mean fire emissions, 327 temperature, VPD, RH, and ERC are the dominant variables controlling the seasonal variation of fire emissions. 328 These factors have relatively stronger seasonality than other variables (e.g., VPD is usually higher in the summer). 329 On the other hand, large-scale circulation patterns, including SVD1 SElag2, SVD2 SElag2, and SVD1 RM, are 330 important variables controlling both the seasonal and interannual variability of fire emissions, while SVD2 RM and SVD2 NCA mainly control interannual variability. Some identified large-scale meteorology has significant 331 332 seasonality (e.g., SVDs SElag2 are predominant in spring and SVD1 RM is strongest in summer), and most of them have interannual variability, as shown in Fig. 8. Overall, the SHAP analysis shows different dominant 333 334 predictors for fire emissions at various time scales.

#### 335 4.2 General comparison between GFED, ML, and FireMIP models

This section compares the performance of the ML and FireMIP models benchmarked against observations from GFED, and the evaluations are based on spatial distributions, seasonality, and interannual variability of fire PM<sub>2.5</sub> emissions. Since the spatial resolutions of the GFED data, ML models, and FireMIP models are different, they are all regridded to  $1^{\circ} \times 1^{\circ}$  using bilinear interpolation. Note that the simulation period of FireMIP models ends in 2012, so we use the overlapping period of 2000-2012 for comparison and exclude the MC2 model because its simulation ends in 2008.

#### 342 4.2.1 Spatial distributions of fire PM<sub>2.5</sub> emissions and sensitivities to RH and temperature

343 Fig. 3 compares the observed and simulated spatial distributions of long-term mean monthly fire  $PM_{25}$ 344 emissions averaged over 2000-2012. Among the models, the ML model, CLM, and JULES have better performance in reproducing the spatial distributions of fire emissions over CONUS, with a correlation coefficient of 0.83, 0.52, 345 0.40, respectively. The ML model shows the best agreement with GFED, though it overestimates fire emissions 346 347 over Northern California. Both CLM and JULES simulate more PM2.5 emissions over southeastern US, and JULES overestimates fire emissions in Northern California. Some other models, such as CTEM, JSBACH, and LPJ-SIP. 348 349 tend to overestimate fire emissions over central US (e.g., Great Plains and Texas). LPJ-SIM captures the hotspots 350 of fire emissions over western US and southeastern US, but it simulates much more PM<sub>2.5</sub> emissions over the Rocky 351 Mountain and northeastern US. In terms of the total amount of PM<sub>2.5</sub> emissions, all models except ORCHIDEE-SPITFIRE overestimate PM<sub>2.5</sub> emissions (8.33-79.49 Tg), compared to the GFED estimate of 4.98 Tg during 2000-352 353 2012 over CONUS (Table 4).

The overestimations in some models may be explained by the sensitivities of fire emissions to individual meteorological variables. Fig. 4 shows the slopes for the dependence of annual mean fire  $PM_{2.5}$  emissions on annual mean RH from the CRUNCEP atmospheric forcing data for GFED and the ten models based on linear regression. Since the ML model uses NARR meteorology as predictors, we also include sensitivities of the fire emissions predicted by the ML model to the NARR meteorology (Fig. 4b). Almost all models capture the negative dependence of  $PM_{2.5}$  emissions on RH over western US (r=-0.06~0.84), but the sensitivities in the models are much stronger (steeper negative slope) than in GFED. For temperature, positive sensitivity is shown over western US in GFED

(Fig. 5), with the most significant slope in northern California. The sensitivities to temperature in models agree 361 362 with the observed sensitivities ( $r=-0.06\sim0.64$ ), but some models show much stronger sensitivities over western, central, and southeastern US. Generally, the spatial distributions of the long-term mean fire emissions shown in 363 364 Fig. 3 match well with the spatial distributions of sensitivities to RH or temperature, suggesting an important role 365 of the sensitivities in the model biases of predicting fire emissions. However, the correspondence of large fire emissions to the sensitivities to RH or temperature shows regional differences. For instance, in western US, the 366 367 stronger sensitivities to both RH and temperature correspond to the overestimations in this region for most models, including the ML model, CLM, CTEM, JSBACH, JULES, LPJ-SIM, and LPJ-SPI (Figs. 4 and 5). On the other 368 hand, over central US, larger PM<sub>2.5</sub> emissions simulated by CTEM and JSBACH only correspond to stronger 369 sensitivity to temperature (Fig. 5). Similar to central US, in southeastern US, the overestimations in CLM and 370 371 JULES only correlate with stronger sensitivity to temperature (Fig. 5). Regional differences in the correspondences between the predicted fire emissions and their sensitivity to meteorology can be explained by several factors. For 372 373 western US, the overestimations of fire emissions correspond to both stronger sensitivities to RH and temperature, given that fire activities are sensitive to fuel aridity that is controlled by temperature and fuel moisture (Abatzoglou 374 375 and Williams, 2016; Holden et al., 2018). As for southeastern US, fuels in this region typically burn at higher RH and the interannual RH variation (standard deviation) is smaller (Balch et al., 2017; Brey et al., 2018). With higher 376 RH values and less variation in RH, the fire emissions in southeastern US show weaker sensitivity to RH than to 377 378 temperature in observation (Table S2). The above analysis shows that the overestimation of fire emissions in the 379 models may be attributed to the stronger sensitivities to meteorology. However, fire activities are controlled by 380 meteorology and other factors such as vegetation and human, so the analysis of fire emission sensitivity to 381 meteorology only provides a potential explanation to the overestimation of fire emissions in the models (Forkel et 382 al., 2019).

#### 383 4.2.2 Seasonality and interannual variability over CONUS

384 In addition to evaluating spatial distributions, it is also important to compare the models' ability to 385 reproduce the temporal variability of fire emissions. As the models may systematically over-or underestimate fire 386 emissions, we normalize the emissions by the mean and standard deviation and focus only on its temporal variability. Fig. 6a shows the seasonality of normalized fire PM<sub>2.5</sub> emission over CONUS. Most models capture the 387 388 seasonality of fire emission successfully (r>0.85), except LPJ-SIM which simulates peak emission in August-389 October (r=0.65). Among the models, the ML model has the highest correlation coefficient between prediction and 390 observation from GFED (r=0.98) and successfully reproduces the peak in August. The seasonal peaks simulated by the FireMIP models are broader and flatter than the peak in GFED, with an early peak in June-July continuing 391 392 to September (Fig. 6a).

393 In terms of interannual variability (Fig. 6b), the ML model, CLM, and JULES perform better than other 394 models, with larger correlation coefficient between simulated and observed fire  $PM_{2.5}$  emissions (r=0.87, 0.71, and 0.55 for ML, CLM, and JULES, respectively; Table 4). Other models have relatively poor performance in capturing 395 396 the interannual variability. The interannual variability of fire emissions shows several peaks in 2002, 2007, and 397 2012 (black line in Fig. 6b), when western US contributes 76% of the total emissions to the peaks in these years. Almost all models except ORCHIDEE capture the peak in 2012. However, most models miss the peaks in 2002 398 399 and 2007. Among all models, LPJ-Glob model simulates the peaks in the two years, while ML, JULES, and CLM 400 only capture the largest emission in 2007 (Fig. 6b).

#### 401 4.2.3 Seasonality and interannual variability by regions

402 As the temporal variability of fire activities varies by region, we compare the performance between GFED and the ML and FireMIP models by the regions defined in Sec. 4.1. Fig. 7 shows the seasonality and interannual 403 variability of normalized fire PM<sub>2.5</sub> emission over western forest area, Mediterranean California, southwestern US, 404 and the southeastern US. All models generally capture the seasonality of the western forest area peaking in summer, 405 with correlation coefficients larger than 0.8 (Table 4). Even though the FireMIP models generally reproduce the 406 407 peaks in summer, the predicted peaks are broad and flat, indicating a relatively longer fire season starting in June 408 and ending in September (Fig. 7a). When looking at the interannual variability, we find that the ML model has the 409 best performance with a correlation coefficient of 0.93, and it successfully captures the largest fire emission in 2007. CLM, JULES, and LGJ-Glob perform better than the rest of the models (r=0.70, 0.60, and 0.51 for CLM, 410 411 JULES, and LPJ-Glob, respectively; Table 4), but all of them still miss the peaks in 2007 and overestimate fire emissions in 2001 and 2003 (Fig. 7b). The emission peak in 2007 is mainly attributed to the large fires in Idaho, 412 which were associated with synoptic weather patterns characterized by positive geopotential height and temperature 413 414 anomalies over the Pacific Coast and western US (Zhong et al., 2020). Consistent with prior findings, SHAP 415 importance shows that in the ML model SVD predictors (SVD NCA and SVD RM in July and August 2007 Fig. 416 8a) are the dominant factors of fire emissions in 2007 (contribute 27% and 28% for July and August 2007, respectively), which are characterized by high pressure, low RH, and northeasterly winds over western US (Figs. 417 418 S1 and S2). Thus, the underestimation of peak emission in 2007 may be explained by the fact that the influences 419 of large-scale meteorology on fire activity are not fully considered in the FireMIP models, which are point models 420 driven only by local atmospheric forcing.

421 In Mediterranean California, the seasonality of fire emissions shows a bimodal pattern, peaking in August 422 and October. The peak in October is mainly due to the extremely large fires associated with Santa Ana winds in 423 2003 and 2007 (Keeley et al., 2009; Yue et al., 2014). The ML model simulates a flatter peak from July to October, 424 while all the FireMIP models except ORCHIDEE capture the first emission peak in summer but fail to simulate the 425 large fire emission in October (Fig. 7c). The underestimation associated with the Santa Ana winds is also shown in 426 the interannual time series in Fig. 7d. Several models, including LPJ-Glob, CTEM, LPJ-SPI, and JULES, capture 427 the peak in 2007 but only the ML model predicts both peaks in 2003 and 2007 even though the peak in 2003 is 428 underestimated. According to the SHAP importance from the ML model, the peak emissions in October 2003 and 429 October 2007 are mainly contributed by the SVD predictors and ERC (SVD2 NCA and SVD1 RM together 430 contribute 20% to the fire emissions for October 2003 and SVDs SElag2 and SVD2 RM together contribute 31% 431 to the fire emissions for October 2007) and ERC (15% and 18% for October 2003 and 2007, respectively) (Fig. 8b). The results indicate that the ML model captures the effect of synoptic weather patterns on fire activity by 432 433 including the SVD predictors. Even though the wind speed is included in simulating fire spread in the FireMIP 434 models, the spatial resolutions of the models and/or the atmospheric forcing data may not be fine enough to resolve the strengthened offshore winds through the complex terrain, and subsequently, they may not well capture the 435 436 effects of Santa Ana winds on fires. As shown in Fig. S8, the wind speeds from NARR are significantly larger than 437 from CRUNCEP for the strong wind days (daily wind speed > 4.5 m/s) over southwestern California (116-119 °W, 32.6-34.8 °N) during 2000-2012 October as well as the during Oct 2003 and 2007 (Table S3). The results indicate 438 439 the lower wind speeds in the CRUNCEP atmospheric forcing used in FireMIP may partially explain the model 440 biases for the events associated with Santa Ana winds. Besides the above-mentioned shortfall, all the models have problems reproducing the interannual variability of the fire emissions over Mediterranean California, with very 441 442 low correlations (r<0.25) for the FireMIP models and a relatively low correlation (r=0.72) for the ML model (Table 4; Fig. 7d). The poor performance for this region may be due to the complex relations between fires and multiple 443 444 factors, including meteorology, complex terrain, fuel, and human, which may not be fully represented in the models (Mann et al., 2016; Radeloff et al., 2018). 445

446 Both the ML model and LPJ-SIM successfully reproduce the seasonality of fire emission in southwestern 447 US peaking in June (r=0.99 and 0.94 for ML and LPJ-SIM, respectively), while other models simulate relatively smooth seasonality (Fig. 7e and Table 4). The ML model, LPJ-SIM, and ORCHIDEE have better performance for 448 the interannual variability, with correlation coefficients of 0.95, 0.40, and 0.45, respectively (Table 4). However, 449 450 most FireMIP models show larger variability in fire emissions than the GFED, and they all fail to capture the extremely large fire emission in 2011 (Fig. 7f). The peak fire emission in 2011 over southwestern US was caused 451 by extremely low atmospheric moisture along with moderately high temperature, leading to record-breaking VPD 452 453 and wildfire activities (Williams et al., 2015). To explain why the FireMIP models fail to capture the peak of 2011, we compare the VPD calculated from CRUNCEP data and the VPD data from gridMET used in the ML model. As 454 455 Fig. S9 shows, CRUNCEP shows smaller positive anomalies of VPD over southwestern US in 2011 summer, while gridMET data demonstrates a significantly larger VPD anomaly. The biases in CRUNCEP data may partially 456 explain the underestimations in all FireMIP models. 457

458 For southeastern US, the seasonal cycle of fire  $PM_{2.5}$  emissions displays a bimodal pattern, peaking in spring (March-April) and fall (September and October) (Fig. 7g). Most models fail to reproduce the bimodal fire 459 emissions, but the ML model, LPJ-SIM, and LPJ-SPI can capture the bimodal pattern. Although LPJ-SIM and LPJ-460 SPI predict the bimodal peaks, the first peak simulated by LPJ-SIM shows a one-month delay, and the second peak 461 simulated by LPJ-SIM and LPJ-SPI is one month early and one month late, respectively (Fig. 7g). In addition, the 462 ML model, CLM, and JSBACH reproduce the interannual variability of fire  $PM_{2.5}$  emissions relatively well (r=0.96, 463 0.57, and 0.72 for the ML model, CLM, and JSBACH, respectively) (Table 4 and Fig. 7h). Interestingly, CLM and 464 JSBACH can capture several peaks in 2007, 2010, and 2011 but they do not simulate seasonality correctly, which 465 466 may be explained by the underestimation in spring compensated by the overestimations in summer related to abnormal dryness or drought. 467

#### 468 **4.3 Performance in modeling extreme events**

Fire activity in the US is becoming more hazardous, particularly over western US, due to more frequent hotter and drier conditions as climate continues to warm (Williams et al., 2019). Thus, it is necessary to assess whether the ML model and process-based models can capture the extreme events in terms of their magnitude, frequency, timing, and location, which is essential to future projection and adaptation. As CLM performs relatively well among the FireMIP models, we select CLM for comparison with the ML model at  $1^{\circ} \times 1^{\circ}$  resolution, focusing on the spatial patterns of extreme event frequency and two case studies with extremely large fire emissions.

#### 475 **4.3.1 Frequency of extreme event occurrence**

Fig. 9 shows the frequency maps of months with large fire emissions during 2000-2012 for GFED, the ML 476 model, and CLM. Large fire emission is defined as monthly fire PM<sub>2.5</sub> emissions greater than the 95<sup>th</sup> percentile of 477 fire  $PM_{2.5}$  emission considering all the grids over CONUS in 2000-2012. GFED shows hot spots with a higher 478 479 frequency over northern California, the Pacific Northwest, and southeastern US, with total counts ranging from 15 480 to 105 (Fig. 9a). The ML model captures the spatial patterns (r=0.74), but it overestimates the number of months 481 by a factor of two to three compared to GFED, especially over western US (Fig. 9b). The spatial patterns of large fire emission occurrence simulated by CLM are generally consistent with the observed distribution by GFED 482 483 (r=0.35). However, it overestimates the frequency, particularly over Idaho and northeastern US, and simulates more 484 significant numbers of months with extreme events over large spatial extents, may be due to its coarse spatial 485 resolution (Fig. 9c).

#### 486 **4.3.2 Case studies**

487 To evaluate how well the models simulate the large fire emissions, we compare model performance for the two recent cases reported to be the largest fire events during 2000-2012, including the fires in southern US in 2011 488 and western US in 2012. During 2011, a severe drought leading to large wildfires was observed over southern US, 489 including Arizona, New Mexico, and Texas (NOAA, 2012; Wang et al., 2015). Fig. 10 shows the maps of annual 490 491 mean fire PM<sub>25</sub> emissions over southern US from GFED, the ML model, and CLM. GFED shows the largest fire 492 emissions close to the border of Arizona and New Mexico in conjunction with other small hotspots over New 493 Mexico, Texas, and Louisiana (Fig. 10a). The ML model overall reproduces the spatial distributions of the fire 494 emissions (r=0.96) and captures the largest fire emission in Arizona and New Mexico in 2011 (Fig. 10b). However, 495 CLM does not capture the hotspots observed in GFED over Arizona and New Mexico but simulates larger fire emissions in Louisiana instead (Fig. 10c). In terms of the time series, the ML model reproduces the temporal 496 497 variability of fire emissions and successfully captures the peak of total fire PM<sub>2.5</sub> emissions in June 2011 (r=0.98; 498 Figs. 10d and 10e). Although CLM simulates the peak in June, it overestimates fire emissions in the following 499 months by a factor of 4 (r=0.52; Figs. 10d and 10e).

In 2012, western US experienced several major wildfires (NOAA, 2013). The warm and dry conditions led 500 501 to large wildfires in California, Oregon, New Mexico, and Colorado (Fig. 11). Both the ML model and CLM 502 capture the hotspots with large fire emissions (Fig. 11b and 11c) and have correlation coefficients of 0.56 and 0.37, 503 respectively. However, the ML model tends to overestimate fire emissions, especially in areas surrounding the 504 grids with extremely large fire emissions (Fig. 11b). CLM misses some large fire emissions in Colorado and New 505 Mexico and underestimates the larger fire emissions in several hotspots (Fig. 11a), which may be explained by its 506 coarse resolution. The time series of normalized fire  $PM_{2.5}$  emissions in 2012 show one peak in August. The ML 507 model captures the peak and presents a high correlation between the simulated and observed normalized and total 508  $PM_{2.5}$  fire emissions (r=0.98). CLM captures the peak in August but overestimates emissions in September and October (r=0.84; Figs. 11d and 11e). To test model generalization, we train the model using data of 2000-2009 and 509 510 2013-2020 and test on 2010-2012 and compare the ML performance with CLM (Figs. S10-11). The ML model 511 performance is as good as the 10-fold cross-validation, demonstrating that the ML model performs well on predicting unseen data. 512

#### 513 5. Discussion and conclusions

514 This study provides the first assessment to evaluate the performance of data-driven and process-based 515 models in predicting fire PM<sub>2.5</sub> emissions over CONUS. We first demonstrate that the developed ML model performs well in predicting monthly fire PM<sub>2.5</sub> emissions nationwide at grid cells of  $0.25^{\circ} \times 0.25^{\circ}$  resolution from 516 517 2000 to 2020, with an RMSE of 0.16 g/m<sup>2</sup> and IoA of 0.84. The ML model outperforms prior statistical models predicting fire activities at similar spatial and temporal scales (Carvalho et al., 2008; Bedia et al., 2014). 518 519 Considering the performance at a regional scale, the ML model reproduces the interannual variability of fire 520 emissions for the selected regions, with correlation coefficients ranging from 0.84 to 0.98. Therefore, the ML model 521 has a promising performance in predicting fire emission over CONUS at a relatively fine spatial resolution. Compared to the wildfire burned area model in Wang et al. (2021), the fire emission model in this study shows 522 523 slight degradations in capturing the interannual variability of fire emission at grid level (e.g., percentage of grids 524 with correlations larger than 0.4). This may be explained by the fact that the fire emission model may not effectively 525 resolve the relationships between fires and predictors when more grids with less fire occurrence are included (i.e., 526 more zeros or unburned grids) without reliable information about ignition. As a side note, both burned area and 527 emission ML models have relatively poor performance over Mediterranean California, indicating the challenges in 528 modeling fire activities in this region where the terrain and land use are complex. The SHAP variable importance 529 shows that meteorology at both local and synoptic scale as well as fuel loads are important variables controlling 530 fire emissions over CONUS. Regional analysis of predictors indicates that fuel dryness such as fuel moisture and 531 energy release component (ERC) and fuel load are important for predicting fire emissions in western US, while 532 large-scale meteorological patterns (SVDs\_SElag2) contribute more to fire emissions in southeastern US.

We then compare the simulated fire  $PM_{2.5}$  emissions from the ML model and FireMIP models against 533 GFED from 2000 to 2012 at the spatial resolution of  $1^{\circ} \times 1^{\circ}$ . The ML model, CLM, and JULES reproduce the 534 535 spatial distribution more reasonably than the rest of the FireMIP models (r=0.83, 0.52, and 0.40 for the ML, CLM, and JULES, respectively). Both CLM and JULES simulate more fire PM<sub>2.5</sub> emissions over southeastern US, which 536 can be explained by several reasons. First, it has been shown that the satellite-observed burned areas in southeastern 537 538 US are much smaller than the burned areas estimated from the ground-based fire records, which might have resulted 539 from the small prescribed and agricultural fires (Hu et al., 2016; Nowell et al., 2018). In addition, large differences 540 exist among different satellite estimated fire  $PM_{2.5}$  emissions in southeastern US (Li et al., 2019). As a consequence, 541 these studies highlighted uncertainties about the GFED estimated burned area and emission over southeastern US. 542 Second, cropland fires are one of the predominant fire types in this region. Among the FireMIP models, CLM is 543 the only model that simulates cropland fires (Li et al., 2013). For JULES, even though it does not simulate cropland 544 fires, it treats croplands as natural grasslands. The emission factors of grasslands and croplands used in the FireMIP 545 models are larger than in GFED4s, thereby causing larger fire PM<sub>2.5</sub> emissions in southeastern US in CLM and 546 JULES (van der Werf et al., 2017; Li et al., 2019). Furthermore, Li et al. (2019) noted that CLM4.5 simulates higher fuel loads in croplands than the CASA model used by GFED4s, leading to higher fire carbon emissions 547 548 estimated by CLM than by GFED. It is worth noting that the ML model incorporates fuel load simulated by CLM4.5 549 but it predicts fire emissions closer to GFED4s, indicating a smaller sensitivity of fire emission to fuel load in the 550 ML model. The overestimation of fire  $PM_{2.5}$  emissions can also be explained by the sensitivity to meteorology. The 551 spatial distributions of the long-term mean fire emissions shown in Fig. 3 correlate with the spatial distributions of 552 sensitivities to RH and/or temperature, with regional differences. For western US, large fire emissions are associated with stronger sensitivities to both RH and temperature in the ML and most FireMIP models. For central 553 and southeastern US, overestimation of fire  $PM_{2.5}$  emissions only corresponds to stronger sensitivity to temperature 554 555 in some FireMIP models.

556 Besides comparing model performance aggregated over CONUS, we analyze the model performance for 557 several regions, including the western forest area, Mediterranean California, southwestern US, and southeastern 558 US. For the western forest area, the ML model performs well in capturing both seasonality and interannual 559 variability of fire  $PM_{2.5}$  emissions, with correlation coefficients of 0.98 and 0.96, respectively. In contrast, the 560 FireMIP models generally reproduce the seasonality well but do not simulate the interannual variability well, 561 especially underestimating the peak in 2007, which related to large-scale meteorological patterns favorable for fires 562 in Pacific Northwest (Zhong et al., 2020). For Mediterranean California, all FireMIP models only capture the first 563 peak in August but fail to simulate the second peak in October, which is caused by large fires related to Santa Ana 564 winds in 2003 and 2007. Such lack of peak emission is also shown in the interannual variability, as all FireMIP models show limited ability to simulate the peaks in these two years. By contrast, the ML model successfully 565 566 predicts the bimodal seasonality and the large fire emissions related to the Santa Ana winds in 2003 and 2007. The underestimation of the peak in the FireMIP models may be attributed to the underrepresentation of the effects of 567 large-scale meteorology in the two regions, as the ML model and SHAP importance show that SVD predictors 568 569 have larger contributions to the fire emissions in both events. The results of the two regions in the western US suggest that fire parameterization in the FireMIP models could be improved by including the effects of regional 570 571 and large-scale meteorology (e.g., Santa Ana winds) on fire activity (Yue et al., 2014). Modeling the effect of Santa 572 Ana winds on wildfires may be particularly challenging as the offshore Santa Ana winds exhibit variability related

to both synoptic scale pressure anomaly over the Great Basin and local thermodynamic forcing associated with strong desert-ocean temperature gradient (Hughes and Hall, 2010).

575 As for southwestern US, the ML model and LPJ-SIM estimate the peak in June (r=0.99 and 0.94 for ML and LPJ-SIM, respectively), which highly agrees with the GFED observation. Interestingly, most FireMIP models 576 577 fail to capture the extremely large fire emission in the 2011 summer mainly due to the low biases of VPD anomalies 578 in CRUNCEP (Tang et a., 2017). Unlike southwestern US, the seasonality of southeastern US has peaks in March-579 April and September-October. The two peaks of fire emissions correspond to wildfires (Mar-Apr and Sep), 580 cropland fires (Feb-Mar and Aug-Oct), and prescribed fires (Feb-Apr and Oct) that include burnings for pest 581 controls and land cleaning (Knapp et al., 2009; Lin et al., 2014). Most models fail to reproduce the bimodal fire 582 emissions, but the ML model, LPJ-SIM, and LPJ-SPI can capture the bimodal pattern. Even though the seasonality 583 of fires over this region is not simulated accurately, the CLM and JSBACH well reproduce the interannual 584 variability of fire PM<sub>2.5</sub> emissions and predict the peaks. The FireMIP models' shortfall in reproducing the bimodal 585 seasonality can be explained by two reasons. First, the relationships between human and fire spread implemented in the process-based models may not be realistic compared to the observed relationships. Parisien et al. (2016) 586 587 demonstrated the large spatial variability of human impacts on burned areas in North America, which is not well 588 represented in the FireMIP models (Li et al., 2019). Second, drier conditions in winter would promote fires in 589 springtime (Wear and Greis, 2013; Wang et al., 2021), which may not be directly considered in the FireMIP models 590 but are incorporated as SVD predictors in the ML model. Overall, the representations of the effects of human and 591 large-scale meteorology on fires may explain why the models simulate the seasonality incorrectly in southeastern 592 US. In addition to the comparison of general model performance, we also compare the ability of the data-driven 593 and processed-based models in predicting extremely large fire emissions. Both ML and CLM models reproduce the spatial pattern of extreme fire events and reasonably simulate the historical events of large fires in southwestern 594 and western US. 595

596 It is known that different fire emission inventories have their uncertainties and prior studies have compared 597 fire emission inventories over the globe or CONUS (Urbanski et al., 2018; Liu et al., 2020). The GFED fire 598 emissions used in this study are known to underestimate the fire emission peak in springtime over the southeastern 599 US, which may be explained by the fact that other products such as FINN or QFED capture more small fire activity compared to the GFED approach (Koplitz et al., 2018; Carter et al., 2020). Although FINN can capture more small 600 601 fires, it underestimates the intensity of large fires for some cases, which has been attributed to the cloud coverage 602 on daily scale detection (Paton-Walsh et al., 2012). QFED and GFAS, which estimate emissions using fire radiative 603 power (FRP) from satellites, are also more sensitive to small fires than GFED. However, QFED tends to estimate 604 much larger emissions than other products, which can be explained by the fact that the emission coefficients used 605 to obtain emissions are constrained by MODIS AOD and the uncertainties within FRP (Pan et al., 2020). Despite 606 the known discrepancy between GFED and other data products, the GFED data still shows bimodal peaks in spring 607 and fall over the southeastern US, while most FireMIP models fail to reproduce the first peak (Fig. 7g in the 608 manuscript). For the western US, GFED and FINN are generally consistent regarding the magnitude and variability 609 of fire emissions (Urbanski et al., 2018). As stated above, different fire emission inventories have uncertainties. 610 Future works are required to include other fire emission datasets for model evaluation.

To summarize, we utilize the ML model with SHAP importance to diagnose the fire emissions simulated 611 612 by process-based models and attributed model biases to several factors. First, the sensitivities of fire emissions to 613 meteorology in the models are stronger than the observed, leading to overestimations. Second, the large-scale 614 meteorological patterns conducive to fires are not fully considered in the process-based models, which are 615 important contributors of large fire emissions in western US and southeastern US. Third, the spatial resolutions of 616 models and/or the atmospheric forcing they used may be too coarse to resolve the effects of regional weather 617 phenomenon such as Santa Ana winds. Fourth, biases in the atmospheric forcing data may result in biases of fire 618 emission predictions. Last but not least, human activities are a critical component shaping fire regimes but the

human effects on fire activities in the FireMIP models may not reflect the human-fire relationships in the real-619 world. This is also an issue in the ML model as the human-related predictors in the ML model may be too simple 620 621 to represent the human influences. The underrepresentation of human effects in both types of models may cause additional uncertainties in projecting future fire activities and their impacts on climate. By training the ML model 622 623 using the GFED emissions, the ML model is able to better explain fire emissions in the US, which makes it a useful 624 tool for diagnosing processes or relationships that may be missing or not well represented in the process-based models to guide future development for improving their performance. Besides its use in diagnosing process-based 625 626 models, the ML model with SHAP provides a different and novel approach to simulate fire emissions more 627 accurately and identify the important predictor variables. While the ML model generally has higher accuracy than the FireMIP models, the feedbacks between fire emissions and climate are not included, which could potentially 628 affect the reliability of ML-based models in fire emission prediction under future climate change scenario (Zou et 629 al., 2020). Lastly, due to limited training data, the ML model cannot predict fires in regions with longer fire return 630 631 intervals, posing additional uncertainties in their use for making future projections.

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- 634 *Code availability*. Model code is available upon request to the first author.
- 636 *Data availability*. The ML prediction and predictor dataset used in this study are publicly accessible online at 637 <u>https://zenodo.org/record/5076646#.YOZI4zZKjOQ</u>.
- 638

*Author contributions.* SW, YQ, RL conceived the research ideas. SW wrote the initial draft of the paper, performed
 analyses, and model development. All authors contributed to the interpretation of the results and the preparation of
 the manuscript.

- 642
- 643 Acknowledgements.

644 This research was performed at PNNL and funded under Assistance Agreement No. RD835871 by the U.S.

645 Environmental Protection Agency to Yale University through the SEARCH (Solutions for Energy, AiR, Climate,

646 and Health) Center. It has not been formally reviewed by EPA. The views expressed in this document are solely

647 those of the SEARCH Center and do not necessarily reflect those of the Agency. EPA does not endorse any products

648 or commercial services mentioned in this publication.

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- **Table 1.** Advantages and limitations of different types of fire models

	Representative method	Advantages	Limitations
Data-driven model	Multiple Linear regression	1. Computationally efficient	1. It cannot capture the non-
	(MLR)	2. Simple model	linear relationships between fires
		3. It is easy to interpret	and predictors
			2. It assumes that the predictor
			variables are independent
			3. It is sensitive to outliers
	Machine learning method	1. Computationally cheap	1. It requires a lot of training data
	(e.g., neural network,	2. The performance improves	2. It is relatively hard to interpret
	decision tree etc.)	when more training data are	3. The interactions between fires
		included	and vegetation/atmosphere
		3. It can easily handle multi-	cannot be updated to the model
		dimensional data	
Process-based model	Dynamic global vegetation	1. Physics-driven	1. Computationally expensive
	model (DGVM)	2. The simulations can include	2. The same parameterization
		feedbacks between fires and	may not be applied to all regions
		climate or vegetation	3. It only parameterizes the
			known processes or phenomena

- 927 Table 2. Predictor variables used in the ML model

Variables	Abbreviation	Categories	Temporal resolution	Spatial resolution	Data Source	References
Monthly mean surface temperature	temp	Local meteorology	monthly	32 km	North American Reanalysis (NARR)	Mesinger et al. (2006)
Monthly mean relative humidity	RH	Local meteorology	monthly	32 km	North American Reanalysis (NARR)	Mesinger et al. (2006)
Monthly mean of daily precipitation	precip	Local meteorology	monthly	32 km	North American Reanalysis (NARR)	Mesinger et al. (2006)
Monthly mean zonal component of wind speed	U	Local meteorology	monthly	32 km	North American Reanalysis (NARR)	Mesinger et al. (2006)
Monthly mean meridional component of wind speed	V	Local meteorology	monthly	32 km	North American Reanalysis (NARR)	Mesinger et al. (2006)
Monthly Standardized Precipitation Evapotranspiration Index	SPEI	Local meteorology	monthly	0.5°×0.5°	SPEI	Vicente- Serrano et al. (2010)
Monthly mean 1000- hour dead fuel moisture	FM1000	Local meteorology	daily	4 km	gridMET	Abatzoglou (2013)
Monthly mean energy release component	ERC	Local meteorology	daily	4 km	gridMET	Abatzoglou (2013)
Monthly mean vapor pressure deficit	VPD	Local meteorology	daily	4 km	gridMET	Abatzoglou (2013)
Monthly lightning flashes density	lightning	Local meteorology	daily	0.1°×0.1°	SWDI/NLDN	NOAA (2006); Cummins and Murphy (2009)
Monthly standard deviation of daily SVDs for northern California	SVD1_NCA and SVD2_NCA	Large-scale meteorological patterns	monthly	Regional	North American Reanalysis (NARR)	Wang et al. (2021)
Monthly standard deviation of daily SVDs for southern Rocky Mountain	SVD1_SRM and SVD2_SRM	Large-scale meteorological patterns	monthly	Regional	North American Reanalysis (NARR)	Wang et al. (2021)

Monthly standard deviation of daily SVDs for southeastern US (with 2-month lag)	SVD1_SElag2 and SVD2_SElag2	Large-scale meteorological patterns	monthly	Regional	North American Reanalysis (NARR)	Wang et al. (2021)
Monthly mean evapotranspiration	ET	Land-surface properties	monthly	0.25°×0.25°	North American Land Data Assimilation System (NLDAS-2)	Xia et al. (2012)
Monthly mean surface soil moisture	soilm	Land-surface properties	monthly	0.25°×0.25°	Global Land Data Assimilation System (GLDAS-2)	Xia et al. (2012)
Monthly mean vegetation fraction	Veg_frac	Land-surface properties	monthly	0.25°×0.25°	Global Land Data Assimilation System (GLDAS-2)	Xia et al. (2012)
Monthly mean Leaf Area Index	LAI	Land-surface properties	8 days	500 m	MODerate resolution Imaging Spectroradiometer (MODIS); LAI classification scheme	Myneni et al. (2015)
Monthly fuel load/normalized fuel load	fuel_load/fuel_load_nor	Land-surface properties	monthly	0.9°×1.25°	Community Land Model (CLM)	Lawrence et al. (2019)
Land cover percentage	p_	Land-surface properties	Yearly	0.05°×0.05°	MODerate resolution Imaging Spectroradiometer (MODIS); LAI classification scheme	Friedl (2015)
Median Topography (slope and elevation)	Slope and elevation	Land-surface properties	Not change by time	100 km		Amatulli et al. (2018)
Gross domestic product	GDP	Socioeconomic and coordinate variables	Yearly	5 arc		Kummu et al. (2018)
Population density	Рор	Socioeconomic and coordinate variables	Yearly	30 arc	Gridded Population of the World data collection (GPW v4)	CIESIN- Columbia University (2017)

# **Table 3.** The ML model performance for different regions: western forest area, Mediterranean California, southwestern US, and southeastern US

	Western	Medi	terranean	Sout	hwestern US	Sc	outheastern	Whole US	
	forest area	a Calife	ornia			US	8		
Grid scale (individual	grid)								
RMSE (km <sup>2</sup> )	0.29	0.32		0.10		0.0	02	0.16	
Correlation (r)	0.79	0.51		0.76		0.8	84	0.76	
IoA	0.86	0.60		0.85		0.9	90	0.84	
Percentage of grids with	68	47		52		80	)	74	
correlation $> 0.4$ (%)									
Regional scale (summa	tion over the	e region)							
RMSE (km <sup>2</sup> )	37.80	13.94	ŀ	2.76		3.3	37	49.98	
Correlation (r)	0.98	0.81		0.94		0.9	97	0.97	
IoA	0.98	0.81		0.95		0.9	98	0.97	
Table 4. The model perfo	ormance for the ML	<u>he ML mo</u> CLM	del and Fire CTEM	MIP models JSBACH	LPJ-SPI	LPJ-	LPJ-SIM	ORCHIDEE	JULES
Table 4. The model perfo	mance for the ML of ML of Model	he ML mo CLM	del and Fire CTEM	MIP models JSBACH	LPJ-SPI	LPJ- Glob	LPJ-SIM	ORCHIDEE	JULES
Table 4. The model perfo	ML 0 model	he ML mo CLM	del and Fire CTEM	MIP models JSBACH 89 Tg)	LPJ-SPI	LPJ- Glob	LPJ-SIM	ORCHIDEE	JULES
Table 4. The model performanceTotal amounts of fire PMTotalfirePM2.5emissionsover2000-2012 (Tg)00	Image: system of the system	he ML mo CLM ( <b>Tg=10<sup>12</sup> g</b> 16.54	del and Fire CTEM () (GFED: 4.8 41.50	MIP models JSBACH 89 Tg) 19.92	LPJ-SPI 16.23	LPJ- Glob 79.49	LPJ-SIM 35.38	ORCHIDEE 2.43	JULES 33.43
Table 4. The model performanceTotal amounts of fire PMTotal fire PM2.5emissions over 2000-2012 (Tg)Correlation of interannual	ML of model 12.5 emissions 8.33	<u>he ML mo</u> CLM ( <b>Tg=10<sup>12</sup> g</b> 16.54 <b>riability fo</b>	del and Fire CTEM () (GFED: 4.8 41.50 r the CONUS	MIP models JSBACH 39 Tg) 19.92	LPJ-SPI 16.23	LPJ- Glob 79.49	LPJ-SIM 35.38	ORCHIDEE 2.43	JULES 33.43
Table 4. The model performanceTotal amounts of fire PMTotal fire PM2.5emissions over 2000-2012 (Tg)Correlation of interannualCorrelation(interannual/seasonal)	ormance for th         ML       0         model       0         12.5 emissions       0.87/0.98	he ML mo CLM (Tg=10 <sup>12</sup> g 16.54 riability fo 0.71/0.92	del and Fire CTEM () (GFED: 4.8 41.50 r the CONUS 0.28/0.87	MIP models JSBACH <b>39 Tg)</b> 19.92 <b>5</b> 0.15/0.89	LPJ-SPI 16.23 0.15/0.92	LPJ- Glob 79.49 0.02/-	LPJ-SIM 35.38 0.23/0.65	ORCHIDEE 2.43 0.03/0.91	JULES 33.43
Table 4. The model performance         Total amounts of fire PM         Total fire PM2.5         emissions over 2000-2012 (Tg)         Correlation of interannual         Correlation of interannual         Correlation of interannual         Correlation of interannual	ormance for th         ML         model <b>12.5 emissions</b> 8.33         al/seasonal val         0.87/0.98         al/seasonal val	he ML mo CLM (Tg=10 <sup>12</sup> g 16.54 riability fo 0.71/0.92 riability fo	del and Fire CTEM () (GFED: 4.8 41.50 r the CONUS 0.28/0.87 r the selected	MIP models JSBACH 39 Tg) 19.92 8 0.15/0.89 I regions	LPJ-SPI 16.23 0.15/0.92	LPJ- Glob 79.49 0.02/-	LPJ-SIM 35.38 0.23/0.65	ORCHIDEE 2.43 0.03/0.91	JULES 33.43
Table 4. The model performance         Total amounts of fire PM         Total fire PM2.5         emissions over 2000-         2012 (Tg)         Correlation of interannual         Correlation of interannual         Western forest area	ormance for th         ML       0         model       0         12.5 emissions       0         8.33       0         al/seasonal val       0         0.87/0.98       0         al/seasonal val       0         0.93/0.98       0	he ML mo CLM (Tg=10 <sup>12</sup> g 16.54 riability fo 0.71/0.92 riability fo 0.70/0.93	del and Fire CTEM (GFED: 4.8 41.50 r the CONUS 0.28/0.87 r the selected 0.33/0.88	MIP models JSBACH 89 Tg) 19.92 5 0.15/0.89 1 regions 0.21/0.88	LPJ-SPI 16.23 0.15/0.92 0.38/0.79	LPJ- Glob 79.49 0.02/-	LPJ-SIM 35.38 0.23/0.65 0.46/0.98	ORCHIDEE 2.43 0.03/0.91 0.05/0.94	JULES 33.43 0.55/0. 0.60/0.
Table 4. The model performance         Total amounts of fire PM         Total fire PM2.5         emissions over 2000-         2012 (Tg)         Correlation of interannual         Correlation of interannual         Correlation of interannual         Western forest area         Mediterranean         Correlation	ormance for th         ML       0         model       0         12.5 emissions       0         8.33       0         al/seasonal val       0         0.87/0.98       0         0.93/0.98       0         0.72/0.97       -	he ML mo CLM (Tg=10 <sup>12</sup> g 16.54 riability fo 0.71/0.92 riability fo 0.70/0.93 -0.01/0.87	del and Fire CTEM (GFED: 4.8 41.50 r the CONUS 0.28/0.87 r the selected 0.33/0.88 0.05/0.94	MIP models JSBACH 89 Tg) 19.92 6 0.15/0.89 1 regions 0.21/0.88 -0.30/0.89	LPJ-SPI 16.23 0.15/0.92 0.38/0.79 -0.07/0.90	LPJ- Glob 79.49 0.02/- 0.51/- -0.14/-	LPJ-SIM 35.38 0.23/0.65 0.46/0.98 -0.19/0.83	ORCHIDEE 2.43 0.03/0.91 0.05/0.94 0.25/0.13	JULES 33.43 0.55/0. 0.60/0. -0.21/0
Table 4. The model performants         Total amounts of fire PM         Total fire PM2.5         emissions over 2000-2012 (Tg)         Correlation of interannus         Correlation of interannus         Western forest area         Mediterranean         California	ormance for th         ML       0         model       0         12.5 emissions       0         8.33       0         al/seasonal val       0         0.87/0.98       0         0.93/0.98       0         0.72/0.97       -	he ML mo CLM (Tg=10 <sup>12</sup> g 16.54 riability fo 0.71/0.92 riability fo 0.70/0.93 -0.01/0.87	del and Fire CTEM () (GFED: 4.8 41.50 r the CONUS 0.28/0.87 r the selected 0.33/0.88 0.05/0.94	MIP models JSBACH 89 Tg) 19.92 5 0.15/0.89 1 regions 0.21/0.88 -0.30/0.89	LPJ-SPI 16.23 0.15/0.92 0.38/0.79 -0.07/0.90	LPJ- Glob 79.49 0.02/- 0.51/- -0.14/-	LPJ-SIM 35.38 0.23/0.65 0.46/0.98 -0.19/0.83	ORCHIDEE 2.43 0.03/0.91 0.05/0.94 0.25/0.13	JULES 33.43 0.55/0.9 -0.21/0
Table 4. The model performance         Total amounts of fire PM         Total fire PM2.5         emissions over 2000-         2012 (Tg)         Correlation of interannual         Correlation of interannual         Western forest area         Mediterranean         California         Southwestern US	ormance for th         ML       0         model       0         12.5 emissions       0         8.33       0         al/seasonal val       0         0.87/0.98       0         0.93/0.98       0         0.72/0.97       -         0.95/0.99       0	he ML mo CLM (Tg=10 <sup>12</sup> g 16.54 riability fo 0.71/0.92 riability fo 0.70/0.93 -0.01/0.87 0.14/0.85	del and Fire CTEM () (GFED: 4.8 41.50 r the CONUS 0.28/0.87 r the selected 0.33/0.88 0.05/0.94 -0.26/0.62	MIP models JSBACH 39 Tg) 19.92 5 0.15/0.89 1 regions 0.21/0.88 -0.30/0.89 -0.28/0.45	LPJ-SPI 16.23 0.15/0.92 0.38/0.79 -0.07/0.90 0.34/0.42	LPJ- Glob 79.49 0.02/- 0.51/- -0.14/- 0.30/-	LPJ-SIM 35.38 0.23/0.65 0.46/0.98 -0.19/0.83 0.40/0.94	ORCHIDEE 2.43 0.03/0.91 0.05/0.94 0.25/0.13 0.45/0.72	JULES 33.43 0.55/0.9 0.60/0. -0.21/0 -0.07/0





**Fig. 1.** (a) The map of temporal correlation between observed and predicted PM<sub>2.5</sub> fire emission for each grid. Time series of observed (black) and predicted (red) PM<sub>2.5</sub> fire emission average across (b) western forest area (red box in 1a), (c)

940 boserved (black) and predicted (red) 1 M<sub>2.5</sub> me emission average across (b) western forest area (red box in 1a), 941 Mediterranean California (blue box), (d) southwestern US (dusty box), (e) southeastern US (pink box).





943 Fig. 2. Top 20 variables for the model based on the mean absolute SHAP value with the 95% confidence intervals.



946 Fig. 3. Spatial distributions of the monthly mean  $PM_{2.5}$  fire emission (g/m<sup>2</sup>/month) over 2000-2012.



**Fig. 4.** Spatial distributions of the linear regression slope for the dependence of annual mean  $PM_{2.5}$  fire emissions on annual mean RH. Only the grids with slopes that are statistically significant (p<0.05) are shown.



**Fig. 5.** Spatial distributions of the linear regression slope for the dependence of annual mean  $PM_{2.5}$  fire emissions on annual mean temperature. Only the grids with slopes that are statistically significant (p<0.05) are shown.



Fig. 6. (a) Seasonality and (b) interannual variability of the normalized averaged PM<sub>2.5</sub> fire emission from the GFED (black
line), ML model (red line), and the FireMIP models (color lines). The PM<sub>2.5</sub> fire emissions are first averaged over CONUS
and normalized by the monthly (annual) mean and standard deviation for seasonality (interannual variability) plots.



Fig. 7. Seasonality and interannual variability of the PM2.5 fire emission from the GFED (black line), ML model (red line),
and the FireMIP models (color lines) for (a, b) western forest area, (c, d) Mediterranean California, (e, f) southwestern US,
and (g, h) southeastern US.



967 Fig. 8. Time series of the average SHAP values (bar) and predicted normalized PM<sub>2.5</sub> fire emission (line) for (a) western forest 968 area from 2006 to 2008, (b) Mediterranean California from 2003 to 2007, and (c) southeastern US from 2008 to 2009. The 969 SHAP values indicate the contribution of the predictors to the prediction of normalized fire emission.

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**Fig. 9.** Spatial distributions of number of months with large fire emissions (> 95<sup>th</sup> percentiles of PM<sub>2.5</sub> fire emission over all the grids in 2000-2012) for (a) GFED, (b) ML model, and (c) CLM.



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Fig. 10. Top panel: Spatial distributions of the annual mean PM<sub>2.5</sub> fire emission in 2011 for (a) GFED, (b) ML model, and (c)
CLM. Bottom panel: Time series of the (d) total PM<sub>2.5</sub> fire emissions and (e) normalized PM<sub>2.5</sub> fire emission over southern US
domain during 2011.



Fig. 11. Top panel: Spatial distributions of the annual mean PM<sub>2.5</sub> fire emission in 2012 for (a) GFED, (b) ML model, and (c)
 CLM. Bottom panel: Time series of the (d) total PM<sub>2.5</sub> fire emissions and (e) normalized PM<sub>2.5</sub> fire emission over western US

984 domain during 2012.