

15 **Abstract**

16 Wildfire smoke frequently blankets the U.S. throughout the agricultural growing season, and this
17 will likely increase with climate change. Studies of smoke impacts have largely focused on air
18 quality and human health; however, understanding smoke's impact on photosynthetically active
19 radiation (PAR) is essential for predicting how smoke affects plant growth. We compare surface
20 shortwave irradiance and diffuse fraction (DF) on smoke-impacted and smoke-free days from
21 2006-2020 using data from multifilter rotating shadowband radiometers at ten U.S. Department
22 of Agriculture (USDA) UV-B Monitoring and Research Program stations and smoke plume
23 locations from operational satellite products. On average, 20% of growing season days are
24 smoke-impacted, but smoke prevalence increases over time ($r = 0.60$, $p < 0.05$). Smoke presence
25 peaks in the mid- to late growing season (i.e., July, August), particularly over the northern Rocky
26 Mountains, Great Plains, and Midwest. We find an increase in the distribution of PAR DF on
27 smoke-impacted days, with larger increases at lower cloud fractions. On clear-sky days, daily
28 average PAR DF increases by 10 percentage points when smoke is present. Spectral analysis of
29 clear-sky days shows smoke increases DF (average: +45%) and decreases total irradiance
30 (average: -6%) across all six wavelengths measured from 368-870 nm. Optical depth
31 measurements from ground and satellite observations both indicate that spectral DF increases
32 and total spectral irradiance decreases with increasing smoke plume optical depth (i.e., plume
33 thickness). Our analysis provides a foundation for understanding smoke's impact on PAR, which
34 carries implications for agricultural crop productivity under a changing climate.

35 **Plain Language Summary**

36 Wildfires in the United States (U.S.) are occurring more often and burning larger areas, and
37 smoke from these fires impacts incoming solar radiation across the country. Sunlight is a
38 necessary ingredient for photosynthesis with the total amount and diffuse fraction of light
39 affecting plant growth. Smoke particles absorb and scatter light resulting in less total and more
40 diffuse radiation, respectively. Since smoke is present over agricultural regions during the
41 growing season (April-September), understanding how smoke affects sunlight is essential for
42 determining smoke's impact on crops. We use ground-based measurements of solar radiation and
43 satellite-based observations of smoke plume location and thickness to examine how sunlight
44 varies on days with and without smoke at ten agriculturally-important locations across the U.S.
45 from 2006-2020. We show that smoke is present most often during the mid- to late growing
46 season when light characteristics most impact plant growth. One in five growing season days is
47 smoke-impacted and smoke is becoming more frequent over time. The diffuse fraction is higher
48 on smoke-impacted days with the largest increase occurring when cloud cover is low. While the
49 diffuse fraction increases with smoke, total irradiance decreases, and these shifts grow stronger
50 as smoke plumes become thicker.

51 **1 Introduction**

52 Since the mid-1980s, higher spring and summer temperatures, earlier snowmelt, and
53 increased fuel aridity have led to longer wildfire seasons with fires that burn longer and cover
54 larger areas (Abatzoglou & Williams, 2016; Westerling, 2016; Westerling et al., 2006). Much of
55 the increase in U.S. wildfire activity has been centered in the Pacific Northwest and Southwest
56 (Westerling, 2016). The increase in wildfire activity is increasing wildfire smoke emissions
57 (Ford et al., 2018; Yue et al., 2013). Existing smoke climatologies show that wildfire smoke
58 from the western U.S. travels far from active fire sources to affect the atmospheric column and

59 air quality nationally (Brey et al., 2018; O'Dell et al., 2021). However, the widespread reach of
60 wildfire smoke was documented prior to the severe western U.S. wildfire seasons of 2018, 2020,
61 and 2021 (Brey et al., 2018), which may be emblematic of future wildfire conditions
62 (Abatzoglou et al., 2021; Higuera & Abatzoglou, 2021).

63 Increases in wildfire activity are causing measurable changes in atmospheric properties
64 over the U.S. (e.g., Buchholz et al., 2022; Xue et al., 2021). For example, near the surface, fine
65 particulate matter (PM_{2.5}) attributable to anthropogenic sources is declining over the U.S. due to
66 regulations that have substantially reduced anthropogenic emissions over the last two decades.
67 At the same time, studies of surface PM_{2.5} concentrations show that wildfire smoke emissions are
68 offsetting the reductions in PM_{2.5} caused by declining anthropogenic emissions, particularly in
69 the Pacific Northwest (McClure & Jaffe, 2018; O'Dell et al., 2019). Climate-driven wildfire
70 emissions are projected to become the dominant source of summertime PM_{2.5} in the western U.S.
71 during the 21st century (Ford et al., 2018; Val Martin et al., 2015).

72 Recent trends in surface PM_{2.5} are similar to aerosol optical depth (AOD) trends (e.g.,
73 Hallar et al., 2017; McClure & Jaffe, 2018), which account for aerosols throughout the
74 atmospheric column. Aerosols throughout the atmospheric column change the amount and
75 characteristics of shortwave irradiance reaching the Earth's surface. Direct interactions between
76 aerosols and radiation stem from aerosol absorption and scattering of downwelling shortwave
77 solar radiation. Absorption decreases total downwelling solar irradiance while scattering changes
78 the ratio of direct-to-diffuse irradiance by increasing the diffuse fraction (DF). There are also
79 indirect aerosol effects from aerosol-cloud interactions. Ultimately, by changing surface
80 shortwave radiation levels, aerosols, including those from wildfires, can influence Earth systems
81 that rely on radiation to function, such as plant productivity.

82 Photosynthetically active radiation (PAR) refers to solar radiation at wavelengths from
83 400-700 nm, which plants use for photosynthesis. Direct radiation benefits sunlit leaves, while
84 diffuse radiation is able to reach shaded leaves and boost productivity, particularly when sunlit
85 leaves reach saturation. Reducing total PAR via aerosol absorption can negatively impact plant
86 productivity, but increasing the DF via aerosol scattering can result in more efficient use of
87 available light, a phenomenon known as the diffuse radiation fertilization effect (DRFE;
88 Greenwald et al., 2006; Kanniah et al., 2012; Knohl & Baldocchi, 2008; Schiferl & Heald, 2018).
89 The degree to which the DRFE benefits productivity depends the tradeoff between decreasing
90 total PAR and increasing PAR DF as well as on plant traits such as canopy structure, leaf area
91 index, and photosynthetic pathway (e.g., C₃ or C₄), which determine the extent of shaded leaves
92 and light saturation (Kanniah et al., 2012). Few studies examine wildfire smoke's impact on the
93 DRFE, but the existing literature indicates that understanding how smoke affects surface
94 radiation may be important for productivity (Hemes et al., 2020; Lee et al., 2022; McKendry et
95 al., 2019). Therefore, large-scale longitudinal studies of smoke-radiation interactions that are
96 based on observational data are needed to better understand smoke's impact on ecosystems and,
97 given the prevalence of smoke over agricultural land, on food systems (Brey et al., 2018).

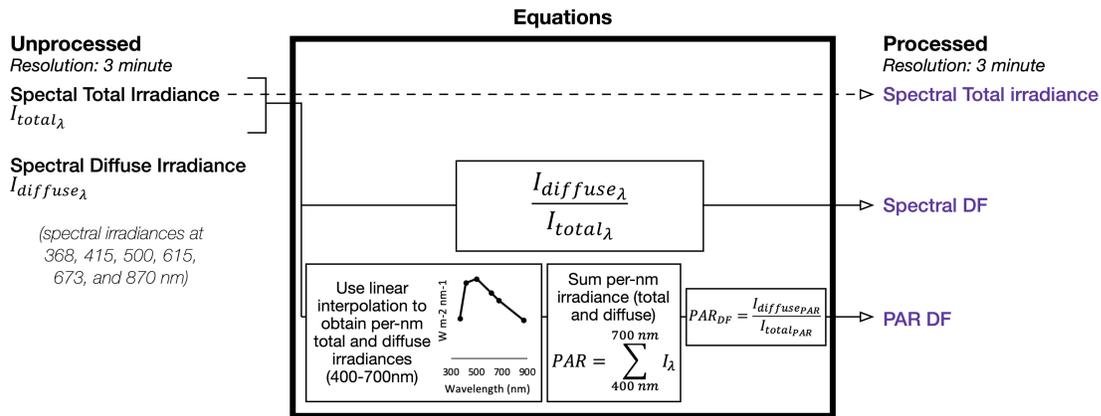
98 We present an analysis of smoke trends and associated changes to surface-level
99 shortwave radiation at 10 sites across the contiguous U.S. from 2006-2020. We leverage
100 observational data from ground-based in-situ radiation measurements and satellite observations
101 of wildfire smoke, clouds, and AOD to examine 1) how wildfire smoke varies spatially and
102 temporally during the growing season across the U.S. and 2) how total PAR and PAR DF at the

103 surface vary with wildfire smoke. We focus our analysis on the main agricultural growing season
104 (April-September) in the U.S. and over agriculturally-important regions.

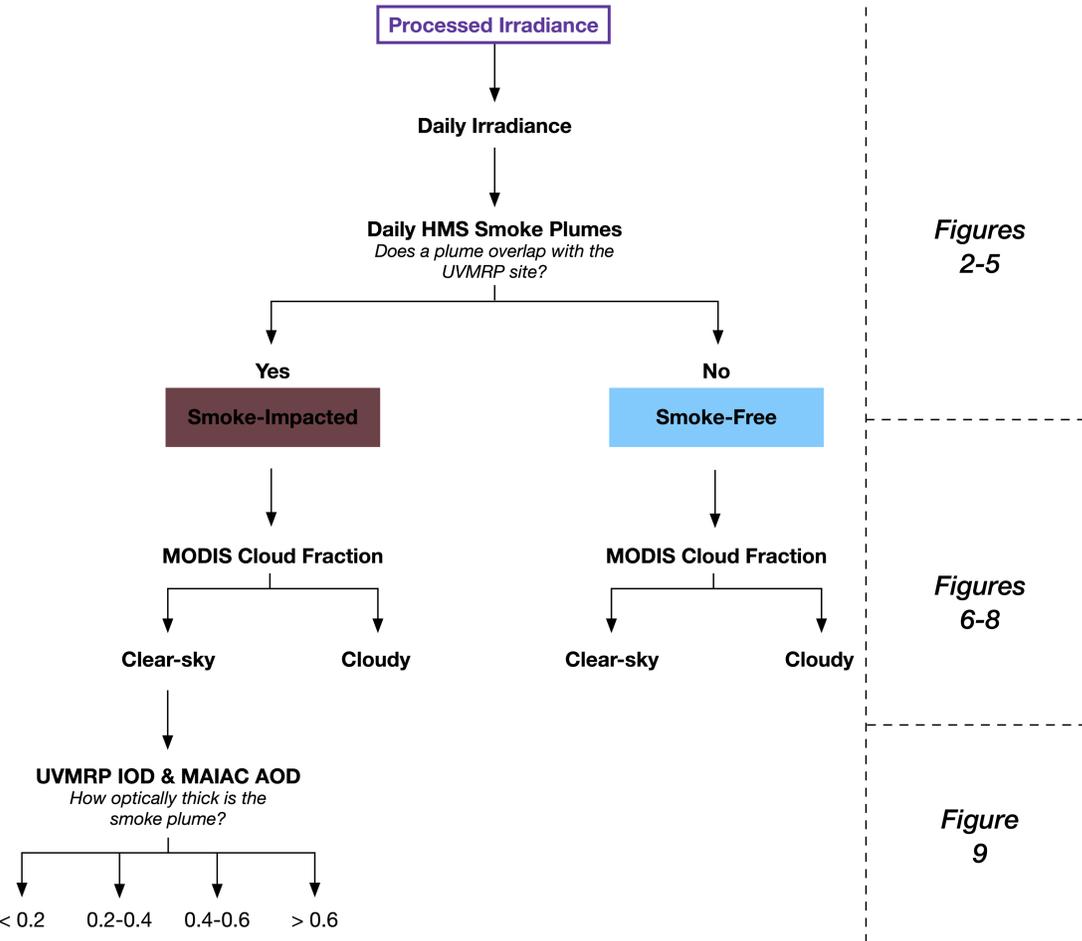
105 **2 Methods**

106 This analysis leverages radiation, smoke plume, cloud, and aerosol datasets from ground
107 and satellite observations. Detailed descriptions of each dataset are presented in the following
108 sections. Data processing and analysis are summarized in Figure 1.

1. Process UVMRP irradiance observations



2. Calculate and integrate daily smoke and meteorological metrics



109

110 **Figure 1:** Diagram summarizing data processing and integration for the irradiance (UVMRP),
 111 smoke plume (HMS), cloud (MODIS), and optical depth (UVMRP & MAIAC) datasets used for
 112 this analysis.

113

114 2.1 UVMRP Shortwave Radiation Data

115 The United States Department of Agriculture’s (USDA) UV-B Monitoring and Research
116 Program (UVMRP; <https://uvb.nrel.colostate.edu/UVB>; Bigelow et al., 1998) observes surface-
117 level solar radiation using a network of 38 active sites across the U.S., Canada, South Korea, and
118 New Zealand. Most monitoring sites (34) are distributed across the continental U.S. in
119 agriculturally-important regions as the program’s primary goal is to develop a UV-B climatology
120 to better understand how UV-B radiation impacts agricultural crop and animal production
121 (Bigelow et al., 1998). We focus on data from 10 UVMRP sites (Table 1) selected for their
122 proximity to agricultural areas and, with the exception of the California site, their distance from
123 major metropolitan areas that contribute to aerosol loading. The sites are distributed across eight
124 of the U.S. regions analyzed in the Brey et al. (2018) smoke climatology, which are largely
125 similar to the EPA regions, allowing broad spatial coverage. We refer to these sites by their
126 geographical region code listed in Table 1.

127

128 **Table 1**
 129 Description of UVMRP Site Locations and Data Availability

Site	Location	Region ^a	Smoke indicator ^b	Irradiance (Total & DF) ^c	IOD ^c	AOD ^d	CF ^e	Overall	Smoke-free days	Smoke-impacted days
Davis, California	38.53 N, 121.78 W	Southwest (SW)	99%	98%	92%	89%	100%	80%	1868	334
Pullman, Washington	46.76 N, 117.19 W	Northwest (NW)	99%	95%	78%	70%	100%	53%	1050	398
Poplar, Montana	48.31 N, 105.10 W	Rocky Mountain (RM)	99%	94%	98%	66%	100%	62%	1156	541
Pawnee, Colorado	40.81 N, 104.76 W	Rocky Mountain (RM)	99%	78%	75%	70%	100%	51%	1176	232
Fargo, North Dakota	46.90 N, 96.81 W	Great Plains (GP)	99%	94%	92%	59%	100%	51%	843	570
Billings, Oklahoma	36.60 N, 97.49 W	Southern Plains (SP)	99%	89%	82%	67%	100%	53%	1099	356
Grand Rapids, Minnesota	47.18 N, 93.53 W	Midwest (MW)	99%	95%	97%	51%	100%	48%	825	500
Bondville, Illinois	40.05 N, 88.37 W	Midwest (MW)	99%	83%	84%	53%	100%	43%	836	335
Starkville, Mississippi	33.47 N, 88.78 W	Southeast (SE)	99%	84%	79%	61%	100%	45%	1095	133
Geneva, New York	42.88 N, 77.03 W	Northeast (NE)	99%	91%	97%	53%	100%	48%	1125	201

130 *Note:* Analyses that contain a subset of the data products listed used the maximum number of data points available. At each site, 100%
 131 coverage of 15 growing seasons equals 2,745 days. ^aRegions from Brey et al. (2018). ^bHMS smoke product. ^cUVMRP irradiance and
 132 instantaneous cloud-aerosol optical depth product. ^dMAIAC aerosol optical depth product. ^eMODIS cloud fraction product.

133

134 Each UVMRP station is equipped with two multifilter rotating shadow-band radiometers
135 (MFRSR) that measure total horizontal and diffuse-horizontal solar irradiance at seven
136 wavelength passbands with a three-minute temporal resolution. The ultraviolet instrument (UV-
137 MFRSR) measures irradiance at 300, 305, 311, 317, 325, 332, and 368 nm with a full-width at
138 half maximum (FWHM) of 2 nm. The visible instrument (VIS-MFRSR) measures irradiance at
139 415, 500, 615, 673, 870, and 940 nm with a FWHM of 10 nm. The simultaneous collection of
140 total and diffuse irradiance by the same MFRSR instrument allows for the real-time calculation
141 of spectrally-resolved direct normal irradiance which supports continued calibration via Langley
142 analysis (Harrison et al., 1994) and the determination of total optical depth and instantaneous
143 cloud-aerosol combined optical depth at the same temporal resolution. Langley calibration
144 eliminates concerns that independent sensor drift could bias diffuse fraction calculations. Drift
145 may impact total PAR calculations, but all UVMRP sites maintain broadband PAR pyranometers
146 for independent validation of total PAR. Calibration and validation details are available in
147 Bigelow et al. (1998). As an operational program, the UVMRP provides routine maintenance and
148 calibration of sensors to ensure reliable and relatively consistent data products for public use;
149 however, the instrument fleet is aging as coverage spans nearly three decades at some sites.

150 We examined fifteen years (2006-2020) of irradiance records for the 10 sites in Table 1.
151 We limited our study to the six UV- and VIS-MFRSR bands that provide full coverage of the
152 PAR wavelength range: 368, 415, 500, 615, 673, and 870 nm. We performed multiple data
153 cleaning and quality control operations that are described in detail below. From the remaining
154 three-minute UVMRP records, we calculated daily average values for the following variables:
155 total spectral irradiance, spectral DF, total PAR irradiance, PAR DF, and instantaneous cloud-
156 aerosol combined optical depth (IOD). All analyses were performed using daily average values
157 for integration with satellite smoke, aerosol, and cloud products. An outline of the data
158 processing and integration steps with associated figures is provided in Figure 1.

159 For data cleaning and quality control, we removed missing data and records with quality
160 control flags that indicated whole instrument or individual channel damage or degradation. We
161 only considered records for which irradiance data were available across all six wavelengths of
162 interest. Occasional gaps exist due to instrument damage or maintenance. After implementing
163 quality controls, we removed any records where the solar zenith angle was greater than 75
164 degrees to focus on core daylight hours when plants may reach light saturation and experience
165 benefits from the DRFE. We removed all records containing negative irradiance values in the
166 total, direct, and diffuse component and any time periods in which all spectrally-resolved total
167 irradiance values equal zero.

168 Data anomalies were present across multiple sites and years, characterized by irradiance
169 values that far exceeded the peak solar irradiance at the measured wavelengths. These anomalies
170 impacted all bands on either the UV- or VIS-MFRSR but occurred infrequently, affecting only
171 0.09% of the nearly 8.29 million three-minute cleaned records across all ten sites. To ensure that
172 only physically reasonable values were included in the analysis, we removed records with total
173 irradiances in excess of threshold values. Since the UVMRP site in New Mexico observes some
174 of the highest irradiance values and lowest cloud interference in the network, we used data from
175 the New Mexico UVMRP site to approximate the maximum spectral irradiance possible for use
176 as a network threshold. We removed all records with an irradiance greater than 110% of the
177 maximum spectrally-resolved irradiance recorded in New Mexico from 2006-2020. As such, we

178 remove records that exceed the following thresholds: 1.26 W/m² for 368 nm, 2.42 W/m² for 415
179 nm, 2.53 W/m² for 500 nm, 2.42 W/m² for 615 nm, 2.27 W/m² for 673 nm, and 1.37 W/m² for
180 870 nm. Overall, the volume of data available helps reduce the impact of anomalies removed
181 during the data cleaning process.

182 Ultimately, we are interested in understanding how the overall diffuse fraction of PAR
183 varies, which requires estimating the total and diffuse irradiance over the entire 400-700 nm
184 range. We performed a linear interpolation between six adjacent wavelength bands spanning
185 368-870 nm to estimate the per-nanometer irradiance from 400-700 nm for both total and diffuse
186 irradiance (Figure 1). While the solar spectrum is not linear, we can approximate the overall
187 shape of the spectral curve using these six closely-spaced MFRSR bands, especially since the
188 500 nm channel nearly captures the peak wavelength of solar irradiance. We summed the
189 interpolated values to obtain total and diffuse PAR. A comparison of the interpolated total PAR
190 values to total PAR measured by a collocated broadband PAR LI-190SA Quantum Sensor from
191 LI-COR for a subset of years (2015-2019) at the Pawnee, CO site is included in the SI (Figure
192 S1). All calculated PAR and retrieved spectral values were then averaged to the daily level, and
193 the resulting site specific data availability ranged from 78% to 98% (Table 1).

194 2.2 HMS Smoke Plume Data

195 The Hazard Mapping System (HMS;
196 <https://www.ospo.noaa.gov/Products/land/hms.html>) operated by the National Oceanic and
197 Atmospheric Administration's (NOAA) National Environmental Satellite, Data, and Information
198 Service (NESDIS) uses data from polar orbiting and geostationary satellites to provide daily
199 operational smoke plume extents across North America in near real-time. The HMS became
200 operational in 2003 for the U.S. and Canada, expanding to full North American coverage with
201 the incorporation of Mexico and Central America in 2006 (Ruminski et al., 2006). Spatial
202 coverage of the HMS spans from 14.6°N to 72°N and 50°W to 170°W and captures each
203 region's primary biomass burning season. Smoke plumes are identified and outlined manually by
204 analysts using 2-km or finer resolution visual-band imagery from the GOES satellites. Analysts
205 rely on a series of images taken throughout the day, but primarily those near sunset and sunrise
206 when smoke plumes are most visible. Occasionally, analysts reference observations from polar-
207 orbiting satellites to identify smoke as well as use infrared bands to distinguish between clouds
208 and smoke (Rolph et al., 2009).

209 Multiple limitations characterize the HMS smoke plume data and impact potential uses of
210 the data. Because the smoke product relies on visible imagery, no information about smoke
211 plume location or extent is available at night. Analysts make no attempt to identify the smoke's
212 source. As such, smoke plumes may originate from wildfires, agricultural burning, or prescribed
213 burning. The HMS also struggles to distinguish between smoke and anthropogenic haze when
214 smoke becomes lofted, travels far from its source, and mixes with pollutants. The difference
215 between clouds and smoke is similarly difficult to discern from visual imagery, and although
216 infrared channels can help, untangling when clouds obscure smoke is a challenge. Overall, the
217 greatest area of uncertainty exists at the edge of the plume, where determining the extent of thin
218 smoke is difficult. Areas with high albedos, such as snow, also pose a challenge for identifying
219 smoke particles. These limitations make the HMS smoke product a conservative estimate of
220 smoke plume number and extent (Brey et al., 2018).

221 We use the HMS smoke product to distinguish between smoke-free and smoke-impacted
222 days at each UVMRP station. We use the HMS shapefiles, extract the smoke plume polygons,
223 and determine if a polygon overlaps with a UVMRP station. Site-specific results for growing
224 season days are merged with the associated daily average radiation metrics for analysis (Figure
225 1). HMS data coverage is 99% at all UVMRP sites as missing data between April 1 and
226 September 30 for 2006-2020 impact all sites equally.

227 2.3 MODIS Cloud Fraction Data

228 The Moderate Resolution Imaging Spectroradiometer (MODIS) instrument provides
229 daily satellite imagery from the National Aeronautics and Space Administration (NASA) Earth
230 Observing System's (EOS) Terra and Aqua satellites. The MODIS level-3 gridded atmosphere
231 daily global joint product (Platnick et al., 2015) provides average cloud fraction (CF) at a spatial
232 resolution of 1 x 1 degree. Terra and Aqua overpasses capture morning (~10:30 AM local time)
233 and afternoon (~1:30 PM local time) conditions, respectively. We use both the Terra
234 (MOD08_D3) and Aqua (MYD08_D3) products to calculate an average daytime CF for all days
235 over each site. Since we are interested in daylight hours when the solar zenith angle is smallest
236 and plant light saturation is most likely to occur, the absence of observations in the early
237 morning and late afternoon when the solar zenith angle is large is expected to be less important
238 for applications of the current work. Additionally, the resolution of MODIS products captures
239 the region surrounding UVMRP sites but may not represent the exact conditions observed by the
240 MFRSR. For example, irradiance and optical depth measurements can be heavily influenced by
241 an optically thick but isolated cloud over the site while the satellite-observed CF will remain low.
242 The temporal resolution helps mitigate the impact of rapidly changing cloud cover on daily
243 average irradiance and optical depth measurements. Finally, using MODIS to determine cloud
244 cover under smoke-impacted conditions poses a challenge because MODIS algorithms struggle
245 to distinguish clouds from smoke, leading to the misclassification of thick smoke as cloud cover.
246 However, smoke-impacted days with high CFs (> 0.8) make up only 3.4% of all days across the
247 ten UVMRP sites selected and 1.1% of days that also have UVMRP radiation data available. As
248 such, we expect that cloud-smoke confusion is a minor issue at most sites we examine. We note
249 where cloud-smoke misclassification may impact our analyses below.

250 2.4 MAIAC Aerosol Optical Depth Data

251 The Multi-Angle Implementation of Atmospheric Correction (MAIAC; <https://modis-land.gsfc.nasa.gov/MAIAC.html>) algorithm determines AOD using MODIS data from both the
252 Terra and Aqua satellites. Described in detail by Lyapustin et al. (2018) and Lyapustin and Wang
253 (2018), MAIAC leverages the different spatial and temporal variability of land surfaces and
254 aerosols to improve cloud masking capabilities and retrieve high resolution (1 km) AOD. Land
255 cover can change quickly over short distances but remains relatively stable over short periods of
256 time. In contrast, aerosols are relatively uniformly distributed spatially (i.e., in 1 km x 1 km
257 grids) but can change rapidly over a short period of time. MAIAC uses time series analysis of the
258 land surface reflectance to identify recent clear-sky land cover conditions and detect changes due
259 to clouds or aerosols.
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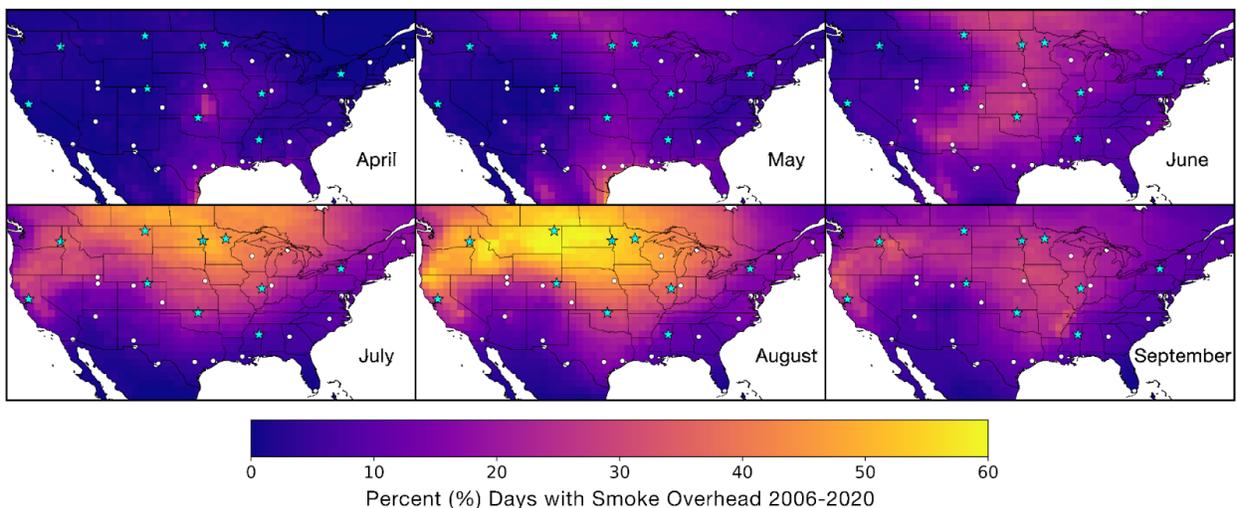
261 More precisely, MAIAC transforms the 1 km gridded L1B MODIS data into 1200 km²
262 tiles corresponding to the MODIS sinusoidal grid. Terra and Aqua overpasses are combined, and
263 the number of orbits recorded for each tile ranges from 1-2 at the equator to up to 16 at higher

264 latitudes. MAIAC uses a sliding window technique to store MODIS imagery from previous days
 265 and identify a recent clear-sky reference image for each 1 km grid cell. MAIAC compares the
 266 most recent image to the clear-sky reference to construct a cloud mask and then performs a
 267 smoke test to reduce the misclassification of thick plumes as clouds and ensure an AOD
 268 retrieval. The smoke test compares changes in the deep blue (0.412 μm) shortwave band to
 269 reflectance at longer red (0.646 μm) and blue (0.466 μm) wavelengths. Smoke increases
 270 attenuation in the 0.412 μm band because of greater multiple scattering by aerosols and stronger
 271 shortwave absorption by organic carbon. If smoke is detected, MAIAC retrieves an AOD even if
 272 the cloud mask indicates a possibly cloudy pixel. Otherwise, MAIAC AOD is only retrieved for
 273 clear-sky conditions. The improved cloud detection and screening with MAIAC allows for more
 274 accurate AOD computations. MAIAC has been shown to correspond well with AERONET
 275 measurements (Lyapustin et al., 2018) and outperform the Dark Target and Deep Blue AOD
 276 retrieval algorithms on multiple metrics (Jethva et al., 2019).

277 We use the 550 nm AOD retrievals available in the daily atmosphere MAIAC product
 278 (MCD19A2) to calculate an average daily AOD for all growing season days from 2006-2020.
 279 We include data from both the morning (Terra) and afternoon (Aqua) orbits in our calculations to
 280 better characterize the overall daytime average AOD. After identifying which MODIS tile
 281 contains each of the 10 UVMRP sites in Table 1, we identify the 1 km grid cell (pixel)
 282 containing the site location. We extract the overlapping pixel and the 16 nearest neighbors to
 283 create a 5 x 5 km box around each site. Given our focus on smoke plumes, which often exhibit
 284 high spatial variability, we include possibly cloudy skies in our analysis in addition to the clear-
 285 sky best quality AOD values. Prior to calculating an average AOD for each site, we remove any
 286 AOD surrounded by eight cloudy pixels (i.e., entirely surrounded by clouds) as this value may
 287 represent an anomalous detection.

288 3 Results and Discussion

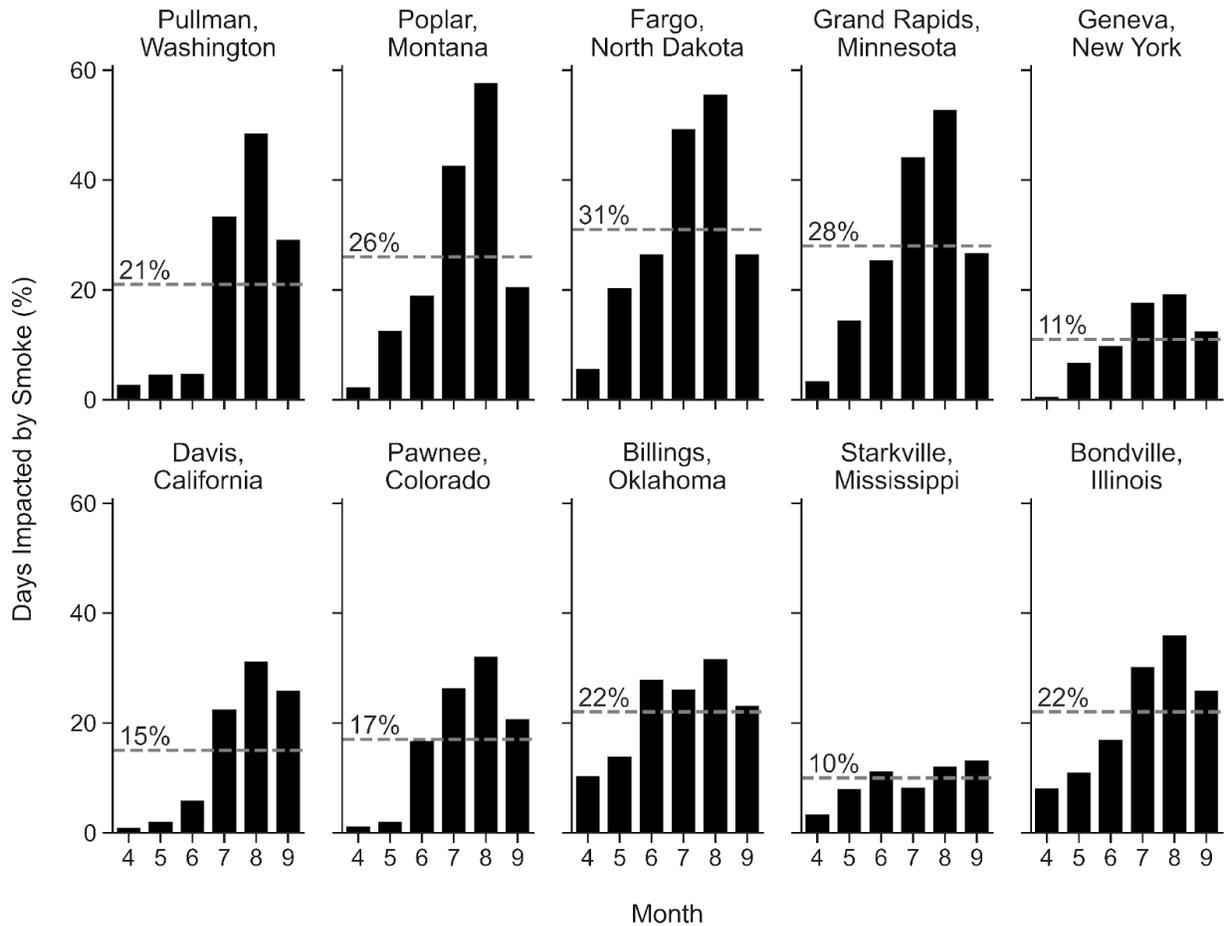
289 3.1 Monthly Average Smoke Frequency During the Growing Season



291 **Figure 2:** Average percentage of smoke-impacted days per growing season month (April-
 292 September) from 2006-2020 based on the overlap of the HMS Smoke Product plume polygons

293 with the centroid of a 1-degree grid. Blue stars indicate the ten sites analyzed here and the white
294 circles show the remaining UVMRP network sites in the continental U.S.

295 Smoke frequency and timing varies regionally across the continental U.S. between April
296 and September, the primary agricultural growing season (Figure 2). At the start of the growing
297 season, smoke-impacted days are infrequent but most common in the SP, GP, and western MW.
298 The particularly high frequency of smoke over eastern Kansas in April (~25% of days) coincides
299 with the Flint Hills region. Prescribed fires are used to preserve Flint Hills grasslands in the
300 spring with the bulk of the burning occurring in April (Baker et al., 2019; Möhler & Goodin,
301 2012). In May, smoke-impacted days remain infrequent and still mainly occur in the SP, GP, and
302 MW. The higher frequency of smoke-impacted days in the SP and GP in the early growing
303 season may result from smoke transported from southern Mexico and Central America where
304 fire starts are common in April and May (Peppler et al., 2000; Rogers & Bowman, 2001; J.
305 Wang et al., 2009; S. C. Wang et al., 2018). In June, an increase in smoke-impacted days is
306 evident over Arizona and New Mexico, which is consistent with earlier fire start times
307 (Westerling et al., 2003) and the predominance of local smoke (Brey et al., 2018) in this region.
308 Fire starts shift north and northwest as the season progresses (Westerling et al., 2003), which
309 results in increasingly frequent locally-sourced smoke over California and the NW and RM
310 regions in July and August. At the same time, almost all areas of the GP and MW, which are
311 major agricultural regions, experience smoke overhead for at least 30% of August days, which is
312 consistent with findings in Brey et al. (2018) that smoke is transported into these regions from
313 the SW, NW, RM, and Canada. Locations in the northern RM and GP regions, including western
314 Montana and North Dakota, experience smoke on nearly 60% of all August days on average.
315 Ultimately, smoke frequency peaks during the mid- to late growing season across most of the
316 U.S. due to large western wildfires. Smoke-impacted days decline in September, persisting
317 mostly over California and the NW where local fires continue to produce smoke (Westerling et
318 al., 2003).



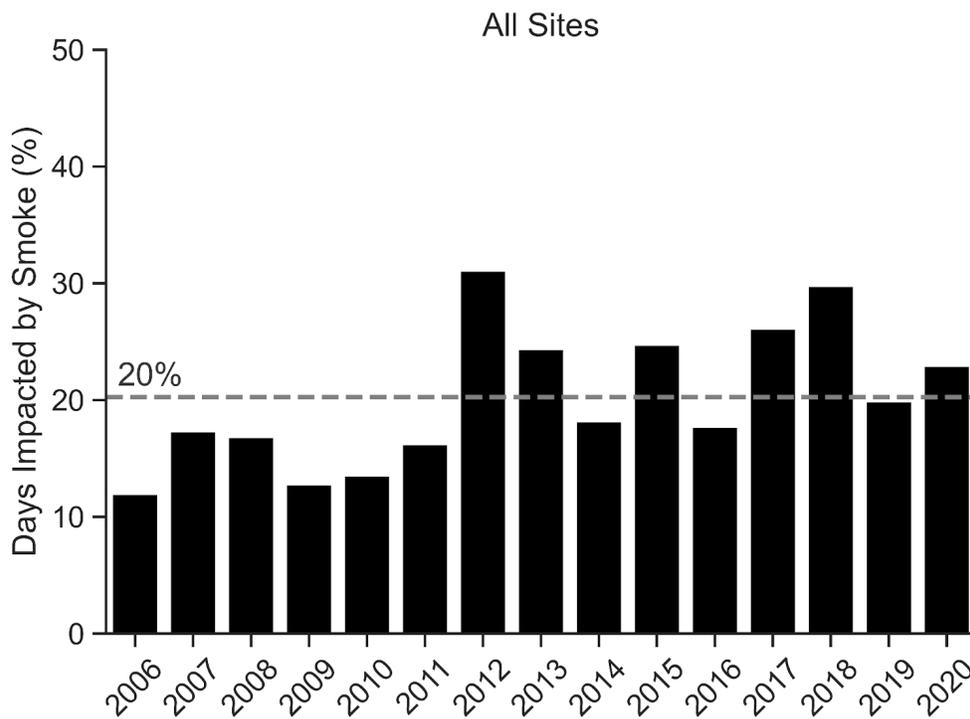
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320 **Figure 3:** Overall (dashed line) and monthly (black bars) percentage of growing season (April-
 321 September) days impacted by smoke at each UVMRP site from 2006-2020. The top row
 322 corresponds to more northern sites and the bottom to more southern sites with western sites on
 323 the left and eastern sites on the right.

324 Similar to the HMS trends shown in Figure 2, the 10 UVMRP sites demonstrate distinct
 325 differences in monthly smoke frequency across the 15 years of growing seasons analyzed (Figure
 326 3). At all sites, smoke impacts an average of 20% of all growing season days, ranging from 4%
 327 in April to 38% in August (Figure S2). Smoke-impacted days are most common in the mid- to
 328 late growing season across sites in all regions except the SE. Smoke becomes increasingly more
 329 frequent as the growing season progresses with a peak in August at all sites where the smoke
 330 primarily stems from wildfires in the western U.S. (i.e., SW, NW, and RM; Brey et al., 2018)
 331 and Canada. Northern sites in the RM, GP, and MW regions experience the most smoke-
 332 impacted days during the growing season with over a quarter (26-31%) of all days, and over half
 333 (53-58%) of all August days, characterized by smoke overhead. Sites in the SW, NW, and
 334 southern RM regions experience similar monthly smoke patterns, but the magnitude of smoke
 335 frequencies is lower (average: 15-21%). The SW and NW sites tend to experience smoke from
 336 local sources compared to the northern RM, GP, and MW regions where smoke from multiple
 337 regions is transported overhead, leading to more smoke-impacted days (Brey et al., 2018).

338 The NE and SE sites experience the least number of smoke-impacted days across the 10
 339 UVMRP locations (Figure 3). The NE site is characterized by temporal smoke patterns similar to
 340 those found at other sites, which is consistent with the similar smoke origins documented by
 341 Brey et al. (2018). However, the SE site exhibits distinctly different smoke patterns with minimal
 342 variability in smoke frequency between May and September. Smoke in the SE region is sourced
 343 from a different location than smoke over most other U.S. regions, consistent with this
 344 difference. The SE is primarily impacted by local smoke stemming from nearby fires as opposed
 345 to the fires in the SW, NW, RM, or Canada (Brey et al., 2018).

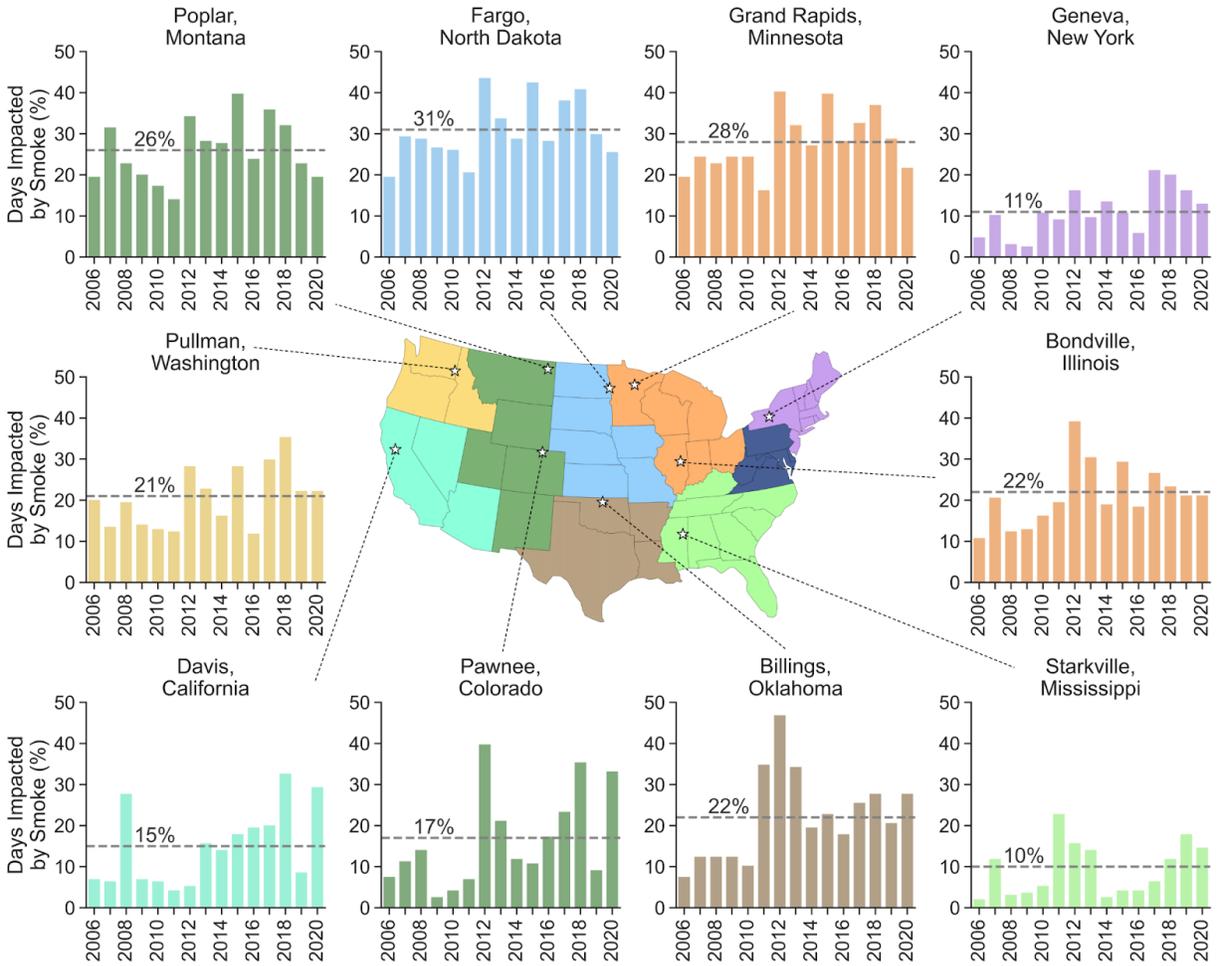
346 3.2 Interannual Variability Of Smoke Overhead During the Growing Season between
 347 2006 and 2020



348

349 **Figure 4:** Overall (dashed line) and yearly (black bars) percentage of days during the growing
 350 season (April-September) from 2006-2020 with smoke present in the atmospheric column above
 351 the 10 UVMRP sites analyzed.

352 Between 2006 and 2020, the 10 UVMRP sites experienced smoke overhead on 20% of
 353 growing season days on average (Figure 4). However, sizable interannual variability in smoke
 354 exposure is evident in Figure 4; annual smoke frequencies at the 10 stations range from 12% to
 355 31% of growing season days. Multiple heavy smoke years are included in the record, including
 356 2012 and 2018, which result in 31% and 30% smoke-impacted days, respectively. The
 357 percentage of growing season days impacted by smoke increases over time with a positive
 358 Pearson's correlation coefficient of 0.60 (p -value < 0.05). Such an increase in smoke frequency is
 359 consistent with increasing wildfire frequency, burn area, and season length (Abatzoglou &
 360 Williams, 2016; Westerling, 2016; Westerling et al., 2006).



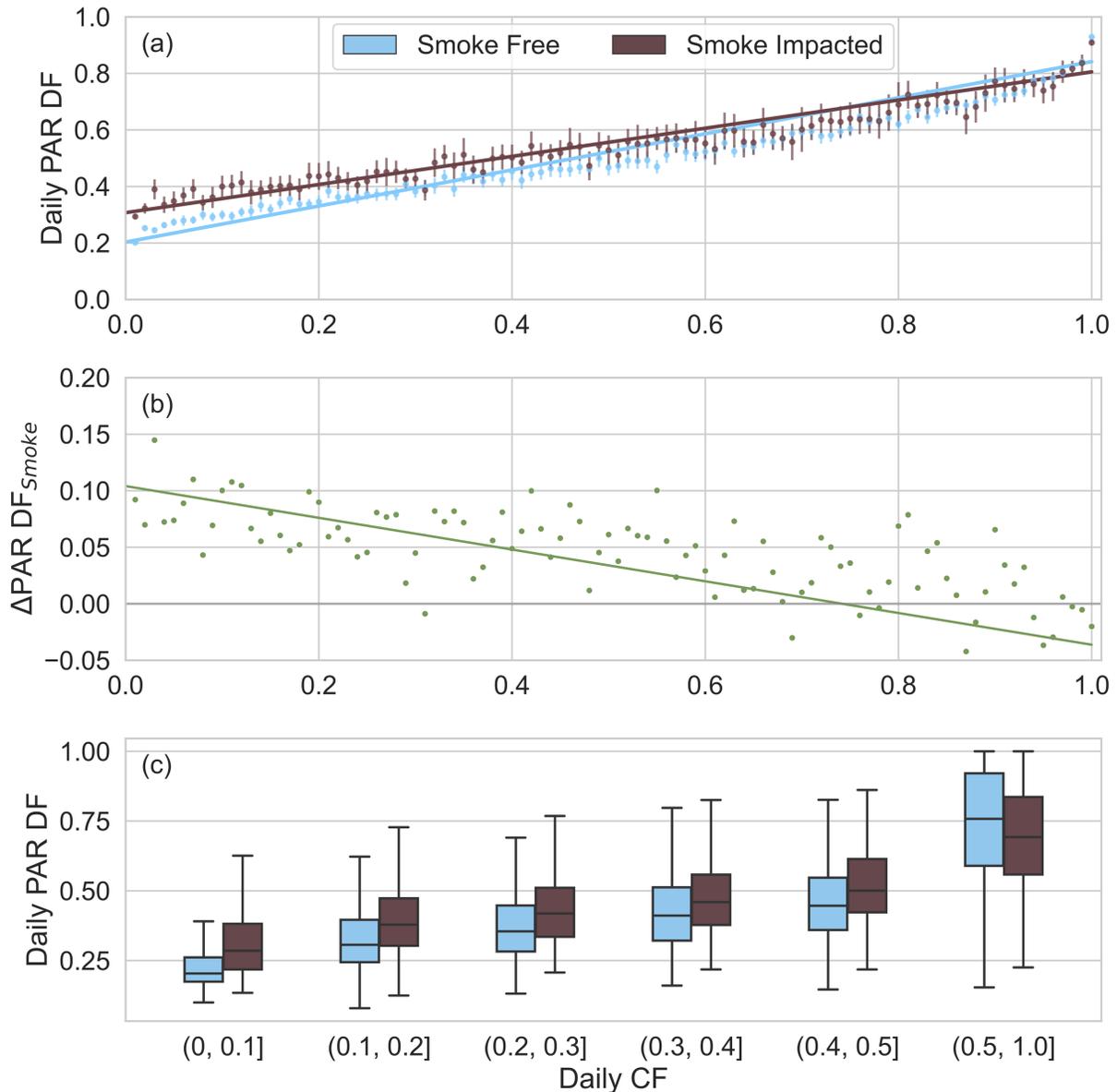
361

362 **Figure 5:** Overall (dashed line) and yearly (region-colored bars) percentage of smoke-impacted
 363 days during the growing season (April-September) at each UVMRP site analyzed showing the
 364 spatial and temporal variability of wildfire smoke across the U.S. from 2006-2020.

365 Figure 5 shows that smoke affects all sites during the growing season across all years
 366 from 2006-2020. The northern RM, GP, and MW sites are located far downwind of western
 367 wildfires but generally experienced higher percentages of smoke-impacted days (26-31%) during
 368 the growing season than do sites in the SW, NW, and southern RM (15-21%) that are closer to
 369 fires. Northern and Midwestern sites face smoke from multiple western U.S. regions and Canada.
 370 Smoke frequency peaks at the SW and southern RM sites during locally severe wildfires seasons.
 371 The 2008, 2018, and 2020 wildfire seasons were some of the worst in California state history,
 372 and the percentage of smoke-impacted days is 18 percentage points higher in these high smoke
 373 years (30%) than the average across all other years (11%). Similarly, Colorado's severe wildfire
 374 seasons in 2012, 2018, and 2020 increased smoke-impacted days by 24 percentage points on
 375 average (high smoke average: 36%; low smoke average: 12%). Even within different regions,
 376 smoke frequency varies substantially with latitude. In the RM region, the interannual trends
 377 differ between the Montana and Colorado sites. The former is more consistently impacted during
 378 the growing season while the latter shows distinct peaks in exposure amid overall fewer smoke
 379 days. A similar trend is evident in the MW when comparing the Minnesota and Illinois sites.

380

3.3 Impact of Smoke on PAR Diffuse Fraction Under Variable Cloud Conditions



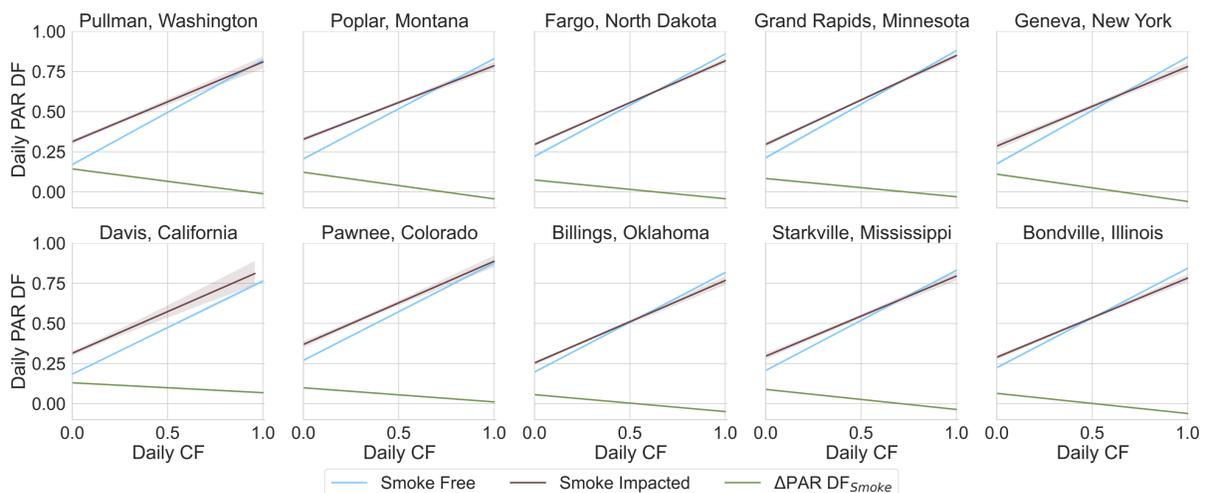
381

382 **Figure 6:** (a) Daily PAR DF based on daily CF on smoke-impacted (brown) and smoke-free
 383 (blue) days. Lines show the results of a linear regression analysis using data from all growing
 384 season days and all sites from 2006-2020 on smoke-impacted ($\text{PAR DF} = 0.50\text{CF} + 0.31$, $r = 0.78$,
 385 $p < 0.0001$, $n = 4,967$) and smoke-free ($\text{PAR DF} = 0.64\text{CF} + 0.20$, $r = 0.88$, $p < 0.0001$, $n =$
 386 19,486) days. Data variability is visualized as points representing the average daily PAR DF in
 387 each CF bin (interval = 0.01) and vertical lines displaying the 95% confidence intervals for each
 388 point. (b) Change in daily PAR DF ($\Delta\text{PAR DF}_{\text{Smoke}}$) between smoke-impacted and smoke-free
 389 days across all CFs. The green line shows the difference between the two linear regression
 390 lines in panel a and the green points show the difference between the average daily PAR DF for
 391 each CF bin (interval = 0.01). (c) Distribution of daily PAR DF on smoke-impacted (brown) and

392 smoke-free (blue) days grouped by daily CF at an interval of 0.1 up to a CF of 0.5. The midline
 393 refers to the median, and the whiskers indicate the spread of all remaining data excluding
 394 outliers. Outliers are defined as PAR DF values falling outside 1.5 times the interquartile range.
 395 The bottom and top of the boxes represent the lower and upper quartile, respectively.

396 Figure 6 compares PAR DF on all study days based on smoke and cloud conditions to
 397 approximate the relative importance of the smoke. Linear regression analyses (Figure 6a) show
 398 that daily PAR DF increases with increasing CF for both smoke-impacted ($DF = 0.50CF + 0.31$, r
 399 $= 0.78$, $p < 0.0001$) and smoke-free ($DF = 0.64CF + 0.20$, $r = 0.88$, $p < 0.0001$) days. PAR DF on
 400 smoke-impacted days increases the most under clear-sky conditions (+0.10; Figure 6b). This 10
 401 percentage point increase in clear-sky PAR DF results in a PAR DF equivalent to what is
 402 experienced on smoke-free days with a CF of 0.16. A PAR DF of 0.45, which Knohl and
 403 Baldocchi (2008) determined produced the optimal DRFE, occurs at lower CF values on smoke-
 404 impacted (CF = 0.29) than smoke-free (CF = 0.39) days. As cloud cover increases, smoke's
 405 relative influence on scattering decreases, resulting in progressively smaller increases in PAR DF
 406 on smoke-impacted days. When daily CF reaches 0.75, PAR DF no longer increases with the
 407 addition of smoke (Figure 6b).

408 Figure 6c shows how the distribution of daily PAR DF varies by CF and focuses on days
 409 with minimal cloud cover ($CF \leq 0.5$) since Figure 6b shows these days exhibit the largest
 410 increase in PAR DF. A clear upward shift in the PAR DF distribution occurs on smoke-impacted
 411 days with a CF at or below 0.5. Data from days with $CF > 0.5$ are grouped together and show
 412 that smoke fails to increase PAR DF at high CFs. Much of the interquartile range for smoke-
 413 impacted days overlaps with that for smoke-free days with the addition of smoke. We expect the
 414 impact of smoke on PAR DF to decline with increasing CF as scattering from clouds
 415 overwhelms the contribution of smoke scattering to PAR DF. Historically, MODIS CF
 416 algorithms have struggled to distinguish between thick smoke plumes and clouds, which results
 417 in artificially high CFs under thick smoke conditions. A subset of the smoke-impacted days in
 418 the high CF bin should be redistributed across the lower CF bins, thereby adding more thick
 419 smoke days with high PAR DF to the lower CF bins. Such a redistribution would increase PAR
 420 DF at low CFs, meaning the increase in PAR DF on smoke-impacted days shown in Figure 6
 421 represents a conservative estimate of smoke's radiative effects.

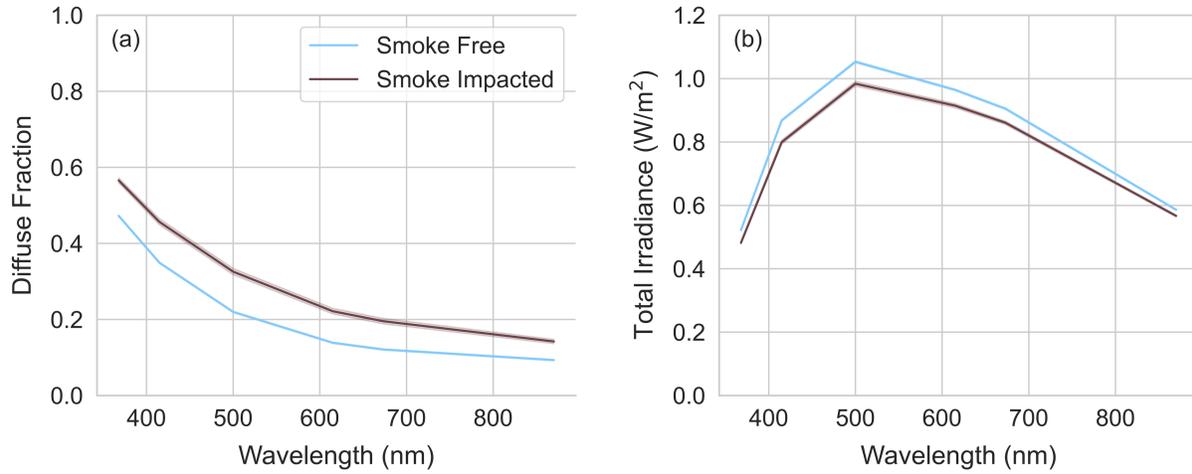


423 **Figure 7:** Linear regressions showing daily PAR DF by CF for all growing season days at each
 424 UVMRP site analyzed from 2006-2020 on smoke-impacted (brown) and smoke-free (blue) days.
 425 Shading of the same color indicates the 95% confidence intervals. The change in PAR DF
 426 ($\Delta\text{PAR DF}_{\text{Smoke}}$) between smoke-impacted and smoke-free days is presented in green.

427 The site-specific analysis presented in Figure 7 indicates similar trends across all 10
 428 sites—daily PAR DF increases on smoke-impacted days, particularly those with minimal to no
 429 clouds. On clear-sky days, the increase in PAR DF ($\Delta\text{PAR DF}_{\text{Smoke}}$) with smoke ranges from
 430 0.06 to 0.14. The greatest increase in PAR DF occurs at sites in the NW (0.14) and SW (0.13),
 431 which are closer to large wildfire ignitions. Sites further east and south in the GP, SP, MW, and
 432 SE exhibit smaller increases in PAR DF with smoke (0.06-0.08). Sites in the RM region
 433 experience increases in PAR DF from 0.10-0.12, while the NE site has a similar clear-sky
 434 increase in PAR DF of 0.11. Smoke-impacted days correspond to an increase in PAR DF across
 435 all cloud fractions at two sites: California and Colorado. At the other sites, PAR DF increases
 436 with smoke until high CF conditions are reached with this CF threshold ranging from 0.52 at the
 437 Illinois site to 0.93 at the Washington site. At all sites, the rate at which smoke increases PAR
 438 DF declines with increasing CF. Overall, smoke corresponds to higher PAR DF across more CF
 439 conditions at sites in the SW, NW, and RM regions, which are located closer to large western
 440 wildfires.

441 3.4 Impact of Smoke on Spectral Diffuse Fraction and Total Spectral Irradiance Under 442 Cloud Free Conditions

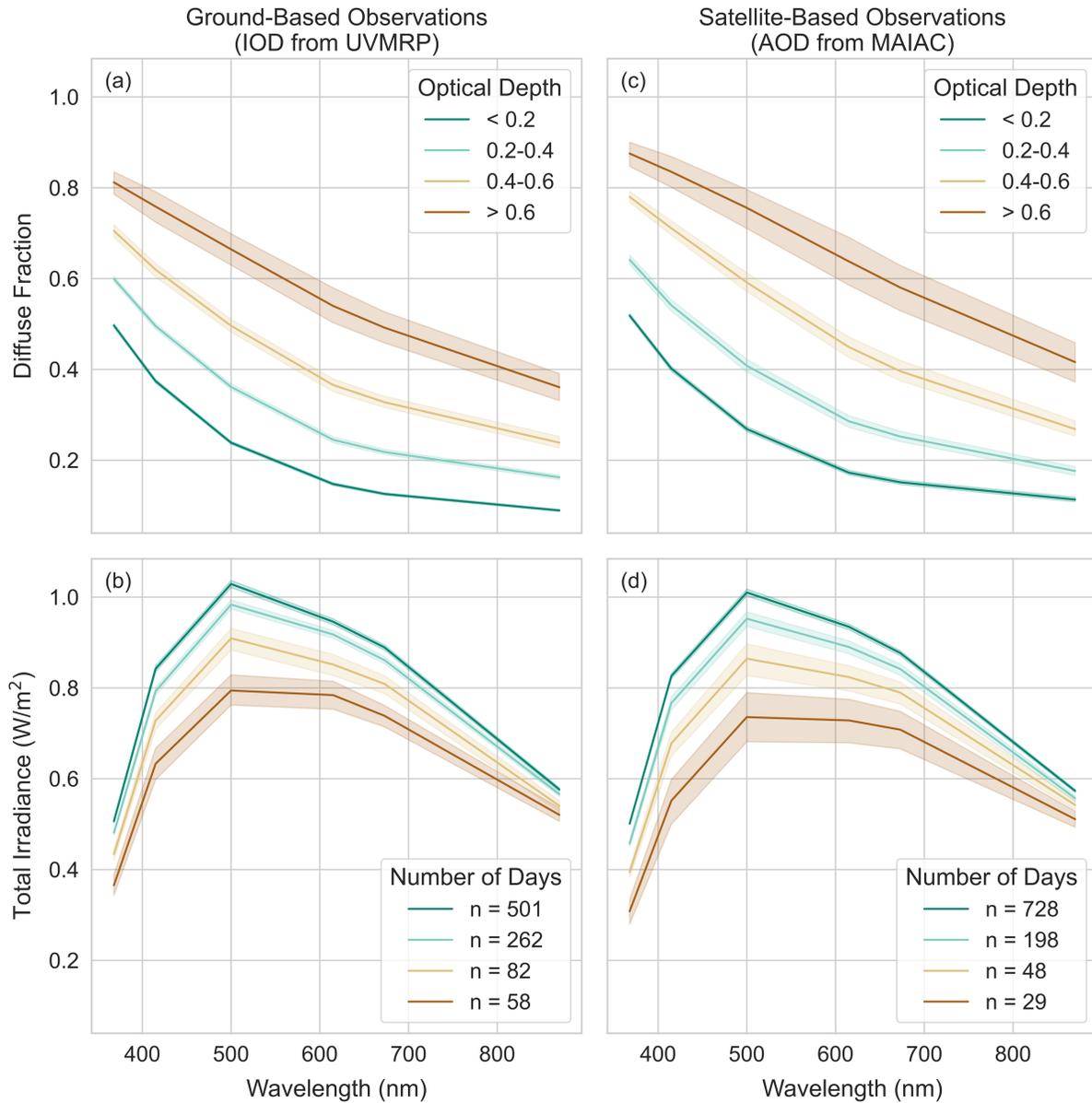
443 Given that smoke-driven increases in PAR DF are greatest under clear-sky conditions, we
 444 present a more detailed spectral analysis of DF and total irradiance on clear-sky days ($\text{CF} < 0.01$)
 445 in Figures 8 and 9. Across the six MFRSR wavelengths measured between 368-870 nm, spectral
 446 DF is higher (Figure 8a) and total spectral irradiance is lower (Figure 8b) on smoke-impacted
 447 clear-sky days. The increase in spectral DF is greatest at 415 nm and 500 nm (+0.11) and least at
 448 870 nm (+0.05). In the visible range, Mie scattering by smoke aerosols and absorption by brown
 449 carbon and NO_2 are more efficient at shorter wavelengths, preferentially increasing the diffuse
 450 component and decreasing total irradiance, respectively. As such, both processes work to
 451 increase DF at shorter wavelengths, which means that systems reliant on shorter wavelengths in
 452 the visible range will be more strongly impacted by smoke than those reliant on longer
 453 wavelengths. The reduction in total spectral irradiance is also greatest at 415 nm and 500 nm (-
 454 0.07 W/m^2) and least at the shortest (368 nm: -0.04 W/m^2) and longest wavelengths (870 nm: -
 455 0.02 W/m^2). Spectral DF increases on average by 45% (range: 20-62%) and total spectral
 456 irradiance decreases on average by 6% (range: 3-8%) with smoke.



457

458 **Figure 8:** Variation in spectral diffuse fraction (a) and total spectral irradiance (b) at six MFRSR
 459 measured wavelengths on smoke-impacted (brown) and smoke-free (blue) clear-sky days during
 460 the growing season ($n_{\text{smoke-free}} = 2,562$; $n_{\text{smoke-impacted}} = 1,003$). Solid lines indicates the average
 461 value and shading shows the 95% confidence interval.

462



463

464 **Figure 9:** Variation in spectral diffuse fraction (a, c) and total spectral irradiance (b, d) across the
 465 six MFRSR wavelengths measured on smoke-impacted clear-sky days during the growing
 466 season. The impact of smoke plume thickness on irradiance measures is shown using different
 467 optical depths based on ground measurements of IOD from the UVMRP (a, b) and satellite
 468 retrievals of AOD by MAIAC (c, d). Solid lines indicates the average value and shading shows
 469 the 95% confidence interval ($n_{\text{uvmrp}} = 903$; $n_{\text{maiac}} = 1003$).

470 Isolating smoke-impacted clear-sky days, Figure 9 shows the impact of smoke plume
 471 thickness on DF and total irradiance at the spectral level. We use optical depth as a plume
 472 thickness proxy and compare results from the site-specific ground-based MFRSR measurements
 473 (Figure 9a/b) to those from satellite retrievals (Figure 9c/d). The former relies on optical depths
 474 calculated using Langley analysis and represents instantaneous cloud-aerosol optical depths

475 (IOD). The latter are aerosol optical depths (AOD) computed using the MAIAC algorithm to
476 minimize smoke-cloud confusion and ensure AOD retrieval on smoke-impacted days.

477 The ground measurements show that DF (Figure 9a) becomes progressively larger as
478 optical depth increases on smoke-impacted clear-sky days, which indicates a larger increase in
479 DF under thick smoke plumes than under thin smoke plumes. Conversely, total irradiance
480 (Figure 9b) decreases with increasing optical depth or plume thickness. Changes to total
481 irradiance based on plume thickness are greatest at 500 nm, and least at 368 nm and 870 nm.
482 Changes to DF, on the other hand, are relatively consistent across individual wavelengths. An
483 optical depth increase from < 0.2 to $0.2-0.4$ results in an increase in DF between 0.07 and 0.12
484 (average: +0.10) depending on the wavelength. A similar magnitude increase occurs when the
485 optical depth increases to $0.4-0.6$ (range: +0.08-0.13; average: +0.11) and again to > 0.6 (range:
486 +0.11-0.17; average: +0.15). Days with thick smoke plumes (> 0.6 ; $n = 58$) occur less frequently
487 than days with thin smoke plumes (< 0.2 ; $n = 501$), which results in wider 95% confidence
488 intervals.

489 Ground-based sensors provide detailed information about radiation at specific sites;
490 however, monitoring networks like the UVMRP are sparsely distributed. To expand beyond
491 single sites and examine the impact of smoke on radiation at a national level requires satellite
492 observations. Figure 9 compares DF and total irradiance trends from ground-based measures of
493 plume thicknesses to measures from the MODIS satellite instrument. Using the MAIAC AOD
494 (Figure 9c/d) as a plume thickness proxy results in similar spectral DF and total spectral
495 irradiance trends to those found using the MFRSR IOD observations (Figure 9a/b). DF becomes
496 progressively larger as the optical depth increases on clear-sky days, indicating that thick smoke
497 plumes increase DF more substantially than thin plumes.

498 However, DF values for each wavelength and optical depth bin are slightly higher (range:
499 +0.01-0.10; average: +0.05) when plume thickness is determined using MAIAC AOD rather than
500 MFRSR IOD. The offset in DF values between the two methods is smaller when optical depths
501 are lower (i.e., smoke plumes are thinner). Across the six wavelengths assessed, the average
502 offset between the two methods for the optical depth bins < 0.2 , $0.2-0.4$, $0.4-0.6$, and > 0.6 are
503 +0.03, +0.04, +0.07, and +0.08, respectively. Total irradiances decrease with increasing optical
504 depth for plume thicknesses regardless of which optical depth measure is used, but most
505 irradiances are slightly lower when plume thicknesses are calculated with the MAIAC AOD. As
506 with the DF comparison, the difference between the two methods is smaller when optical depths
507 or plume thicknesses are lower. The average difference between the two methods for the optical
508 depth bins < 0.2 , $0.2-0.4$, $0.4-0.6$ are -0.01, -0.02, -0.03, and -0.05, respectively. Overall, Figure
509 9 highlights the similarity between DF and total irradiance trends derived using the MFRSR and
510 MODIS instrument data, which supports the use of MAIAC AOD to examine smoke-driven
511 radiation changes at larger scales.

512 **4 Conclusions**

513 We combine ground and satellite observations to examine spatial and temporal trends in
514 smoke presence across the U.S. during the growing season as well as smoke's impact on diffuse
515 fraction and total irradiance at the surface. The following conclusions stem from this analysis:

- 516 1. On average, smoke was present overhead on 20% of growing season days from 2006-
517 2020 at the ten UVMRP sites analyzed. Over that 15 year period, interannual trends show
518 an increase in smoke frequency.
- 519 2. Annual site-specific smoke frequency varies with the prevalence of wildfires in smoke
520 source regions, but northern sites in the RM, GP, and MW regions consistently
521 experience smoke the most often.
- 522 3. Monthly trends show that smoke frequency increases as the growing season progresses
523 and peaks in August at sites in all regions, except the SE where the smoke source is
524 distinctly different. The high frequency of smoke over most of the U.S. in July and
525 August aligns with the mid- to late growing season when plants have larger leaf areas and
526 more developed canopies that result in more shaded leaves. As such, smoke coincides
527 with the period when plants benefit most from increases in PAR DF through the DRFE.
- 528 4. Using the UVMRP data, we show elevated daily PAR DF values occur on smoke-
529 impacted days across a wide range of cloud conditions. There is an increase in the median
530 and interquartile range of PAR DF on smoke-impacted days up to a CF of 0.5. Previous
531 literature shows that increasing PAR DF to 0.45 is optimal for improving plant
532 productivity (Knobl and Baldocchi, 2008). Our analysis shows that a PAR DF of 0.45 is
533 achieved at a CF of 0.29 on smoke-impacted days, compared to a CF of 0.39 on smoke-
534 free days. PAR DF increases most substantially on smoke-impacted days under cloud-
535 free conditions (+0.10). On clear-sky days, the presence of smoke increases spectral DF
536 and decreases total spectral irradiance at all six wavelengths measured by the MFRSR
537 from 368-870 nm.
- 538 5. When smoke is present, spectral DF increases and total spectral irradiance decreases with
539 increasing smoke plume thickness. Optical depth observations from ground (UVMRP)
540 and satellite (MODIS MAIAC) instruments produce similar trends for the impact of
541 plume thickness on DF and total irradiance.

542 Our analysis provides a foundation for further research on the impact of smoke on PAR
543 and the use of the UVMRP network data. The observed interannual and seasonal variability in
544 smoke exposure supports the use of UVMRP sites to characterize changes in PAR DF and total
545 PAR associated with wildfire smoke and, in the future, to examine smoke-induced changes to
546 agricultural crop yields within and across sites. Future work could focus on developing a model
547 of PAR DF and total PAR on smoke-impacted days using data from all 34 UVMRP sites in the
548 contiguous U.S. Expanding the number of stations included will allow us to better characterize
549 smoke and irradiance variability within regions, especially in the Great Plains and Midwest
550 where understanding smoke's impact on PAR is essential for understanding smoke's impact on
551 agricultural production. The inclusion of satellite AOD measurements supports scaling this
552 analysis to the regional and national level and may allow for additional atmospheric chemistry
553 applications.

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561

562 **Open Research**

563 UVMRP data used in this analysis are publically available at <https://uvb.nrel.colostate.edu/UVB/>.
564 HMS data used in this analysis are publically available at
565 <https://www.ospo.noaa.gov/Products/land/hms.html>. MAIAC data used in this analysis are
566 publically available at <https://modis-land.gsfc.nasa.gov/MAIAC.html>. MODIS data used in this
567 analysis are also publically available. The MOD08_D3 (Terra) product can be found at
568 https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MOD08_D3. The
569 MYD08_D3 (Aqua) product can be found at [https://ladsweb.modaps.eosdis.nasa.gov/missions-](https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MYD08_D3)
570 [and-measurements/products/MYD08_D3](https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MYD08_D3). The final cleaned and merged dataset used in this
571 analysis will be made available in Mountain Scholar upon publication along with all Python code
572 files used to clean, merge, analyze, and visualize these data.

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