

Leveraging NASA Soil Moisture Active Passive for Assessing Fire Susceptibility and Potential Impacts over Australia and California

Nazmus Sazib, John D. Bolten, Iliana E. Mladenova

Abstract— Wildfires are a major concern around the globe because of the immediate impact they have on people's lives, local ecosystems, and the environment. Soil moisture is one of the most important factors that influences wildfire occurrences and spread. However, it is also one of the most challenging hydrological variables to measure routinely and accurately. Therefore, soil moisture is significantly underutilized in operational wildfire risk applications. Thus, the aim here is to use a well-established operational soil moisture product to isolate the soil moisture-fire relationship and assess the utility of using soil moisture as a leading indicator of potential fire risk. We evaluated the value of remotely-sensed soil moisture observations from the Soil Moisture Active Passive (SMAP) sensor for monitoring and predicting fire risk in Australia and California. We quantified the relationship between observed fire activity and soil moisture conditions and analyzed the soil moisture conditions for two extreme fire events. Our findings show that fire activity is strongly associated with soil moisture anomalies. Lagged correlation analysis demonstrated that a remote-sensing based soil moisture product could predict fire activity with a 1-2 month lead-time. Soil moisture anomalies consistently decreased in the months preceding fire occurrence, often from normal to drier conditions, according to a spatiotemporal analysis of soil moisture in two extreme fire events. Overall, our findings indicate that soil moisture conditions prior to large wildfires can aid in their prediction and operational satellite-based soil moisture products such as the one used here have real value for supporting wildfire susceptibility and impacts.

Index Terms— Soil Moisture Active Passive (SMAP), Wildfire, Drought, Soil moisture

I. INTRODUCTION

Wildfire is an increasing natural hazard with serious consequences which can impact ecological health, as well as jeopardize people's livelihoods, and security. Another

unanticipated effect of wildfires is that their secondary effects, such as erosion, landslides, and changes in water quality, can be more damaging than the fire itself [1]. Wildfire, on the other hand, can sometimes be beneficial to the environment in other ways. For example, it contributes to overall global vegetation productivity and biodiversity, which in turn enables improvements in ecosystem health, such as assisting in the mitigation of weather extremes, including heat waves or droughts, or removing CO₂ from the atmosphere [2].

Because wildfires play such an important role in ecosystem health, many studies have been conducted to investigate the impact of climate conditions on fire occurrence, spread, and severity. Keeley et al. [3], for example, evaluated the association between fire activity and climate in central and southern California and found that summer temperatures were positively correlated with the number of fires in the central coast region, while autumn precipitation was negatively associated with fire occurrence in the south coast region. Fuller and Murphy et al. [4] investigated the spatial-temporal patterns of fire in the island of South East Asia between July 1996 and December 2001. When compared to geo-referenced climate and land-cover data from a variety of sources, the Southern Oscillation Index (SOI) in forested land-covered areas was found to be highly associated with fire counts. As expected, variations in precipitation also have a significant impact on the extent and severity of fires, as demonstrated in a study of the Gila National Forest in the southwestern United States [5].

Soil moisture, defined as the volumetric water content of the soil, is an important indicator of soil dryness and is considered to be a key variable that influences wildfire occurrence [2], [6]. In the specific context of the soil moisture-fire relationship, several studies have enhanced the understanding of the influence of soil moisture on fire activity. For example, Krueger et al. [7] demonstrated that large growing-season wildfires only occurred in conditions of low soil moisture. According to Yebra et al. [8], improving wildfire assessments entails using soil moisture as a proxy for fuel moisture, which is a key factor in wildfire ignition and spread. Westering et al. [9] investigated the relationship between snowmelt time and wildfire activity in the western United States and concluded that

Nazmus Sazib is with the Hydrological Sciences Lab, NASA Goddard Space Flight Center, Greenbelt, MD 20771 USA, and also with Science Application International Corporation, Lanham, MD 20706 USA (e-mail: nazmus.s.sazib@nasa.gov).

John D. Bolten is with the Hydrological Sciences Lab, NASA Goddard Space Flight Center, Greenbelt, MD 20771 USA (e-mail: john.bolten@nasa.gov).
Iliana Mladenova is with the United States Department of Agriculture (USDA) Washington, DC 20250, USA (e-mail: iliana.e.mladenova@usda.gov).

81 earlier snowmelt and increased soil dryness in the summer can
 82 be related with wildfire activity. Cooke et al. [10] examined the
 83 likelihood of wildfires and various soil moisture-based drought
 84 metrics derived from gridded meteorological data and
 85 simulated soil moisture data available from the North American
 86 Land Data Assimilation System (NLDAS-2) over southern
 87 Mississippi and noticed that soil moisture-based indices are
 88 strong predictors of fire occurrence in that region. 145
 89 Due to the lack of in-situ based soil moisture data, many
 90 previous studies relied on model-based soil moisture
 91 information or secondary drought indices. In addition to the use
 92 of model-based soil moisture products, advances in remote
 93 sensing over the last two decades have enabled satellite-based
 94 microwave sensors to provide continuous, consistent, and
 95 timely information of soil moisture conditions. Aubrecht et al.
 96 [11] assessed the soil water index (SWI) developed from the
 97 Advanced Scatterometer (ASCAT) sensor and reported a high
 98 regional association between dry soils and detected fires. Jensen
 99 et al. [12] examined the satellite soil moisture from NASA's
 100 Gravity Recovery and Climate Experiment (GRACE) and the
 101 historical fire data from the USDA Forest Service in the U.S.
 102 from 2003–2012 and suggested that the GRACE's soil moisture
 103 correlated with wildfire activity. However, their study is limited
 104 by spatial resolution of the GRACE data and authors
 105 recommended using SMAP data to generate more accurate
 106 regional predictive fire maps. Sungmin et al. [2] investigated
 107 the association between soil moisture anomalies and large
 108 wildfire events around the globe between 2001 and 2018 over
 109 the humid and wet region and found soil moisture anomalies
 110 continuously decrease in the months prior to fire occurrence
 111 often from above-normal to below-normal in both regions.
 112 Because the fire-moisture interactions vary between
 113 ecosystems and temporal and spatial scales, various drivers can
 114 play an important role depending on the local context. As a
 115 result, there are limitations to transferring findings from one
 116 location to another or generalizing conclusions from this global
 117 scale analysis to local scales. Ambadan et al. [13] investigated
 118 the performance of the remotely sensed soil moisture products
 119 derived from the Soil Moisture and Ocean Salinity
 120 (SMOS) data over the wildfire areas, across fourteen eco-zones
 121 in Canada and found that SMOS soil moisture products could
 122 be useful in spotting soil moisture anomalies near possible
 123 wildfire hotspots. One drawback of those studies is the quality
 124 of the satellite soil moisture product in high vegetation areas
 125 (e.g., forests), where the product can be influenced by
 126 considerable vegetation water content, which affects the
 127 computation of soil moisture climatology and soil moisture
 128 anomaly maps. To address these constraints, we employed data
 129 from NASA's Soil Moisture Active Passive (SMAP) satellite
 130 which collects L-band soil emissions that penetrate clouds and
 131 more easily pass through forest cover, resulting in enhanced soil
 132 moisture estimates. We demonstrate the value of readily
 133 available, satellite-based, near-surface soil moisture
 134 observations. Even though the spatial resolution of satellite
 135 based remote sensing products is significantly coarser than in-
 136 situ based observations (i.e., on the order of 10s of magnitude),
 137 we argue that the value of satellite-based remote sensing can

realized in the regional perspective, increasing data record, and frequent overpass times that these data allow.

We analyzed the role of soil moisture in the occurrence of wildfires across fire-prone regions in Australia and California using satellite-based derivation of surface soil moisture and fire products. Wildfires in Australia have increasingly become larger and more frequent during the last several decades, contributing to greater environmental degradation, property damage, and economic losses. According to the USDA Forest Service report, the cost of fire suppression in the United States is predicted to increase to nearly \$1.8 billion per year by 2025 [14]. We focused on these case studies of wildfire hotspots observed over various Australia and California regions to demonstrate the value of routine satellite-based soil moisture products for forecasting wildfire risk. In addition to temporal correlation analysis, we looked at the spatiotemporal evolution of soil moisture during major fire events. The findings from this study will aid in developing routine strategies for assessing the vulnerability of fire-affected areas, improving fire planning and resource management at the national and county levels.

II. MATERIALS AND METHODS

Data:

The NASA Global Inventory Modeling and Mapping Studies (GIMMS) Global Agricultural Monitoring (GLAM) system provided the soil moisture data used in this study (<https://gimms.gsfc.nasa.gov/>). A well-established operational global soil moisture product was applied, which was generated by incorporating Soil Moisture Active Passive (SMAP) soil moisture observations into the two-layer Palmer model via a Kalman Filter (EnKF) data assimilation approach [15]–[17]. The Palmer Model used by the United States Department of Agriculture-Foreign Agriculture Service (USDA-FAS) is a water balance model driven by daily precipitation and minimum and maximum temperature data provided by the U.S. Air Force Weather Agency (AFWA) [18]. The AFWA dataset was derived using multiple sources, including remotely sensed observations and gauge data acquired from the World Meteorological Organization (WMO) [9]–[11].

The SMAP mission was launched by NASA in January 2015, and data collection began in late March 2015. The sensor monitors the Earth's soil moisture and freeze/thaw states twice a day, at approximately 6 a.m. and 6 p.m. local solar time, from a near-polar, sun-synchronous orbit. The current SMAP passive microwave data archive covers the period from March 31, 2015 to present [12]. SMAP offers a variety of soil moisture products based on these passive microwave observations each developed using a different algorithm. The baseline Level 2 (L2) SMAP SM product produced by the single-channel algorithm (SCA) and SMAP V-pol brightness temperature observations were used while integrating to the Palmer model. The GIMMS system offers various soil moisture products, including surface and root-zone soil moisture, soil moisture profile, surface and root zone-soil moisture anomalies at 0.25° spatial resolution. For this study, the surface soil moisture products (i.e., 0 - 1 inch depth) from 2015 to 2019 were used.

194 To assess fire activity, NASA's Moderate Resolution
 195 Imaging Spectroradiometer Active Fire (MOD14A1) product
 196 which provides fire count, location, and radiation power, was
 197 used [19]. MOD14A1 is suitable for our study because it has
 198 global coverage, high data completeness, and is satellite
 199 operational, allowing real-time fire event analysis. The MODIS
 200 instrument is installed on both the Terra and Aqua platforms
 201 providing observations of the Earth's surface four times per day.
 202 The fire count product utilized here provides the number of fires
 203 in a pixel ranging from 0 to 30. The product utilizes MODIS 4-
 204 and 11-micrometer brightness temperature to identify the fire
 205 pixel [20], [21]. Fire activity throughout this study is
 206 characterized using the MODIS-based fire count product.

207
 208 Data preprocessing:

209
 210 The daily fire count data were aggregated up to generate
 211 total month count. Then, the monthly total fire data were re-
 212 gridded to $0.25^\circ \times 0.25^\circ$ resolution in order to match the
 213 spatial resolution of the soil moisture data. The MODIS data
 214 are available through present, but the study focused on the
 215 2015–2019 period to match the soil moisture datasets in our
 216 analysis. First, we used surface soil moisture and fire count
 217 data to explore their spatial and temporal variability over
 218 different regions across Australia and California. For each
 219 study region, annual total fire count and surface soil moisture
 220 were calculated using monthly data from 2015 to 2019. The
 221 variability of fire count statistics was summarized for major
 222 fire prone locations in Australia and California. To
 223 characterize the relationship between fire count and soil
 224 moisture, the fire count was compared to soil moisture with
 225 varying time lags. We computed Spearman's rank correlation
 226 coefficient between fire activity and soil moisture anomalies
 227 to quantify the strength of the relationship between them. The
 228 Spearman's rank correlation was chosen as the Pearson
 229 correlation has the tendency to underestimate or overestimate
 230 the significance of the relationship when the interaction is not
 231 linear [22]. Monthly standardized soil moisture anomalies
 232 were computed using the Z- score which were calculate using
 233 following equation:

$$234 \quad Z_{score} = \frac{x_i - \mu}{\sigma}$$

235
 236 where μ and σ represent mean and standard deviation values
 237 of the data for that month over all the years and x_i is the data
 238 value for a given month in year i .

239
 240 Fire events are fairly rare at local and daily scales, and hence,
 241 highly random in nature. Therefore, fire counts and soil
 242 moisture anomalies for each location in California and
 243 Australia were first averaged spatially and then averaged
 244 temporally across each month before performing the correlation
 245 analysis. Monthly lag correlation analysis was performed to
 246 identify any lags related with the highest correlations and to
 247 assess the predictability of fire danger based on the antecedent
 248 soil moisture condition.

249 Furthermore, soil moisture anomalies were investigated on
 250 a regional scale for the most recent fire episodes in Australia
 251 and California. The first case study focusses on the 2019–2020

bushfire in Australia, which occurred in the southeastern part
 of the country (New South Wales, NSW). This event is
 considered to be the most catastrophic in terms of burnt area
 and severity [23]. Similar analysis was performed over
 California, which experienced a record breaking number of
 large fires in 2020 [24].

259

III. RESULTS

A. Spatial and temporal variability of fire count and soil moisture

The soil moisture conditions over Australian range from wet tropical conditions in the north through arid conditions in the

277 Analysis indicated substantial fire activity in the Queensland, Northern Territory and Western part of the country during all five years examined in this study (Figure 1). The Northern Territory's climate is primarily influenced by the annual monsoon, which is particularly moist from November to April and dry from April to October. As a result, plant growth

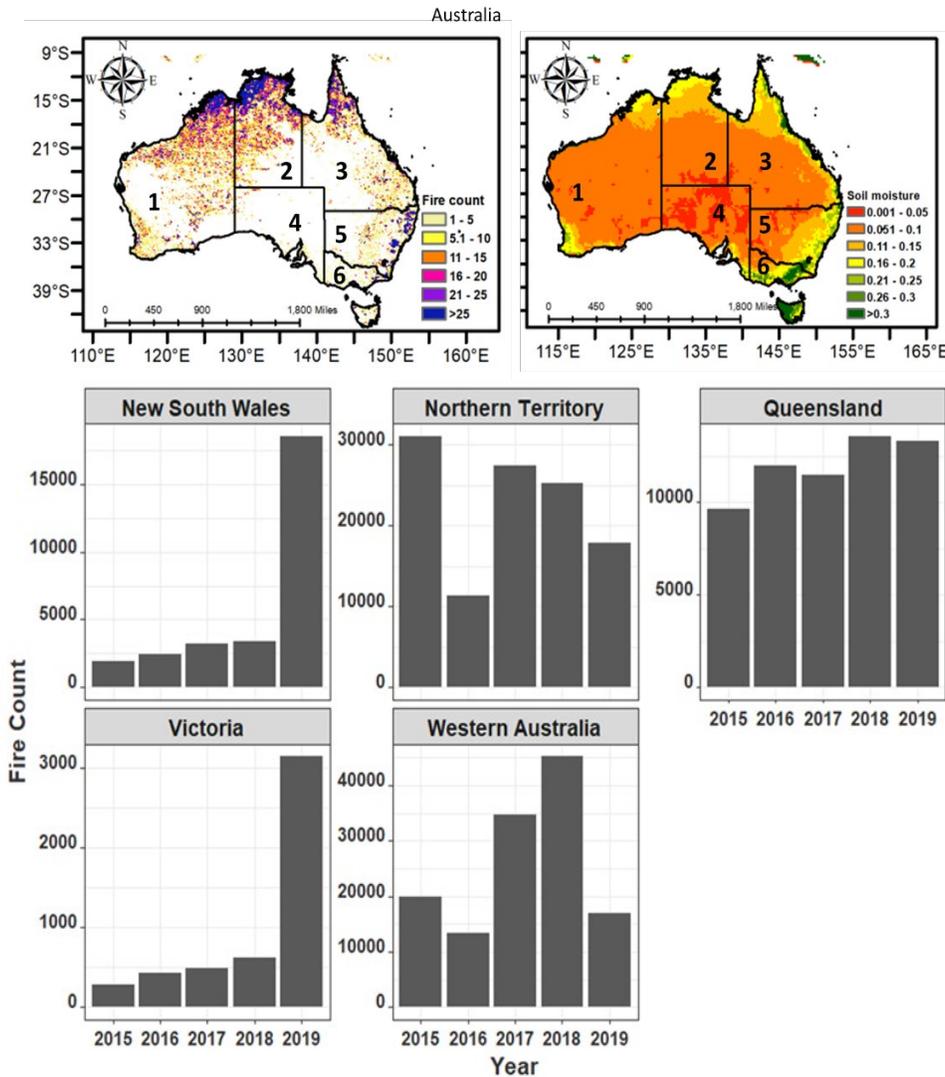


Figure 1: Spatial variability of fire count and surface soil moisture (top) and annual variation of fire count (bottom) for different provinces over Australia for the period of 2015-2019. The locations of each province of Australia (1: Western Australia, 2: Northern Territory, 3: Queensland, 4: South Australia, 5: New South Wales (NSW), 6: Victoria) are also indicated.

264 interior to temperate sub-humid to humid conditions in the
 265 south. According to the fire count map, the most fire-prone
 266 areas are primarily in the country's north. Fires are also common
 267 in the southeastern parts of New South Wales and Victoria
 268 (Figure 1). The El Niño–Southern Oscillation (ENSO) and
 269 Indian Ocean Dipole (IOD) have a significant influence on the
 270 spatial variability of soil moisture over Australia. During the
 271 negative phase of the ENSO cycle, rainfall in northern and
 272 eastern Australia is reduced, which frequently results in drought
 273 conditions [25]. ENSO is also associated with higher land
 274 surface temperatures that last longer than the drought conditions
 275 resulting in higher evaporation and drier soils, which leads to
 276 increased fire activity [26], [27].

283 increases during the monsoon season, leading to increased fuel
 284 accumulation and fire activity [27]. Rainfall in Western
 285 Australia becomes increasingly infrequent and episodic with
 286 distance inland, and significant plant production occurs only
 287 after major and sustained rainfall events. Extensive fires in the
 288 region occur only after prolonged and widespread rainfall when
 289 production and fuel accumulation are high. Furthermore,
 290 firefighting resources, equipment, and infrastructure are limited
 291 outside of the state's major cities and towns, as Western
 292 Australia's population density is below one person per square
 293 kilometer. This also means that wildfires in remote areas tend
 294 to be bigger and cover a larger area [28]. In 2019, there was a
 295 large bushfire in New South Wales and Victoria, which

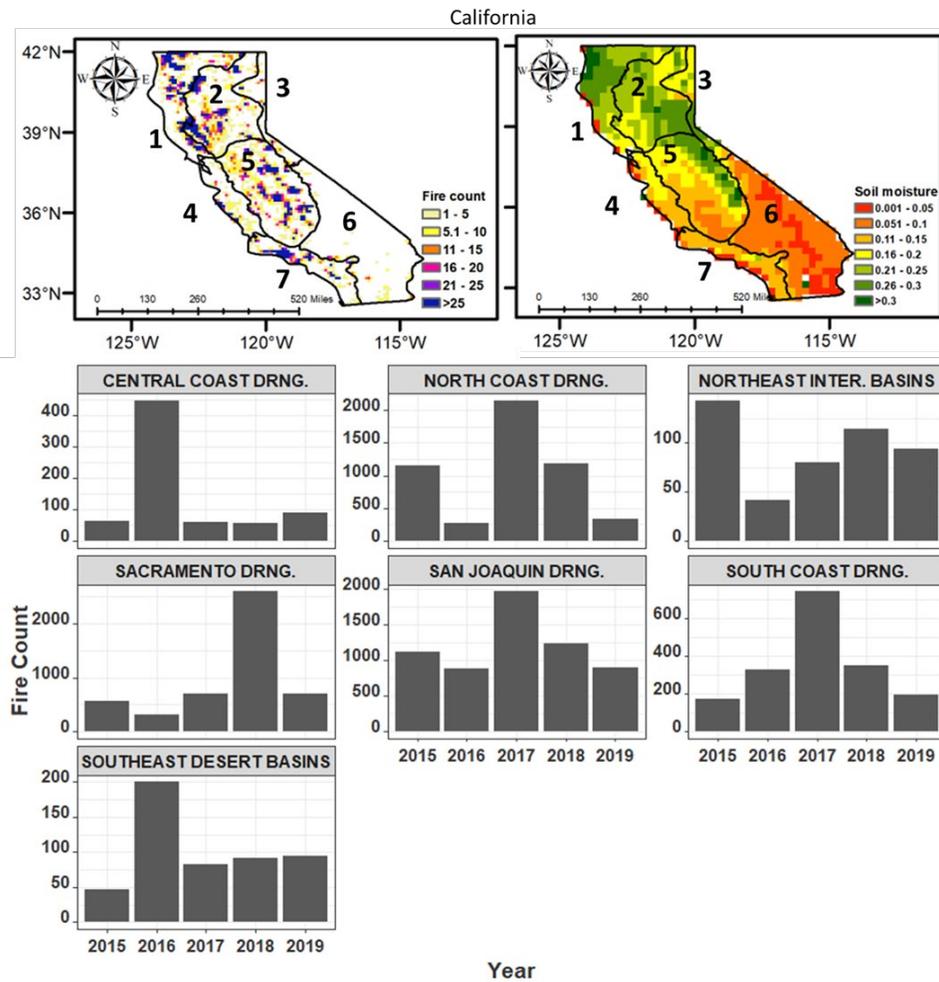


Figure 2: Spatial variability of fire count and surface soil moisture (top) and annual variation of fire count (bottom) for different climate divisions over California for the period of 2015-2019. The locations of each climate divisions of California (1: North coast, 2: Sacramento, 3: Northeast interior, 4: Central coast, 5: San Joaquin, 6: South coast, 7: Southeast desert) are also indicated.

296 accounted for a significantly larger than normal area fire
 297 activity. (Figure 1). Satellite fire detection in New South Wales
 298 and Victoria were more than four and five times higher than the
 299 previous year, respectively. Despite large wildfires in southern
 300 Queensland, fire counts in Queensland remained consistent
 301 with previous years, owing to the state's total fire activity being
 302 dominated by savanna fires in northern Queensland, which are
 303 a natural part of these ecosystems (Figure 1).
 304 In the case of California, significant wildfires were observed
 305 throughout northern and southern California, with the exception
 306 of the southeast desert regions, where large areas of sparse
 307 vegetated desert ecosystems inhibit large fires (Figure 2).
 308 California's diverse climate, combined with a wide range
 309 vegetation cover and topography, has a significant impact on
 310 the spatial pattern of its wildfires. Furthermore, population
 311 growth and geographic development have an impact on fire
 312 regimes because of their effects on fuel availability and
 313 continuity [9]. Fire counts differ noticeably across climate
 314 divisions. For all these years, fire counts have been higher along
 315 the North coast, in Sacramento and the San Joaquin region, with

some exceptions on the south coast (Figure 2). While estimating
 the mean soil moisture values, we considered each month of the
 year (wet and dry periods) rather than the dry season (when the
 majority of fires occur) which results in a high fire count in
 higher soil moisture regions (e.g., North coast). The hot spring
 and summer temperatures, as well as the dry soil moisture
 condition during and before fire seasons, are the primary drivers
 of wildfire activity in North coast, Sacramento, and San Joaquin
 regions. Southern California's Mediterranean climate, extreme
 winds in autumn, and frequent drought conditions, on the other
 hand, further contributed to frequent and severe wildfires [29].

B. Correlation between fire count and soil moisture

In general, negative correlation coefficients were found
 between soil moisture anomalies and fire count, especially
 when the soil moisture preceded or is concurrent with the fire
 count, indicating that fire is more likely to occur in drier soil
 moisture conditions (Figure 3). Dry soil moisture conditions
 increase fuel flammability because fuel moisture is depleted

334 not only by a prolonged lack of rainfall but also by moisture
 335 out flux (loss) from vegetation into the atmosphere [30]. The
 336 correlation values varied considerably with lag time, showing
 337 a tendency for high correlation values with shorter lags and
 338 low correlation values with longer lags. The negative
 339 correlations also varied by region, with the southeastern part
 340 of the Australia having a higher negative correlation than the
 341 northern part. Some of this variation can be explained by
 342 ecosystem-climate connection. Ecosystems in the northern,
 343 monsoonal tropics experience prolonged annual wet and dry
 344 seasons, whereas those in southern, temperate regions
 345 experience severe drought on a multi-decadal cycle, which
 346 alters the soil moisture status and thus directly affected fire
 347 activity [31]. The southern part of the country typically has
 348 plenty of fuel, but extended periods of dryness or drought are
 349 required to dry out the fuel before it can be burned. This has
 350 significant effects on the flammability of the fuels and the fire
 351 in these areas can be attributed to the weather conditions [27].

California (e.g., South coast drainage). In the Central and South
 Coast, the relationship between fire count and soil moisture
 anomaly was relatively weak. This is likely due in part to the
 fact that the fire-climate relationship in these regions are
 strongly altered by anthropogenic activity such as ignitions,
 suppression, and land cover [32], [33].

Previous studies have found similar pattern of association
 between soil moisture anomalies and fire activity in Australia
 and California. For example, Beth and Brown, [34] found
 strong correlation between the short term Palmer Drought
 Severity Index and the number of wildfires and acres burned in
 the Western U.S. Riley et al. [35] also noted the association
 between short-term drought indices and fuel moisture content,
 the primary drivers of wildfire in the Western USA. Ehsani et
 al. [36] examined the relationship between recent wildfires,
 various hydro-climatological variables, and satellite-retrieved
 vegetation indices, concluding that the lack of precipitation
 before the wildfire prevented the soil from having enough
 moisture to supply demand and paved the way for the spread of
 fires. Our correlation analysis indicates that the soil moisture -
 fire link gets stronger during the pre-fire season, which is
 particularly essential for determining the next season's wildfire
 events. The lagged relationship between soil moisture and fire
 demonstrates that remotely sensed soil moisture can be used for
 the prediction of fire at 1-2 months lead-time, which is essential
 for early warning and mitigation.

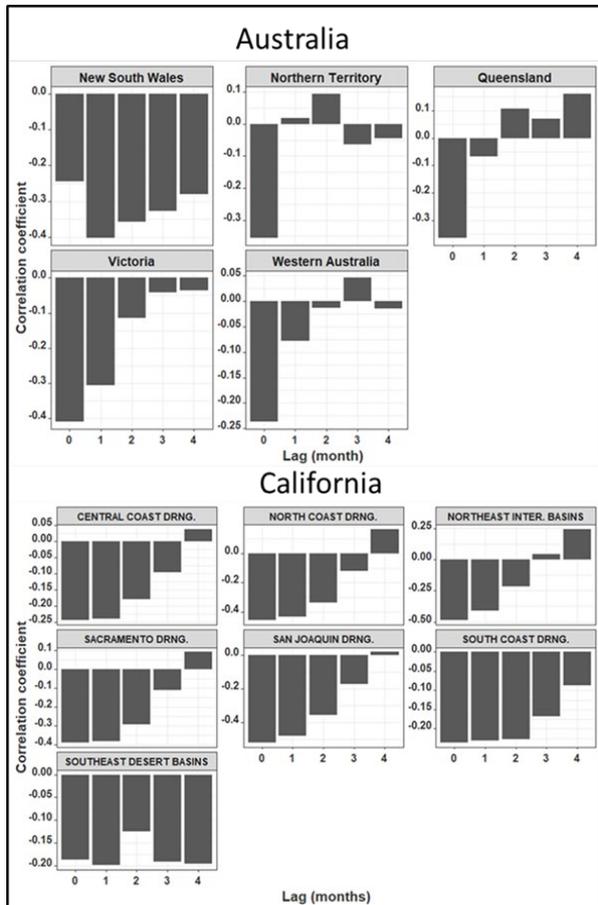


Figure 3: Correlation coefficient between fire count and surface soil moisture anomalies for different lag times over Australia and California.

354 In general, the correlation between soil moisture anomaly
 355 and fire count varied according to California's climate
 356 divisions. In the northern part of the states (e.g., North coast
 357 drainage), we found a higher average correlation between fire
 358 count and soil moisture anomalies than in the southern parts of

387 *C. Spatial response of soil moisture and fire activity*
 388 *during major fire events*

389 Of the study areas, the most recent bushfire season (2019-
 390 2020) in Australia was the most severe in terms of burnt area
 391 and intensity, resulting in 33 deaths, the destruction of over
 392 3000 homes, and the annihilation of approximately one billion
 393 animals, including several endangered species [23]. The
 394 potential for fire activity is clearly visible in drier-than-usual
 395 soil moisture conditions in the preceding months. Soil moisture
 396 anomaly values indicate that all hot spot fire regions
 397 experienced droughts with magnitudes ranging from -0.25 to -
 398 2.0 during the 2019–2020 bushfire season (Figure 4). During
 399 November and December 2019, New South Wales and Victoria
 400 experienced significant rainfall deficits as a result of a very
 401 strong positive Indian Ocean Dipole (IOD) [37]. The impact of
 402 the period's low rainfall had been exacerbated by a record high-
 403 temperature anomaly of nearly 1 °C above normal since 2003
 404 [36]. The increased temperature elevated evapotranspiration
 demand, resulted in drier soil moisture conditions, which
 further increased the dryness of the vegetation and set the stage
 for the faster wildfire spread. The number of fires and burned
 areas of the Victorian bushfires was the largest in the state's
 history, resulting in over a million hectares burned, over 400
 houses destroyed, and five people killed. Due to significant
 rainfall deficit, Victoria experienced below-normal soil
 moisture conditions during the 2019-2020 bush fire season,
 particularly along the coast and in the foothill forests of

414 Gippsland. Combined with above-average temperatures, 421 moisture anomalies and observed fire counts show an inverse
 415 resulted in an increase in surface fuel loads and high 422 trend, with dryer soil moisture conditions generally associated
 416 flammability in live vegetation [23]. 423 with increased fire activity. The time series analysis of fire

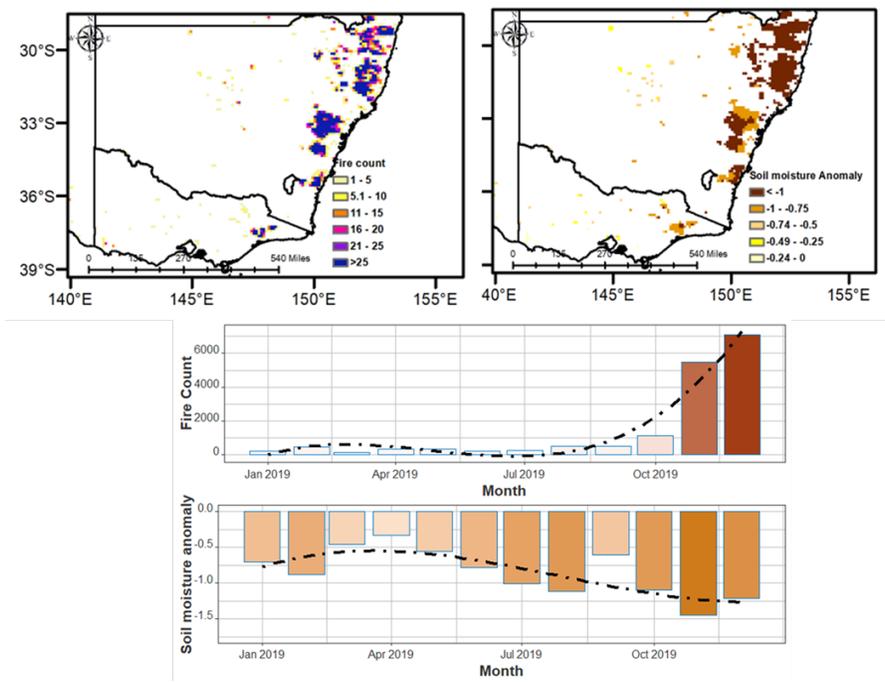


Figure 4: Spatial distribution of observed fire counts (top-left) and soil moisture anomalies (top-right) over New South Wales, Australia for the November-December 2019. Time series of monthly soil moisture deviations from average conditions (anomalies) and observed fire counts over New South Wales, Australia from January 2019 to December 2019 (bottom).

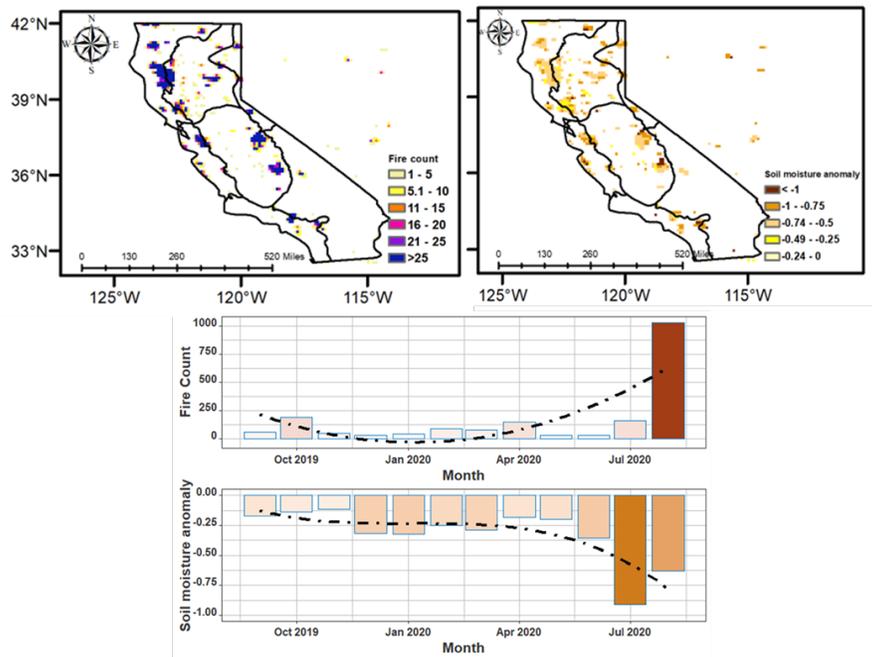


Figure 5: Spatial distribution of observed fire counts (top-left) and soil moisture anomalies (top-right) over California for July-August, 2020. Time series of monthly surface soil moisture deviations from average conditions (anomalies) and observed fire counts over Northern California from September 2019 to August 2020 (bottom).

417 The 2020 fire season in the western United States was 424
 418 staggering: over 2.5 million ha burned, including over 425
 419 million ha in California (3.7% of the state), due in part to fire 426
 420 of the six largest fires in state history [38]. As expected, the soil 427
 count data revealed a higher number of fire activity during
 August 2020 (Figure 5). The fire count map was mostly
 consistent with the soil moisture anomaly map, following the
 premise that fires were more likely to occur in drought-affected

428 areas. Lower precipitation and record-breaking heat waves 484
 429 mid-August caused severe drought and a large amount of fuel 485
 430 for wildfires across northern California. In general, soil 486
 431 moisture anomalies were negative during the two notable fire 487
 432 events. This suggests that satellite-based observations are 488
 433 capable of capturing valuable fire-relevant information for the 489
 434 region. Even at a relatively coarse spatial scale (i.e., 0.25°), the 490
 435 observed trend in soil moisture anomalies has a significant 491
 436 relationship with fire activity. However, not all dry soil 492
 437 moisture conditions lead to a high number of fire activity. The 493
 438 relationship also depends on the length and intensity of the 494
 439 meteorological and agricultural drought (i.e., a deficit of soil 495
 440 moisture). Furthermore, the coincidence of low soil moisture 496
 441 and high temperatures is important in determining the number 497
 442 of fire activity [39]. 498

443 IV. DISCUSSION 500

444 It is well understood that soil moisture conditions can serve 501
 445 as a proxy for wildfire fuel accumulation and fuel moisture 502
 446 conditions. Therefore, properly measuring and observing soil 503
 447 moisture is of critical for understanding the fire-soil moisture 504
 448 relationship and developing strategies that leverage remote 505
 449 sensing-based approaches that could be employed in a strategic 506
 450 operational framework. We examined the impact of regional 507
 451 soil moisture trends on fire activity in fire-prone areas in 508
 452 Australia and California during the notable wildfire seasons of 509
 453 2019 and 2020, as well as demonstrated the utility of satellite- 510
 454 based coarse resolution soil moisture for assessing future fire 511
 455 risk. As expected, soil moisture has value in explaining fire 512
 456 occurrence across different provinces in Australia and 513
 457 California. Our lag correlation analysis revealed that the fire- 514
 458 soil moisture relationship was stronger during the pre-fire 515
 459 event, which is critical for forest fire early warning systems. 516
 460 More importantly, by isolating the fire count–soil moisture lag 517
 461 correlation, we demonstrated the value of soil moisture as a 518
 462 leading indicator for wildfire risk. The magnitude of the 519
 463 correlation indicates a higher possibility of fire occurrence due 520
 464 to drought conditions. Areas with a higher negative correlation, 521
 465 such as New South Wales and Victoria, are more prone to fire 522
 466 activity due to drier soil moisture conditions. The current and 523
 467 previous month's soil moisture conditions had a significant 524
 468 correlation with fire activity in most of the fire prone regions in 525
 469 Australia and California, which could be related to land cover 526
 470 type. The dominant land cover type in those regions is forest, 527
 471 which has deeper root systems that allow access to the water 528
 472 below the surface, resulting in slower drought response. In the 529
 473 northern part of Australia, however, only concurrent soil 530
 474 moisture is likely to influence wildfire occurrence. This is due 531
 475 in part, to the fact that those areas are dominated by grassland, 532
 476 where roots are shallow and respond quickly to dry soil 533
 477 moisture conditions [40]. 534

478 Our paper demonstrates that soil moisture is significantly 535
 479 related to wildfire activity. However, no wildfire danger models 536
 480 currently incorporate soil moisture due to the lack of adequate 537
 481 operational dataset [41]. This study demonstrated the utility of 538
 482 an operational SMAP-based soil moisture product, which can 539
 483 guide wildfire managers on how to use this data when assessing 540

wildfire danger in Australia, and California. We also
 investigated the spatial pattern of soil moisture anomalies
 during extreme fire events in Australia and California, and
 noticed that the spatial soil moisture anomalies map
 corresponds to the fire hot spot regions. 2019 rainfall was 40%
 below average on a national level, making it Australia's driest
 year since records began in 1900 [37]. Our SMAP-based soil
 moisture anomalies also revealed more severe drought
 conditions over New South Wales and Victoria, which affect
 both the rate of vegetation growth and its dryness during 2019-
 2020 extreme bush fire events. Dry soil moisture conditions are
 associated with fires, but fires can also reduce soil water
 availability and have a negative impact on crop health and
 production. As a result, our current method of identifying fire-
 prone areas can assist local governments and emergency
 response agencies in better anticipating and preparing for an
 active fire season, as well as tracking the potential impact of fire
 on crop production.

Our findings are consistent with previous research. For
 example, Chaparro et al. [39] investigated the relationship of
 forest fires with soil moisture and temperature patterns in the
 Iberian Peninsula and the Balearic Islands and found that most
 forest fires burned in drier and hotter soils than the yearly
 averaged conditions in the Iberian Peninsula. Jensen et al. [12]
 quantified the relationships between pre-fire-season soil
 moisture and subsequent-year wildfire occurrence by land-
 cover type and concluded that larger fires occur more
 frequently when soil moisture is low. Ambadan et al. [13]
 investigated soil moisture anomalies prior to the onset of each
 wildfire occurrence in Canada between 2010 and 2017 across
 14 eco-zones and concluded that soil moisture products could
 be useful in identifying wildfire hotspots.

We have built upon these previous studies and focused on a
 satellite-only approach, leveraging remotely-sensed, SMAP-
 based soil moisture data. Soil moisture was found to be an
 important variable in drought detection and fire risk assessment,
 paving the way for the use of remotely-sensed soil moisture
 data in early warning systems preventing forest fires. However,
 there is still much work to do on this topic - multiple sources of
 remotely-sensed based soil moisture data are available, and the
 choice of data source can have an impact on the fire-soil
 moisture relationship, as well as the application of these data
 and how they are integrated into a fire detection decision
 support framework. Here, only soil moisture condition was
 considered among a multitude of factors that cause wildfires.
 Therefore, other factors such as precipitation, land surface
 temperature, vapor pressure deficit, wind, as well as other non-
 climate variables such as topography, soil type, vegetation type,
 and vegetation dynamics could be taken into consideration to
 further outline the role of satellite based soil moisture products
 for predicting fire activity. It should be noted that the results of
 this analysis are not intended to be an exact prediction of actual
 fire occurrence and severity. Rather, they assess the relationship
 between an operational satellite-based soil moisture product
 and wildfire, specifically the sensitivity of fire occurrence to
 pre-season soil moisture conditions. It is envisaged that the
 main findings of our study will encourage the improvement of

541	existing models and support leveraging SMAP and similar	595
542	satellite-based remote sensing soil moisture instruments	596
543	improved wildfire forecasting and prediction.	597
		598
544	V. CONCLUSION	599
545	Understanding the wildfire-soil moisture relationship is	600
546	critical for better wildfire management practices and	601
547	developing more effective forecasting and mitigating	602
548	strategies of wildfire occurrence. This potential translation	603
549	from data to actionable information is particularly important	604
550	for developing operational applications, which will aid in	605
551	mitigating the effects of fire events on the environment,	606
552	agriculture, and human activities. This becomes even more	607
553	evident when considering the extreme cases of wildfire in	608
554	Australia and California during 2019 and 2020 fire seasons,	609
555	respectively. Obviously, there were strong relationships	610
556	between soil moisture anomalies and fire, but the nature of	611
557	those relationships varied depending on geographic location,	612
558	vegetation type, and climatic zone. Over the southeastern part	613
559	of Australia, negative correlations between fire and soil	614
560	moisture anomalies were observed to be stronger than in the	615
561	northern part of the country. Our lagged correlation analysis	616
562	confirmed the ability of soil moisture to predict fire activity	617
563	with 1 to 2 months lead-time, which could be used for	618
564	wildfire early warning and monitoring. Our analysis also	619
565	demonstrated that remote sensing-based soil moisture data	620
566	could help explain the observed spatial and temporal	621
567	clustering of wildfires, which can be useful in identifying	622
568	wildfire-prone areas. To this end, this relatively	623
569	straightforward analysis gives a clear indication of the value of	624
570	satellite-based soil moisture observations for helping identify	625
571	wildfire risk and provides a strong foundation for further	626
572	studies and decision support system design targeting regional	627
573	wildfire modeling, prediction, and analysis.	628
574		629
		630
575	ACKNOWLEDGMENT	631
576	The NASA Applied Sciences Program supports this work.	632
577	The SMAP based soil moisture product used in this study was	633
578	processed and produced by the NASA/Goddard Space Flight	634
579	Center's Global Inventory Modeling and Mapping Studies	635
580	(GIMMS) Group through funding support of the Global	636
581	Agricultural Monitoring project by USDA's Foreign	637
582	Agricultural Service (FAS).	638
583		639
584		640
585		641
586		642
587		643
588		644
589		645
590		646
591		647
592		648
593		649
594		650
		651

652
653

654

REFERENCES

- [1] “Wildfire hazards—A national threat,” Reston, VA, Report 2006–3015, 2006. doi: 10.3133/fs20063015.
- [2] S. O. X. Hou, and R. Orth, “Observational evidence of wildfire-promoting soil moisture anomalies,” *Scientific Reports*, vol. 10, no. 1, p. 11008, Jul. 2020, doi: 10.1038/s41598-020-67530-4.
- [3] J. E. Keeley, “Impact of antecedent climate on fire regimes in coastal California,” *International Journal of Wildland Fire*, vol. 13, no. 2, pp. 173–182, 2004, doi: 10.1071/WF03037.
- [4] D. O. Fuller and K. Murphy, “The El Niño–Fire Dynamic in Insular Southeast Asia,” *Climatic Change*, vol. 74, no. 4, pp. 435–455, Feb. 2006, doi: 10.1007/s10584-006-0432-5.
- [5] Z. A. Holden, P. Morgan, M. A. Crimmins, R. K. Steinhorst, and A. M. S. Smith, “Fire season precipitation variability influences fire extent and severity in a large southwestern wilderness area, United States,” *Geophysical Research Letters*, vol. 34, no. 16, Aug. 2007, doi: 10.1029/2007GL030804.
- [6] K. Burapapong and R. Nagasawa, “Mapping Soil Moisture as an Indicator of Wildfire Risk Using Landsat 8 Images in Sri Lanna National Park, Northern Thailand,” *Journal of Agricultural Science*, vol. 8, p. 107, Sep. 2016, doi: 10.5539/jas.v8n10p107.
- [7] E. Krueger, T. E. Ochsner, D. M. Engle, J. D. Carlson, D. Twidwell, and S. D. Fuhlendorf, “Soil Moisture Affects Growing-Season Wildfire Size in the Southern Great Plains,” *Soil Science Society of America Journal*, vol. 79, pp. 1567–1576, 2015.
- [8] M. Yebra *et al.*, “A global review of remote sensing of live fuel moisture content for fire danger assessment: Moving towards operational products,” *Remote Sensing of Environment*, vol. 136, pp. 455–468, Sep. 2013, doi: 10.1016/j.rse.2013.05.029.
- [9] A. L. Westerling *et al.*, “Climate change and growth scenarios for California wildfire,” *Climatic Change*, vol. 109, no. 1, pp. 445–463, Dec. 2011, doi: 10.1007/s10584-011-0329-9.
- [10] W. H. Cooke, G. V. Mostovoy, V. G. Anantharaj, and W. M. Jolly, “Wildfire Potential Mapping over the State of Mississippi: A Land Surface Modeling Approach,” *Null*, vol. 49, no. 4, pp. 492–509, Jul. 2012, doi: 10.2747/1548-1603.49.4.492.
- [11] C. Aubrecht, C. Elvidge, K. Baugh, S. Hahn, and N. Jorge, “Identification of wildfire precursor conditions: Linking satellite based fire and soil moisture data,” *Computational Vision and Medical Image Processing: VipIMAGE*, pp. 347–353, 2011.
- [12] D. Jensen, J. T. Reager, B. Zajic, N. Rousseau, M. Rodell, and E. Hinkley, “The sensitivity of US wildfire occurrence to pre-season soil moisture conditions across ecosystems,” *Environmental Research Letters*, vol. 13, no. 1, p. 014021, Jan. 2018, doi: 10.1088/1748-9326/aa9853.
- [13] J. Thomas Ambadan, M. Oja, Z. Gedalof, and A. A. Berg, “Satellite-Observed Soil Moisture as an Indicator of Wildfire Risk,” *Remote Sensing*, vol. 12, no. 10, 2020, doi: 10.3390/rs12101543.
- [14] U. S. F. Service, *The Rising Cost of Wildfire Operations: Effects on the Forest Service’s Non-fire Work*. USDA Forest Service, 2015. [Online]. Available: <https://books.google.com/books?id=THxXnQAACAAJ>
- [15] J. D. Bolten and W. T. Crow, “Improved prediction of quasi-global vegetation conditions using remotely-sensed surface soil moisture,” *Geophysical Research Letters*, vol. 39, p. 19406, 2012.
- [16] J. D. Bolten, W. T. Crow, X. Zhan, T. J. Jackson, and C. A. Reynolds, “Evaluating the utility of remotely sensed soil moisture retrievals for operational agricultural drought monitoring. Selected Topics in Applied Earth Observations and Remote Sensing,” *IEEE Journal of*, vol. 3, pp. 57–66, 2010.
- [17] I. E. Mladenova *et al.*, “Evaluating the Operational Application of SMAP for Global Agricultural Drought Monitoring,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 12, no. 9, pp. 3387–3397, Sep. 2019, doi: 10.1109/JSTARS.2019.2923555.
- [18] W. C. Palmer, “Meteorological drought u.S.,” *Weather bureau research. U.S. Weather Bureau Research*, p. 45, 1965.
- [19] L. Giglio and C. Justice, “MOD14A1 MODIS/Terra Thermal Anomalies/Fire Daily L3 Global 1km SIN Grid V006,” 2015, Accessed: Jun. 02, 2021. [Online]. Available: <https://lpdaac.usgs.gov/products/mod14a1v006/>
- [20] C. O. Justice *et al.*, “The MODIS fire products,” *Remote Sensing of Environment*, vol. 83, no. 1, pp. 244–262, Nov. 2002, doi: 10.1016/S0034-4257(02)00076-7.
- [21] N. Earl and I. Simmonds, “Spatial and Temporal Variability and Trends in 2001–2016 Global Fire Activity,” *Journal of Geophysical Research: Atmospheres*, vol. 123, no. 5, pp. 2524–2536, Mar. 2018, doi: 10.1002/2017JD027749.
- [22] K. M. de Beurs and G. M. Henebry, “Northern Annular Mode Effects on the Land Surface Phenologies of Northern Eurasia,” *J. Climate*, vol. 21, no. 17, pp. 4257–4279, Sep. 2008, doi: 10.1175/2008JCLI2074.1.
- [23] R. H. Nolan *et al.*, “Causes and consequences of eastern Australia’s 2019–20 season of mega-fires,” *Global change biology*, vol. 26, no. 3, pp. 1039–1041, 2020.
- [24] J. E. Keeley and A. D. Syphard, “Large California wildfires: 2020 fires in historical context,” *Fire Ecology*, vol. 17, no. 1, p. 22, Aug. 2021, doi: 10.1186/s42408-021-00110-7.
- [25] W. Cai, P. van Rensch, T. Cowan, and H. H. Hendon, “Teleconnection Pathways of ENSO and the IOD and the Mechanisms for Impacts on Australian Rainfall,” *Journal of Climate*, vol. 24, no. 15, pp. 3910–3923, Aug. 2011, doi: 10.1175/2011JCLI4129.1.
- [26] L. Felderhof and D. Gillieson, “Comparison of fire patterns and fire frequency in two tropical savanna bioregions,” *Austral Ecology*, vol. 31, no. 6, pp. 736–746, 2006.
- [27] S. Harris and C. Lucas, “Understanding the variability of Australian fire weather between 1973 and 2017,” *PloS one*, vol. 14, no. 9, p. e0222328, 2019.
- [28] M. Ladbrook, E. J. B. van Etten, and W. D. Stock, “Contemporary Fire Regimes of the Arid Carnarvon Basin Region of Western Australia,” *Fire*, vol. 1, no. 3, 2018, doi: 10.3390/fire1030051.

- 770 [29] D. Rother and F. De Sales, "Impact of Wildfire on the 828
771 Surface Energy Balance in Six California Case Studies," 829
772 *Boundary-Layer Meteorology*, vol. 178, no. 1, pp. 143–166, 830
773 Jan. 2021, doi: 10.1007/s10546-020-00562-5. 831
- 774 [30] Z. Luo, H. Guan, X. Zhang, C. Zhang, N. Liu, and G. Li 832
775 "Responses of plant water use to a severe summer drought for 833
776 two subtropical tree species in the central southern China," 834
777 *Journal of Hydrology: Regional Studies*, vol. 8, pp. 1–9, Dec 835
778 2016, doi: 10.1016/j.ejrh.2016.08.001. 836
- 779 [31] L. E. Cullen and P. F. Grierson, "Multi-decadal scale 837
780 variability in autumn-winter rainfall in south-western 838
781 Australia since 1655 AD as reconstructed from tree rings of 840
782 *Callitris columellaris*," *Climate Dynamics*, vol. 33, no. 2–3, 841
783 pp. 433–444, 2009. 842
- 784 [32] J. K. Balch, B. A. Bradley, J. T. Abatzoglou, R. C. Nagler, 843
785 E. J. Fusco, and A. L. Mahood, "Human-started wildfires 844
786 expand the fire niche across the United States," *Proceedings* 845
787 *of the National Academy of Sciences*, vol. 114, no. 11, pp. 846
788 2946–2951, 2017. 847
- 789 [33] A. D. Syphard, J. E. Keeley, A. H. Pfaff, and K. 848
790 Ferschweiler, "Human presence diminishes the importance of 849
791 climate in driving fire activity across the United States," 850
792 *Proceedings of the National Academy of Sciences*, vol. 114, 851
793 no. 52, pp. 13750–13755, 2017. 852
- 794 [34] L. Beth and T. J. Brown, "A comparison of precipitation 854
795 and drought indices related to fire activity in the US," 2003. 855
- 796 [35] K. L. Riley, J. T. Abatzoglou, I. C. Grenfell, A. E. Klenz, 856
797 and F. A. Heinsch, "The relationship of large fire occurrence 857
798 with drought and fire danger indices in the western USA, 858
799 1984–2008: the role of temporal scale," *Int. J. Wildland Fire* 859
800 vol. 22, no. 7, pp. 894–909, 2013. 860
- 801 [36] M. R. Ehsani *et al.*, "2019–2020 Australia Fire and Its 861
802 Relationship to Hydroclimatological and Vegetation 862
803 Variabilities," *Water*, vol. 12, no. 11, 2020, doi: 863
804 10.3390/w12113067. 864
- 805 [37] A. I. Filkov, T. Ngo, S. Matthews, S. Telfer, and T. D. 865
806 Penman, "Impact of Australia's catastrophic 2019/20 bushfire 866
807 season on communities and environment. Retrospective 867
808 analysis and current trends," *Journal of Safety Science and* 869
809 *Resilience*, vol. 1, no. 1, pp. 44–56, Sep. 2020, doi: 870
810 10.1016/j.jnlssr.2020.06.009. 871
- 811 [38] P. E. Higuera and J. T. Abatzoglou, "Record-setting 872
812 climate enabled the extraordinary 2020 fire season in the 873
813 western United States," *Global Change Biology*, vol. 27, no. 874
814 pp. 1–2, Jan. 2021, doi: 10.1111/gcb.15388. 875
- 815 [39] D. Chaparro, M. Piles, M. Vall-llossera, and A. Camps, 876
816 "Surface moisture and temperature trends anticipate drought 877
817 conditions linked to wildfire activity in the Iberian Peninsula," 878
818 *Journal of Arid Environments*, vol. 49, no. 1, pp. 955–971, Jan. 2016, doi: 879
819 10.5721/EuJRS20164950. 880
- 820 [40] A. J. Schaefer and B. I. Magi, "Land-Cover Dependent 882
821 Relationships between Fire and Soil Moisture," *Fire*, vol. 2, 883
822 no. 4, 2019, doi: 10.3390/fire2040055. 884
- 823 [41] E. S. Krueger, T. E. Ochsner, J. D. Carlson, D. M. Engle, 885
824 D. Twidwell, and S. D. Fuhlendorf, "Concurrent and 886
825 antecedent soil moisture relate positively or negatively to 887
826 probability of large wildfires depending on season," *Int. J.* 888
827 *Wildland Fire*, vol. 25, no. 6, pp. 657–668, 2016. 889
890
891
892

893
894
895



Nazmus Sazib received the M.S and Ph.D. degrees in civil engineering from the University of Louisiana and Utah State University in 2012 and 2016 respectively.

He is currently working as a research scientist at the Hydrological Sciences Branch,

905 NASA Goddard Space Flight Center, Greenbelt, MD. His
906 research interest includes remote sensing, data assimilation,
907 development of software and tools to advance the utility of
908 remote sensing data for hydrologic and agriculture application.



Iliana E. Mladenova received the M.S. degree in hydrology from Free University, Amsterdam, The Netherlands, and the Ph.D. degree in geological sciences from the University of South Carolina, Columbia, SC, USA, in 2006 and 2009, respectively. Her major expertise are in the areas of land surface hydrology and remote

sensing. Her research interests include the use of satellite-based microwave techniques, land surface modeling, and data assimilation for improved monitoring of the different components of the water cycle, and their potential integration for enhanced earth system modeling.



John D. Bolten's research focuses on the application of satellite-based remote sensing and land surface hydrological modeling for improved ecological and water resource management. He is involved in several water resources management efforts addressing flood monitoring, flood damage assessment, and agriculture drought forecasting and mitigation around the globe. He received the M.S. and Ph.D. degrees in geology with an emphasis in hydrology and remote sensing from the University of South Carolina.