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**ABSTRACT**
Globally, managing wildland fire is increasing in complexity. Satellite Earth Observation (EO) data, specifically active fire 'hotspot' data, is often used to inform wildland fire management. This study explores hotspot data usage via web traffic data ('user counts') for the FIRMS, GWIS and EFFIS web portals between September 2019 and April 2023. Global active fire data use is characterized by multi-month periods of relatively low, stable user counts, interspersed with periodic spikes (4.1x median monthly activity) of activity broadly aligned with the North American / European fire season (late summer-fall). Users from the Americas (45%) and Europe (36%) dominate web traffic. We also examined correlative relationships between web page user counts and environmental and social variables at multiple spatial scales. Globally, the strongest relationships were found between user counts and the total number of fires, total burned area, number of fire disaster events; country population levels and internet proliferation. Notably, at a country level, the strongest (and weakest) relationships between weekly user counts and fire activity were found in a diverse range of countries suggesting that a variety of hotspot data use situations exist and further investigation is needed to better understand EO active fire data usage.

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Wildland fire; hotspots; NASA FIRMS; GWIS; EFFIS

## 1. Introduction

Although wildland fires generate ecological benefits in selected landscapes, the negative economic, environmental, and social impacts (Johnston et al. 2020a; Stephens et al. 2014; Tymstra et al. 2020) that can result from unwanted wildland fires (fire) demand multiple approaches to management (Gill, Stephens, and Cary 2013). Many countries and regions with fire activity have developed organizations and policies for fire management (e.g. Pandey et al. 2023; Tymstra et al. 2020). These fire management organizations are facing increasingly complex issues: a growing number of anthropogenic features on the landscape (e.g. Johnston and Flannigan 2017), climatic conditions

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more conducive to fire activity and increasing fire frequency and severity (Coogan et al. 2019; Flannigan et al. 2009; 2013; Jones et al. 2022). A risk management approach is often taken when managing fire (Johnston et al. 2020b) and these risk-based decisions need credible and reliable fire information.

Fire monitoring information can come from many sources, including on-the-ground-monitoring from towers (Rego and Catry 2006), aircraft/drone surveillance (McFayden et al. 2019), or satellite-based Earth Observations (EO) (Allison et al. 2016; Chuvieco et al. 2020; Crowley et al. 2023). Although all information types are valuable, EO active fire data products provide a landscape-level perspective which may improve decision-making outcomes (Johnston et al. 2020a; Simon, Crowley, and Franco 2022). Satellite EO active fire data products (providing information on the location and characteristics of actively burning fires at the time of observation), are one of the most widely used types of EO data (Xu and Wooster 2023). However, there is little research documenting the magnitude or impact associated with these EO data in a fire management context (Herr et al. 2020; McFayden et al. 2023; Mouillot et al. 2014). There is some evidence to suggest that in general, EO data and related products are not used to their fullest potential (Lacava et al. 2020; McFayden et al. 2023; Sadlier 2018). Identifying and addressing use limitations could lead to increased EO data use and maximize any benefits resulting from data use (CEOS N.D.a). Measuring current EO data use is a necessary first step towards understanding the impact of EO data and addressing potential barriers, whether for fire related EO products or EO products more generally.

People seek out information from internet-based sources in times of natural disasters and hazards (e.g. Dargin, Fan, and Mostafavi 2021; Rahmi, Joho, and Shirai 2019). Some studies have focused on the adoption of information technology for disaster risk management, addressing factors such as perceived usefulness and ease of use (e.g. Meechang et al. 2020). The specific drivers of general website traffic are not well known, although factors impacting attitudes and the general use of websites have been explored through technology acceptance models (Van der Heijden 2003). Although there have been studies on public interest in fire via web searches (Santín, Moustakas, and Doerr 2023) and drivers of internet use related to local interests (Tranos and Stich 2020), analysis of the factors driving the use of EO-based fire monitoring information web-sources have not been performed to our knowledge.

The purpose of this paper is to provide an exploratory analysis of website traffic data collected from three public web platforms providing near real-time access to active fire data: the Fire Information for Resource Management System (FIRMS), the Global Wildland fire Information System (GWIS) and European Forest Fire Information System (EFFIS). We explore the number of users visiting the webpages for trends and correlation with social and environmental variables related to fire.

## 2. Background

### *2.1. EO data and fire management*

EO data have been available and used in fire management practices for many years (Allison et al. 2016; Crowley et al. 2023; Wooster et al. 2021). A range of different products are available across multiple platforms and formats. These data provide details on fire timing and location, insights into fuel types and surrounding values at risk (Crowley et al. 2023), and a range of fire characteristics (Chuvieco et al. 2020; Leblon, Bourgeau-Chavez, and San-Miguel-Ayanz 2012). Two of the most widely used Satellite EO fire products are active fire and burned area products.

Active fire products are primarily derived from thermal EO imagery collected at the time fires are ‘actively’ burning on the landscape (Wooster et al. 2021). ‘Hotspot’ products (a series of point features with associated metadata) are a commonly generated active fire product widely used for detecting or confirming reported fire activity by a wide range of stakeholders and are operationally available from both polar orbiting and geostationary imaging satellites. Hotspot data is often available in near real-time (from several minutes up to a few hours) after image collection and downlinking (Davies et al. 2015), making them useful for supporting fire management decisions. Burned area products primarily use change detection techniques with visible and shortwave infrared imagery to map recent fire scars. Traditionally, burned area mapping is less timely than active fire mapping, being provided weeks to months after fires have occurred, but recent efforts have been made to reduce this time delay (Chuvieco et al. 2019). The present study focuses on the use of active fire hotspot products, due to their timeliness and their known use by fire management agencies.

Globally, the most widely available operationally produced fire hotspot products from polar orbiting satellites are those generated using data from the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments flown onboard National Aeronautics and Space Administration's (NASA) Aqua and Terra satellites (Giglio, Schroeder, and Justice 2016), and the Visible Infrared Imaging Radiometer Suite (VIIRS) instruments (Schroeder et al. 2014) flown onboard the NASA/NOAA Suomi National Polar-orbiting Partnership and Joint Polar Satellite System satellites. Fire hotspot products are also produced operationally for a number of geostationary satellites, including the NASA Geostationary Operational Environmental Satellites (GOES) satellite series over the Americas (Xu et al. 2021), EUMETSAT Meteosat series over Europe and Africa (Wooster et al. 2015), and the JAXA Himawari satellite series over East Asia and Australasia (Xu et al. 2017). Data from these satellites are open and publicly available and multiple public-facing websites display this data for visualization and download by users. User data from three such major online platforms (FIRMS, GWIS and EFFIS) are the subject of the current study and are discussed further below.

### 2.2. Public platforms for active fire hotspot data

#### 2.2.1. FIRMS

Originally developed in response to an extreme fire season and data-requests from fire management agencies in the United States (Davies et al. 2009), FIRMS (https://firms.modaps.eosdis.nasa.gov/map) is the primary provider of EO hotspot data for fire management agencies in North America and supplies global hotspot data to the public on an hourly basis. A program of NASA, FIRMS provides date and location information for hotspots detected by MODIS and VIIRS (Davies et al. 2009) and more recently Landsat and provisional geostationary sources (Smith 2022). FIRMS allows users to visualize and download filtered current and historical hotspots, create active fire alerts, and access additional fire-relevant resources.

#### 2.2.2. GWIS and EFFIS

The European Commission's Joint Research Centre maintains GWIS (https://gwis.jrc.ec.europa.eu/) and EFFIS (https://effis.jrc.ec.europa.eu/) which redistribute and visualize MODIS and VIIRS hotspot data from FIRMS, amongst other fire relevant datasets (e.g. fire weather forecasts and burned area statistics) (McInerney et al. 2013) to provide fire-related insights globally (GWIS) and for the European Union and neighbouring countries (EFFIS). Like FIRMS, GWIS and EFFIS produce updated spatial data products hourly in accordance with the data availability from MODIS and VIIRS (San-Miguel-Ayanz et al. 2012). Although GWIS and EFFIS provide similar data, their purpose differs. Developed first, EFFIS was designed to address the need for harmonized fire information across European and Mediterranean countries (McInerney et al. 2013), supporting domestic and trans-boundary fire decision-making and resource sharing (San-Miguel-Ayanz et al. 2012). GWIS is a more recent extension of EFFIS, providing fire data and decision support assistance to countries beyond the European and Mediterranean regions (Borges et al. 2023; San-Miguel-Ayanz et al. 2015). Both the GWIS and EFFIS websites provide hotspot data services like those found on the FIRMS website; historical and current hotspot data can be viewed, filtered on a variety of criteria, and downloaded.

## 3. Data and methods

### 3.1. Data

#### 3.1.1. Website user count data

Although FIRMS, GWIS and EFFIS provide hotspot data in a variety of formats, our analysis focuses on web traffic data for the pages that map active fire hotspots – the 'Fire Map' page for FIRMS (https://firms.modaps.eosdis.nasa.gov/map) and the 'Current Situation Viewer' for both GWIS (https://gwis.jrc.ec.europa.eu/apps/gwis_current_situation/index.html) and EFFIS (https://forest-fire.emergency.copernicus.eu/apps/effis_current_situation/index.html). These webpages (Figure S1) provide interactive visualizations of current and historical hotspots overlaying contextual maps and/or satellite or arial imagery, and other relevant fire information layers (e.g. smoke concentrations, fire weather) that can be toggled on and off. We opted to analyse map page data uses rather than data file download statistics because these webpages typically see the most user activity overall for the respective websites, and anecdotal evidence suggests that these statistics likely capture a wider range of users (including more 'casual' users) than other sections of these sites. Web traffic data from all three platforms was provided upon request by the respective organizations and collected via internal website analytical processes (e.g. internal or third-party services that provide metrics on website use). These data were supplied at the level of the individual web page visit, inclusive of the date of a user's visit and their country of origin. We do not differentiate between visits from unique and repeat users. These data were compiled into a single dataset and aggregated at different spatial and temporal scales in our analyses and are hereafter referred to as 'user count data'. For FIRMS, we included data from the primary website and a duplicate website (FIRMS2) that responds to overflow traffic when FIRMS capacity is exceeded or is inaccessible due to maintenance or repairs. We analysed all data that were readily available to us at the time of writing: FIRMS data spanning September 2019 – April 2023 inclusive and both EFFIS and GWIS data spanning July 2020 to April 2023, inclusive. These data were combined to create a comprehensive dataset spanning September 2019 to April 2023, representing our defined study period.

#### 3.1.2. Use influencing variables

We explored the relationship between user count data and variables thought to encourage use (here after, 'use influencing variables') as described in Table 1. Borrowing concepts from the Technology Acceptance Model (TAM) (e.g. Legris, Ingham, and Collerette 2003), we focused on variables thought to affect the user's perceived usefulness and the ease of use of these platforms. Use-influencing variables were categorized as either 'environmental' or 'social', modelling categories frequently used within the fire domain (e.g. Ambrey, Fleming, and Manning 2017; Crowley 2015; Fujioka et al. 2008; McCaffrey 2010). Fire activity data (number of fires and burned area) were obtained at a weekly temporal resolution. All other use influencing variables were collected as a single, annual value for each country within the analysis; in each case, the most recent observation available was used (see below for further details).

*3.1.2.1. Environmental variables.* Country-level fire activity data was obtained from the GWIS Statistics Portal (GWIS 2023a). Data containing the number of hectares burned (burned area) and number of fires per country per week were obtained for the 2002–2022 period. GWIS active fire data are derived from the NASA MODIS (MCD14DL) and VIIRS (VNP14IMGTDL_NRT and VJ114IMGTDL_NRT) active fire products provided by NASA FIRMS (Davies et al. 2009). GWIS burned area data (GWIS 2023b) are derived from the NASA MODIS MCD64A1 Burned Area Product (Giglio et al. 2018), which incorporates MODIS active fire observations to improve accuracy of fire timing estimates.

Using the aforementioned GWIS burned area data, we calculated the maximum potential fire season length for each country as an indicator of the number of months with fire activity. Our

**Table 1.** Variables thought to influence the degree of use of the FIRMS, GWIS and EFFIS platforms.

| Variables | TAM Influential factor type | Rationale narrative example |
|---|---|---|
| **Environmental:** | | |
| Fire activity (weekly count of active fires and burned area) | Perceived usefulness | The more active fires and burned area, the more emergency services, public responders, and concerned citizens will want to access fire information for situational awareness, communicating hazard, and informing decisions (e.g. Woolford et al. 2021). |
| Months with fire activity | Perceived usefulness | Internet interest in fire information is expected to follow seasonal patterns (Santín, Moustakas, and Doerr 2023). Areas that experience more time (months) of fire activity are expected to see more interest in fire information. |
| Number of domestic disaster fire events | Perceived usefulness | Fire disasters lead to interest on social media (Dufty 2015) both locally and beyond the immediate jurisdiction (Windmar et al. 2022). The larger the impact (or expected impact) of a disaster, the greater the demand for fire information, both locally and internationally. |
| Proportion of forested land and grassland | Perceived usefulness | Akin to exposure (e.g. Beverly and Forbes 2023), larger areas prone to fire lead to increased detection and monitoring needs for new and active fires, especially for remote fires where aircraft use is prohibitive (e.g. Johnston et al. 2018). |
| **Social:** | | |
| Total population | Perceived usefulness | Greater populations yield larger potential numbers of users (e.g. Crowley 2015). |
| Internet proliferation/access | Perceived ease of use | As a requirement for use of FIRMS, GWIS and EFFIS, proliferation of internet access was thought to represent the ease of use (e.g. Greshake 2016). |

approach is based on that used by Archibald et al. (2013). For each country, monthly burned area data grouped by year were ranked in descending order, and the minimum number of months required to reach 80% of the annual total burned area was used to identify months that belong to the fire season. We then calculated the maximum (rather than mean, as used by Archibald et al. 2013) number of months with fire activity over the 2002–2022 period to better represent potential season length rather than the average situation for each country.

Global fire disaster event data were acquired from the International Disaster Database, maintained by the Centre for Research on the Epidemiology of Disasters (2023). To be included in this dataset, a disaster event must satisfy one of three criteria: ten or more people were killed, 100 or more people were impacted (affected, injured, or lost their homes), or a state of emergency was declared by the affected country and/or there was a request for international aid. Disaster data included the country impacted, the disaster type, and the start and end dates of the disaster. Subsetting the dataset by country, we filtered for fire disasters, calculated the number of disaster events per country over the 2019–2023 study period.

The proportion of vegetated (forested and grassland) area within each country in 2023 was obtained from the World Bank (2023a, 2023b).

*3.1.2.2. Social variables.* Total population and internet proliferation ('Individuals using the Internet, % of population') data were taken from the World Bank online database (2023c; 2023d). In both cases, we used the most recent annual values for each country. Population data are based on 2022 observations, while internet proliferation data are mostly available for 2020 or 2021 (83% of countries had internet proliferation data dated 2020 or later). For those countries missing 2020 or 2021 internet proliferation data, the most recent data were used.

### *3.1.3. Gross Domestic Product (GDP) data*

Although not considered a use influencing variable, we also explored relationships between user counts and GDP. A standardized indicator of value created via the domestic production of goods and services (World Bank Group 2022e), the GDP metric provides insights into a country's current economic situation. For GDP, 93% of data were from 2021 or 2022. As with the social variables described above, for those countries missing data, the most recently available estimate of GDP was used. A map of GDP values is included in Figure S2.

### 3.2. Methods

All data manipulation and analyses were performed using the R programming language (R Core Team 2022). The specific packages used are as follows: *countrycode* (Arel-Bundock, Enevoldsen, and Yetman 2018), *maps* (Becker et al. 2022), *data.table* (Dowle, Srinivasan, and Barrett 2023), *lubridate* (Grolemund and Wickham 2011), *RColorBrewer* (Neuwirth 2022), *ggforce*(Pedersen 2022), *GGally* (Schloerke et al. 2021), *ggpubr* (Kassambara 2023), *corrplot* (Taiyun and Simko 2021), *ggplot2* (Wickham 2016), *dplyr* (Wickham et al. 2023a), *scales* (Wickham and Seidel 2022), *tidyr* (Wickham, Vaughan, and Girlich 2023b).

#### 3.2.1. Inter- and intra-country correlation analysis

Global and country level relationships between hotspot website user count data and use-influencing variables were explored through inter-country (i.e. between countries) and intra-country (i.e. within individual countries) correlations. Given the count nature of the dependent variable (user count) dataset, we use Spearman's rank correlation coefficient for analysis of the relationships between user count data and use-influencing variables. For the inter-country correlation analysis, each country is represented as a single data point. User count data were aggregated as the total number of visitors from all hotspot web platforms (FIRMS, GWIS and EFFIS) over the 2019–2023 study period, per country. For the use-influencing variables (number of months with fire activity, number of disaster events, proportion of forest/grassland, total population, internet proliferation), in most cases, raw data were already represented as a single value per country for the study period (see Section 3.1.2). For the use-influencing variables with higher temporal resolution (weekly sum of burned area and count of fires), data were summed over the 2019–2023 study period prior to analysis. Based on this correlation analysis, we further examined regional scale relationships using linear regression between log transformed user count data and the use-influencing variables with the strongest correlation with user count data (burned area, count of fires, domestic disaster events, population and internet proliferation; Section 4.2.3). For the intra-country analysis, we examined correlations between weekly user counts and both the weekly sum of burned area and the weekly counts of active fires. Thirty-three countries lacked some combination of hotspot website user count data or use-influencing variable data and were excluded from correlation analysis. All countries, their study inclusion, and corresponding regions are listed in Table S1, alongside a regional summary.

## 4. Results

### 4.1. Temporal and spatial variations in user count data

Temporal and spatial patterns of hotspot website user count data are shown in Figures 1 and 2. Global user count data across all three platforms (FIRMS, GWIS and EFFIS) are characterized by periodic spikes, coupled with periods of lower activity (Figure 1). Spikes in user counts are sharp, suggesting a sudden drastic increase in users over a short period of time (4.1x median monthly activity, which is 741,312 users). FIRMS is the most popular platform overall with a mean annual user count of 3,376,201 and a maximum annual user count of 6,463,990. FIRMS user counts are dominated by users from the Americas (45% of total users) and Europe (36% of total users). GWIS and EFFIS are used less (205,467 mean and 521,421 maximum annual peak users, combined), but are extensively used by Europeans (83% of users; Figure 1 and Figure S3).

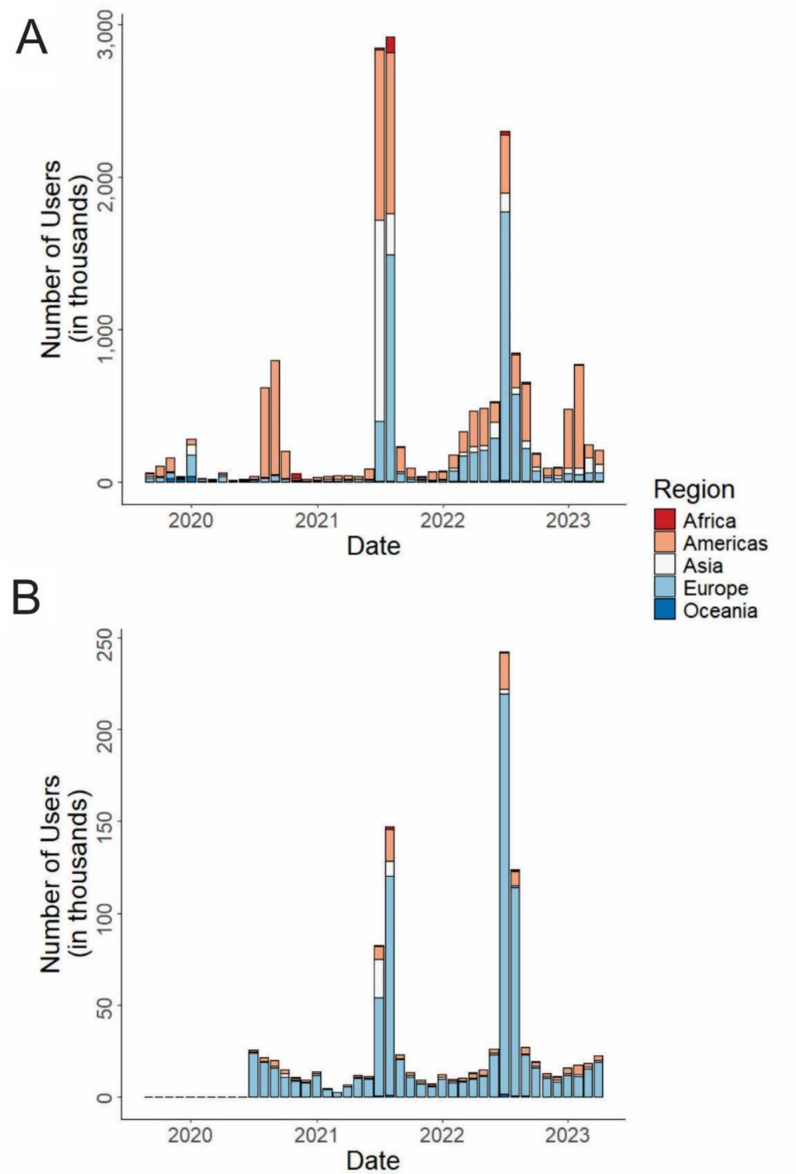


**Figure 1.** Monthly total user counts for (**A**) FIRMS users and (**B**) GWIS and EFFIS users combined, by region. Note the different date range across the panels: FIRMS 2019–2023; GWIS & EFFIS 2020–2023. Regional totals are based on the sum of weekly user counts for all countries within that region; see Table S1 for region groupings.

Both total global and regional user counts are dominated by a small number of countries with very high user counts (Figure 2(A)). Algeria dominates user counts (125 thousand users in total across the study period) in Africa, the U.S.A. (>4.9 million total users) in the Americas, Turkey (>1.7 million total users) in Asia, France (1.1 million total users) in Europe, and Australia (13 thousand total users) in Oceania. Globally, the greatest number of users were from the U.S.A., Turkey, France and Germany with over a million users recorded across the study period and all platforms. Figure 2(B) shows the proportion of total users relative to country population over the study period. Countries with the greatest number of users relative to population size are Greece (8.0%), Chile (4.9%), Cyprus (2.9%), Slovenia and Montenegro (2.5%).

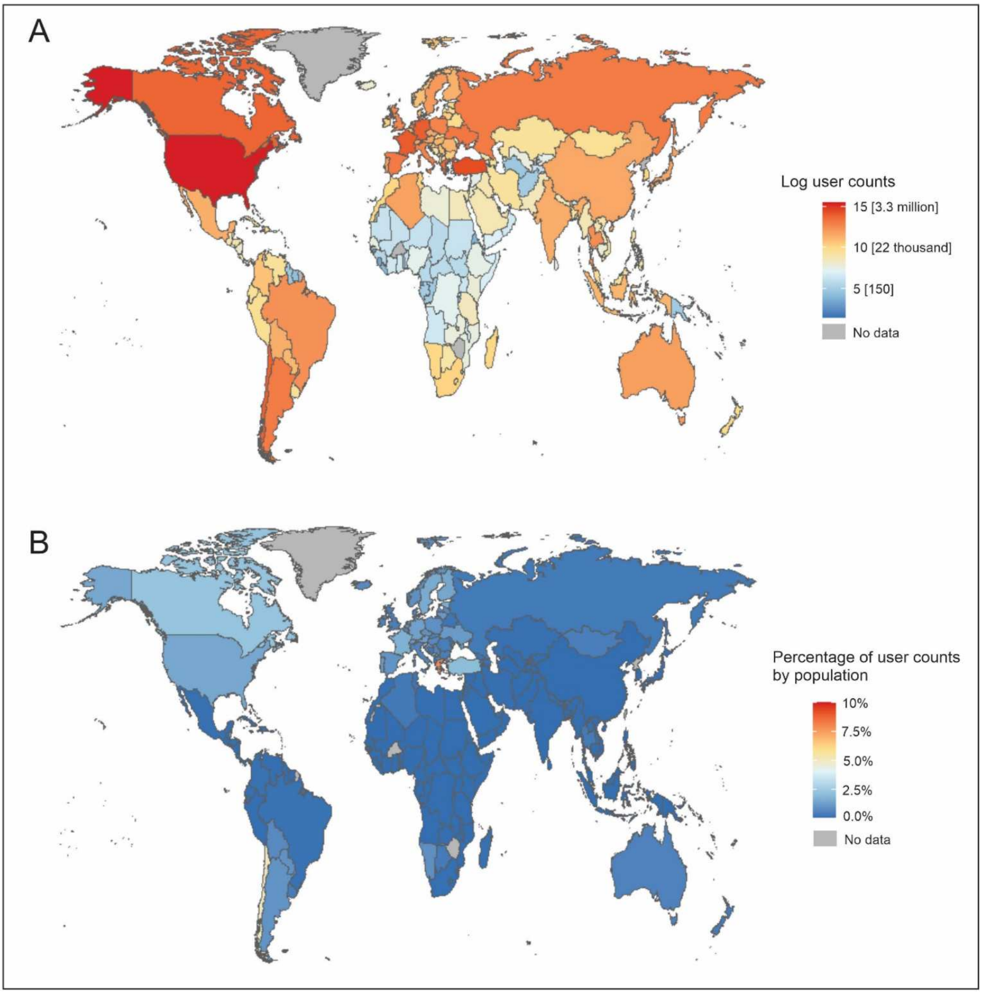


**Figure 2.** (**A**) the natural log of the country level user count from FIRMS, GWIS and EFFIS combined over the 2019–2023 study period. Approximate untransformed values in brackets. (**B**) The total number of weekly users over the study period by country as a proportion of the 2022 population.

### 4.2. Use-influencing variables

Figure 3 shows the spatial variation in use-influencing variables examined over the study period. The total burned area (Figure 3(A)), and the number of fires (Figure 3(B)) show similar spatial patterns, with most fire activity occurring in Brazil (114.0 million ha burned) and Australia (87.9 million ha burned). Months with fire activity, represented by the maximum historic number of months with fire activity (Figure 3(C)), shows considerable regional and inter-country variation. Season length ranges from 8 months in Argentina, Australia, Iran, Iraq, and the U.S.A., to 0-to-1-month of fire activity (see Table S1 for those countries with 0-to-1 months of fire activity). Median regional number of months with fire activity is 4.5 months in the Americas, 4 months in Africa and Asia, 3 months in Europe, and 2 months in Oceania. Domestic fire disaster events (Figure 3(D)) were most common in the U.S.A., Bolivia, and Australia (56, 44, 29 events, respectively). 163 countries (84%) experienced zero fire disasters in the study period. Figure 3(E, F) shows the proportion of vegetated forest land and grass land, respectively, relative to the total country area. Countries with high forest cover are primarily located in the tropics and Northern Eurasia, while countries with high grassland cover are concentrated in Europe and South Asia. Total population

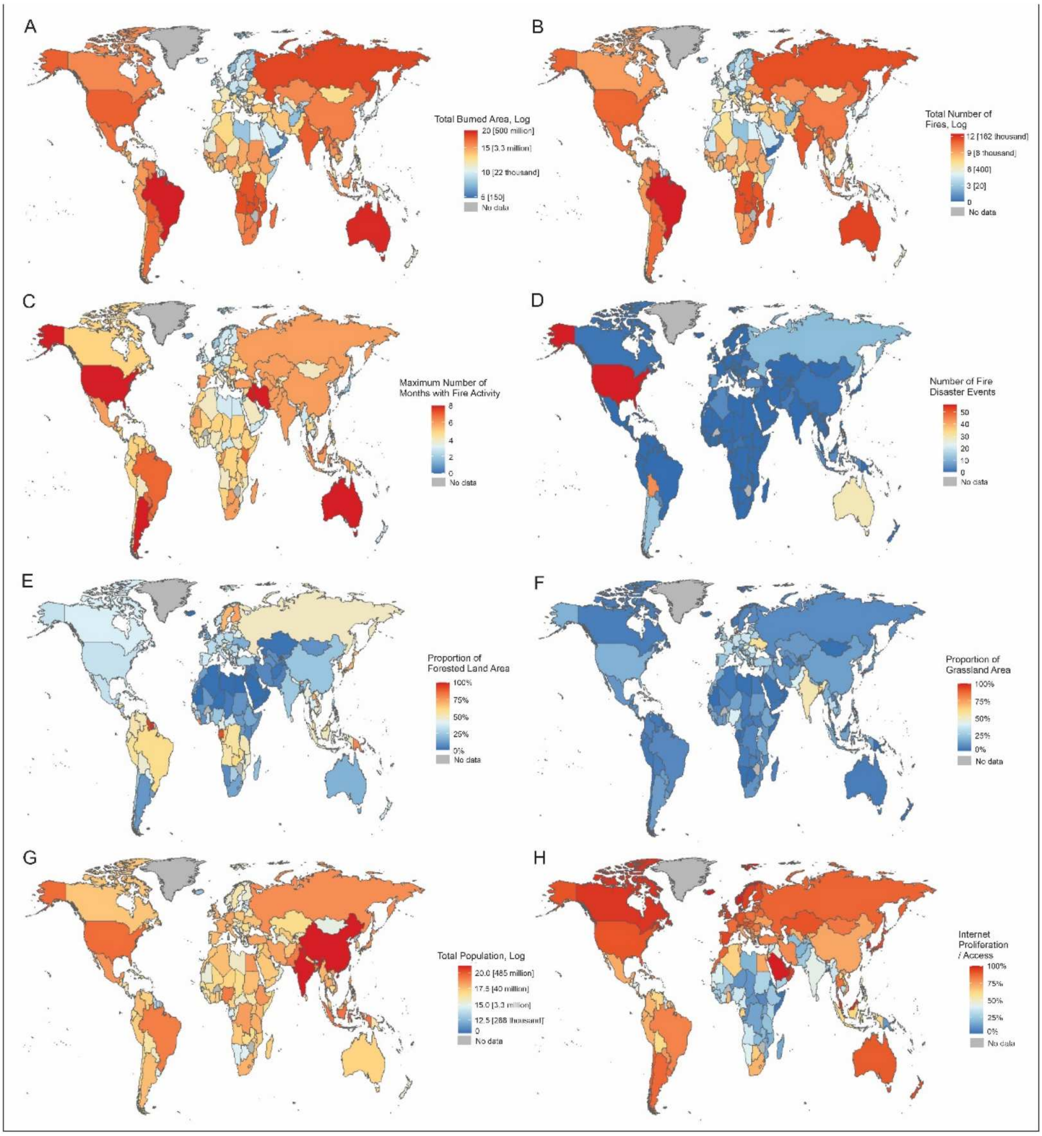


**Figure 3.** Use influencing variables, by country: (**A**) Total burned area over the 2019–2023 study period, logged; (**B**) Total number of fires over the 2019–2023 study period, logged; (**C**) Maximum number of months with fire activity over the 2002–2022 period; (**D**) number of fire disaster events over the 2019–2023 study period; (**E**) proportion of forested land area (2023); (**F**) proportion of grassland area (2023); (**G**) Total population (2022), logged; (**H**) internet proliferation, the proportion of the population with internet access (most recent year available between 2020-2023). Approximate untransformed values included in brackets where appropriate.

(Figure 3(G)) is highest in China and India. Internet proliferation (Figure 3(H)) is moderate to high (> 50% of population) in most regions of the world, with lower levels of access (< 50% of the population) in most of Africa and southern Asia.

### 4.3. Relationships between user count data and use influencing variables

#### 4.3.1. Inter-country relationships

We examined the correlation between all variables at the global scale. Illustrated in Figure 4, the correlation value between each pair of variables can be found by reading the matrix left to right,

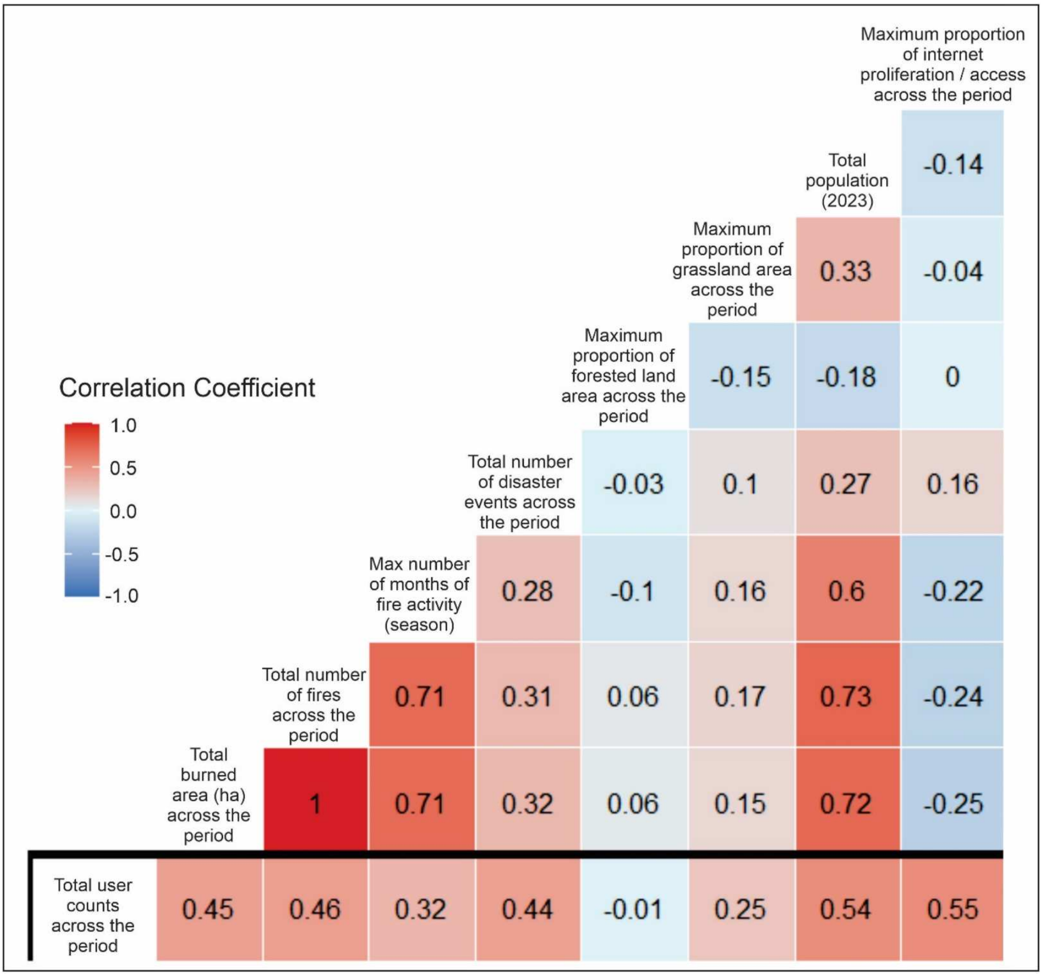


**Figure 4.** Correlation (Spearman's ρ) between the total user count within each country and the independent social and environmental use influencing variables over the entire study period (see Section 3.1.2).

top to bottom. For example, the correlation value between the burned area variable and the month variable can be found in the matrix row corresponding to burned area, and the matrix column corresponding to the month variable. The colour of the matrix cell represents the direction of correlation (positive or negative), and the colour saturation represents the strength of that correlation; matrix cells that are very light in colour imply very low levels of correlation. Correlation matrices are common visualizations across multiple fields (see Haas, Switanek, and Birk 2018; Matta et al. 2024; and Williams et al. 2022 for other examples of correlation matrices in an Earth observational context). The bottom row of the correlation matrix (Figure 4, outlined in black) illustrates the relationships between total hotspot data users and use-influencing variables, the primary focus of this analysis. Statistically significant (Spearman's ρ, $p < 0.05$) correlation was found between total user counts and all use-influencing variables except for the proportion of forested area ($p = 0.847$). Correlation between total users and burned area, number of fires, number of disaster events, population, and internet access is moderate (Spearman's $\rho = 0.44$–$0.55$), suggesting that these environmental and social use-influencing variables are all positively influencing user counts. Correlation between user counts and both number of months with fire activity (Spearman's $\rho = 0.32$) and grassland proportion (Spearman's $\rho = 0.25$) are weak.

For five of the use-influencing variables showing the strongest correlation with user counts at the global level (Figure 4), regional scale relationships are presented in Figure 5. Statistically significant ($P < 0.05$) linear relationships exist for use-influencing variables across most regions, albeit of varying strength. We only report on those relationships that are statistically significant at the 0.05 level (i.e. the relationship between user counts in Europe and the use-influencing variables is often insignificant, and thus not discussed here). Moderate to strong relationships exist between the log of user counts and both the log of burned area and count of fires in the Americas and Oceania ($R^2 = 0.66–0.79$ and $R^2 = 0.64–0.82$ for burned area and count of fires, respectively), with weaker statistically significant relationships in Africa and Asia ($R^2 = 0.14–0.31$ and $R^2 = 0.13–0.31$ for burned area and count of fires, respectively) (Figure 5(A and B)). The strength of the relationship between user counts and the number of months with fire activity was higher for the Americas, Europe, and Oceania ($R^2 = 0.40–0.57$), but quite weak for Africa ($R^2 = 0.08$) (Figure 5(C)). Total population is the only use-influencing variable significantly correlated with user counts in all regions, with moderate to strong relationships in Europe, the Americas, and Oceania ($R^2 = 0.52–0.89$) (Figure 5(D)). User counts and

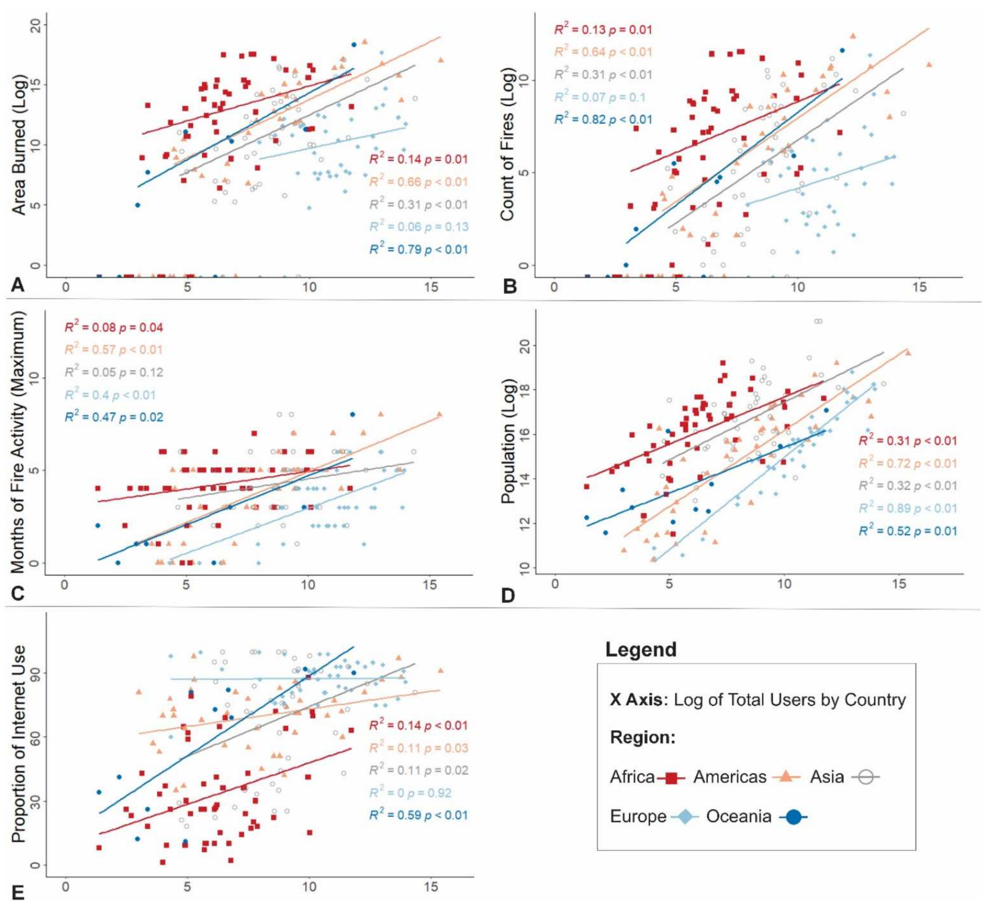


**Figure 5.** Relationships (ordinary least squares regression) between user counts and a subset of use influencing variables, by region. Each data point represents an individual country. Natural log of weekly user counts vs. (**A**) natural log of burned area over the 2019–2023 period, (**B**) natural log of the count of fires over the 2019–2023 period, (**C**) the maximum number of months with fire activity, (**D**) natural log of population counts from 2022, (**E**) the proportion of the maximum internet proliferation value for the most recent year available between 2020 and 2021. R-squared and *P*-values for each regional regression is shown on the plot.

internet proliferation are moderately related in Oceania ($R^2 = 0.59$), and weakly related in Africa, Asia and America ($R^2 <= 0.14$) (Figure 5(E)).

### 4.3.2. Intra-country relationships

Intra-country relationships between weekly user counts and weekly burned area are mostly positive (73% of countries with Spearman's $\rho > 0$) but vary considerably in strength between countries (Figure 6(A); Spearman's ρ global median = 0.11, maximum = 0.79, minimum = −0.52) Examining country-level correlation between weekly user counts and the weekly number of fires (Figure 6(B)) yielded extremely similar results (Spearman's ρ global median = 0.10, maximum = 0.79, minimum = −0.52). In general, countries with high fire activity are more likely to have stronger positive correlation between weekly user counts and weekly fire activity than countries with low fire activity (See Figure 3(A and B)), though exceptions exist (e.g. several countries in sub-Saharan Africa and central Asia, Australia). Countries with particularly strong or weak correlations between weekly user counts and fire activity ('outlier' countries, defined here as countries with correlation values

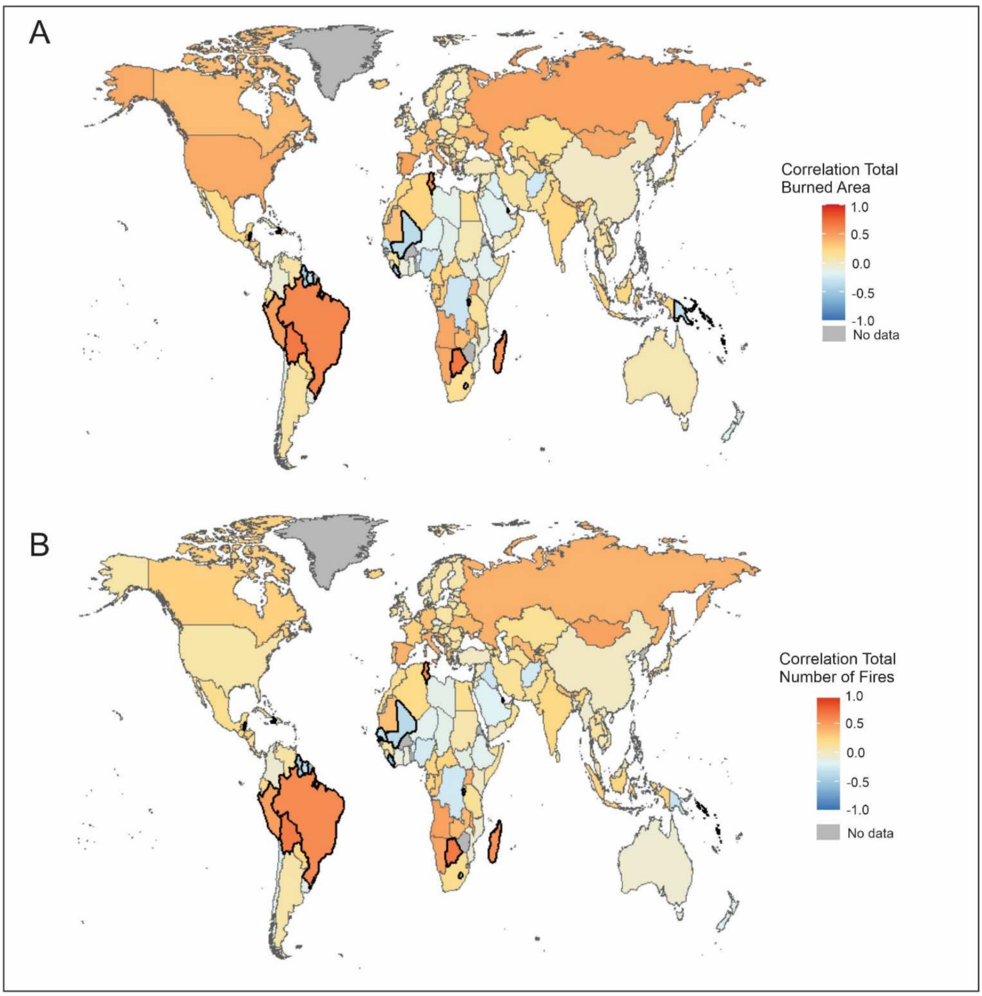


**Figure 6.** Correlation (Spearman's ρ) for total weekly user counts vs. weekly burned area (**A**) and number of active fires (**B**) by country for the 2019–2023 study period. Countries where correlation values were considered outliers (<5th or >95th percentile) are highlighted with a thick black outline.

**Table 2.** Correlation (Spearman's ρ) coefficients for weekly total user counts vs. weekly burned area and vs. number of fires and GDP values for 2022 for 'outlier' countries (countries with Spearman's ρ <5th or >95th percentile value).

| Country | Region | Correlation Coefficient | | 2022 GDP (in millions) |
|---|---|---|---|---|
| | | Users and Burned Area | Users and Number of Fires | |
| Belize | Americas | 0.67 | 0.67 | 2824 |
| Bolivia | Americas | 0.66 | 0.65 | 43,068 |
| Botswana | Africa | 0.66 | 0.66 | 20,352 |
| Brazil | Americas | 0.59 | 0.57 | 1,920,095 |
| Burundi | Africa | 0.70 | 0.70 | 3,073 |
| Guyana | Americas | −0.45 | −0.45 | 15,357 |
| Haiti | Americas | −0.40 | −0.40 | 20,253 |
| Lesotho | Africa | −0.33 | −0.33 | 2,553 |
| Liberia | Africa | −0.52 | −0.52 | 4,001 |
| Madagascar | Africa | 0.55 | 0.54 | 14,954 |
| Mali | Africa | −0.37 | −0.38 | 18,827 |
| Papua New Guinea | Oceania | −0.31 | NA | 30,633 |
| Peru | Americas | 0.49 | 0.48 | 242,631 |
| Qatar | Asia | −0.40 | −0.41 | 237,295 |
| Senegal | Africa | NA | −0.31 | 27,684 |
| Solomon Islands | Oceania | 0.79 | 0.79 | 1,595 |
| Suriname | Americas | −0.34 | −0.34 | 3,620 |
| Tunisia | Africa | 0.57 | 0.55 | 46,664 |
| Vanuatu | Oceania | −0.47 | −0.47 | 983 |

below the 5th or above the 95th percentile) are outlined in black in Figure 6(A and B) and summarized in Table 2. Notably, both negative outlier countries (Guyana, Haiti, Lesotho, Libera, Mali, Papua New Guinea, Qatar, Senegal, Suriname, and Vanuatu) and positive outlier countries (Belize, Bolivia, Botswana, Brazil, Burundi, Madagascar, Peru, Solomon Islands and Tunisia) for both weekly burned area and number of fires span a wide range of GDP values (Table 2; negative outlier country GDP range: US$983–237,295 million, positive outlier country GDP range: US$1595–1,920,095 million).

## 5. Discussion

### *5.1. Use (and drivers of use) of active fire hotspot products*

The complexities of fire management decision-making require accurate and timely information (Johnston et al. 2020a; Stephens et al. 2014; Tymstra et al. 2020). Satellite-based EO data in the form of active fire 'hotspot' products provide information on the location, timing and characteristics of actively burning fires in near real time. As such, hotspot products are a potentially useful source of fire intelligence both for fire managers and a wide range of other stakeholder groups whose decision making is influenced by fire activity, however, the extent of hotspot data use globally has not been studied. This study addressed this shortcoming by exploring the global use of EO hotspot data from three established web portals (NASA's FIRMS, and the European Commissions' GWIS and EFFIS) via web page user count data. We then compared the user count data to environmental and social variables we believed likely to influence the level of use at the global and individual country level.

Between September 2019 and April 2023, we found that active fire data use is characterized by multi-month periods of relatively low user activity, interspersed with one- or two-month spikes in activity (Figure 1). The largest activity spikes coincide with late summer and early autumn in the Northern Hemisphere (July-September) when fire activity is peaking in many parts of Europe and North America, indicating that most users of fire products are accessing data at the time that major fire events are occurring rather than retrospectively. This observation is reinforced by the intra-country correlation analysis of contemporaneous weekly user count data and fire activity (Figure 6); a positive relationship exists between the two variables in most of the globe. Use of active fire data is highly varied around the world, with a disproportionate number of users coming from

Europe and the Americas (Figure 1), a pattern which in turn is driven by a small number of countries (Figure 2(A and B)). Just 7 countries (United States of America, Turkey, France, Germany, Chile, Canada, and Greece) account for 70% of all EO platform data use. Furthermore, a small number of countries (Greece, Chile, and Cyprus Slovenia, Montenegro, Canada and Turkey) have noticeably more use counts relative to their total population (>2%) than the global mean (0.38%). The countries with the greatest absolute and relative user counts are surprisingly dissimilar, suggesting that a diverse range of factors may be affecting use on a case-by-case basis, which warrants further exploration into the factors impacting the usage in these countries.

Our results suggest that countries with strong positive or negative relationships between user counts and fire activity (Figure 6) are varied in nature. These outlying countries were spatially distributed around the globe and have a range of socio-economic situations as indicated by GDP values, a general indicator of economic progress (The World Bank 2023e). Although the negative outlier countries were more likely to be below the 50$^{th}$ percentile of GDP (The World Bank 2023e; see Table 2 for GDP values of outliers), some positive outlier countries have lower GDP values (e.g. Belize). This may indicate that these countries are more reliant on the freely available hotspot data-providing platforms. Other positive outlier countries have high GDP values (e.g. Brazil), suggesting that the existing platforms also suit their fire management needs. Alternatively, negative outlier countries may be accessing hotspot data via different pathways, sourcing alternative datasets, or may have limited fire management needs (e.g. Qatar which has limited annual burned area, Andela et al. 2017) or be facing access barriers. Our inability to draw general inferences from the outliers spatially or by an aggregate indicator such as the GDP likely indicates that the situation in each country is unique. Further interpretation of these results requires additional investigations that are beyond the intent and scope of this analysis.

At a global level, most (5 of 8) of the potential use-influencing variables that we identified were moderately positively correlated with total (2019–2023) user counts (Spearman's $\rho = 0.44–0.55$, $P < 0.05$) suggesting that these variables are all positively influencing user counts to some degree (Figure 4). Closer examination of these relationships for the most strongly correlated use-influencing variables (Figure 5) reveals several different regional narratives. Despite all four regions containing countries with relatively high fire activity (Figure 3(A and B)), stronger relationships between fire activity (burned area and fire counts) and user counts are found in the Americas and Oceania (R2 = 0.66–0.82, $P < 0.05$) than in Africa and Asia (R2 = 0.13–0.31, $P < 0.05$) (Figure 5(A and B)). While determining the cause of this is beyond the scope of the current study, lower levels of internet proliferation in Africa and Asia (Figure 3(H)) may be a contributing factor. However, internet proliferation is not the primary driver of use everywhere: more than 75% of the population in Europe has internet access (Figure 3(H)) but no discernible relationship exists between internet access and user counts (Figure 5(C)). Moreover, no relationship exists between fire activity and user counts (Figure 5(A and B)), suggesting that other factors not captured here are driving European hotspot product use.

### 5.2. Limitations and opportunities for future work

Several factors and challenges should be considered when interpreting our results. It is important to note that due to limitations in the data collected about users, we are unable to distinguish between types of users. While we know anecdotally that many fire management agencies do make use of these platforms, many users that were included in this analysis may not be involved in the management of fire and instead represent other stakeholders (e.g. academia, the media, or the public). Additionally, we do not discern unique vs. repeat users of active fire hotspots in our dataset and are unable to determine whether there is a baseline set of users that check web pages repeatedly (either manually or via automated web scraping), whether use is driven primarily by unique users. Opportunities exist to overcome these data type limitations by conducting a direct survey of users that identifies types of users and their usage types (e.g. manually, web scraping, etc.). Future studies led by the FIRMS, GWIS, and EFFIS data platforms could also aim to gather increased information about users through complementary surveys.

Although we analyse user count data from several major global hotspot EO data providers, we do not assess alternative means of accessing the data and other types of EO data used within the fire management community. Other e-distributors that re-package FIRMS data for select user groups exist in Canada (https://cwfis.cfs.nrcan.gc.ca/maps/fm3?type = tri), Australia (https://hotspots.dea.ga.gov.au/#/), and South Africa (https://www.afis.co.za/) (among others) and some domestic fire management agencies have their own internal data platforms for displaying EO-derived wildfire data. Other EO data providers, including private companies that use different satellite platforms or generate their own products from raw data, may also be supplying hotspot data to fire management agencies that would otherwise use data from these publicly available platforms (Xu and Zhong 2017). Some users may be directly downloading and processing swath-level MODIS and/or VIIRS data directly from data providers rather than using the higher-level hotspot products provided on the map pages of the web portals examined here. There are multiple ways to better understand the alternative methods for accessing other types of EO data within the fire management community. Interviews and survey data with fire management practitioners could improve this knowledge gap in other missing sources for EO hotspot data around the world. Additionally, a bibliometric study or investigation into news article sources could also improve our understanding of the various sources for data. Both approaches would build upon the findings in this paper, while also broadening our understanding about the various needs and priorities of targeted fire management users when they seek out EO hotspot data.

Additional opportunities exist to gain a deeper understanding of the facilitators and barriers to the use of EO active fire products on the global scale. Statistical modelling could be used to cluster different countries in to 'archetypes' of users, explore the interactions between variables, and provide more insight into which factors help or hinder the use of these platforms. Targeted interviews or surveys with in-country fire managers would also be valuable to further illustrate country specific drivers and barriers that cannot be understood from numerical data analysis alone. Additionally, with a strong presence of impactful EO capacity building hubs around the world (e.g. GOFC GOLD regional networks, NASA SERVIR hubs, Digital Earth programs), it would be valuable to explore the impact of these global organizations on local uptake and usage of global fire data platforms like FIRMS, GWIS, and EFFIS.

## 6. Conclusions

EO use barriers will always exist, although space agencies are actively invested in overcoming them (Kalluri, Gilruth, and Bergman 2003; Tassa et al. 2022). Efforts have included providing multi-language support, funding for technological infrastructure, additional training and information programs, and domestic support systems (Sadlier 2018). Lack of internet proliferation is a known barrier for some countries accessing online EO data (Ifejika et al. 2023; Trigg and Roy 2007) and our findings here suggest that to some extent, the use of active fire hotspot data is no different. EO data represents a significant investment for space agencies (satellite platforms, program redundancies, downstream processing, etc.); the under-use of this data due to usage barriers is undesirable and limits the benefit of this investment.

Detailed information about data users and the factors that encourage (or discourage) use can provide information to those addressing capacity issues for the uptake and implementation of EO active fire data in operational fire management. Theoretically, these data better position fire management agencies to address the negative impacts of fires under current and future conditions. User data can also be helpful in supporting additional satellite investments (Le Cozannet et al. 2020; Macauley 2006). Starting with a first-order analysis of how much existing EO active fire data is used as we have done here is a much-needed first step.

Arguably, the website user count data alone suggests that users in many countries, and presumably their fire management agencies, already possess some of the capabilities necessary to access and use hotspot data. We can infer from this usage that some implementation is occurring within fire management agencies, however, the degree of use is unknown without agency specific engagement. For example, use of EO hotspot data varies considerably within Canadian fire management agencies (McFayden et al. 2023). Some agencies likely have maximized their uptake EO data, while others employ different datasets for their fire decision making. The results of this study also show there is little overlap between the countries that have the most absolute use of hotspot data, the most use relative to their total population, and the strongest relationships between week-to-week fire activity and user counts. These observations suggest that the factors that drive the global use of hotspot data (and likely other EO data products) at the individual country – and fire management agency – level are highly varied. Reasons behind the differing levels of uptake likely include limitations on agency resources, a lack of trust by decision makers (Molder et al. 2022), or the fact that hotspot data that provides little to no value for specific decision making. Future studies can explore nuances in the relationships and characteristics of the users and the way hotspot data is used in fire management. This will improve the capacity for EO fire data use around the globe.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Data availability statement

The data that support this study not otherwise cited were provided by and used with permission of NASA FIRMS, GWIS and EFFIS. Web traffic data for NASA FIRMS, GWIS and EFFIS available from corresponding authors [DKD, JS-M] upon reasonable request.

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