

Increases in the world's most extreme wildfire events probably driven by fire size and simultaneity

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In contrast to the widespread perception of increases in extreme wildfire behaviour, quantitative evidence supporting presumed global increases of fire intensity is rare. Recently, Cunningham et al.¹ analysed temporal patterns of fire radiative power (FRP) and claimed that there had been an “increasing frequency and intensity of the most extreme wildfires on Earth between 2003 and 2023”. We applaud their intent at addressing the complex issue of changes in fire intensity, but note that major misunderstandings on the meaning and drivers of FRP challenge these findings. Our revised analyses, which control for active fire detections, indicate that the intensity of the “most extreme wildfire events”, as selected by them (ref. 1), has probably decreased. We will first explain the problems in using their FRP product as an indicator of fire intensity and then revise their conclusions on changes in the frequency and intensity of fire events. Evidence for increases in global wildfire intensity remain elusive and the results from ref. 1 probably indicate increases in either size or number of simultaneous fires.

ΣFRP is not a metric of fire intensity

Fire intensity refers to the energy output of a fire² (its power integrated over time and space^{3–5}) and, unlike fire severity, it does not include social or ecological impacts². However, ref. 1 measure fire intensity with summed fire radiative power (ΣFRP, W), a measure previously used to estimate fire severity⁶, which has no consideration for the confounding effect of changes in fire area. Cunningham et al.¹ calculate the ΣFRP within a “wildfire event” by aggregating all FRP values as measured by the MODIS instruments aboard the Aqua and Terra satellites for 1 day within a cell of a global 0.2° grid. However, MODIS provides FRP values for roughly each 1 km² containing fire (these pixels are hereafter referred to as hotspots). Consequently, the ΣFRP emitted by a fire event within a 0.2° grid is directly influenced by the number of active hotspots within the grid cell. A larger fire area generates more hotspots, each contributing FRP values which, when aggregated, result in a higher ΣFRP.

The influence of the hotspot count on ΣFRP can be observed by re-analysing the data from ref. 1, who defined extreme wildfire events as those 2,913 events with ΣFRP higher than, or equal to, the 99.99th percentile. Using their methodology, we observed a 27% increase in the ΣFRP emitted by extreme wildfires between 2003 and 2023 (Fig. 1a; P value of the smoothed year effect in the generalized additive model (GAM) ($P_{f(\text{year})} < 0.0001$). However, we also observed a 43% increase in the hotspot count during that period (Fig. 1b; $P_{f(\text{year})} < 0.0001$) and a strongly significant and positive relationship between ΣFRP and hotspot count (Fig. 1c; $P_{f(\text{hotspot count})} < 0.0001$, $R^2 = 0.6$). This strong relationship means that in ref. 1 the observed temporal trends in events with high ΣFRP might simply result from an increasing number of simultaneous wildfires (more hotspots) or a growing size in wildfires (also more hotspots) and not necessarily from higher wildfire intensities.

Lack of evidence for increasing intensity in the most extreme wildfire events

One of the two main conclusions from ref. 1 was that fire intensity (or the “magnitude”) had more than doubled between 2003 and 2023. Considering our previous analyses, we sought to separate the effects of hotspot detections from those of fire intensity on ΣFRP and therefore estimated the average FRP for each fire event (FRP_{mean} , the ratio between ΣFRP and the number of hotspots). In contrast to the 27% increase in ΣFRP that occurred between 2003 and 2023, we observed a 24% decrease in FRP_{mean} (Fig. 1d; $P_{f(\text{year})} = 0.0017$).

It could be argued that this analysis does not consider variation within the 0.2° grid, and that it is simply a measure of mean fire intensity, while the focus of ref. 1 was on extreme fires. To address this limitation, we performed a second analysis where we also examined changes based on the peak FRP (FRP_{max} , the one showed by the ‘hottest’ hotspot) per event. FRP_{max} also decreased, but only by 4% (Fig. 1e; $P_{f(\text{year})} = 0.0357$). These decreases in FRP_{mean} and FRP_{max} further strengthen our hypothesis that increasing hotspot detections are the main driver underlying trends in extreme ΣFRP.

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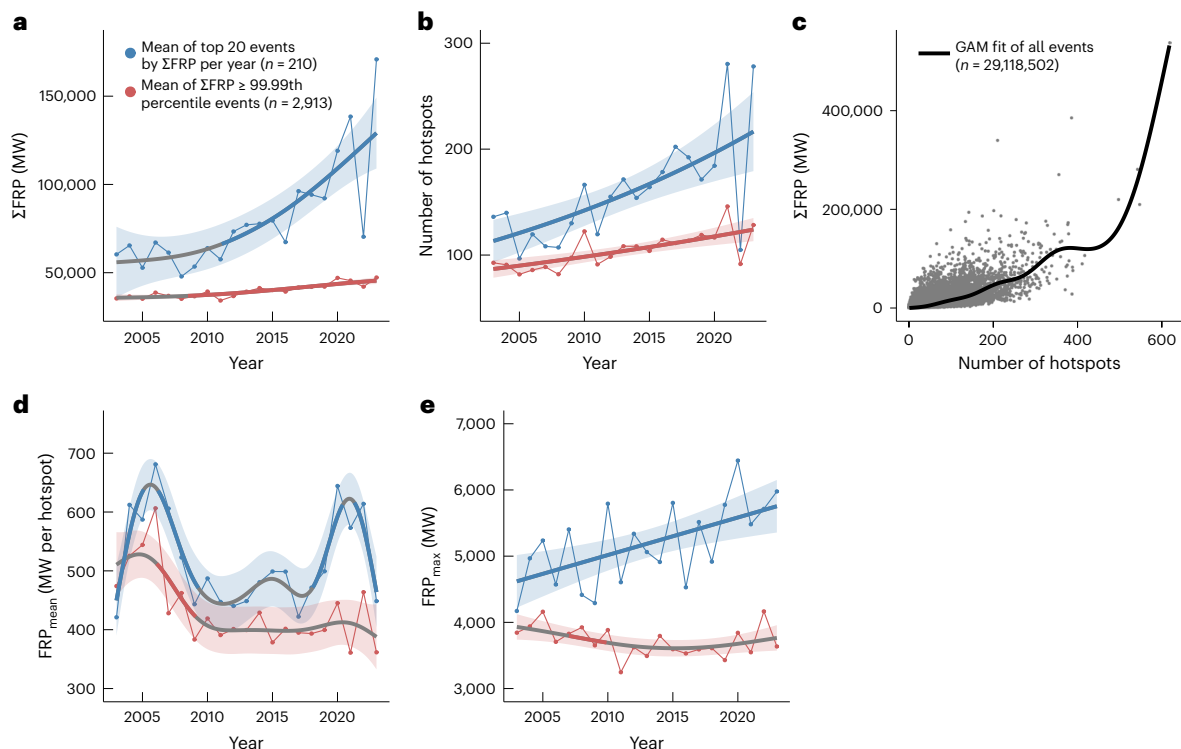


Fig. 1 | Measuring fire intensity of fire events. **a**, Trends of ΣFRP as calculated by ref. 1 during the 21-yr study period. **b**, Temporal trends of the number of hotspots. **c**, Relationship between ΣFRP and the number of hotspots by fitting a GAM between ΣFRP and the hotspot count (smoothed) based on all fire events (displayed as grey dots). **d**, **e**, Temporal trends of FRP_{mean} (ΣFRP relative to the number of hotspots) (**d**) and FRP_{max} (maximum FRP within each event) (**e**).

Note: In **a**, **b**, **d**, **e**, values indicate the annual mean of each of the selected events. Figures include the best-fit line and the 95% confidence interval of a GAM, with coloured and grey line sections indicating significant and non-significant temporal trends, respectively. Significance is determined from the first derivative of the 95% confidence interval following previously published methods^{10,11}.

Cunningham et al.¹ only examined changes in ΣFRP in the top 20 fire events per year, for which they reported a 2.3-fold (131%) increase in ΣFRP (Fig. 1a; $P_{f(\text{year})} < 0.0001$). Selecting the top 20 events is a more arbitrary criterion than the previous, well-established usage of the 99.99th percentile. Regardless, these top 20 fire events only show a 3% increase in FRP_{mean} (Fig. 1d; $P_{f(\text{year})} = 0.0003$) and a 25% increase in FRP_{max} during the study period (Fig. 1e; $P_{f(\text{year})} = 0.0026$). Thus, even for this arbitrary subselection of the extreme events, fire intensity is still far from doubling, which again points towards other processes that influence hotspot detections, such as fire count or size, as playing major roles in explaining the increase in ΣFRP .

The frequency of events of extreme intensity has not doubled in the last 20 years

The other main conclusion from ref. 1 was that extreme wildfire events have more than doubled in frequency between 2003 and 2023. This change in event frequency is affected by the definition of extreme events which was based solely on ΣFRP and, as we just described, it does not necessarily represent those with the highest intensity. Given that ref. 1 call their extreme events also “events of extreme intensity”, we performed an additional frequency analysis where we selected the 99.99th percentile of events based on those with the highest FRP_{mean} and FRP_{max} within each 0.2° grid cell.

We observed a 35% decrease in the frequency of events with highest FRP_{mean} (Fig. 2a; $P_{f(\text{year})} < 0.0001$). This downward trend is statistically significant until 2012 and seems to be mostly driven by the 33% decrease observed during the daytime (Fig. 2b; $P_{f(\text{year})} < 0.0001$). Despite the overall negative trend, it is worth noting that the frequency of high FRP_{mean} events during the night-time has increased by 26%, although the significance is only marginal (Fig. 2c; $P_{f(\text{year})} = 0.0599$).

The frequency of events with the highest FRP_{max} follows a ‘smile’ trend (Fig. 2d; $P_{f(\text{year})} = 0.0007$): there is a significant decrease until 2007 and then a significant increase after 2016. Furthermore, there is a substantial difference between the frequency changes during day and night and only night-time patterns show a consistent increasing trend (Fig. 2f; $P_{f(\text{year})} = 0.0005$). Summing up, there is not a consistent increase in the frequency of extreme events when assessed based on intensity proxies such as FRP_{mean} and FRP_{max} , except for night-time FRP_{max} , where a significant increase is observed.

Implications

Cunningham et al.¹ documented an upward trend in frequency and ΣFRP of “extreme wildfire events”, and here we have shown that these trends are probably driven by increases in hotspot detections from a growing fire count and size. Increases in fire count and size are probably leading to raising social and ecological fire impacts. However, this should not be confused with increases in fire intensity, for which direct evidence is still lacking. Future studies using FRP for quantifying fire intensity need to consider the number of hotspot detections, fire front length or area as well as its temporal integration.

Data availability

All data used in the analysis are available through the Code Ocean platform at <https://doi.org/10.24433/CO.0207669.V2> (ref. 7). The data were downloaded from ref. 1 data repository at <https://doi.org/10.6084/m9.figshare.25132151.v1> (ref. 8) and the original FRP product is available from the University of Maryland SFTP server and can be downloaded following the guide in the MODIS Collection 6 and Collection 6.1 Active Fire Product User's Guide⁹.

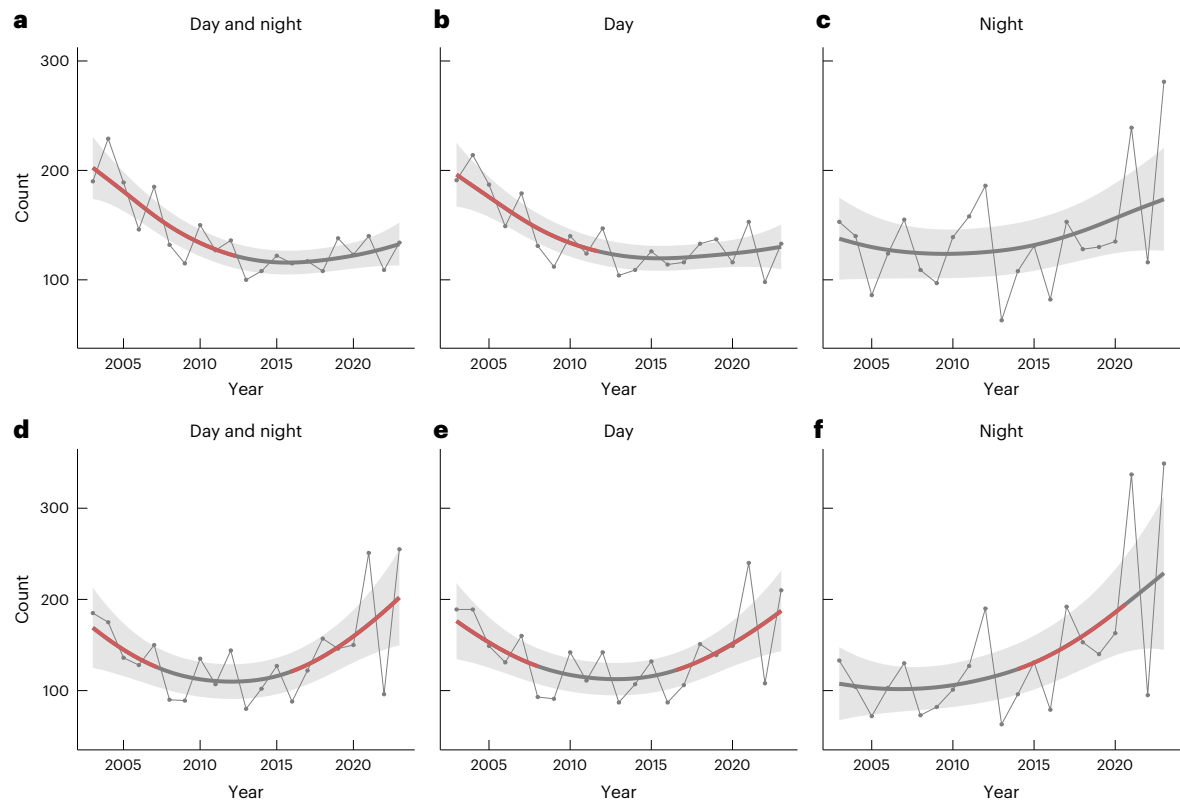


Fig. 2 | Trends in the frequency of events with extreme intensity. **a–f**, Top 2,913 events selected on the basis of the 99.99th percentile with the highest FRP_{mean} (**a–c**) or FRP_{max} in each fire event (**d–f**). Frequency changes are shown for day and night (**a,d**), day only (**b,e**) and night only (**c,f**). Figures include the best-fit

line and the 95% confidence interval of a GAM, with coloured and grey line sections indicating significant and non-significant temporal trends, respectively. Significance is determined from the first derivative of the 95% confidence interval following previously published methods^{10,11}.

Code availability

The full code used in the analysis is available through the Code Ocean platform at <https://doi.org/10.24433/CO.0207669.V2> (ref. 7).

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Author contributions

S.J.S. and V.R.D. jointly conceived and designed the study, drafted the manuscript and contributed to revisions. S.J.S. performed the data analysis.

Competing interests

The authors declare no competing interests.

Additional information

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