


Enhancing fire emissions inventories for acute health effects studies: integrating high spatial and temporal resolution data

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ABSTRACT

Background. Daily fire progression information is crucial for public health studies that examine the relationship between population-level smoke exposures and subsequent health events. Issues with remote sensing used in fire emissions inventories (FEI) lead to the possibility of missed exposures that impact the results of acute health effects studies. **Aims.** This paper provides a method for improving an FEI dataset with readily available information to create a more robust dataset with daily fire progression. **Methods.** High temporal and spatial resolution burned area information from two FEI products are combined into a single dataset, and a linear regression model fills gaps in daily fire progression. **Key results.** The combined dataset provides up to 71% more PM_{2.5} emissions, 69% more burned area, and 367% more fire days per year than using a single source of burned area information. **Conclusions.** The FEI combination method results in improved FEI information with no gaps in daily fire emissions estimates. **Implications.** The combined dataset provides a functional improvement to FEI data that can be achieved with currently available data.

Keywords: acute health effects studies, burned area, cloud cover, environmental epidemiology, exposure modelling, fire remote sensing, PM_{2.5}, wildfire smoke exposure, wildfire smoke transport.

Introduction

Inhaling wildfire smoke can cause various health effects in humans (Yao *et al.* 2016; Borchers Arriagada *et al.* 2019; Liu *et al.* 2019). Wildfire smoke can be transported through the atmosphere, impacting communities far from the actual fire. As wildfire frequency, intensity, and duration are projected to increase under a changing climate (Liu *et al.* 2016; Aguilera *et al.* 2021), understanding the health effects of inhaling wildfire smoke is essential. Some of the most important health effects to understand are acute health effects, which occur shortly after exposure and are typically short-lived (Ye *et al.* 2022). To estimate the acute health effects of inhaling wildfire smoke, a public health study requires estimates of the concentration of pollutants from wildfire smoke on a daily time scale.

Information on fire behaviour or activity is needed to estimate the concentration of pollutants from wildfire smoke in a specific area. An FEI is a combination of fire behaviour information (i.e. data that accounts for burned area, the amount of vegetation burned (fuel loading)), and emissions factor (i.e. data that accounts for the compound of interest and fuel characteristics) to estimate the amount of emissions released by each individual fire (Urbanski *et al.* 2018). Single-fire information is useful for health effects studies because it allows for the linking of health effects to combustion type and fuel type. It can also be helpful to incorporate plume ageing and smoke transport factors when more than one smoke plume impacts a specific area. There is no definitive method to measure the amount of emissions released from a single fire (Hao and Larkin 2014; Black *et al.* 2017). FEIs offer a reasonable estimate of fire emissions for use in health effects studies.

While prior studies recognise the importance of understanding the health effects of inhaling wildfire smoke (Gao *et al.* 2023; Pan *et al.* 2023; Reid *et al.* 2023), existing literature reveals notable gaps in methods for estimating acute human exposure (Black *et al.* 2017). Challenges in estimating acute smoke exposure are related to limitations with FEIs, atmospheric models, and remote sensing technologies. While there have been recent advancements in geostationary satellite remote sensing capabilities, historically, satellite remote sensing fire and smoke products struggle to capture the high temporal resolution required for acute exposure estimates (Wooster *et al.* 2021). Satellite remote sensing also faces issues with cloud cover (Hawbaker *et al.* 2017), has difficulty sensing small fires (Laris 2005; Roteta *et al.* 2019), and lacks a conclusive method of direct measurement of fire emissions that would allow for validation (Giglio and Roy 2020). These challenges underscore the need for development of more robust methodologies for estimating acute exposure to wildfire smoke.

Currently, FEIs rely heavily on satellite remote sensing to determine the input variables for the emissions model, especially for near real-time fire detection. Fire ignition, fire progression, burned area, and fuel loading are often determined using remote sensing, but can also be supplemented with fire spread models or burn reports (i.e. bottom-up approaches). Remote sensing provides many advantages, including global coverage and the ability to provide information in near real-time (Wooster *et al.* 2021). However, many FEIs currently do not focus on providing real-time data; instead, they provide a consistent long-term dataset for understanding historical fire trends. The current state of the science for high temporal resolution remote sensing of fires uses geostationary satellites (Li *et al.* 2022), which constantly monitor the same region, providing a constant record of the fire. The state of the science for high spatial resolution remote sensing of burned area relies on changes in land reflectance over time (Eidenshink *et al.* 2007). Products with the shortest latency for remotely sensing fires can be accessed within hours (Soja *et al.* 2009).

Other issues with FEIs include emissions factors that are difficult to measure, and those emissions factors that can be measured may lack generalisability due to the complex nature of fire behaviour (Larkin *et al.* 2014). Because of the complexities of fire behaviour, there is no way to measure fire emissions directly to create a validation dataset (Black *et al.* 2017). Additionally, fuel load can be incredibly diverse in properties and vary highly in time and space, creating uncertainties in estimating fuel loading (Keane 2013). The complex nature of fire behaviour means many FEI datasets are created using several different methods for estimating the components of fire emissions (i.e. emissions factors and fuel loading), and the lack of validation data means we cannot determine which method is most accurate (Faulstich *et al.* 2022).

Although the fire science community understands the shortcomings of FEIs, many suggestions for improvement

concentrate on enhancing input datasets or seeking validation through costly, in-depth field campaigns (Roy *et al.* 2007; Soja *et al.* 2009). While these in-depth studies improve our understanding of fire emissions, using current available information to explore alternative possibilities for enhancing existing datasets is crucial to make improvements in current studies that rely on FEIs. This study aims to improve existing FEIs by combining high spatial and temporal resolution data from two existing FEI products.

The focus of this paper is to present a method to create a combined FEI and discuss the advantages of the method, with a focus on using the combined FEI for public health research. Combining two sources of burned area information into one FEI allows models to use both high spatial and high temporal resolution satellite products. High spatial resolution data is essential to capture the most reliable burned area estimates, often used to approximate the fire size and intensity. Capturing the daily emissions profile is vital to understanding the acute health effects of inhaling wildfire smoke, making high temporal resolution data crucial. Combining these two sources of fire information can mitigate some of the disadvantages associated with each individual method for determining burned area. Adding a cloud cover interpolation eliminates gaps in daily fire emissions information. These two improvements allow the utilisation of the combined dataset as input data into a smoke exposure model for an acute health effects study.

Methods

Each FEI uses a unique method to estimate overall fire emissions, meaning combining data from one FEI with data from another FEI is very difficult. However, one FEI, the Wildland Fire Emissions Information System (WFEIS), has separate emissions estimates products that use the high-resolution spatial product from Landsat Monitoring Trends in Burn Severity (MTBS) and the high-resolution temporal burned area product from the Moderate Resolution Imaging Spectrometer (MODIS) individually (French *et al.* 2014). WFEIS uses estimates of fuel loading, burned area, and fire characteristics to estimate total emissions from a fire. Fuel loading is multiplied by burned area to determine the amount of fuel burned, and this is scaled by an emissions factor to determine how much of a specific compound was released by that burned fuel. Further discussion of how WFEIS uses this information to estimate fire emissions can be found in French *et al.* (2014). Since the two emissions estimates are both from WFEIS, they have a consistent method to determine overall fire emissions and thus they can be combined into a single product with the advantages of both burned area products. Combining these two WFEIS emissions estimates products retains the high-quality spatial resolution information from MTBS while leveraging MODIS to include a daily temporal profile.

High spatial resolution (30 m) fire information comes from the LandSat Monitoring Trends in Burn Severity (MTBS) product (Eidenshink *et al.* 2007). MTBS provides burned area information using the LandSat remote sensing of land cover reflectance changes resulting from fires. The high spatial resolution LandSat data used in the MTBS product provides the most reliable burned area estimate for an individual fire. Because burned area plays a significant role in the emissions calculations, this value can have a large impact on the FEI emissions estimates. While the spatial resolution from the MTBS product is not retained in our FEI combination, the high spatial resolution burned area provides better emissions estimates than other inventories (Faulstich *et al.* 2022). This is, in part, because the MTBS product is less affected by cloud cover and provides better detection for small fires. The LandSat satellite overpass frequency is every 8 days, meaning it only collects data from a specific location once every 8 days. Because of this frequency, MTBS does not include high temporal resolution data that can provide information on daily fire progression.

The Moderate Resolution Imaging Spectrometer (MODIS) active fire detection product (Giglio *et al.* 2016) provides high temporal resolution (i.e. daily) fire information. The MODIS active fire detection product comes from MODIS retrievals on two polar orbiting satellites that provide fire information for a specific location every 24 hours (Giglio *et al.* 2016). The two satellites overpass each location at different times, providing two measurements of the location per day, meaning that the MODIS active fire product can give information on daily fire progression. However, the spatial resolution is 500 m × 500 m, meaning small fires and prescribed burns may not be detected.

We combined the two WFEIS burned area products to create a single FEI that uses high spatial and temporal resolution data. WFEIS was selected due to the complex fuel characteristics, the inclusion of both flaming and smouldering combustion, and the two different burned area products available (Faulstich *et al.* 2022). This dataset was created for a domain within the western United States (Fig. 1) from 2007 to 2019 to support retrospective health studies of smoke exposure in Nevada. In this paper, results from 3 years with several large wildfires (2013, 2016, 2018) are presented. Because of the heavy reliance on remote sensing data, even after combining both burned area products, there are still missing days due to cloud cover. To address this, we fit a linear regression model to gap-fill the missing days resulting from cloud cover issues in the remote sensing products. The combination and interpolation methods are outlined below and shown in Fig. 2, and a step-by-step list of instructions can be found in Supplementary Material S1.

Assigning daily fire progression to MTBS data

To assign daily fire progression information to the high spatial resolution MTBS data, we assign unique fire IDs to

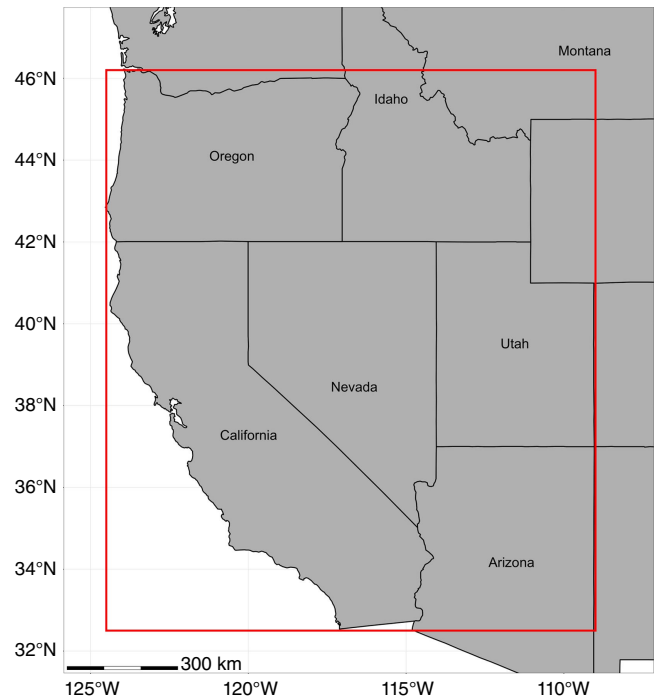


Fig. 1. A map of the spatial domain used in this study. The domain is indicated by the red box.

each fire in the MTBS dataset. Pairing the MTBS fire information with daily MODIS fire progression data involves utilising the location centroid and burned area information provided in the MTBS dataset. We use the fire burned area to calculate a search radius around the fire centroid used only for pairing the fires from MTBS and MODIS. Since fires are not a perfect circle, the calculated radius is multiplied by 1.5 to ensure that this radius captures all MODIS fire points. When checked using a geographical map, we found this method did not produce overlapping radii or assign multiple fire IDs to a single grid cell. After assigning a fire ID to these MODIS fire points, we further refine the data corresponding to each fire to ensure there is only one point per fire, per day. We use a single point per fire that includes daily burned area (i.e. a new fire location each day based on MODIS data) to input fire information into the atmospheric dispersion model. We aggregate data points with the same fire ID to accomplish this, determining a single daily location using a weighted spatial average based on the daily MODIS emissions. Utilising the amount of PM_{2.5} emissions, the weighted average emphasises points with substantial PM_{2.5} emissions on a given day when determining fire location.

After assigning the daily fire progression, the MTBS burned area and PM_{2.5} are allocated to the corresponding daily MODIS points. The fire emissions or burned area total from MODIS is calculated based on the fire ID and compared with the totals per fire from MTBS. A daily percentage of the total per-fire emissions or burned area is assigned to each MODIS day. This MODIS daily percentage is then multiplied

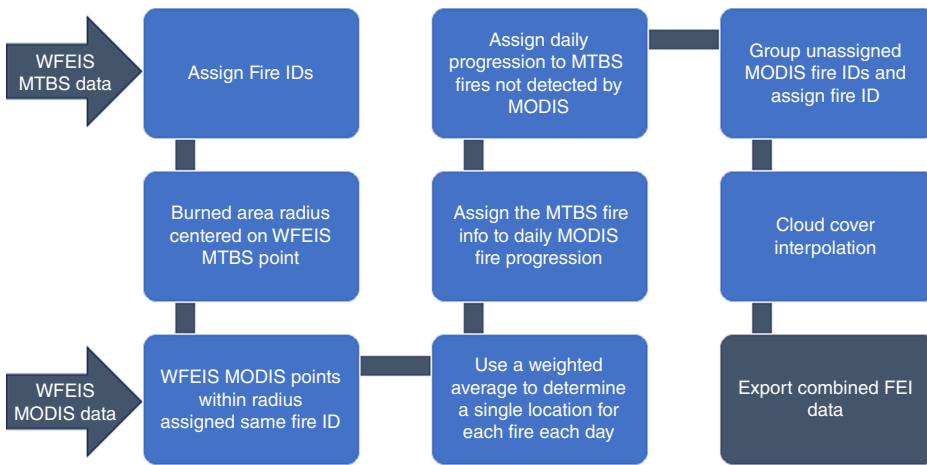


Fig. 2. Flowchart of the FEI combination method using WFEIS MTBS and MODIS. WFEIS MTBS data are input in the first step, and the WFEIS MODIS data are input in the third step.

by the total fire emissions or burned area from MTBS to allocate the MTBS burned area and emissions information daily. Now, the daily fire information from MODIS represents the complete fire information reported by MTBS. After completing this process, MTBS burned area and emissions reflects the daily fire progression from MODIS.

Resolving discrepancies

Through this daily fire progression method, discrepancies between the datasets emerge, including cases where MODIS fails to identify fires that MTBS sensed, leading to an absence of daily fire progression. With its higher spatial resolution, MTBS detects some small fires that MODIS does not. In such instances, the fire duration needs to be determined to allocate daily emissions. To address the lack of fire duration provided by MTBS, we established a linear correlation between burned area and fire length for the entire spatial domain using data from other fires in the same year. Because the burned area for all unassigned MTBS fires was smaller than 25 km², any fires larger than this were excluded from the linear correlation. The linear regression between the MODIS burned area and the fire length is used to infer the fire length for the unassigned MTBS fires based on the burned area. Additionally, some MODIS fires do not correspond to MTBS fires due to the differences in methods between the two burned area datasets. For example, MTBS may miss fires that have low burn severity (Hawbaker *et al.* 2017). Since these fires already have daily progression, they are grouped by location and date and assigned a fire ID. The burned area and emissions estimates from MODIS are used to provide fire information for these fires that are not captured by MTBS.

Cloud cover

After determining the daily fire progression, we can identify any missing days. Nearly all fires are missing at least 1 day, with many missing seven or more consecutive days. Given

that some of these gaps span weeks or months, we split any fires with more than seven consecutive days missing between sensed points into two fires. Because we primarily use the fire IDs to determine fuel type, inadvertently breaking one fire into two poses no downsides. Once the long fires are separated, a linear interpolation can be applied to provide information on missing fire days. The linear interpolation looks for a sequential gap in the fire progression and then uses the two nearest sensed points to determine the slope of the line for both PM_{2.5} and burned area. The slope of this line determines what the value of PM_{2.5} or burned area should be for the missing day. The location of each interpolated point is the average of the location of the two nearest sensed points.

After completing these steps, the combined FEI dataset now incorporates data from both high spatial (MTBS) and high temporal (MODIS) resolution data sources, including gap-filled data to provide emissions estimates when remote sensing does not detect a fire. This combination provides daily information on fire characteristics that can be input into an atmospheric transport model and then used to estimate daily smoke exposures.

Results

Combining two sources of burned area information in a single FEI provides more information on fire emissions. To understand the additional information gained through the combination, we present comparisons of PM_{2.5}, burned area, and number of fire days as estimated by each WFEIS product, the combined FEI that uses both burned area products, and the combined FEI with and without cloud cover interpolation.

Assigning daily fire progression to MTBS data

Using MODIS data, daily fire progression is assigned to MTBS fire perimeters. An example of this process is shown

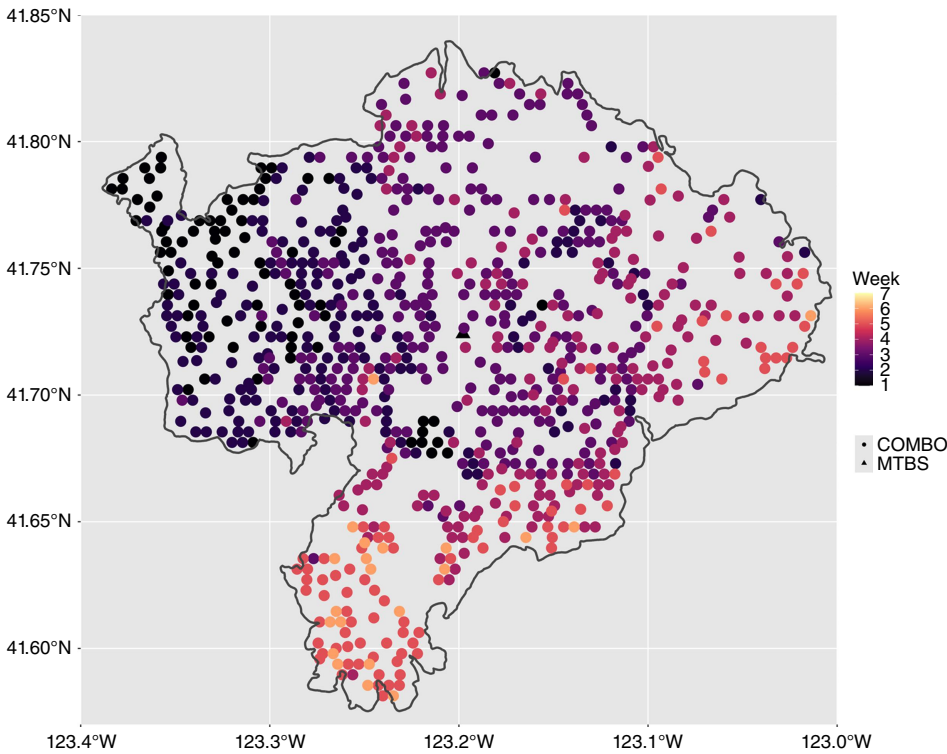


Fig. 3. Fire detections for a single, large fire (the Happy Camp fire in 2014) from WFEIS MTBS and the combination FEI, which gets daily fire detections from WFEIS MODIS. The combo FEI is shown as circles, colour-coded by date. The darker colours were sensed in earlier weeks of the fire, and the lighter colours were sensed in later weeks of the fire. Week 1 represents the first week the fire was sensed and week 7 represents the last week the fire was sensed. WFEIS MTBS is represented as a single triangle. WFEIS MTBS only provides a single centroid and burned area for the fire, whereas WFEIS MODIS provides a daily fire progression for the combination FEI.

in Fig. 3 for the Happy Camp fire in 2014 (Kalamath National Forest, California, USA; 12 August–30 October 2014, 543 km² in burned area (National Interagency Coordination Center 2014)). WFEIS MTBS provides only a single centroid and burned area for the fire, whereas WFEIS MODIS provides a daily fire progression. This figure shows the advantage of the WFEIS MODIS daily fire progression, though the WFEIS MODIS product has a lower spatial (1 km) resolution than WFEIS MTBS (30 m). The combination inventory has an average increase of 7% in the number of fire days per year over WFEIS MODIS and an average increase of 269% in the number of fire days over WFEIS MTBS over the 3 years investigated in depth (2013, 2016, 2018). Because MTBS only provides one date for each fire, the increase in number of fire days represents the daily fire progression assigned to each MTBS fire. The increase in the number of fire days for the combination inventory compared to WFEIS MODIS is because MTBS senses small fires that are not captured by the MODIS dataset. LandSat MTBS provides highly detailed burned area data at low temporal resolutions. The fine spatial resolution allows MTBS to achieve the most reliable burned area assessments, particularly for small fires. Consequently, inventories exclusively relying on MODIS data may overlook these smaller fires.

Assigning a daily fire progression to MTBS data to create a combined FEI provides more information on emissions and burned area. Fig. 4 provides a visual representation of the new information included in the combined FEI. The low fire intensity days at the beginning and end of the fire needed

the most interpolation, likely because the smaller fire intensity days are more susceptible to cloud cover and other remote sensing issues. Table 1 provides the emissions, fire days, and burned area information comparison for each FEI, including the percent increase. The combined FEI provides larger increases for WFEIS MODIS than WFEIS MTBS for both PM_{2.5} and burned area due to the high spatial resolution of MTBS providing more fire information (e.g. on small fires) than the lower spatial resolution of MODIS. This combination enables the incorporation of daily fire progression captured by MODIS and the detection of small fires captured by MTBS into a single FEI.

Resolving discrepancies

For the 3 years investigated in this study, 9–14% of the reported MTBS data had no MODIS data assigned. This accounted for a small percentage (3–4%) of the annual burned area as well as a small percentage (1–6%) of PM_{2.5} emissions. This indicates that these unassigned points are small fires. Though the total emissions impact over the course of a year may be relatively low, it is imperative to include the daily emissions from small fires in models to accurately assess acute smoke exposure. Capturing these daily emissions from small fires can also help with identifying the health effects of prescribed burns, which are primarily small fires. Using linear regression to assign fire length and evenly distribute PM_{2.5} and the burned area may not perfectly reflect real-life scenarios, but it plays a vital role in

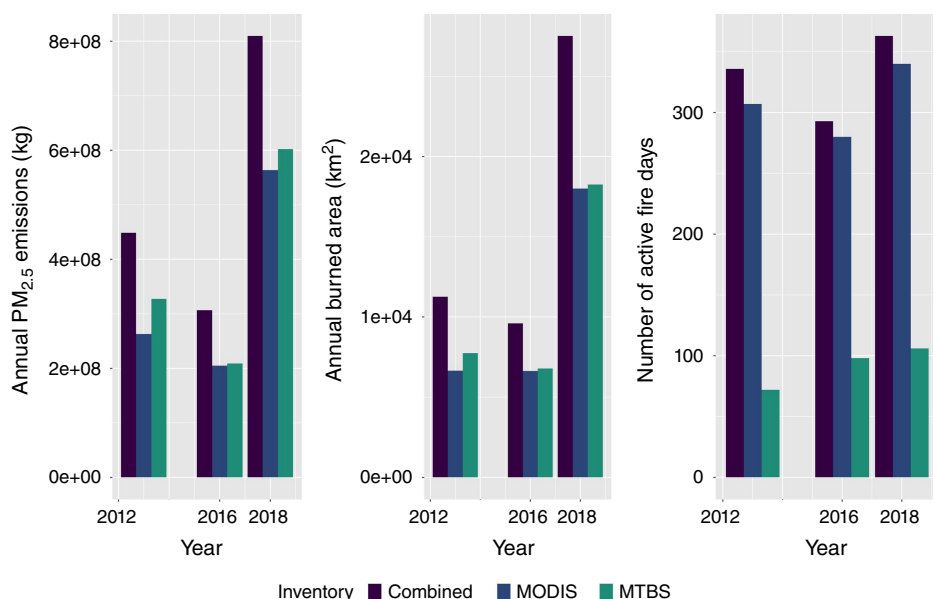


Fig. 4. Annual sum of PM_{2.5} emissions (kg), burned area (km²), and active fire days (days) for WFEIS MTBS (green), WFEIS MODIS (blue), and the combined FEI product (purple).

Table 1. Comparison of PM_{2.5} emissions (kg), burned area (km²), and fire days (days) between the two WFEIS burned area products and the combined FEI.

	Combined FEI	WFEIS MODIS	Combined FEI percent increase (MODIS) (%)	WFEIS MTBS	Combined FEI percent increase (MTBS) (%)
PM_{2.5} (kg)					
2013	4.49 × 10 ⁵	2.63 × 10 ⁵	71	3.28 × 10 ¹⁷	37
2016	3.06 × 10 ⁵	2.05 × 10 ⁵	49	2.09 × 10 ¹⁷	47
2018	8.10 × 10 ⁵	5.63 × 10 ⁵	44	6.02 × 10 ¹⁷	34
Burned area (km²)					
2013	1.13 × 10 ⁴	6.65 × 10 ³	69	7.74 × 10 ⁹	45
2016	9.60 × 10 ³	6.63 × 10 ³	45	6.78 × 10 ⁹	42
2018	2.75 × 10 ⁴	1.80 × 10 ⁴	53	1.83 × 10 ¹⁰	51
Fire days (days)					
2013	336	307	9	72	367
2016	293	280	5	98	199
2018	362	340	6	106	242

The percentages represent the percent increase in the combined FEI as compared to the individual FEIs.

providing daily information on small fires that the MODIS dataset might overlook.

Cloud cover

Table 2 shows the amount of information the cloud cover interpolation added for 2013, 2016, and 2018. For 2013, 2016, and 2018, the interpolation had an average increase of 1% for PM_{2.5} concentration, 5% for burned area, and 4% for fire days per year compared to the combined FEI without the cloud cover interpolation. While these increases may seem slight, it is crucial to note that these fire days were

not previously captured. The cloud cover interpolation adds a relatively small overall percentage of information, confirming that it predominantly accounts for mostly low-intensity fire days. Including low-intensity fire days in the analysis is crucial to ensure that the daily progression needed to understand acute health effects is as accurate as possible.

Fig. 5 shows the daily fire progression for the 2014 Happy Camp fire, indicating both the original FEI and interpolated points. The low fire intensity days at the beginning and end of the fire required the most interpolation, likely because the smaller fire intensity days are more susceptible

Table 2. Comparison of PM_{2.5} emissions (kg), burned area (km²), and fire days (days) for the combined FEI with and without cloud cover interpolation.

Combined FEI	No interpolation	Cloud cover interpolation	Cloud cover percent increase (%)
PM_{2.5} (kg)			
2013	4.46 × 10 ⁵	4.49 × 10 ⁵	1
2016	3.02 × 10 ⁵	3.0 × 10 ⁵	2
2018	8.03 × 10 ⁵	8.10 × 10 ⁵	1
Burned area (km²)			
2013	7.13 × 10 ³	7.49 × 10 ³	5
2016	6.89 × 10 ³	7.37 × 10 ³	7
2018	1.80 × 10 ⁴	1.87 × 10 ⁴	4
Fire days (days)			
2013	317	336	6
2016	281	293	4
2018	359	362	1

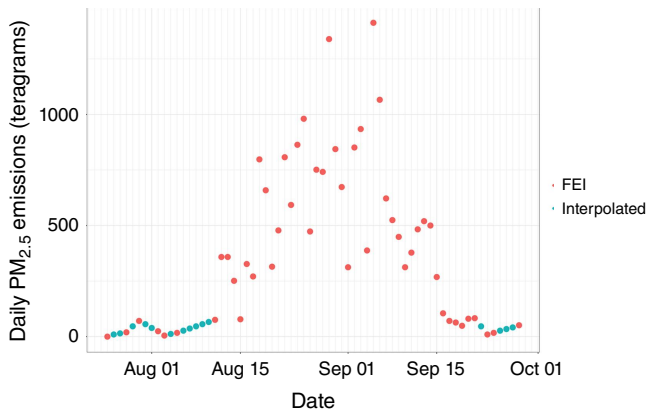


Fig. 5. The 2014 Happy Camp fire in California after cloud cover interpolation. Interpolated points show the daily PM_{2.5} emitted in teragrams (10¹² g), estimated by linear regression between the nearest FEI points.

to cloud cover and other remote sensing issues. A NASA visible satellite image in Fig. 6 shows a day that did not need cloud cover interpolation, Fig. 7 shows a cloudy day during the peak of the fire that did not need cloud cover interpolation, and Fig. 8 shows a cloudy day near the end of the fire that did need cloud cover interpolation. The cloudy day (Fig. 8) has fewer thermal anomaly detections than the clear day (Fig. 6), highlighting the remote sensing issues due to heavy cloud cover. The cloudy day at the end of the fire (Fig. 8) was not captured in the fire emissions inventory and required interpolation. A comparison between fire radiative power (FRP) and MODIS detection confidence level (Fig. 9) reinforces the remote sensing issues shown in the satellite



Fig. 6. Visual satellite image of the Happy Camp fire on 29 August 2014, from NASA WorldView. Orange circles represent MODIS thermal anomalies, showing the location of the fire (the area of interest is denoted by a larger red circle). This is an example of a clear day with no satellite remote sensing issues in the FEI.

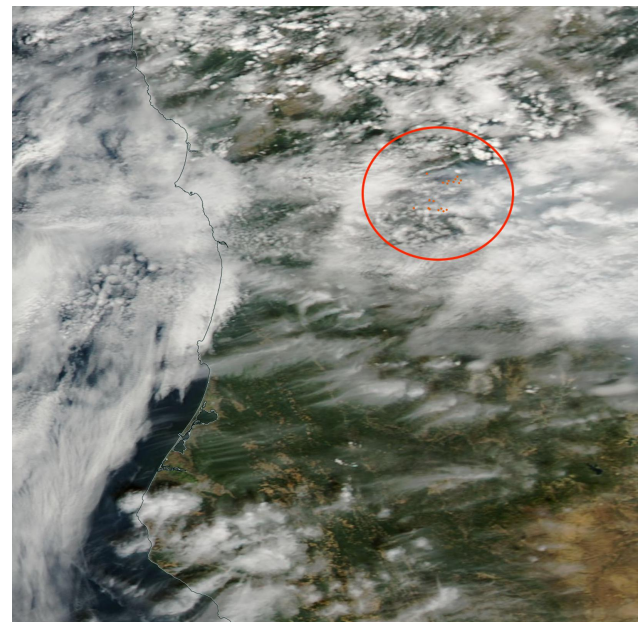


Fig. 7. Visual satellite imagery of the Happy Camp fire on 30 August 2014, from NASA WorldView. Orange circles represent MODIS thermal anomalies, showing the location of the fire (the area of interest is denoted by the larger red circle). This represents a day with clouds where the FEI still captured thermal anomalies, likely because this was a high intensity fire day when the fire was at its largest.

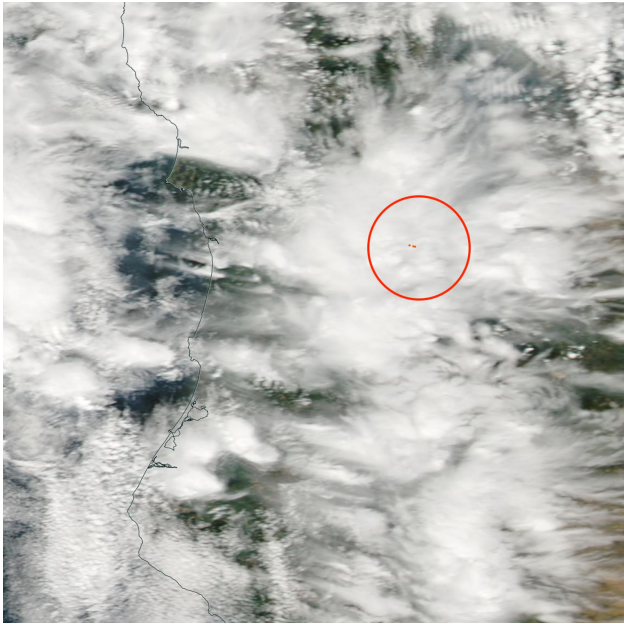


Fig. 8. Visual satellite image of the Happy Camp fire on 22 September 2014, from NASA WorldView. Orange circles represent thermal anomalies sensed by the MODIS satellite, showing the location of the fire (the area of interest is denoted by a larger red circle). There are fewer thermal anomaly detections on this day compared to the previous day, which was clear. This day was not captured in the FEI and required interpolation. This day was near the end of the fire and was a lower intensity fire day.

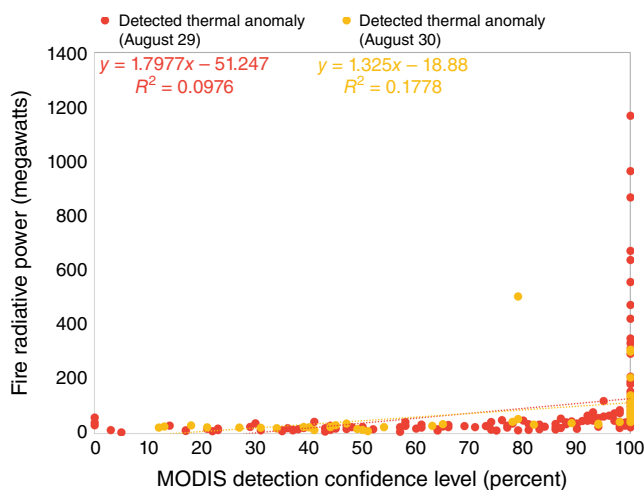


Fig. 9. MODIS detection confidence level versus fire radiative power (FRP) in megawatts for each thermal anomaly detected for the Happy Camp Fire on 29 August (red) and 30 August (yellow) 2014. On the clear day (29 August, red), there is some correlation between FRP and the detection confidence level, meaning that the size and heat of the fire impact the confidence of the detection from MODIS.

visible images. MODIS detects more thermal anomalies on a clear day than on a cloudy day, and several of these thermal anomalies have a high confidence level despite relatively

low FRP. The cloudy day thermal anomaly detections show a higher correlation between FRP and confidence level, indicating that on a cloudy day, MODIS is more confident in detecting larger fires than smaller fires.

Conclusion

Combining two sources of burned area information to create a single FEI captures more information on fire emissions than relying on a single source of burned area information. Further, including a temporal interpolation method to gap-fill missing data addresses remote sensing issues in FEIs (i.e. missing data due to cloud cover). These updates are crucial to providing daily estimates of smoke exposure for acute health effects studies, where missing days of fire emissions data can pose a significant problem. This is important because many FEIs used for health effects studies have uncertainties due to remote sensing issues, and these remote sensing issues cause gaps in daily fire progression information, which may result in missing smoke exposure when used in an acute health effects study (Black *et al.* 2017; Fann *et al.* 2018). Many methods proposed to improve FEIs, like aircraft campaigns or updated remote sensing instruments, require significant resources (Larkin *et al.* 2014). The improvements described in this study to create the combination FEI can be implemented using currently available data. Our combined FEI dataset provides improved fire emissions inputs for models that estimate human exposure to wildfire smoke for acute health effects studies. While there are still uncertainties in the combined FEI, especially related to the fuel loading and emissions factors, for an acute health study, it is critical to have a daily timeseries of smoke exposures. Therefore, this combined FEI is a significant improvement over other approaches because it provides daily fire emissions over a 12-year period (2007–2019) using a consistent method (i.e. no time series differences due to FEI method changes). Previous research in this area reaffirms the importance of combining different data sources to better represent fire activity (Larkin *et al.* 2020; McClure *et al.* 2023).

The data presented on FRP versus MODIS thermal anomaly detection confidence levels show that MODIS struggles to sense low FRP fires on cloudy days, highlighting the solutions addressed by adding a high spatial resolution source of burned area information that is less affected by cloud cover issues and by adding the cloud cover interpolation. A comparison of results using each source of burned area information individually and the combined FEI shows that using the two sources provides more information than the FEI for each source of burned area individually. The cloud cover interpolation provides more information than the combined burned area inventory. It provides a consistent time series for use in acute health effects studies. This approach to addressing missing data is an important improvement for health effects studies. When daily smoke

exposures are missing, public health researchers may be inclined to drop those days from their analyses, which results in a reduction in statistical power and a loss of information about smoke days. Alternatively, public health researchers may decide to implement an interpolation approach to compensate for missing data, and these researchers may not have sufficient expertise in fire science to appropriately adapt for the missing exposure days. The approach we have described for creating a combined FEI offers a practical solution for these challenges.

Assessing the quality of FEI data is crucial because FEIs serve as input for models that estimate the concentration of pollutants from wildfire smoke. Several studies (Roy *et al.* 2007; Soja *et al.* 2009) acknowledge the limitations of current FEIs and propose validation methods. However, many of the proposed validation efforts are often in-depth studies and resource-intensive field campaigns. While these provide invaluable knowledge, these methods also have limitations in terms of scalability, cost effectiveness, and timeliness of data availability. Another major hurdle when looking to validate FEIs is the absence of a method to directly measure the emissions from a single fire (Hao and Larkin 2014; Black *et al.* 2017). The complex nature of fire behaviour makes it impossible to establish a robust validation dataset, so FEIs will continue to face uncertainties. Future work to further understand the relationship between MODIS confidence levels and fire characteristics, as well as understanding the issues that may arise from satellite fire detections in dense canopy cover would be another useful step to improve FEIs.

The combined dataset addresses specific issues with using FEIs to estimate human exposure to wildfire smoke. While it does not solve all problems, it represents a functional improvement achievable with existing datasets. When using FEIs to study acute health effects, it is crucial to have a daily time series of exposure estimates that are as complete as possible. We show that combining two sources of burned area information into a single FEI and using a cloud cover interpolation creates an FEI dataset with more information on fires and no gaps in daily fire progression.

Supplementary material

Supplementary material is available [online](#).

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Data availability. The data that support this study will be shared upon reasonable request to the corresponding author.

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