ConFire

ConFire is a burned area attribution tool, used for trend detection and attribution (*1*), event attribution (*2*) and future projections (*3*). ConFire finds the likelihood of causes of or changes in burned area by optimising a simple, semi-empirical process representation model by applying Bayes Theorem. In our case, Bayes Theorem states that the likelihood of a model configuration described by a parameter set {β} and monthly explanatory variables (i.e model driving data) $\{X_{iv}\}$ given some training observation of monthly burned area $\{Obs_i\}$ from MODIS MCD64A1 (see Section X), for cells *i*, is proportional to the prior probability of {β} ($P(\{\beta\})$) multiplied by the probability of the observations given that model configuration:

$$P(\{\beta\}|\{Obs_i\}, \{X_{iv}\}) \propto P(\{\beta\}) \times P(\{Obs_i\} \mid \{X_v\}, \{\beta\}) \quad (3)$$

As we are targeting a small number of cells that experience extreme levels of burning compared to other cells within the training area, we use the zero-inflated logit distribution introduced by (*2*) as our update distribution, as this is specifically designed to better represent the tails of the distribution during fire events:

$$P(\{Obs_i\} \mid \{X_{iv}\}, \{\beta\}) = \prod_i^N P(Obs_i \mid \{X_v\}_i, \{\beta\})$$

$$P(Obs_i = 0 \mid \{X_v\}_i, \{\beta\}) = (1 - M(\{X_v\}_i, \{\beta_M\})^{p_1}) \times (1 - P_0)$$

$$P(Obs_i > 0 \mid \{X_v\}_i, \{\beta\}) = \left(1 - P(Obs_i = 0 \mid \{\beta\})\right) \times \aleph\left(logit(Obs_i) - logit\left(M(\{X_v\}_i, \{\beta_M\})\right), \sigma\right) \quad \text{(C2)}$$

where $\{\beta_M\}$ is the set of parameters related solely to the underlying model, M, $logit(x) = log\left(\frac{x}{1-x}\right)$, P_0, P_1 and σ are parameters within the full set {β} which describe the model error and $\aleph(\mu, sd)$ is a normal distribution with mean of $\boldsymbol{\mu}$ and standard deviation of sd.

The model, M, simulates burned area via a number of controls. For attribution and outlook, these controls follow (*2*, *4*): Fuel load, fuel moisture, ignitions and suppressions. This follows general model structure of global fire models (*5*, *6*) and is most appropriate for looking at long term, coarse fire drivers [CITE: look up in UNEP]. For driver assessment, we separate out an additional control for "fire weather" and introduce a "snow cover" control. Model burned area is the product of these controls

$$M(\{X_v\}, \{\beta_M\}) = F_{max} \times \prod_c f(\{X_c\}, \{\beta_c\}) \quad \text{(C3)}$$

Where F_{max} describes maximum monthly burned area and is an optimizable parameter in set $\{\beta_M\}$, $\{X_c\}$ are the variables and $\{\beta_c\}$ the parameters related to control c and f is the function that describes the control. Each control describes the expected burned area if all other controls imposed no limitation on burning - i.e when c is fuel, $f(\{X_c\}, \{\beta_c\})$ describes the burned area in perfectly dry conditions with saturated ignitions and no suppression. To achieve this, f, is the logical function:

$$f\left(\{X_c\}, \{\beta_c\}\right) = 1/\left(1 - exp\left(- \beta_{c,0} - \sum_j \beta_{c,j} \times X_j\right)\right) \quad \text{(C4)}$$

where $\beta_{c,j}$ is the contribution of driving variable X_j to the control and $-\ \beta_{c,0}$ is a parameter that can shift the midpoint of the sigmoid curve.

All variables X_v where normalised to be between $[0,\ 1]$ based on the training data to aid priors selection and optimization - though analytically this should have no impact on our results. Our priors fix the direction each drive can influence a control (drivers and direction are listed in Table XX and YY in methods) but beyond this relatively uninformed. Priors for $\beta_{c,j}$ where described by a log-normal distribution with a μ of 0 and σ of 10, and set to be positive for liberative drivers (one that increase the strength of a control) and negative for suppressive (ones that reduce the strength of a control). $\beta_{c,0}$ priors were set to a normal distribution with a mean of 0.5 and a standard deviation of 1. F_{max} and P0 priors were set as a uniform distribution between 0 and 1 $\boldsymbol{\sigma}$ was set to a half-normal with mean of 0 and standard deviation of 10.

We sampled the posterior distribution using Bayesian inference following a similar protocol to (*7*) with the pymc python package version 5 (*8*), employing 100 chains each over 1000 warm-up iterations (that were not subsequently used) and 100 sample iterations using the No-U-Turns Hamilton Monte Carlo sampler (*9*) (HOFFMAN & GELMAN 2014) while utilising 50 % of the data or a minimum of 6000 grid cells. Results then randomly sample 50 iterations from each chain, thereby approximating the posterior with 1000 ensemble members. As per (*7*), for evaluation (Figs SXX-YY) we trained on 2002-2009 and tested against 2010-2019 in order to test the models ability to capture uncertainty when out-of-sample. For the rest of the results in the main text, we trained on the full period (2014-2023 for section 2, 2002-2019 for section 3 and 4).

ConFire offers two probability, which we have adapted slightly from (*2*) :

1. The likelihood of different levels of burning for a specific event (i.e a grid cell in a given timestep) which considers uncertainty explained by the model and residual uncertainty described by our error parameter, $\boldsymbol{\sigma}$. We use this when we are comparing a single grid of cells and months, such as for evaluation and direct evaluation of fire events in section 2. The likelihood of a Burned Area, BA, under drivers, X, which can be out-of-training sample, is:

   $$P(\ BA|\ (X_v,\ \ \beta|\ \{Obs_i\},\ \{X_{iv}\}))\ \ =\ \int_{\beta} P(\beta|\ \{Obs_i\},\ \{X_{iv}\})\ \times\ P(BA|\beta)\ d\beta \quad \text{(C5)}$$

   Where $P(BA|\beta)$ is take from equation C2.

   When building distributions for multiple grid cells or time periods, as with building a climatology in section 2, we convolute the probability distributions of individual time periods and cells following equations in (*2*).

2. The emergent probability of different mean levels of burned area over many events explained directly by the model and its driving variables. We use this when assessing the emergent likelihood of burning in section 3 and 4. This is the same as taking the mean of n simulations in equation C5 as n tends to infinity. Doing this, $P(\{Obs_i\}\ |\ \{X_{iv}\},\ \{\beta\})$ from equation 2 will tend towards a burned aread of model Ms output weighted by the likelihood of a zero burny area:

$$\lim_{n \to \infty} \left[\sum_{i=1}^{n} P(\, BA|\, (X_v,\ \beta|\ \{Obs_i\},\ \{X_{iv}\})) \,/\, n \right]$$

$$= \int_{\beta} M(\{X_v\}_i,\ \{\beta_M\})\ \times\ (1\ -\ M(\{X_v\}_i,\ \{\beta_M\})^2)\ \times\ (1\ -\ P_0)\, d\,\beta$$

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