Unusual fire seasons in a changing climate - A Bayesian approach

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INTRODUCTION

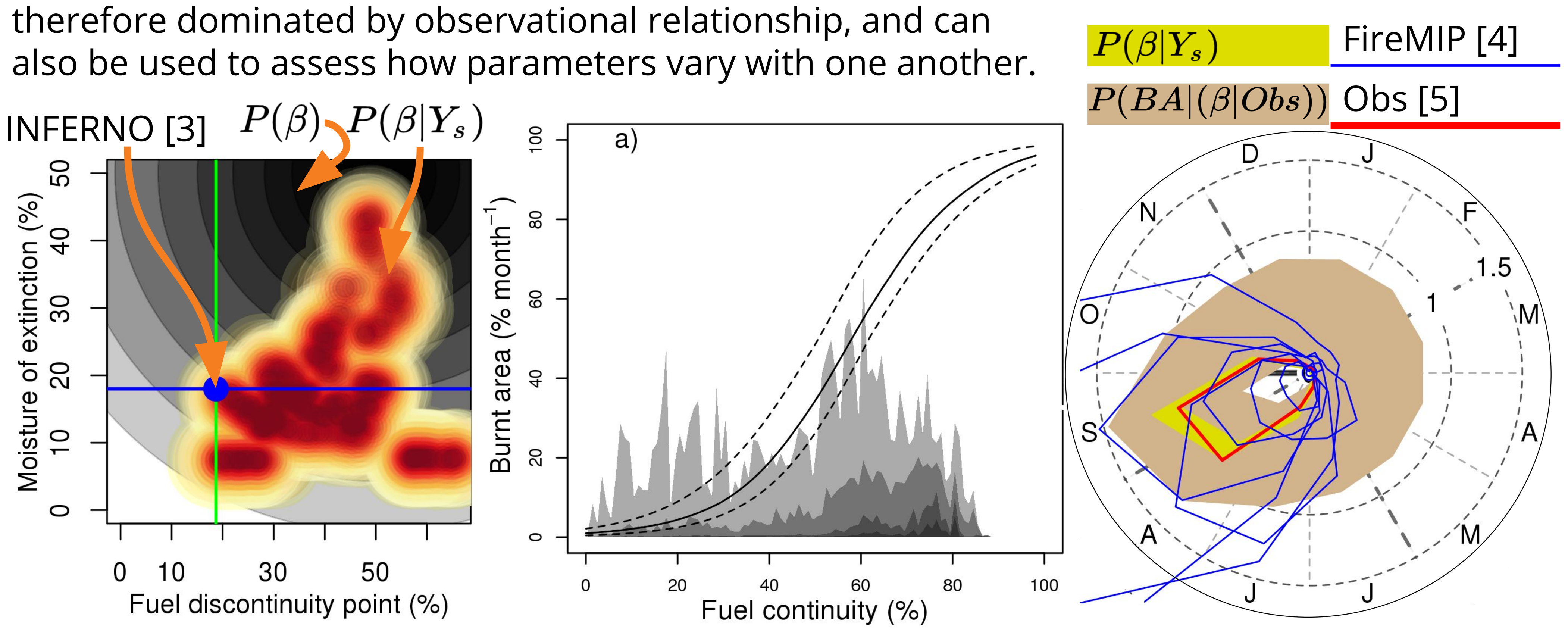
The sudden increase in Amazon fires early in the 2019 fire season made global headlines. While fires were likely caused by deliberate human ignitions or landscape changes, there have also been some suggestions that meteorological conditions could have played a role. Here, we develop a bayesian framework that can track the influence of, and uncertainties in, climate and vegetation changes on fire using the ConFire model [1,2]. We use this framework to ask two questions: were the 2019 fires in the Amazon unprecedented in the historical record?; and did the meteorological conditions contribute to the increased burning?

Bayesian approach to fire modelling

Bayes' theorem states that the likelihood of the values of the set, *ß*, containing model parameters, an error term, and our known model inputs, given a set of observations (*Obs*) is proportional to the prior probability distribution of *ß* (*P(ß)*) multiplied by the probability of (*Obs*) given *ß*

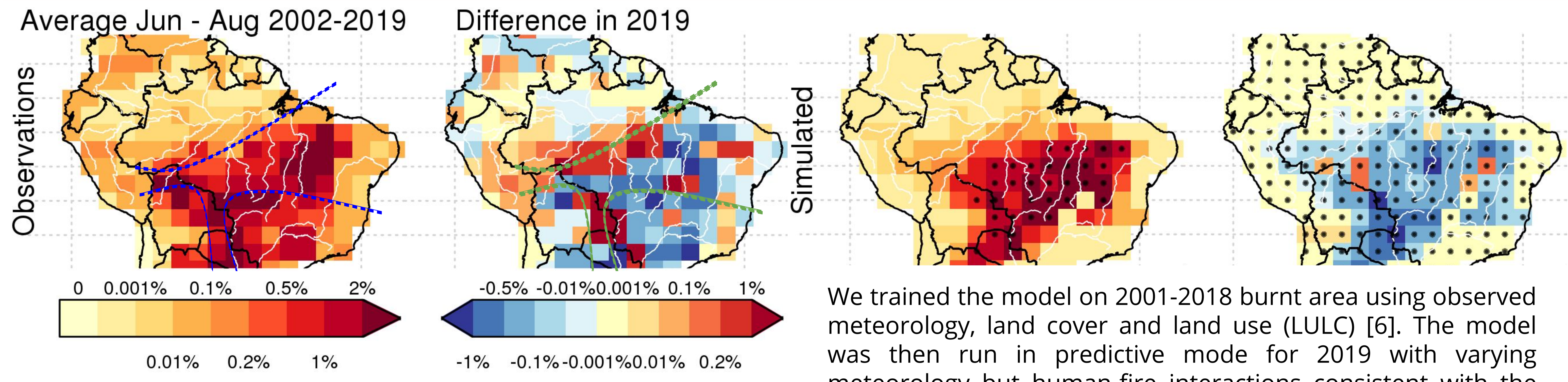
$$P(\beta|Obs) \propto P(\beta) \times P(Obs|\beta)$$

Using Bayesian theorem allows us to account for inherent uncertainty in model parameters based on the observed historic record [2]. Standard fire models allow just one set of parameter combinations (e.g, INFERNO, below left for two common model parameters). For ConFire, nice, large, uninformed priors (*P(ß)* - black blob, left) are used mainly to set physical bounds of parameters. Our resultant posterior distribution (*P(ß|Obs)* - yellow and red) is therefore dominated by observational relationship, and can also be used to assess how parameters vary with one another.



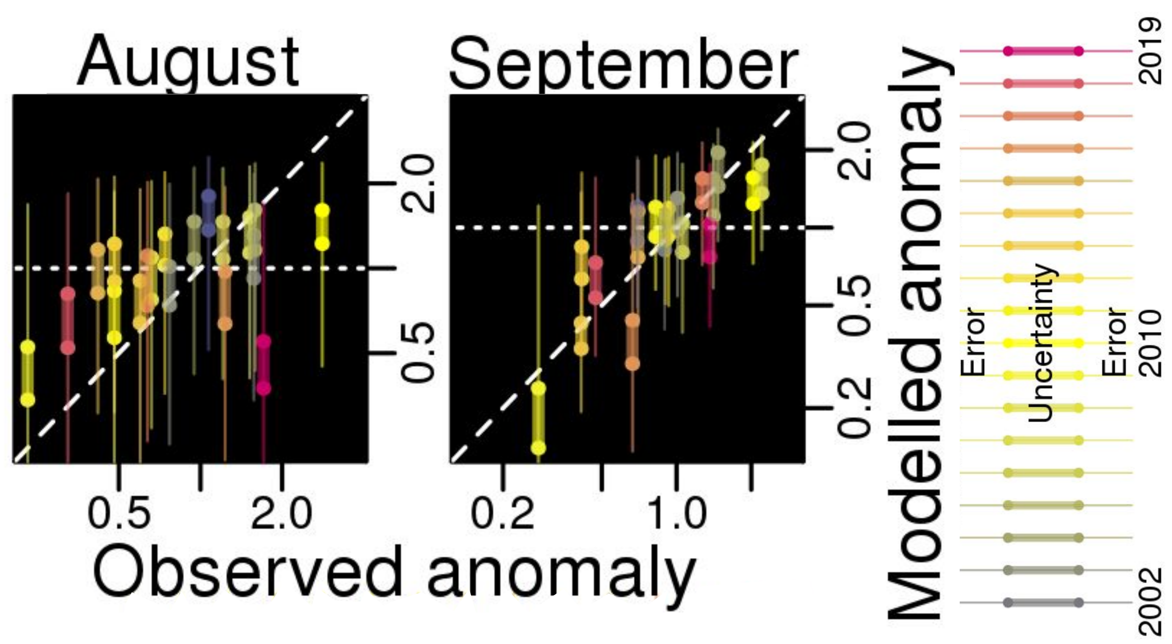
Model curves (e.g. in centre, [2]) propagate this uncertainty. Model output, on the right for 2002-2013 % burnt area climatology in areas of Amazonia deforestation, is expressed in two ways [6]: (yellow) accounting for uncertainty in parameters, used to assess the model skill (i.e vs observed burnt area in red & FireMIP models, blue) and the effect of drivers of burnt area; (tan) including the "error" parameter. By definition, trained observations fall inside the model "error". In predictive mode, burnt area outside model error indicates significant deviation from expectations given the historic record.

Low meteorological influence found in 2019 Amazonia fires



The observed % burnt area [5] for June-August 2019 (right) was much higher in some regions of active deforestation (dotted lines) when compared to the annual average (left). Areas not associated with deforestation showed less than normal fire activity.

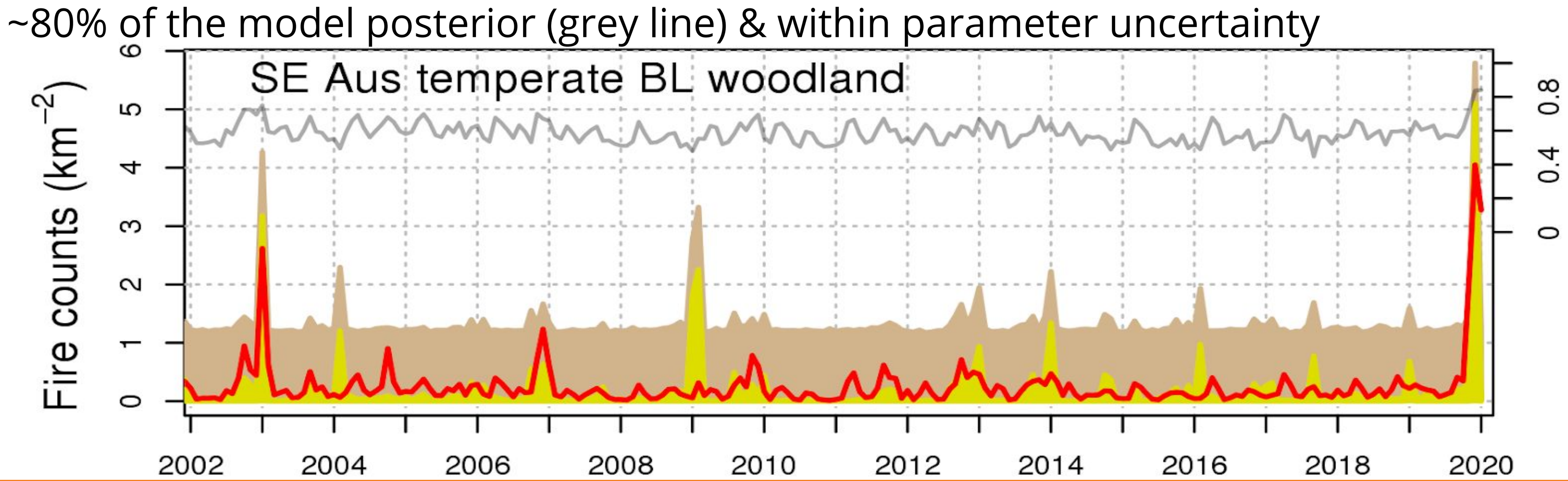
We trained the model on 2001-2018 burnt area using observed meteorology, land cover and land use (LULC) [6]. The model was then run in predictive mode for 2019 with varying meteorology but human-fire interactions consistent with the historic record. Simulated burnt area suggests that areas of low fire activity in 2019 should have extended right across the region. This implies that meteorological conditions did not the contribute to increased fire activity in 2019.



August burnt area anomaly for 2019 (red, left plot) falls at the 93% percentile of the model (thin bar, including model error, vs the white dashed 1:1 line). Only 2010 burnt area also fell so far outside the model posterior (yellow), though the model suggests that meteorological conditions in 2010 still lead to an increase in burning (above the white dotted line). All the sampled model posterior accounting for parameter uncertainty (thick line) suggests that less than average burning should have been experienced in 2019 when accounting for meteorological conditions alone. In September, the model still suggest that less than average burning should have been experienced, though with a 25% probability that observed burning levels could be explained through meteorological conditions. This implies that meteorological conditions were a more significant driver later in the fire season.

2019/2020 Australian fire season

2019/2020 South Eastern Australia fire season also saw high levels of burning. Running the framework for SE Aus temperate woodland shows that the model picks up this increased fire count from [7] (red line, below). Here, meteorological conditions easily explain the unusual fire activity, with fire activity falling within ~80% of the model posterior (grey line) & within parameter uncertainty



Conclusion

It is likely (93% probability) based on past relationships between burnt area and meteorological conditions, that the weather conditions did not trigger the increase in burning in Amazonia during the early fire season in 2019. This result points to social-economic factors, which were kept constant, having a strong role in the high recorded fire activity. Our Bayesian modelling approach can be easily adapted to provide assessment of meteorological drivers of other unusual fire events, such as the recent Australian fires.

See github.com/douglask3/amazon_fires/tree/EGU2020 or use QR code for to run Bayesian modelling framework

ConFire model description in *[1] Kelley, "Modelling Australian fire regimes,"* 2014; *[2] Kelley et al., "How contemporary bioclimatic and human controls change global fire regimes," Nat. Clim. Chang. 2019; [3]* converted from fuel and moisture parameters in *Mangeon et al., "INFERNO: a fire and emissions scheme for the UK Met Office's Unified Model," GMD. 2016* and *[6]*. See Bayesian example for conversion methods.; *[4] S. Hantson et al., "Quantitative assessment of fire and vegetation properties in historical simulations with fire-enabled vegetation models from the Fire Model Intercomparison Project," GMD Discussions, 2020; [5] L. Giglio et al., "The Collection 6 MODIS burned area mapping algorithm and product," Remote Sens. Environ., 2018.; [6] D. I. Kelley, et al., "Low meteorological influence found in 2019 Amazonia fires," Biogeosciences, submitted. [7] Giglio, Schroeder, Justice, "The collection 6 MODIS active fire detection algorithm and fire products," Remote Sens. Environ. 2016.*

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