Investigating causal effects of anthropogenic interventions on global ignitions

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Motivation

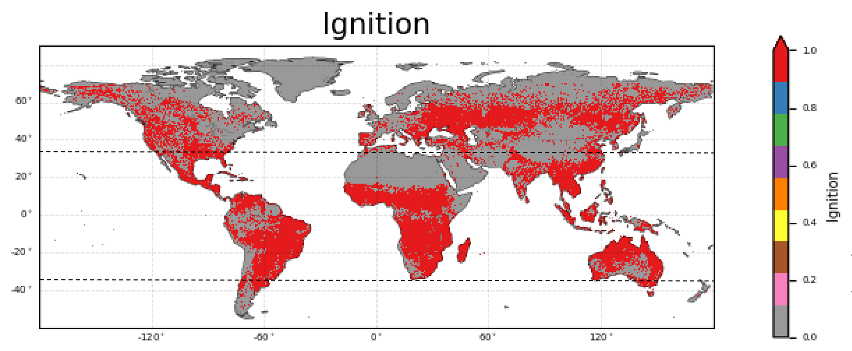


Fig 1.a: Every year 83% of fires occur between 35°N – 35°S …

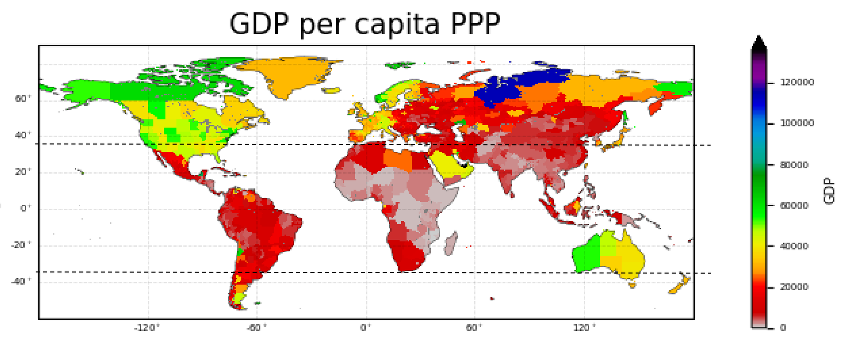


Fig 1.b: … which is primarily home to developing nations

? How do these two facts affect fire modelling when accounting for anthropogenic interventions? ?

Ignitions are a result of a complex interplay of regional physical variables and have a strong probabilistic nature associated with them which makes them difficult to model. For instance, we could have all the necessary physical variables (oxygen, heat, fuel and a triggering reaction) present for an ignition and it might not result in fire.

In addition to this, increasing anthropogenic interventions have a varying spatial and temporal effect on ignitions, which are still unaccounted for.

Hence, there is an urgent need to include causal reasoning in fire modeling to better understand and quantify the fire dynamics and involve Bayesian statistics to do so to incorporate the probabilistic nature varying over space and time.

Data Sources

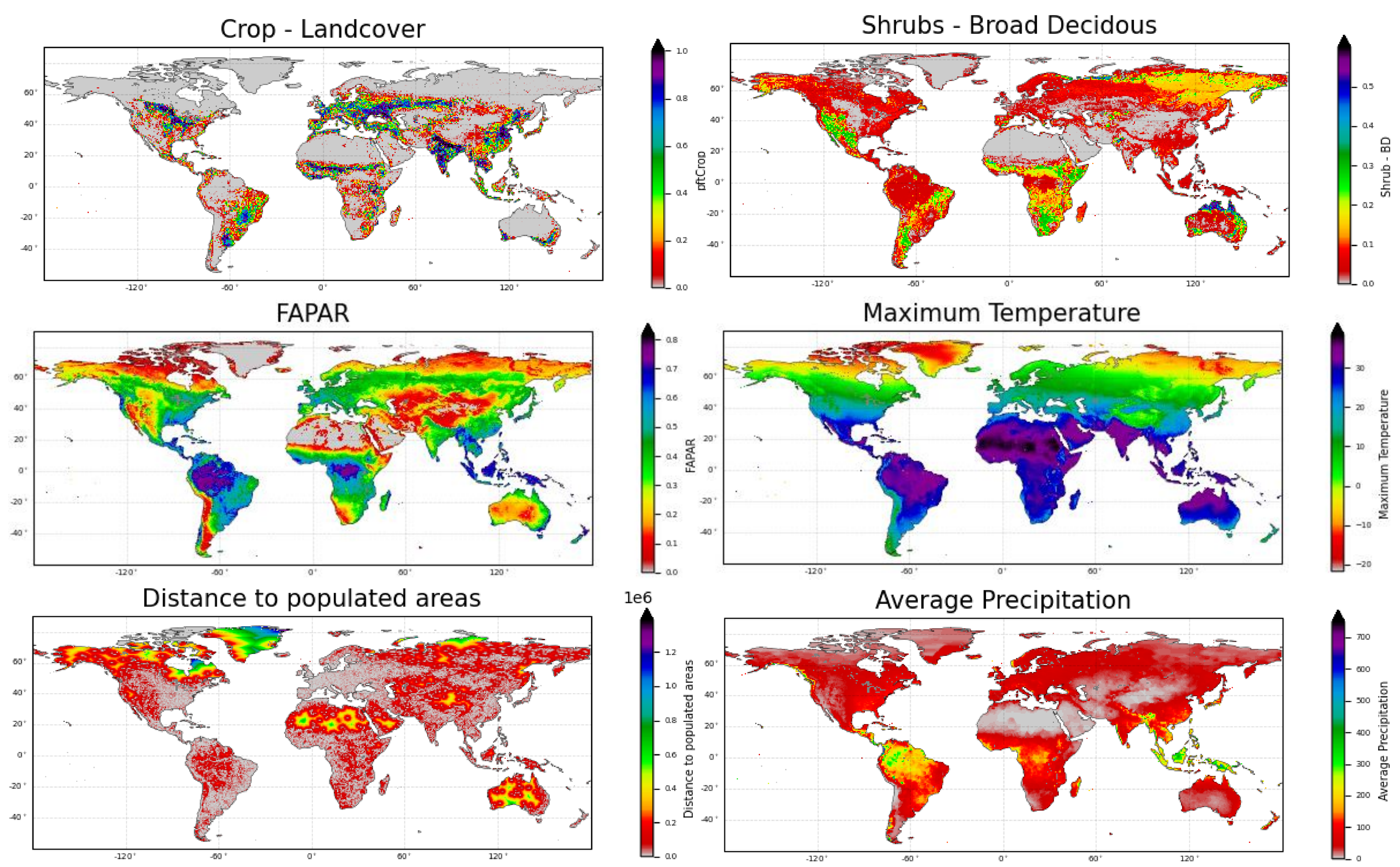


Fig 2: Average global data of input variables

The data above has been averaged over the period of 2003-2011 and the sources are as follows:

Crop Landcover	ESA landcover cci v2.0.7[1]	**ShrubsBD**	ESA landcover cci v2.0.7[1]
FAPAR	MOD15A2H v006[2]	**Max. temperature**	CRU TS4.04 climate data[4] (Harris et al., 2020)
Distance to population	HYDE 3.2[3]	**Avg. Precipitation**	GPCC[5] Schneider, et al. (2015)

Methods

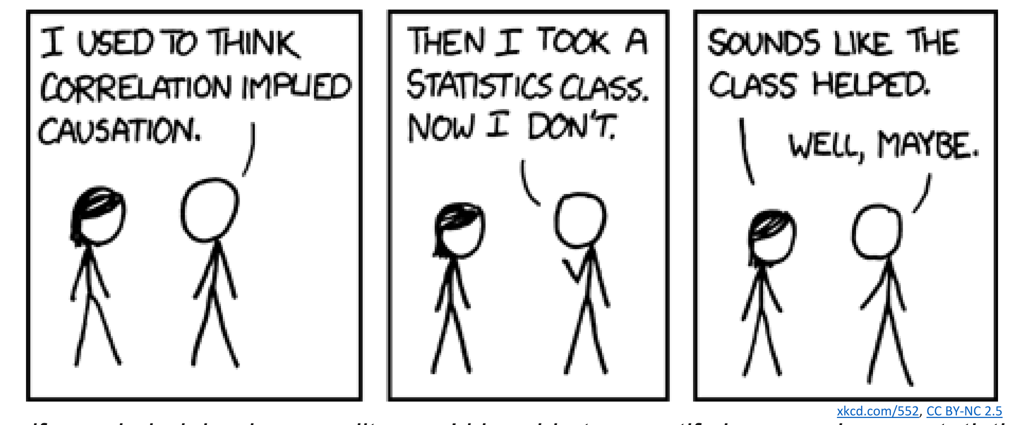
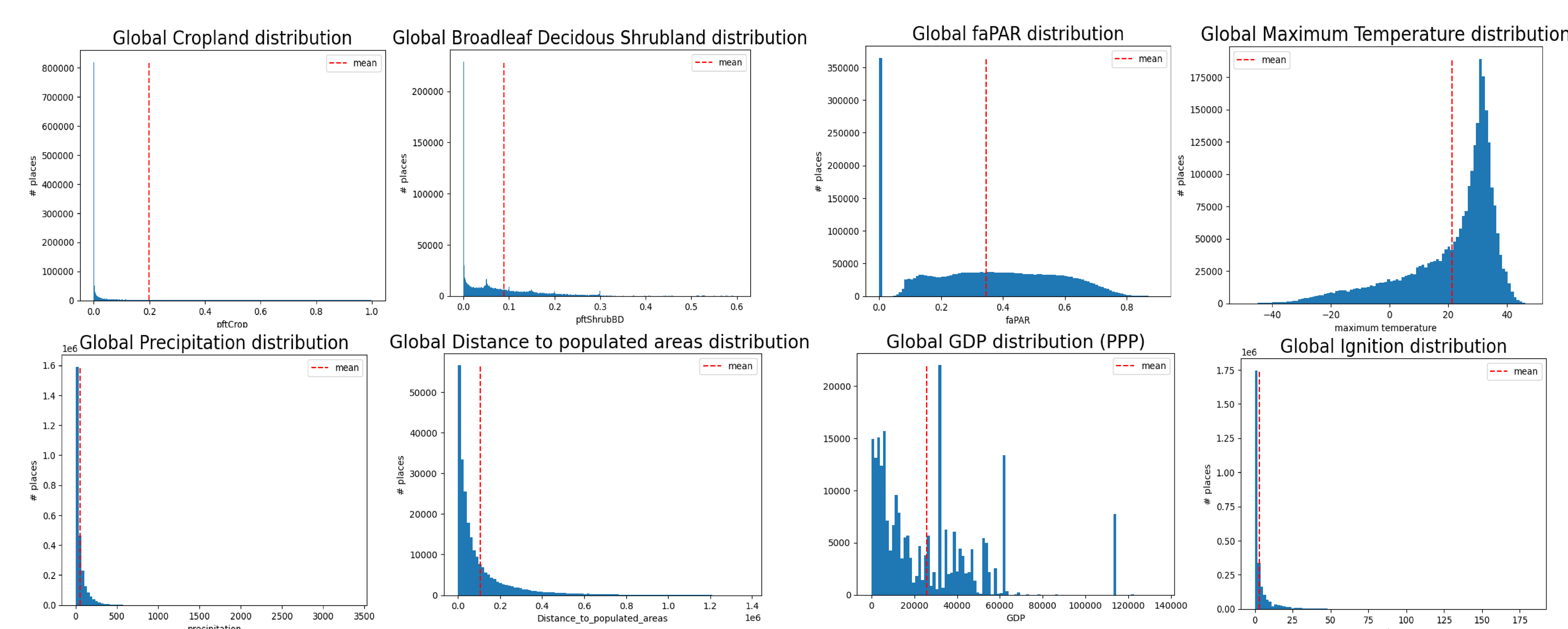


Fig 3: However, if you do indulge in causality, you'd be able to quantify how much your statistics class helped

- We turn to **causal discovery algorithms** to uncover the global ignition process modelling
  - Causal discovery aims at disentangling the effect amongst explanatory variables and their role in while affecting a response variable. In addition to this, it also provides with a direction to the cause and effect as opposed to correlation based modelling.
- Our data comes from **different distributions** and each feature has a different **spatial distribution** which affects ignitions differently globally. Hence, generalizing over features whose effects vary so drastically on the target variable leads to over generalization of the problem statement. (Please refer to the explanation below *Fig 4* for more details)
- Hence, the need for **decentralized causal inference**
- We propose to address this by utilizing **structural and parametric algorithms** in tandem. This is done in two steps:
  - We first develop a **structural causal model** over a large region with similar fires, in our case in accordance to the **Global Fire Emissions Database (GFED) regions[6].** Here we use data to infer causal relations.
  - Using the model obtained from above, we exploit **parametric methods** to test the strengths of these causal relations in smaller areas

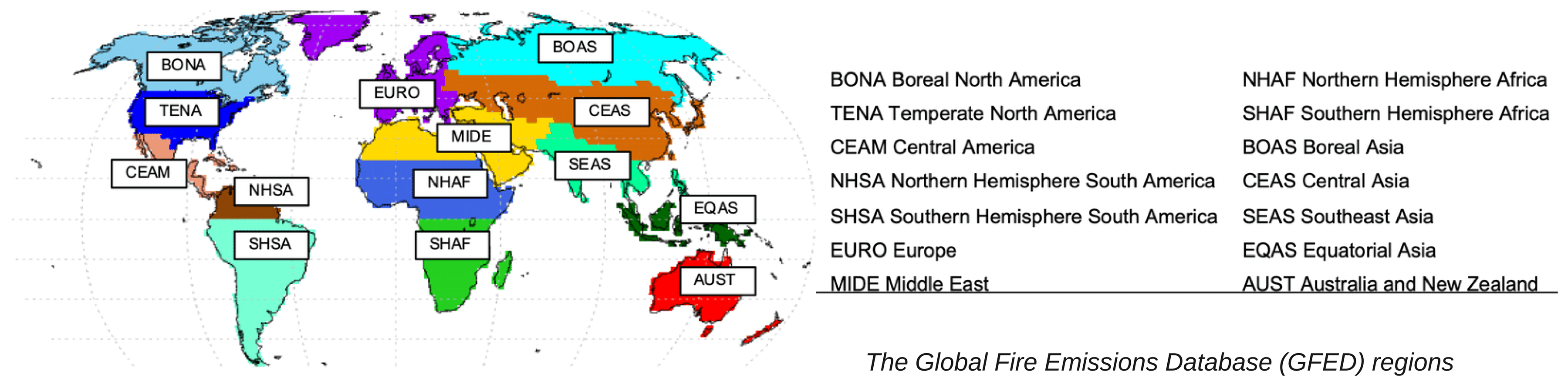
Data Distributions



As observed in the global distributions above, the target variable, ignition has a very different distribution than the explanatory variables. In addition to this, the distributions vary significantly between regions and affect ignitions under very distinct physical processes. For instance, an ignition in the boreal forests is a result of very different set of variables and inter-variable interaction than one in the croplands of the Sub-Saharan Africa. This spatial disparity amongst the variables is unaccounted for when building a correlation driven global ignition model. Hence, we need to build a causal model, which accounts for inter-variable interaction and doing so with an emphasis on Bayesian statistics allows to model the probabilistic nature of ignitions.

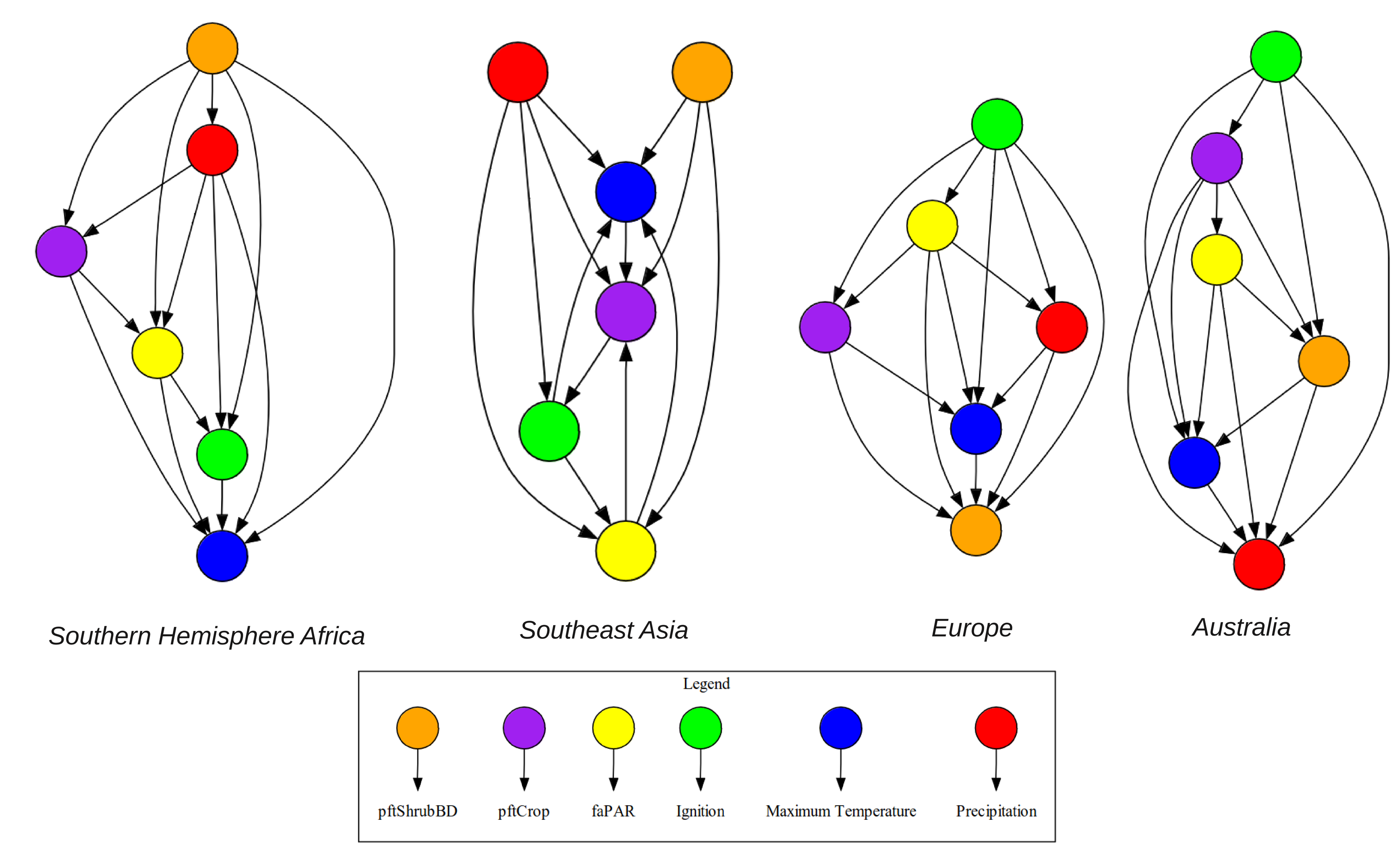
Preliminary results

We divide the globe into regions with similar ignitions in accordance with GFED. The term 'similar ignitions' highlights that the burnt matter in these regions is similar and may help in uncovering similarities in ignition conditions in the regions.



The Global Fire Emissions Database (GFED) regions

- Below, we see Directed Acyclic Graphs (DAGs) obtained from 4 such regions. While we do observe ignition (in green) acting as a response variable in the first 2 graphs, Southern Hemisphere Africa and Southeast Asia, it become a parent node in the rest.
- We conjecture this to be a direct consequence of more ignitions in the aforementioned regions allowing a more realistic model to be developed.
- We also observe some causal relations which are reversed than one would expect in reality. This is an open ended problem.



Discussion

In our current approach, we are able to capture the major interactions with great certainty in GFED regions. We hypothesize ignitions to be a response variable, which is not reflected in all the graphs at the moment. However modeling this is a challenging task as in a certain time frame, globally, 5% of the landcover burns. This presents us with a highly biased and imbalanced dataset. In addition to this, the dataset has a spatial resolution of 0.25°x0.25° and a monthly temporal resolution. This is a very coarse resolution in all 3 dimensions adding on to the challenging aspect of global ignitions.

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References:

1. Hartley, A.J., MacBean, N., Georgievski, G. and Bontemps, S., 2017. Uncertainty in plant functional type distributions and its impact on land surface models. Remote Sensing of Environment, 203, pp.71-89
2. Myneni, R., Y. Knyazikhin, T. Park. MOD15A2H MODIS/Terra Leaf Area Index/FPAR 8-Day L4 Global 500m SIN Grid V006. 2015, distributed by NASA EOSDIS Land Processes DAAC,
3. C.G.M. Klein Goldewijk, 2017, "Anthropogenic land-use estimates for the Holocene; HYDE 3.2", https://doi.org/10.17026/dans-25g-gez3, DANS Data Station Archaeology, V1
4. Harris, I., Osborn, T.J., Jones, P. et al. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Sci Data 7, 109 (2020).
5. Meyer-Christoffer, Anja; Becker, Andreas; Finger, Peter; Rudolf, Bruno; Schneider, Udo; Ziese, Markus (2015): GPCC Climatology Version 2015 at 0.25°: Monthly Land-Surface Precipitation Climatology for Every Month and the Total Year from Rain-Gauges built on GTS-based and Historic Data. DOI: 10.5676/DWD_GPCC/CLIM_M_V2015_025
6. ANDELA, N., D.C. MORTON, L. GIGLIO, and J.T. RANDERSON. "Global Fire Atlas with Characteristics of Individual Fires, 2003-2016." ORNL Distributed Active Archive Center, 2019. https://doi.org/10.3334/ORNLDAAC/1642

I am available for a relevant discussion on causal inference ad Bayesian analysis at : nirliptapande@gmail.com

Sharing is encouraged