How do human and meteorological variables affect the spatio-temporal behavior of Brazilian wildfires?

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Abstract: Global warming and its effects have become increasingly present in everyday life. Because of that, several ways to slow it down have been the object of interest of activists, environmentalists and politicians. In view of this, the role of countries like Brazil, which still has part of its territory covered by native vegetation, must be prominent in the fight against deforestation, monitoring and protecting its forests. However, disasters such as forest fires have become increasingly common in different regions of the world. In Brazil, the frequency of these events has increased as a result of the effects of climate change, that may still be contained or amplified by human action. Based on data on "fire spots" detected via satellite images of the entire Brazilian territory and representing the six Brazilian biomes, between 2011 and 2020, added to meteorological (precipitation, air temperature, humidity and wind speed) and human variables (transition of use of the soil and occupation), a spatial econometric model was constructed that seeks to evaluate the effects of these covariates on the number of fire spots. Based on this model, it was possible to observe that the change in land use, when replacing forest areas with areas for agriculture, has a positive effect on the number of fire spots in all six Brazilian biomes.

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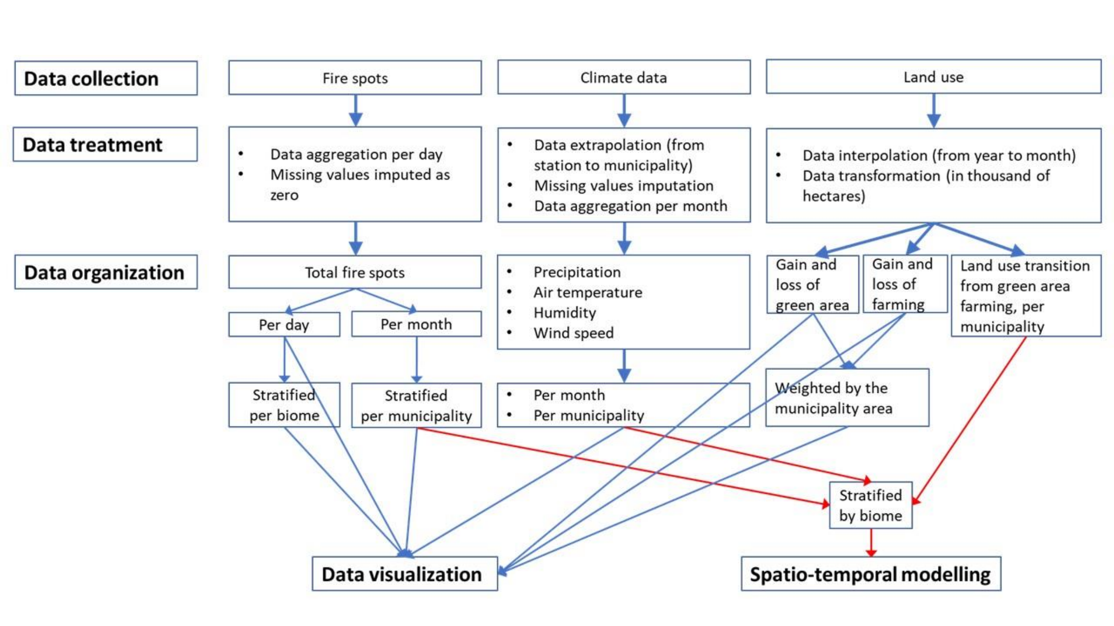
4th Conference on Statistics and Data Science
Salvador, Brazil (online)
December 1-3, 2022

Material and Methods



Our objective with this analysis is to model the total number of fire spots aggregated by municipality and month by including explanatory variables such as precipitation, temperature, or others. Since the standard linear regression model assumes that observations are independent, it does not address our need to accommodate dependencies in time and space. As we are dealing with panel data that varies in time and space, we work with spatial econometric models in this paper. Models of this class help fit areal unit data given in discrete periods while allowing the inclusion of explanatory variables.

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Results

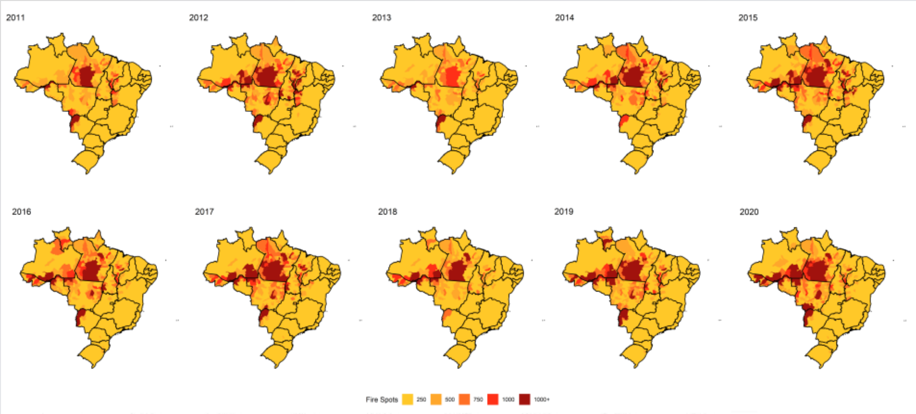

Figure 1 – Heat map with the total number of fire spots per year for each of the 5570 Brazilian municipalities.

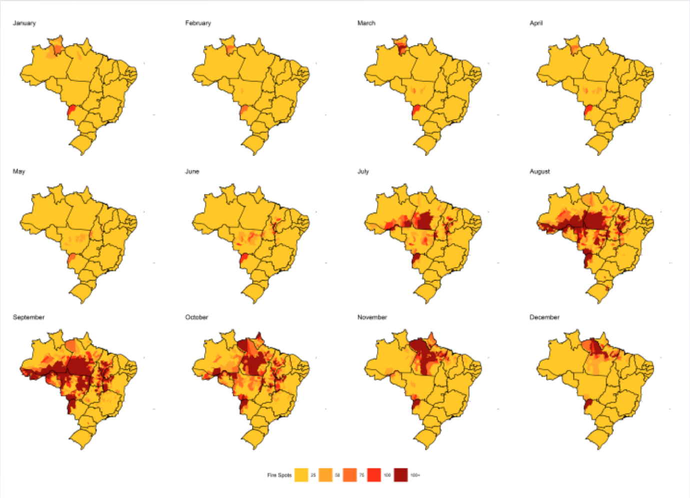

Figure 2 – Heat map with the monthly average number of fire spots for each of the 5570 municipalities between 2011 and 2020

Figure 1 shows the heat map with the total number of fire spots, for each of the 5570 Brazilian municipalities, per year, where we can see the temporal trend for each municipality. It is visible that Amazônia has been fustigated by forest fires year after year, and the Pantanal has had an increase in the number of fire spots in the last couple of years.

Figure 2 shows the heat map with the monthly average number of fire spots, for each of the 5570 municipalities, between 2011 and 2020, i.e., the number of fire spots in a given municipality in a given month is the average of all fire spots in that municipality for that month using the ten years available. The highest number of fire spots are observed in August, September, and October, with a significant incidence in the biomes of Amazônia, Pantanal, and a part of Cerrado.

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Conclusions

Model by biome	Estimate	Std. Error	t-value	P-value
*Amazônia**				
Land-use transition	0.08841198	0.00093319	947.417	$< 2.2 E^{-16}$
Precipitation	-0.43427592	0.04140096	-104.895	$< 2.2 E^{-16}$
Temperature	0.01847163	0.00570571	32.374	0.001206
Humidity	-0.02056734	0.00094774	-217.015	$< 2.2 E^{-16}$
Wind speed	-0.11233701	0.01042717	-107.735	$< 2.2 E^{-16}$
Spatial error parameter	0.12613049	0.00050774	248.41	$< 2.2 E^{-16}$
*Caatinga**				
Land-use transition	0.05122508	0.00082357	621.986	$< 2.2 E^{-16}$
Precipitation	0.21732765	0.03716808	58.472	$5.00 E^{-09}$
Humidity	-0.00940543	0.00027891	-337.218	$< 2.2 E^{-16}$
Wind speed	-0.06110079	0.00335811	-181.950	$< 2.2 E^{-16}$
Spatial error parameter	0.11113243	0.00040577	273.88	$< 2.2 E^{-16}$
*Cerrado**				
Land-use transition	0.17852031	0.00130969	1.363.071	$< 2.2 E^{-16}$
Precipitation	-0.36724318	0.03506423	-104.734	$< 2.2 E^{-16}$
Temperature	0.05880096	0.00153261	383.666	$< 2.2 E^{-16}$
Humidity	0.00151336	0.00053182	28.456	0.0044324
Wind speed	-0.02012603	0.00545488	-36.895	0.0002247
Spatial error parameter	0.11133183	0.00039493	281.9	$< 2.2 E^{-16}$
Mata Atlântica				
Land-use transition	0.8552846	0.0087864	973.422	$< 2.2 E^{-16}$
Temperature	-0.0215570	0.0029923	-72.041	$5.85 E^{-10}$
Humidity	-0.0229869	0.0010910	-210.691	$< 2.2 E^{-16}$
Wind speed	-0.0465133	0.0094243	-49.355	$8.00 E^{-04}$
Spatial error parameter	0.09942325	0.00029809	333.54	$< 2.2 E^{-16}$
Pampas				
Land-use transition	0.188081	0.006581	285.793	$< 2.2 E^{-16}$
Wind speed	-0.111906	0.016331	-68.526	$7.25 E^{-09}$
Spatial error parameter	0.0866531	0.0013991	61.936	$< 2.2 E^{-16}$
*Pantanal**				
Land-use transition	0.1797800	0.0044181	40.692	$< 2.2 E^{-16}$
Humidity	-0.0202643	0.0052417	-3.866	0.0001106
Spatial error parameter	0.0863162	0.0053941	16.002	$< 2.2 E^{-16}$

*The response variable $\mathbf{y}$ is in the transformed form $\log(\mathbf{y}+1)$.

Table 1 shows the results of the spatio-temporal econometric modeling for each of the six biomes, including all significant variables for each model by biome and the spatial error parameter. The columns include the significant variables in each model, the point estimate for the model parameters, their standard errors, t-values, and P-values.

In general, the sign of some coefficients of the meteorological variables varies according to the biome (except for wind speed in models where this variable appears). Furthermore, the sign of the coefficient of the variable "land-use transition" is positive for the six models, meaning a significant increase in land-use transition from the green area (forest and non-forest natural formation) to the farming area. The spatial error parameter is statistically significant for all models, which justifies using a more complex model than the usual multiple linear regression.

The explanatory variable land-use transition (from green areas to farming) was statistically significant for all models/biomes with positive coefficients, representing a considerable increase in the transition from green areas to farming. Whenever significant, precipitation trends to have a negative coefficient (i.e., fewer precipitation results in a higher number of fire spots), and temperature trends to have a positive coefficient (i.e., higher temperature results in a higher number of fire spots) except for Mata Atlântica which is close to the Atlantic Ocean, humidity trends to have a negative coefficient (i.e., fewer humidity results in a higher number of fire spots), and wind speed trends to have a negative coefficient (i.e., lower wind speed results in a higher number of fire spots).

The results of this study increase the awareness about the impact that climate change and public policy have on the devastation by wildfires and, consequently, in the quality of life of local people and society.

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