Uncovering the hidden connection between forest fires and agricultural markets

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Abstract

We investigate the relationship between forest fires in Brazil and global spot and futures commodity prices. We hypothesize that increases in commodity prices incentivize some agricultural stakeholders in Brazil to facilitate or create forest fires as a means of expansion. To test this hypothesis we implement a number of methods to establish Granger causal relationships between commodity prices and forest fires, including 1. F-tests, 2. VAR models with sparsity penalties, and 3. Neural Granger Causality with a component-wise Multi-Layer Perceptron. We find that not only do these methods agree on a number of Granger causal conclusions, but these conclusions also align with recent adjacent work on understanding the relationship between agricultural prices and deforestation in Brazil.

1 Introduction

In this project, we investigate the Granger causal relationships between agricultural commodity prices (i.e. Soybean, Corn, etc.) and forest fires in Brazil. We hypothesize that higher commodities prices create incentives for economic agents (farmers, miners, etc.) to expand their farming area by removing native forest from adjacent unfarmed areas with the help of human created fires or by failing to contain natural ones. Thus, we should observe a statistical correlation between such prices and the overall number of wildfires, once we control for possible cofounders such as seasonal effects and historical trends. We test this hypothesis by conducting tests for Granger Causality between the number of fires observed by satellite monitoring from 1998 to 2021 and the prices (future and spot) of the main commodities produced by Brazilian farmers (in farming area): Soybean, Corn, Coffee, Beef cattle, and Sugar Cane (Chamma et al., 2021).

Our hope is that our analysis can be extended to build a predictive model to forecast fires at specific locations, thus helping regulators better allocate their resources (inspections, fire fighter staff, etc.). If we can show some of these commodities are predictively associated (or Granger cause) the number of fires, we should then investigate further possible mediators and moderators of these potential causal relationship and possibly add them to this future final predictive model.

2 Motivation

Every year, forest fires are responsible for enormous material and health associated damages (Richardson and Loomis, 2012). Moreover, fires make forests less resilient to future damage and interfere in the provision of ecosystem services, compromising forests' ability to capture and store carbon (Xiao et al., 2021). For these reasons, governments have an interest in restricting the impact of these fires, and many have created agencies to enforce regulations and restrict human created wildfires. However, this a difficult task. In fact, monitoring a large extent of land in which these fires can take place and responding quickly when they start is a Herculean effort (Yang et al., 2021). Identifying factors that

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contribute to increases in these fires months in advance can be valuable to make the challenge of controlling the destruction caused by these fires more manageable.

While the relationship between commodities prices and deforestation has been thoroughly studied (see Literature Review section), as far as we know there has not been a comprehensive analysis on the relationship between commodities prices and forest fires in Brazil. If we can show the existence of Granger causal relationship and estimate the lag of such a relationship, this information will be useful for regulators to better direct their resources to monitor specific regions and agricultural products for a higher incidence of criminal wildfire activity in advance. On the other hand, if we are unable to find such relationships, we conclude that commodities prices are not a relevant factor to explain variation in fire activity and motivate further analyses to better understand the main drivers of increasing forest fires.

In Figure 1, we observe that fires are concentrated in the Midwest/Northern regions of the country. Precipitation and temperature alone cannot explain this distribution, since these regions are not especially dry nor especially hot (check Figures 3 and 6 in Appendix). In fact, the fires seem to be concentrated at the "agricultural frontier", that is, right at the intersection of farming activity and protected forest, thus corroborating our hypothesis that many of these fires are human caused.

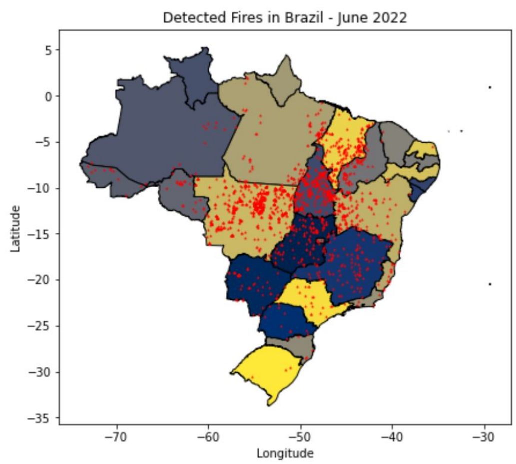


Figure 1: Forest fires locations in Brazil - June 2022

3 Literature Review

3.1 Deforestation and Agricultural Output Prices

The relationship between deforestation and commodity prices (both spot and futures) has been thoroughly studied before. In a literature review of the topic on different countries, Robalino and Herrera (2010) concludes that the relationship between agricultural output prices and deforestation is positive and very robust, since the opportunity cost of preserving forest increases. Higher prices also help finance additional conversion of land from forest to agriculture (Kaimowitz Anderson, 1998).

Specifically for the Brazilian case, soybean and beef cattle seem to be the most relevant agricultural prices driving deforestation, especially in the Amazonian region. Harding et al. (2021) find that environmental regulation on Soy bean production made exposed municipalities more sensitive to non-Soy agricultural commodities international prices. McAlpine et al. 2009 find that in Brazil, beef prices correlate well with the deforestation rates. Faria and Almeida (2015) note that as openness to trade in the Amazon region increases, deforestation also increases, mostly driven by the production of soybeans and beef cattle. Morton et al. 2006 show that the area deforested for cropland and the mean annual soybean price in the year of forest clearing are directly correlated, suggesting that deforestation rates could return to higher levels with a rebound of crop prices in international markets.

While deforestation and forest fires are connected, they are not equivalent. According to reserch by the Climate Policy Initiative/Pontifical Catholic University of Rio de Janeiro, only 11% of the forest area affected by fire is deforested within three years, indicating that forest fires in the Amazon are not systematically used as a first step towards removing vegetation (Menezes et al., 2021).

3.2 Forest fires and Agricultural Output Prices

Wildfires in Brazil have been studied as an environmental, meteorological and socioeconomical event. Eugenio et al. (2019) provide a comprehensive overview of the wildfire regimen in the country and Kganyago and Shikwambana (2020) assess the physical characteristics of the most recent wildfires using remote sensing data.

Forest fire modelling has been attempted on multiple occasions. Arima et al, 2007 spatially model the probability of forest and agricultural fires in the Brazilian Amazon using farm-gate prices of beef and soy and observe that fire is positively correlated with these prices. Morello et al., 2019 improves fire prediction in the Amazonian region by using social end economic indicators and accounting for spatial dependence. Assunção, Gandour and Rocha, 2015 investigates the contribution of agricultural output prices and policies to the 2000s reduction in Amazon deforestation and conclude that deforestation responded positively to agricultural output prices.

4 Data

4.1 Sources

For this analysis, we use the Forest Fires count data from Brazil collected by the Instituto Nacional de Pesquisas Espaciais (INPE, 2022). This data is available at a state level (27 states) and on a monthly basis from July 1998 to November 2021. We also collect the spot and futures prices of soy, corn, beef, coffee, and sugar - extracted from the FRED dataset, organized by St Louis FED. (IMF, 2022). For data on average temperature and precipitation at the national level, we used information from INMET's database (INMET, 2022). For the exchange rate between USD and BRL, we used data from Investing.com. Finally, we retrieved Brazilian annual national consumer prices inflation from the World Bank Data website (World Bank, 2022).

4.2 Data Transformation

Since we believe economic agents ultimately respond to incentives with respect to the increase in purchase power on their local currency, we multiplied the commodities prices data (is USD) by the exchange rate (BRL/USD) at the start of every month in the time series. Additionally, we corrected these nominal prices by dividing them for a multiplicative consumer goods price index.

4.3 Stationarization

Once we had the full dataset, we stationarized the data with the *stationarizer* package (Palachy, 2019). This package automatically tests each time series in the dataset for non-stationarity using the Augmented Dickey-Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. For time series that fail these tests (fail to reject the Null in the ADF test or reject the Null in the KPSS test), the package keeps differentiating and detrending the series until the generated series have low enough p-values for ADF and high enough p-values for KPSS. Since either of the tests is known for having low power, using both tests results to claim stationarity of a time series is useful to avoid type I and type II errors. After applying this transformation, we check that the series are indeed non-stationary with a very high probability (p-value of at most 10^{-4} for ADF and at least 0.60 for KPSS). The same process is applied on the forest fire time series for each state, but the resulting p-values are not shown in the table.

Variable	Pre		Post	
	ADF	KPSS	ADF	KPSS
Soy	0.46	0.00	0.00	0.93
Corn	0.97	0.00	0.00	0.82
Beef	0.92	0.00	0.00	0.89
Coffee	0.99	0.00	0.00	0.99
Sugar	0.32	0.02	0.00	0.96
Future Soy	0.09	0.01	0.00	0.76
Future Corn	0.39	0.01	0.00	0.60
Future Beef	0.10	0.33	0.00	0.87
Future Coffee	0.18	0.01	0.00	0.62
Future Sugar	0.07	0.00	0.00	0.75
Temperature	0.01	1.00	0.00	0.44
Precipitation	0.07	1.00	0.00	1.00

Table 1: Table of p-values for the ADF and KPSS tests before and after differencing and detrending

5 Methods

5.1 ADF Test

The Augmented Dickey-Fueller tests the Null Hypothesis that there is a unit root is present in the time series sample (Mushtaq, 2011). For the model

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + ... + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_t \tag{1}$$

we test the hypothesis that $\gamma = 0$. That is, we test that the lagged level of the series will provide no relevant information in predicting the change in y_t besides the one obtained in the lagged changes. If we can reject that $\gamma = 0$, then the time series does not have a unit root and thus presents reversion to a constant mean. This is an extension for the p lag setting for the original Dickey-Fueller test (Dickey & Fuller, 1979).

5.2 KPSS Test

The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test is used for testing a null hypothesis that an observable time series is stationary around a deterministic trend (trend-stationarity) (Kwiatkowski et al., 1992). The test is based on a Linear Regression:

$$y_t = w_t + \beta t + \epsilon_t \tag{2}$$

where w_t is a random walk, βt is a deterministic trend and ϵ_t is a stationary error. The test uses OLS to estimate $\hat{\sigma}_\epsilon^2$ and tests for the hypothesis that $\hat{\sigma}_\epsilon^2 = 0$, i.e., no trend in the time series. It's important to note that rejecting a KPSS test implies the series is non-stationary (the opposite of ADF, where a low p-value implies stationarity).

5.3 Granger Causality

Granger causality allows us to test if a time series is predictive of another ("predictive association"). Granger proposed the following test for identification of Granger causality of X on Y (Granger, 1969):

$$\mathbb{P}[(Y)(t+1) \in A | \mathbf{I}(t)] \neq \mathbb{P}[(Y)(t+1) \in A | \mathbf{I}_{-\mathbf{X}}(t)] \tag{3}$$

where $\mathbf{I}(t)$ and $\mathbf{I}_{-X}(t)$ represent, respectively, the information available at time t in the entire universe and the modified universe in which X is excluded. In the Vector Autoregressive Model (VAR) case, where the time series is modelled as a linear combination of the past K lags of the series

$$x_t = \sum_{k=1}^{K} A^{(k)} x_{t-k} + e_t \tag{4}$$

where A(k) is a matrix that specifies how lag k affects the future evolution of the series and e_t is zero mean noise. In this model, time series j does not Granger-cause time series i if and only if for all k, $A_{ij}^{(k)} = 0$. Some of the shortcomings of Granger causality is that it does not account for latent confounding effects and it does not capture non-linear causal relationships.

We now address the various assumptions of Granger causality before proceeding to describe the methods applied. We begin by noting it is reasonable to assume our series are observed at matched time intervals because we have records for the same months over time. Next, we may assume that we have perfectly observed commodity spot and futures prices, however it may not be the case that state-level forest fires are perfectly observed, as the total monthly numbers recorded are estimates. We also note that it is unlikely that these 38 series capture all relevant information to this system. Next, we do not know whether the dynamics are strictly linear nor do we have know a known lag order - however, we address these by implementing hierarchical group lasso and Neural Granger causality methods described next. Finally, we require our series to be stationary which we addressed in the previous section.

5.4 F-test

Granger causality in VAR models is often tested through F-tests (Granger, 1969), where the reduced models remove the effect of variables not from the series of interest. We begin by fitting a full VAR model using all the variables and selecting the lag order by finding that which minimizes AIC, Hannan–Quinn information criterion, and Akaike's Final Prediction Error. We then perform F-tests on each state's forest fires model for each reduced model that leaves out a single external exogenous variable. We conclude that the variable Granger causes the given state's forest fires if the p-value is significant (<0.05).

5.5 Network Granger Causality

An alternate method of establishing Granger causality is to fit a VAR model subject to an additional sparsity-inducing penalty in the loss function (Fujita et al., 2007). We then directly deduct Granger causal relationships by reading the nonzero values of the lag matrices. There are many ways to construct such a penalty. In our analysis, we apply two established penalties from the BigVAR library (Nicholson et al., 2017) and two which we propose. In all cases we fit a VAR model containing all proposed relevant variables, i.e. forest fires per state, spot and future commodity prices, temperature and precipitation, and tune λ using rolling cross validation.

5.5.1 BigVAR Elementwise Hierarchical Group Lasso (BHLAGE)

The penalty as defined in (Nicholson et al., 2017) is

$$\lambda \sum_{i=1}^{k} \sum_{j=1}^{k} \sum_{\ell=1}^{p} \left|\left| A_{ij}^{(\ell:p)} \right|\right|_2 \tag{5}$$

We see that each term in the summation penalizes the element A_{ij} for lags ℓ through p, where p is a prespecified maximum lag. As a result, coefficients at relatively later lags receive a higher penalty than those at more recent lags. This is one form of the hierarchical group lasso, which not only encourages individual coefficients to be zero, but also allows each series in each marginal model to have its own maximum lag order, thereby avoiding the need to select a definitive overall lag order for the model. Finally, the hyperparameter λ controls the overall magnitude of penalty.

5.5.2 BigVAR Own/Other Hierarchical Group Lasso (BHLAGO)

The penalty as defined in (Nicholson et al., 2017) is

$$\lambda \sum_{i=1}^{k} \sum_{\ell=1}^{p} \left[\left|\left| A_i^{(\ell:p)} \right|\right|_2 + \left|\left| \left(A_{i,-i}^{(\ell:p)}, A_i^{(\ell+1:p)} \right) \right|\right|_2 \right] \tag{6}$$

In this case, we penalize the coefficients within marginal models instead of individual elements. Therefore, the maximum lag order after fitting can vary across marginal models, but not within.

Furthermore, the second term places an additional penalty on coefficients specifically from external endogenous variables and later lags. We therefore expect this latter penalty to encourage only coefficients from external endogenous variables that are highly predictive of the marginal model to persist.

5.5.3 Sparse Elementwise Hierarchical Group Lasso (SEHLAG)

We propose the following modification of (BHLAGE)

$$\lambda \sum_{i=1}^{k} \sum_{j=1}^{k} \sum_{\ell=1}^{p} \left|\left| A_{ij}^{(\ell:p)} \right|\right|_1 \tag{7}$$

In this case, we use the L^1 norm for penalizing A_{ij} for lags ℓ through p, instead of the L^2 norm as in (BHLAGE). The motivation for this is to further encourage sparsity in order to more easily draw various Granger causality conclusions, while maintaining the flexibility of each marginal model to have its own maximum lag order.

5.5.4 Other Hierarchical Group Lasso (OHLAG)

We propose the following modification of (BHLAGO)

$$\lambda \sum_{i=1}^{k} \sum_{\ell=1}^{p} \left[\left|\left| A_{i}^{(\ell:p)} \right|\right|_2 + \left|\left| A_{i,-i}^{(\ell:p)} \right|\right|_2 \right] \tag{8}$$

In this case, we drop the additional higher order lag penalty $A_i^{(\ell+1:p)}$ from the second term in the summation in (BHLAGO). The motivation for this is to maintain the property of encouraging only coefficients from highly predictive external endogenous variables to persist, however, we now allow more flexibility for the model to use higher order lags within each marginal model. As a result, we hypothesize this to result in better forecasting performance.

5.6 Neural Granger Causality

Neural Granger causality is an extension of Granger Causality to Neural Networks proposed by Covert et al., 2018. The main idea is to recover the Granger causal structure of the data through regularization using sparsity-inducing penalties on the weights of first layer of the MLP. This framework allows us to relax the assumption of linear dynamics underlying the Granger causal analysis. The new objective (loss function + penalty) is non-convex, and thus the authors propose using proximal gradient descent with line search to minimize the objective and guarantee that it converges to exact zeros.

6 Results

We implement the aforementioned methods and report the following in Table 2:

- Average RMSE, i.e. the average RMSE across all state-level forest fires marginal models
- Average state max order lag, i.e. the average max order lag for any endogenous variable within a state-level marginal model
- Average number of Granger causal factors, i.e. the average number of Granger causal factors within a state-level marginal model (computed according to the corresponding method mentioned in the previous section)

For the cMLP, we applied a parameter for nonsmooth regularization of 3 (we vary this in Figure 2) and a parameter for ridge regularization on output layer of 1000. We also changed the learning rate to 0.001 to further minimize the objective function. The number of hidden units and early stopping policy are the same from the original paper.

Model	Avg RMSE	Avg State Max Order Lag	Avg # Granger causal factors
cMLP Group Lasso	26.48	3.63	7.4
cMLP Sparse Group Lasso	30.72	3.81	2.6
cMLP Hierarchical Group Lasso	32.47	5.93	3.4
VAR	86.11	4	6.13
BHLAGE	89.64	3.82	7.14
OHLAG	96.29	4.97	6.41
BHLAGO	102.47	5.12	8.27
SEHLAG	112.6	4.1	4.35

Table 2: Summary of Granger causality methods applied

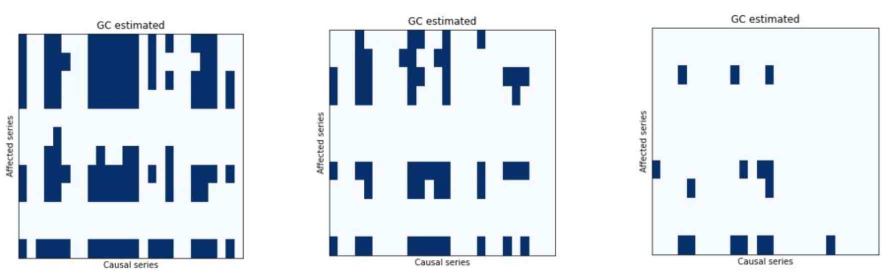
In Table 3 for each method we report the top-5 Granger causal factors, ranked according to the average magnitude of coefficients across state-level marginal models.

Model	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
cMLP Group Lasso	Precipitation	Spot Soy	Soy Futures	Spot Beef	Spot Corn
cMLP Sparse Group Lasso	Precipitation	Spot Soy	Soy Futures	Spot Beef	Spot Corn
cMLP Hierarchical Group Lasso	Precipitation	Soy Futures	Spot Soy	Spot Beef	Spot Corn
VAR	Precipitation	Temperature	Spot Soy	Soy Futures	Beef Future
BHLAGE	Precipitation	Temperature	Spot Soy	Spot Beef	Soy Futures
OHLAG	Precipitation	Temperature	Spot Soy	Spot Beef	Soy Futures
BHLAGO	Precipitation	Spot Soy	Temperature	Soy Futures	Spot Corn
SEHLAG	Temperature	Precipitation	Soy Futures	Beef Future	Spot Soy

Table 3: Top-5 Granger causal factors on average across states

We see that the nonlinear MLP methods perform the best w.r.t. average RMSE, in particular when applying the Group Lasso penalty. Amongst the linear models, we see that the VAR model without sparsity penalty performs the best and SEHLAG performs the worst, w.r.t average RMSE. We also note that OHLAG outperforms BHLAGO and SEHLAG w.r.t. average RMSE, which appears to corroborate our hypothesis in 5.5.4 that using this penalty would result in better forecasting performance.

Across all methods, we see that the average number of Granger causal factors is significantly less than the total number of endogenous variables used as inputs to each model, i.e. 38. In Figure 2 we vary the nonsmooth regularization parameter and clearly observe that the number of Granger causal coefficients decrease as regularization increases.



(a) $\lambda = 0.03$ (b) $\lambda = 0.3$ (c) $\lambda = 3$

Figure 2: Granger Causal Effects for the cMLP for varying regularization parameters

From Table 3 we see that average national precipitation is the most predictive of state-level forest fires for nearly all methods. For the next most important factors, however, there is some disagreement.

Linear models seem to be capturing a strong Granger causal relationship between average national temperature and the number of forest fires, while the cMLP based models give more relevance to Soy prices. Both types of models (and their different regularizations) agree that the most important commodities in predicting forest fires are soy, beef cattle and corn, respectively. Finally, we note that in many cases amongst both linear and nonlinear models, coffee and sugar does not appear to Granger cause state-level forest fires.

7 Conclusions

Overall, we believe the results elicited from our Granger causal analysis align with the work exposed in the Literature Review. Particularly, other authors found that soy and cattle Prices were strongly correlated to both deforestation and forest fires in Brazil. Furthermore, we believe it is reasonable to conclude that Precipitation and Temperature have some effect on forest fires, since drier and warmer temperatures increase the likelihood of natural fires occurring.

Moreover, we note that the states where the model coefficients are most prevalent are also the states in the "Agricultural Frontier", where Soy and Cattle production occurs in proximity to the Amazonian forest (check Table 4 in Appendix). This reinforces our initial hypothesis that commodity prices affect number of fires through a higher incentive to increase production.

We also believe the maximum order lags of the various state-level marginal models to be in accordance with what we would expect from reality. Most Granger causal nonzero coefficients for relevant states start at lags 4 or 5 and are active all the way to lag 10 (the max lag we tested). We believe that it would take a few months for the incentive of higher prices to transmit into an increase in fires, and for this effect to extend to a few months afterwards.

Finally, it's important to emphasize that our analysis does not allows us to claim (counterfactual) causality between agricultural prices and forest fires, but it does show that these two variable are associated (especially soy and beef prices) and calls for adding this information to a future predictive model.

8 Next Steps and Limitations

One limitation of our current analysis is that our wildfires data is restricted to counts of wildfires in a specific region. We would like to add information on the size of such wildfires so that we can measure the relationship between commodities prices not only to a higher frequency of wildfires, but also to larger total area of fire. However, we were unsuccessful in finding this information on online databases.

Another limitation related to the data available is the fact that our variables for Temperature and Precipitation are at a national level (instead of state level). Since Brazil is a large country with multiple different sub-climates, this adds to much noise and prevents us from understanding the relationship between local weather conditions and forest fires. Unfortunately, we were unable to find this information online, but it is possible that additional research succeeds in this task.

Lastly, we would like to further explore non-linear models to understand if the differences we found between the cMLP case and the VAR models is consistent. We could easily extend our Neural Granger Causality analysis to a Recurrent Neural Network setting (i.e., LSTM) as implemented in the original paper.

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10 Appendix

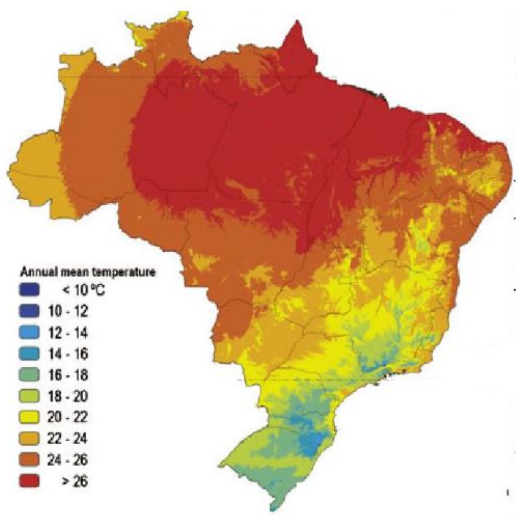

Figure 3: Mean Annual Temperature - Brazil

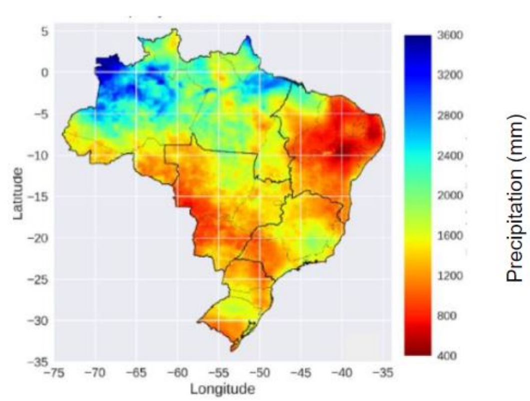

Figure 4: Total Annual Precipitation - Brazil

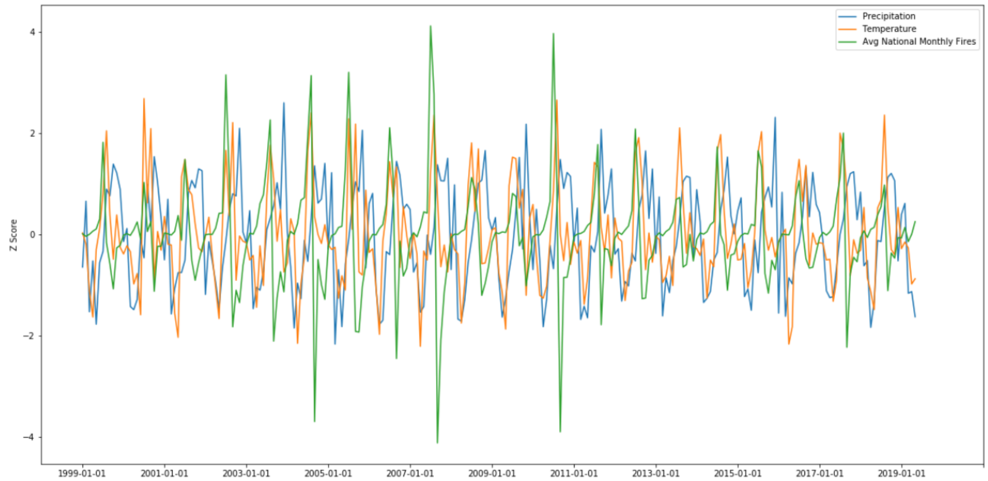

Figure 5: Transformed Precipitation, Temperature and Average National Monthly Fires Overlayed

Figure 6: Transformed Soy, Beef, Corn and Average National Monthly Fires Overlayed

State	Number of Significant Granger Causal Coefficients (all lags)
Amazonas	23
Acre	17
Pará	16
Maranhão	15
São Paulo	14

Table 4: Top 5 States with most nonzero Granger Causal Coefficient across all lags - cMLP with Group Lasso penalty