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A SHOCK RESPONSE MODEL IN GROWING GREENHOUSE GAS EMISSIONS

Um modelo de resposta a choques no crescimento das emissões de Gases de Efeito Estufa

Attawan Guerino Locatel Suela[1]

ABSTRACT

The present article identified what would be the impacts on the productive quantity of five large agricultural segments, if there was an increase in GHG emissions in Brazil. Methodologically, a Structural Vector Auto Regression Model was structured and operated with data between the years 1970 and 2018. The following information was used: the level of emissions produced by the Agriculture, Forestry and Other Land Use (AFOLU) sector, the quantity of sugarcane, corn and coffee produced, as well as the cattle and swine breeding stock. In general, the results obtained reveal the importance of controlling the level of emissions generated, as there was a reduction in the production of all studied segments. Thus, considering emissions from AFOLU, it is concluded that all sectors chosen for the study will suffer losses in production if there is no control over future emissions, indicating the need for pro-environmental public policies for the agricultural sectors.

Key-words: SVAR, Emissions, Agricultural Production.

RESUMO

O presente artigo identificou quais seriam os impactos na quantidade produtiva de cinco grandes culturas agropecuários, caso houvesse crescimento nas emissões de GEE no Brasil. Metodologicamente, foi estruturado e operacionalizado um Modelo de Auto Regressão Vetorial Estrutural com dados entre os anos de 1970 e 2018. Foram utilizadas as seguintes informações: o nível de emissões produzidas pelo setor de Agricultura, Floresta e Outros Usos da Terra (AFOLU), a quantidade produzida de cana-de-açúcar, milho e café, bem como o plantel de gado e suínos. De forma geral, os resultados obtidos revelam a importância de se controlar o nível de emissões geradas, pois houve redução na produção de todas os segmentos estudados. Assim, considerando as emissões oriundas do AFOLU, conclui-se que todos os setores escolhidos para o estudo sofrerão perdas na produção caso não haja controle nas emissões futuras, indicando a necessidade de políticas públicas pró-ambientais para os setores agropecuários.

Palavras-chave: SVAR, Emissões, Produção Agropecuária.

1. INTRODUCTION

Brazilian agricultural production is considered one of the most important in the world (EMPRESA BRASILEIRA DE PESQUISA AGROPECUÁRIA – EMBRAPA, 2018; Food and Agriculture Organization of the United Nation – FAO, 2019). Its performance in recent decades has been excellent, with continuous growth in production, exports and added value. Among the reasons for the growth, scientific and technological progress stands out, with an emphasis on animal genetics

[1] Doutor em Economia Aplicada, UFV, attawan_zull@hotmail.com.

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and the development of new cultivars and varieties that are more productive and resistant to adverse environmental conditions (BROOKS, 2017).

For this reason, Brazil is expected to objectively contribute to future challenges involving food production and food security, combating climate change, population growth and urbanization (STRASSBURG *et al.,* 2014; SÁ *et al.,* 2017; EMBRAPA, 2018; FAO, 2019). According to Observatório do Clima (2014) the country will have sufficient productive performance to meet domestic demand and will still be able to export surpluses to meet external demand.

On the other hand, the country faces a great challenge: to maintain the good performance of agriculture combined with sustainability, especially with regard to its environmental dimension (BROOKS, 2017; COSTANZA *et al.,* 2017; EMBRAPA, 2018). It is likely that meeting the growing food demand will generate negative consequences for the environment, such as increased deforestation, compromised ecosystems and higher levels of pollution, with emphasis on greenhouse gas (GHG) emissions (PFAFF AND WALKER, 2010; EMBRAPA, 2018; FRANKLIN; PINDYCK, 2018; ROCHEDO *et al*., 2018; BOTELHO; SUELA, 2023).

According to data from the synthesis report published by the Sistema de Estimativas de Emissões e Remoções de Gases de Efeito estufa - SEEG (2019)[2], the country in 2018 was the seventh largest GHG emitter in the world, producing about 1.939 billion gross tons. The Agriculture, Forestry and Other Land Uses (AFOLU) sector was responsible for approximately 69% of these emissions (SEEG, 2019), in which a significant portion of these emissions emerged to face the global challenge food security (GODFRAY *et al*., 2010; SÁ *et al*., 2017; FERREIRA-PAIVA *et al*., 2022).

In this sense, it is possible to affirm that there is growing pressure around the world, for the intensification of production (COHN *et al.,* 2014; STRASSBURG *et al*., 2014; SÁ *et al*., 2017). In this way, this establishes eminent commitments to the growth of agriculture, which consist in avoiding the environmental degradation resulting from its rural activities[3]. According to Rockström *et al*. (2017), to achieve such purposes it is necessary that countries invest in the sustainable

[2]Synthesis report: Analysis of Brazilian greenhouse gas emissions and their implications for Brazil's targets (SEEG, 2019).
[3]Since of all economic activities, agriculture is, naturally, the most dependent on the climate and, consequently, the most sensitive to its changes, a fact that requires attention to future goals (SILVA *et al.,* 2018).

intensification of agriculture (ISA), which aims to ensure the production of more food and, at the same time, make the ecological footprint (BAZAN, 1997) sector, increasingly smaller.

SEEG (2019) and Suela et al. (2020) present in their respective researches that the production of grains, sugarcane and animal protein throughout Brazil stand out as some of the largest gross emitters of GHG originating from AFOLU. In order to represent such impact, it was decided to jointly analyze five major production modalities: corn, sugarcane, coffee, beef and pork production. The main purpose is to analyze the impact that these agricultural segments would suffer if GHG emissions throughout Brazil increased considerably.

The present work contributes to the theme by incorporating both theoretical and econometric analysis, analyzing the degrading power that GHG emissions would cause in five of the chosen large productive crops in Brazil. In this sense, this article aims to verify, through a systemic structural approach, the impacts caused by shocks on GHG emissions in some of the main agricultural segments in Brazil, as well as the response of the forecast error variance in GHG production. For this, the database used contains information on the production of the five crops and on GHG emissions generated by the sectors of AFOLU for the years 1970 to 2018, acquired from Instituto Brasileiro de Geografia e Estatística - IBGE (2020), Ipeadata (2020) and SEEG (2020).

2. METHODOLOGY

2.1 Econometric model

The VAR model, proposed by Sims (1980), is an atheoretical time series model in which the dependent variables are a function of their own lags and other variables. In its primitive form, called Structural VAR (SVAR), the model can be estimated based on economic theory by incorporating constraints in the matrix of contemporary relations using the Bernanke procedure, alternative to Cholesky's recursive triangular decomposition and estimates of the conventional VAR. The SVAR can be represented as:

$$Ay_t = \alpha + \theta_1 y_{t-1} + \ldots + \theta_p y_{t-p} + \varphi d_t + Be_t \,, \tag{1}$$

where A is the matrix of contemporary relations of order *kxk*; y_t, a vector of *kx1* stationary endogenous variables; y_{t-p}, a vector of *kx1* stationary lagged variables; $p_i = 1,2,\ldots,p$, the lag; α, an intercept *kx1* vector; $\theta_i, i = 1,2,...,p.$, *kxk* matrices of coefficients; B diagonal matrix *kxk*; e_t, a vector of *kx1* of orthogonal errors, where $E(e_t) = 0$ and $E(e_t e_s^{'}) = \sum_{Diagonal}$; and d_t, a vector of exogenous variables. The estimation of the model can be performed using the Ordinary Least Square method.

Multiplying both sides of the above equation by the inverse of the matrix of contemporary interactions coefficients (A^{-1}), we obtain the standard VAR, also called reduced or conventional:

$$y_t = \psi + \vartheta_1 y_{t-1} + \ldots + \vartheta_p y_{t-p} + \omega d_t + u_t, \tag{2}$$

where $AA^{-1} = I$, $\psi = A^{-1}\alpha$, $\vartheta_1 = A^{-1}\theta_1$, $\vartheta_p = A^{-1}\theta_p$, $\omega = A^{-1}\varphi$, and $Au_t = Be_t$.

The reparametrized version of a VAR model (p), in which the order p can be provided by indication criteria, such as Akaike (AIC) and Schwarz (SC), is given in terms of difference in form:

$$\Delta y_t = \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1} + \Pi y_{t-1} + \varphi d_t + u_t \tag{3}$$

wherein $\Gamma_i = -\sum_{j=i+1}^{p} \theta_j$ e $\Pi = \sum_{i=1}^{p} \theta_i - I = -(I_k - \sum_{i=1}^{p} \theta_i)$, and y_t is a vector of *k* variables; *p*, is the lag; Δ, the difference operator; $u_t \sim N(0, \sum)$; and d_t, a vector of exogenous variables.

This model assumes that the series are stationary. To obtain the order of integration of the variables, I(d), the Dickey-Fuller (DF) unit root test can be used, which tests the hypothesis of the existence of a unit root in the series. However, given the problem of auto-correlation of the residues, the most indicated root test is the Augmented Dickey-Fuller (ADF) unit root, in which it differs from the DF test by incorporating lags for the test equation in the test equation. Elimination of the residual autocorrelation problem. The ADF unit root test equation, in its complete form, with intercept and trend components, is represented by:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + \varepsilon_t \tag{4}$$

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where Δ is the difference operator of the variable under study, in the case y_t; β_1 and β_2, the intercept and trend parameters, respectively; δ, the parameter of the lagged variable; $\alpha_i \sum_{i=1}^{m} \Delta Y_{t-i}$, the term of lagged differences to avoid and remove problems of auto-correlations existing in the residuals, whose lags can be indicated by the statistical criteria of Akaike (AIC) and Schwarz (SC); and ε_t, the random error.

The ADF test is used to analyze the statistical significance of the parameter δ, estimated in equation (2), as follows:

$$\begin{aligned} H_0 &: \delta_0 = 0 \\ H_1 &: \delta_1 \neq 0 \end{aligned} \tag{5}$$

According to Enders (1995), if the tested null hypothesis is rejected, i.e., if the τ_{tau} statistic calculated is such that $|\tau| > |\tau_\tau|$, in absolute value greater than the statistic tabulated τ_τ in equation (2) - a given level of critical statistical significance (1%, 5% or 10%), it is concluded that the series does not have a unit root, being stationary.

However, if the null hypothesis is not rejected, that is, $|\tau| > |\tau_\tau|$, the statistical significance of the intercept and trend terms in the test equation (2) must be analyzed, since the unit root test is sensitive to the presence of these terms. For the test equation (2), with intercept and without trend, the tabled statistic becomes a τ_μ and for the equation without intercept and without trend, τ. Thus, if the null hypothesis is not rejected, one should not immediately accept the existence of a unit root in the series, and the test equation should be estimated following a logical sequence (ENDERS, 1995).

Once the hypothesis of the existence of a unit root in the series is confirmed, it must be differentiated and tested again for the presence of a root in the series in differences, following the previously presented sequence, performing d differentiations until the unit root test is rejected, and the order of integration of the series indicated by I(d).

Transforming the VAR model into a VMA (Moving Average Vector) and promoting the orthogonalization of the residuals and diagonalizing the variance-covariance matrix of the errors to verify the effect of the shock in only one variable on the system, one can obtain the Function Impulse

Response and the Forecast Error Variance Decomposition. In its compact form, the VMA is presented as:

$$y_t = \mu + \sum_{i=0}^{\infty} \phi_i \varepsilon_{t-i} \tag{6}$$

in which the coefficients of (Φ_i) are called the Impulse Response Function, observed from the shocks (ε_{it}) for the defined variables yt, measuring the impact on the variables generated by the respective shocks on the errors.

Using the previous equation to perform the forecast, the forecast error is expressed as a function of its own residuals:

$$y_{t+n} - E_t y_{t+n} = \sum_{i=0}^{n-1} \phi_i \varepsilon_{t+n-i} \tag{7}$$

where yt+1 – Etyt+n is the n-period ahead forecast error; being yt a vector formed by the endogenous variables xt and zt, focusing only on the series {xt}, the forecast n-period ahead error is represented as:

$$x_{t+n} - E_t x_{t+n} = \sum_{i=0}^{n-1} \phi_i \varepsilon_{x\,t+n-i} + \sum_{i=0}^{n-1} \phi_i \varepsilon_{z\,t+n-i} \tag{8}$$

Denoting the forecast error variance of xt+n by σy(n)2:

$$\sigma_y(n)^2 = E_t[(x_{t+n} - E_t x_{t+n})^2] \tag{9}$$

where σy(n)2 is a function of xt and zt, and the error variance can be decomposed in terms of the series {xt} and {zt}, obtaining the Forecast Error Variance Decomposition, in which σy(n)2 increases with the elevation of forecast horizon n, given that Φjk(i)2 > 0 (ENDERS, 1995).

2.2. Data source

For this study, six series were used with annual observations from 1970 to 2018, totaling a horizon of 49 years. Data sources were IBGE (2020), Ipeadata (2020) and SEEG (2020). *EMA* is the gross amount of GHG emitted by the sectors that make up the AFOLU, in tons; *EB* is the number of effective bovine; *PCDA* is the amount of sugarcane produced in tons; *PM* is the amount of corn produced in tons; *ESUI* is the number of swine; *PCF* is the amount of coffee produced in tons.

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The productive series were chosen according to Embrapa (2018), Suela et al., (2020) and Suela et al., (2021), who argue about the importance of focusing on these productive sectors when seeking to propose pro-environmental actions, as research in question point to the large-scale levels of GHG emitted by these crops, which make them likely targets in the fight against pollution from the larger rural areas.

3. RESULTS AND DISCUSSION

3.1 *Descriptive Statistics of the Variables Used in the Study*

Table 1 presents the descriptive statistics of the variables used in the study, referring to the period from 1970 to 2018.

Table 1: Descriptive statistics for the variables involved in the study, 1970 - 2018.

STATISTIC	*EMA*	*EB*	*PCDA*	*PM*	*ESUI*	*PCF*
UNIT	TONS	Nº OF CATTLE HEADS	TONS	TONS	Nº OF SWINE HEADS	TONS
AVERAGE	1172059795	157945433	357320921	37754526	36163374	2732395
MAXIMUM	3513393799	218190768	768594154	97910658	66374000	4405416
MINIMUM	189454503	92495364	79752936	13569401	29292182	751969
Nº OBSERVATIONS	49	49	49	49	49	49

Source: Search Result (2021).

3.2 *Stationarity analysis*

As emphasized, the first step in econometric analysis is to verify whether the variables involved in the study are stationary. For this, the Augmented Dickey-Fuller test was used. The results of the ADF test with the series are shown in Table 2[4].

As can be seen in Table 2, at the levels of 1%, 5% and 10%, the null hypothesis of a unit root cannot be rejected, suggesting, therefore, that the six series are stationary in level and that the series are integrated from order 0 (*I(0)*).

[4]Other unit root tests were done to confirm the ADF test, such as Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Dickey-Fuller GLS (DF-GLS); all provided the same result, that is, a unit root was found.

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Table 2: Result of the ADF unit root test for the EMA, EB, PC, PM, ESUI and PCF series in the period 1970-2018.

	ADF	
VARIABLES	In level	Result
EMA	-5.381	*I(0)*
EB	-4.334	*I(0)*
PCDA	-7.490	*I(0)*
PM	-6.680	*I(0)*
ESUI	-5.420	*I(0)*
PCF	-7.170	*I(0)*
Significance Level	Critical Values	
1%	-3.600	
5%	-2.938	
10%	-2.604	

Note: The Schwarz criterion was used to define the number of lags.
Source: Search result (2021).

Table 4 presents the result of the structural VAR model according to the specification described in (2)[5], remembering that the order of the variables in the estimated model are EMA, EB, PCDA, PM, ESUI and PCF. It is observed that of the 16 estimated coefficients, almost all were significant at 1%, except for C(10), which was significant at 10%.

Table 3: Lag selection criteria for estimating the VAR model.

Lag	LR	FPE	AIC	SC	HQ
0	NA	6.1e-06	-0,65815	-0,497562	-0,598287
1	371,3	3.2e-09*	-8,19809	-7,39513	-7,89875
2	19	4.4e-09	-7,91734*	-6,47201*	-7,37854*

Note: LR: Likelihood ratio. FPE Criterion. AIC: Akaike Criterion. SC: Schwarz Criterion. HQ: Hannan-Quinn.
Source: Search results (2021).

The next step is to determine the number of VAR lags. The maximum number of lags7 (so that many degrees of freedom would not be lost, given the reduced sample size) was 4. Table 3 highlights the lags chosen by each of the criteria (at 5% significance). As can be seen from the 4 statistics tested, 3 consider that the model with 2 lags would be the most suitable for analysis, therefore 2 lags are adopted for estimation.

Table 4 presents the result of the structural VAR model according to the specification described in (2)[6], remembering that the order of the variables in the estimated model are EMA, EB,

[5]The model was estimated using the EViews 10 software and the outputs are in the Appendix.
[6] $Au_t = Be_t$

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PCDA, PM, ESUI and PCF. It is observed that of the 16 estimated coefficients, almost all were significant at 1%, except for C(10), which was significant at 10%.

By observing the results in Table 4, the information can be understood as follows. The 10% increase in the EMA variable (GHG Emissions from AFOLU) implies a 0.097% reduction in the EB (effective Bovine), a 0.011% reduction in the PDCA (Sugar Cane Production), a reduction in the production of Corn (PM) by 0.38%, reduction of 0.007% in ESUI (effective Swine) and reduction of 0.0011% in Coffee production (PCF), contemporaneously. This set of results shows the importance of controlling GHG emissions produced by the sectors that make up AFOLU. The set of results obtained demonstrate the importance of reducing the GHG emissions produced, because by not controlling the level of emissions generated, the agricultural sectors can be negatively affected with the loss of productive capacity (COSTANZA *et al.*, 2017). The main consequence of the accumulation in emissions is the increase in atmospheric temperature, which brings with it several consequences such as the natural imbalance of water and excess solar radiation. Such consequences can cause a reduction in the production of crops, such as those used in the study.

Table 4: Results of the structural VAR model, with the order of the variables given as follows: EMA, PC, EB and PM.

MATRIX A					
1	0	0	0	0	0
C(1)	1	0	C(9)	0	0
C(2)	0	1	0	0	0
C(3)	C(6)	C(8)	1	0	0
C(4)	C(7)	0	C(10)	1	0
C(5)	0	0	0	0	1
MATRIX B					
C(11)	0	0	0	0	0
0	C(12)	0	0	0	0
0	0	C(13)	0	0	0
0	0	0	C(14)	0	0
0	0	0	0	C(15)	0
0	0	0	0	0	C(16)

	COEFFICIENT	STANDARD DEVIATION	STATISTICS Z	PROBABILITY
C(1)	0.009694	0.113332	-0.425299	0.0006
C(2)	0.001095	0.123965	-0.997135	0.0002
C(3)	0.037840	0.069240	0.982768	0.0052
C(4)	0.000683	0.157583	-1.038.429	0.0000
C(5)	0.000107	0.088092	-2.325.015	0.0003
C(6)	-0.851284	0.079797	0.543655	0.0046
C(7)	-0.188827	0.044587	0.382768	0.0100
C(8)	0.385120	0.896452	0.584738	0.0092
C(9)	-0.310577	0.051744	-0.844712	0.0021
C(10)	-0.055388	0.885556	-1.782.758	0.0705
C(11)	3.40E+08	31839.47	9.797.958	0.0000
C(12)	19740412	67182.76	9.797.958	0.0000
C(13)	20401496	58235.13	9.797.958	0.0000
C(14)	21133884	52168.29	9.797.958	0.0000
C(15)	1933376.	31836.47	9.797.958	0.0000
C(16)	658425.0	29556.43	9.797.958	0.0000

Source: Search Result (2021).

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Table 4 shows that the 10% increase in effective bovine (EB) simultaneously causes a 1.9% increase in ESUI and an 8.51% increase in PM. From the information provided by Sá *et al.* (2017) and EMBRAPA (2018), the increase in EB would simultaneously cause an increase in corn, soybean and sorghum crops, as they are the main sources of energy essential for the development and growth of this animal species. Thus, with the increase in EB, there would be a need to expand animal energy sources, which would lead to an increase in the supply of this series to meet the demand required by the segment. The results also indicate that the increase in the supply of corn would lead, at the same time, to the acquisition of new swine matrices. With the greater supply of food, the cost of producing new pigs would be positively affected, which would explain the growth in this sector.

It was also analyzed what would happen if there was a 10% increase in PDCA, contemporaneously. PM would be negatively affected by the drop in production by 3.9%. When verifying the 10% increase in PM, it was noted that there would be an increase in the production of ESUI by 0.56% and an increase of 3.1% in the number of head of cattle, the increase in swine and cattle matrices follows the logic of supply and demand, with the growth in the corn supply on the market, the pig and cattle production chains would be positively affected, as this grain directly influences the production of these animals as it is one of the main energy sources for the growth and development of these species . In this way, with the value of the serial reduced, the incentive to increase the number of matrices is greater, thus causing the growth of these segments (EMBRAPA, 2018).

3.3 *Matrix SVAR*

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0{,}0097 & 1 & 0 & -0{,}311 & 0 & 0 \\ 0{,}0011 & 0 & 1 & 0 & 0 & 0 \\ 0{,}038 & -0{,}85 & 0{,}39 & 1 & 0 & 0 \\ 0{,}0007 & -0{,}19 & 0 & -0{,}056 & 1 & 0 \\ 0.00011 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \times \begin{pmatrix} EMA \\ EB \\ PCDA \\ PM \\ ESUI \\ PCF \end{pmatrix} =$$

$$= \begin{cases} EMA \\ 0{,}0097EMA + EB - 0{,}311PM \\ 0.0011EMA + PCDA \\ 0.038EMA - 0.85EB + 0.39PCDA + PM \\ 0{,}0007EMA - 0.19EB - 0.056PM + ESUI \\ 0.00011EMA + PCF \end{cases} \rightarrow \begin{cases} EMA = TERMOS\ DEFASADOS\ (TD) \\ EB = -0.0097EMA + 0{,}311PM + TD \\ PCDA = -0.0011EMA + TD \\ PM = -0.038EMA + 0.85EB - 0{,}39PCDA + TD \\ ESUI = -0{,}0007EMA + 0.19EB + 0.056PM + TD \\ PCF = -0.00011EMA + TD \end{cases}$$

The variance decomposition is another method that seeks to analyze the influence of a variable on another (as). In this sense, this method originating from the SVAR itself was used to explain the

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participation of each variable in the variance of the residuals of the other. The result of the variance decomposition is shown in Table 5.

Table 5: Decomposition of the variance of the forecast error in the variation in GHG emissions.

YEAR	EMA	EB	PCDA	PM	ESUI	PCF
1	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	90.67127	5.057336	0.258794	2.158710	1.395414	0.458477
3	83.04580	7.240865	3.996938	3.124754	1.427777	1.163862
4	78.99296	7.277104	5.731473	3.011824	1.378603	3.608035
5	78.13054	7.200719	5.883366	3.299805	1.425527	4.060047
6	77.99508	7.312291	5.887327	3.297531	1.431169	4.076606
7	77.97409	7.311766	5.889621	3.316198	1.433409	4.074913
8	77.93147	7.313056	5.899047	3.318989	1.439311	4.098123
9	77.92929	7.313760	5.899295	3.319667	1.439925	4.098064
10	77.92439	7.318420	5.899499	3.319801	1.439832	4.098062
11	77.92404	7.318398	5.899525	3.319809	1.440061	4.098167
12	77.92175	7.318278	5.900275	3.319792	1.440144	4.099763
13	77.92172	7.318263	5.900280	3.319783	1.440154	4.099802
14	77.92159	7.318391	5.900271	3.319792	1.440156	4.099797
15	77.92155	7.318388	5.900275	3.319792	1.440156	4.099837

Source: Research data (2021).

As shown in Table 5, the main variable to explain the variance of the variation in GHG emissions is itself, however over time all the variables in the model gain importance to explain the variance of the error in forecasting the variation in emissions GHG. For example, in the 15th period 7.31% of the variance of the forecast error is due to the effective bovine (EB), and 5.90% due to the production of Sugarcane, the production of corn is responsible for explaining 3.31%, and Coffee production is responsible for 4.09%, the crop with the lowest participation in explaining the variance in the variation in emissions and the production of swine matrices with 1.44%, as previously mentioned, the variation in emissions is responsible for explain most of the emissions, for the case of this research, the portion that competes was around 77.9% of the variance.

4. CONCLUSION

This study aimed to verify contemporaneously what would be the impacts on the main Brazilian productive crops, if there were an increase in GHG emissions, in addition to analyzing the likely impacts on productive cultures, in a contemporary way, if there were growth in each of the variables of the model, as well as the variance response of the forecast error in GHG emissions. For this, it was estimated by the Structural VAR method.

It is noted that all the chosen variables showed a reduction in the quantity produced, in case there were shocks in the emitted quantities of GHG. In general, productive crops respond positively to increases in the productive quantity of other variables. It is possible to conclude from the impulse-response function that a shock of two standard deviations in the increase in EB is what generates greater volatility and longer time to dissipate in the 15-year horizon. Finally, it is also possible to conclude that the increase in EB and PDCA are mainly responsible for explaining the variance of the error in the production variation.

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