Modeling technology diffusion of beef cattle in Brazil using a cellular automata

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RESUMO

Introduzimos um modelo de autômato celular representando a difusão da intensificação do gado de corte considerando a preferencia do fazendeiro. Nos também analisamos as propriedades teóricas do modelo e a sensibilidade dos principais parâmetros. O modelo representa a dinâmica de adoção de dois sistemas de manejos, intensivo (ϕ) e extensivo(ξ). Foi calculado a probabilidade do estado mudar como uma função de proporção de vizinhos em cada estado e a preferencia relativa por ϕ ou ξ. O modelo inclui o efeito da inercia (I), isso é, a resistência (ou dificuldade) inerente do produtor de mudar o seu estado dado um pedaço de terra, e três tipos diferentes de comportamento de adoção (AB). O primeiro (AB_1) esta associado aos primeiros que adotam que são exclusivamente guiados pela sua percepção de vantagem a mudança tecnológica; o segundo (AB_2), esta relacionado com a aversão a riscos, por isso provável que a mudança de estado é voltado para os sistemas com maior frequência na vizinhança

(influenciadores), i.e “comportamento de manada” e o terceiro (AB_3) é o comportamento que considera o efeito interativo da percepção de vantagem e dos influenciadores.

Para fornecer informações para o uso e calibração, executamos uma análise de sensitiva dos parâmetros de velocidade de adoção, o estado de equilíbrio e padrões espaciais. A análise revelou que o nível de agregação espacial esta relacionado com os valores relativos do conjunto de parâmetros.

ABSTRACT

We introduce a cellular automata model representing the diffusion of technological intensification of beef cattle considering farmer’s preferences. We also analyze the theoretical properties of the model and the sensitivity of key parameters. The model represents the dynamics of adoption of two types of management systems, intensive (ϕ) and extensive (ξ). We compute the probability of state change as a function of the proportion of neighbors in each state and the relative preference for ϕ or ξ. The model includes the effect of inertia (I), that is, the inherent resistance (or difficulty) of a producer to change the state of a given plot of land, and three different types of adoption behaviors (AB). The first (AB_1) is associated to “early adopters” that are exclusively guided by their perception of advantages of technological change; the second (AB_2), is related to high risk aversion, so most probable change of state is towards the systems with the highest frequency in the neighborhood (influencers), i.e. “herd behavior”; and the third (AB_3) is a behavior that considers the interactive effect of advantage perception and influencers.

To give insights for use and calibration, we ran sensitivity analysis of parameter values of speed of adoption, equilibrium state, and spatial state patterns.. The analysis revealed the level of spatial aggregation is associated to the relative values of the parameters set.

INTRODUCTION

Brazil is a major global agricultural player and has an ambition to balance growing production with environmental costs (de Oliveira Silva et al. 2018). Particularly beef cattle production has long been linked the loss of biodiversity and greenhouse gas (GHG) emissions, mainly because of methane (CH_4) emitted by the around 200 million heads (M hd) via enteric fermentation process and associated natural conversion for grazing pastures. In the past, 1975 to 1996, beef cattle production was based on extensive grazing, characterized by low input management and low-quality pasture with limited carrying capacities. Along that period, increases in production were highly correlated with pasture expansion (Martha Jr 2012).

However, at least since 1996 the production pattern has changed and beef cattle has embarked on an intensification era, and production growth is now explained by gains in productivity of both pasture and animal performance. Animal growth rates are due to improved genetics through breeding and the use of on-pasture supplements and feedlot systems. Pasture productivity gains are due to better management, via pasture improvement/restoration by chemical and mechanical treatment in the soil. As opposed to extensive systems, these productivity measures characterize intensive systems. Despite Brazil has already embarked on an intensification era extensive cattle ranching, and underutilized pastures remain representative in many regions of the country, meaning current average stocking rates are far relatively low, around 1.1 head/ha (IBGE, 2015).

To increase beef cattle productivity, the government supports the adoption of intensification measures. Those include the restoration of degraded pasture (de Oliveira Silva et al. 2015, 2017; Negra et al. 2014). Research show that intensified system is more profitable and more sustainable, as GHG emissions per kg of beef is reduced (de Oliveira Silva et al. 2017; De Oliveira Silva et al. 2018, 2016). However, there are several barriers of technology adoption, including the lack of technical information and support, skilled labour, access to rural credit, land registration issues and a risk aversion by behaviour by famers (Strassburg et al. 2014). Optimization approaches usually assume a rational decision maker, e.g., adoption of intensification technology is a function of economic return and/or risk alone. These methods have been applied to understand economic return and environmental impacts of intensification of livestock systems in Brazil (Cohn et al. 2014) but they are not able to explore factors other than profit maximization inherent to the decision process of technology adoption. Thus, understanding the influence of geographical specificities, farmers preferences and networking on the adoption of intensification measures is essential to complement traditional approach of maximization of economic returns. Addressing the barriers of adoption and technology diffusion is essential to support governmental policies targeting reduction of deforestation via the sustainable intensification of livestock in Brazil (MOZZER et al 2011, 2015). Unfortunately, applying technology diffusion models to the intensification of livestock production in Brazil is a highly underexplored, most of the time is used with deforestation (KAIMOWITZ ,2008) or with agriculture (Gil et at 2015, 2016; CORTNER et at 2019). This work develops a spatially explicit model of technology diffusion using a cellular automata (CA) approach that introduces farmer's preferences in addition to the network effect. We use historical data to calibrate the model and apply it to explore the barriers and the intensification of beef cattle systems in Brazil.

METHODS

Cellular Automata modelling and implementation

A cellular automata (CA) is a discrete dynamical system, space, time, and the states of the system are discrete values. Each point in a regular spatial lattice, or cell is associated with a state within the a domain called alphabet. The states of the cells in the lattice are updated according to a local rule. That is, the state of a cell at a given time depends only on the previous of the cell and its neighbors.

A cellular automata is characterized by some fundamental properties**. The lattice of cells**, representing the structure or geometry of the grid of cells. The dimension of the lattice of cells can be one, two, or three dimensions in Euclidean space. **Discrete States,** a cell can assume only a finite number of possible states**. Local interactions,** a state of **a** cell can only be influenced by its neighbors**. Discrete dynamics**, every cell update at the same discrete time, according to a transition rule at the model.

In this paper, we use a two-dimensional lattice and the Moore-neighborhood (KRETZ, 2005), consisting of the central cell and the eight adjacent cells

We assume each cell is a plot of land which can assume three different states. The "inactive state" coded as "0" are cells not used for grazing, e.g. a mountain, a river, a city, cropland which are unavailable for state change. State "1" represents an extensive livestock plot; and state "2" represents an intensive livestock plot, where pastures are well managed, animals are supplemented and/or fedloted. The cells in the borders of the latice are assumed as inactives.

We use a transition function f to compute the probability of state change of a plot in time step t, (C_t) to the next one $C_{(t+1)}$:

$$C_{(t+1)} = f\big(C_t(i)\big|i \in N(r)\big), \tag{1}$$

Where $N(r)$ is the set of neighbor cells of the cell r,

Changing a plot from extensive to intensive state is a "big decision" which demands significant investments, more demanding management and long-term consequences for the individual and the land. For that reason, individuals facing changes in type of management tend to be reluctant to change both because of giving up a possibly acceptable current state and the fear of failure (i.e. low perception of control). To account for the trend of the farmer to remain in the current state, we used the consept of “inertia” for the transition rule. The transition rule is then given by:

$$f(N_\phi, E_\phi) = I_{min} + k\left(1 - e^{\left(-\lambda(\alpha * N_\phi + \beta * E_\phi + \gamma * N_\phi * E_\phi)\right)}\right) \tag{2}$$

$$\alpha + \beta + \gamma = 1 \tag{3}$$

$$k = \frac{I_{max} - I_{min}}{e^{-\lambda}} \tag{4}$$

Where, N_ϕ is the number of neighbors in the system ϕ $E_\phi$is the preference for the system ϕ, $I_{min}$is the minimal inertial probability; I_{max} is the maximum probability of keeping current state (1 is the default value); λ is a parameter used to calibrate the speed of convergence to the steady-state. The parameters $\alpha, \beta\ and\ \gamma$ (Eq. 3) are the associated weights of the neighborhood, preference and the crossproduct term, respectively. Thus the terms in the exponential represents the weight of each type of behavior in a given scenario.

In the case a cell has no neighbors in the same system, and the preference for that system is zero, $f(0,0) = I_{min}$. In the opporsite case, all the neighbors are in the same system and with maximum preference for the same system, $f(1,1) = I_{max}$. The parameter *a* (Eq. 4) is derived by combinging f(0,0) and f(1,1,).

Steady-state conditions

A deterministic cellular automata follows a pattern akin to the second law of thermodynamics: starting from a partially disordered state, the system evolves towards a state of equilibrium (TAATI , 2018) In our case, this happens when the flow of cells changing from state ϕ to ξ equals the flow of cells changing from ξ to ϕ. The flows are given by the number of cells in a given state multiplied by their probability of change; i .e.$1 - f(N_\phi, E_\phi)$. Therefore, we can find the equilibrium point through Equation 5.

$$N_\phi * \left(1 - f(N_\phi, E_\phi)\right) = N_\xi * \left(1 - f(N_\xi, E_\xi)\right) \tag{5}$$

$$N_\phi + N_\xi = 1 \tag{6}$$

$$E_\phi + E_\xi = 1 \tag{7}$$

Solving equation (5) analytically is impractible so we solve it numerically.

Evaluation of spatial aggregation

Spatial patterns are observed when a CA is simulated for an extended time (WOLFRAN, 1982), with different parameters. We analyse how each parameter affect the spatial dependence patterns through a semivariogram, which shows the variance from data for separated by specific distance between points (ISAAKS; SRIVASTAVA 1989, VIERIA et al. 1983, VIERIA 2002). After making the curve adjustment in the semivariogram, we calculate the degree of aggregation (gc), given by:

$$gc = \left(\frac{C_1}{C_0 + C_1}\right) * 100 \tag{8}$$

Where C_0 is the nugget of the function, C_1 is the semivariogram effect and $C_0 + C_1$ is the asymptotic value of the function. According to Zimback et al. (2001), $gc > 75\%$ indicate strong spatial dependence; $25\% \geq gc \geq 75\%$ moderate spatial dependence and $gc < 25\%$ weak spatial dependence.

Sensitivity analysis

We evaluate the sensitivity of model outputs to the parameters γ, α, β *and* λ in in a 50 years model runs. We assumed fixed arbitrary values for the preference for the intensive system in $E_\phi = 0.7$, and the preference for the extensive system in $E_\xi = 1 - E_\phi$. We also assumed $I_{max} = 1$ and $I_{min} = 0.8$. We also compared steady-state values simulated and calculated with the equation (5).

RESULTS

Model results

Figure 2 shows the comparison of proportion in different set of parameters. When β is maximum, the model converges slightly faster as the model becomes closer to deterministic behavior and have the highest value of intensive proportion. We noticed λ is related with the proportion in each system, so higher λ higher the difference between the proportion of the management system, furthermore, shows that bigger λ longer it takes to reach the equilibrium

Figure 1 - a) Proportion of intensive System b) Proportion of extensive System

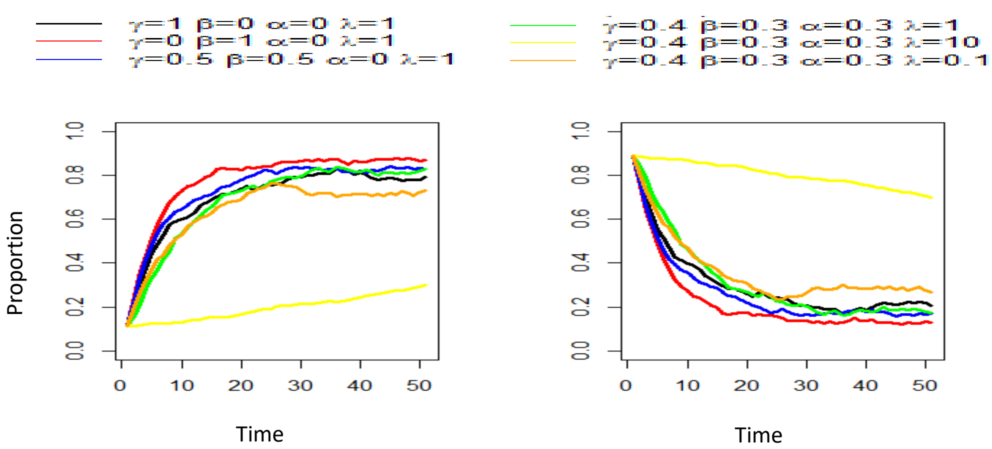


Figure 2 shows the dynamics of extensive and intensive management systems' adoption over time. The simulated value when reaches the equilibrium is approaching the calculated value, with this result we can use the equation (5) to calculate the value of equilibrium without doing the simulations. Also, equilibrium values agree with Figure 1 simulation, i.e., values around 0.2 and 0.8 for extensive an intensive. However, the smallest λ do not reaches equilibrium faster than the others.

Figure 2 - Simulation of -a)γ=1,β=0,α=0 e λ=1 b)γ=0,β=1,α=0 e λ=1 c)γ=0.5,β=0.5,α=0.0 e λ=1 d)γ=0.4,β=0.3,α=0.3 e λ=1 e)γ=0.4,β=0.3,α=0.3 e λ=3 f) e)γ=0.4,β=0.3,α=0.3 e λ=0.1

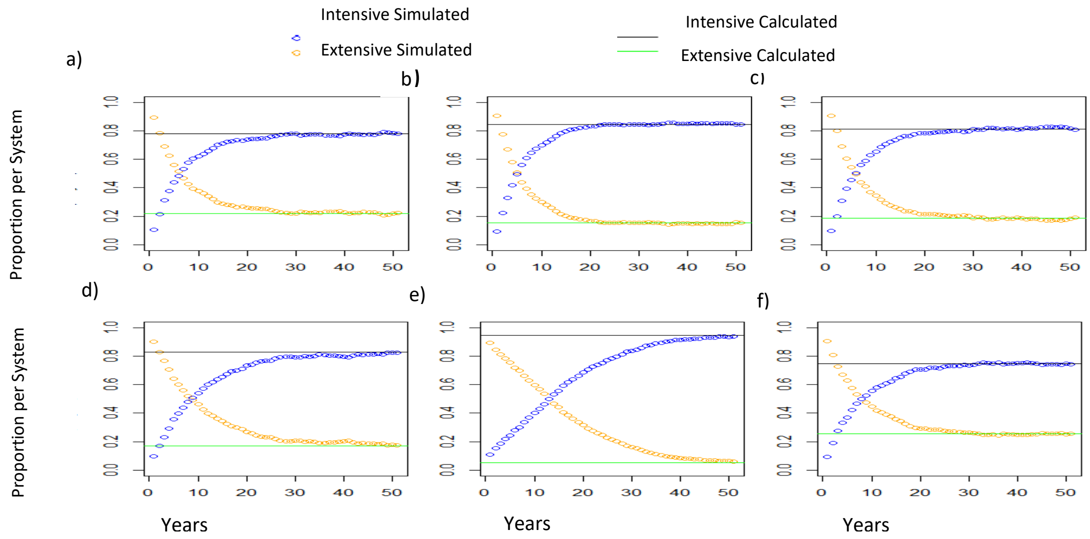
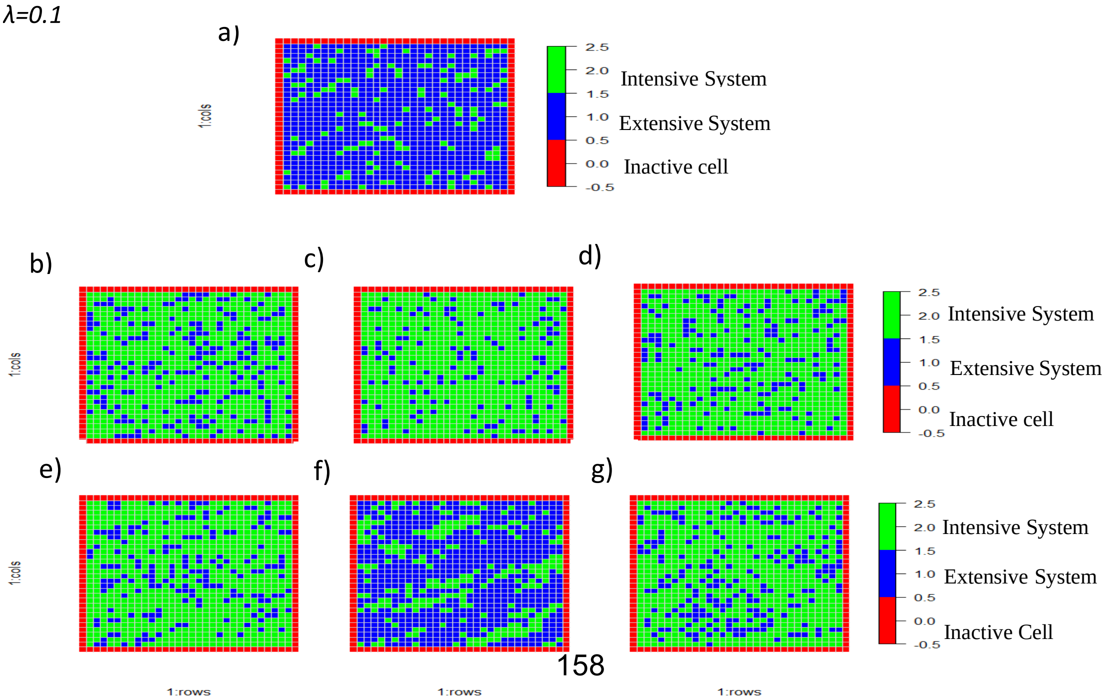


Figure 3 shows the spatial deposition of the plot of the land. We noticed that when β is high, the states are more randomly spread in space while a high α or γ tend to produce secure spatial aggregation as the influence of the neighborhood are taken into account in the automata. We can notice that λ is not related with spatial aggregation.

Figure 3– a) Initial Grid – Final Grid with the parameters b)γ=1,β=0,α=0 e λ=1 c)γ=0,β=1,α=0 e λ=1 d)γ=0.5,β=0.5,α=0.0 e λ=1 e)γ=0.4,β=0.3,α=0.3 e λ=1 f)γ=0.4,β=0.3,α=0.3 e λ=3 g))γ=0.4,β=0.3,α=0.3 e λ=0.1

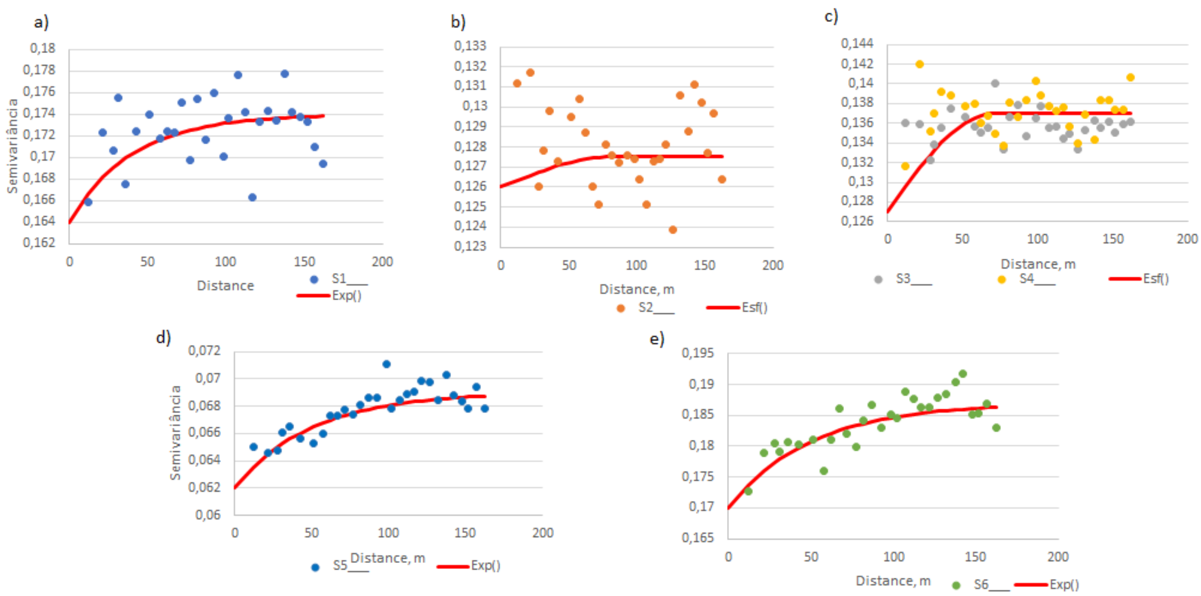


Geostatistics

The spatial aggregation differences shown in Figure 4 ware analyzed through the semivariogram technique for 6 different sets of parameters, $S1 = (\gamma = 1, \beta = 0, \alpha = 0 \text{ e } \lambda = 1)$, $S2 = (\gamma = 0, \beta = 1, \alpha = 0 \text{ e } \lambda = 1)$, $\text{S3} = (\gamma = 0.5, \beta = 0.5, \alpha = 0 \text{ e } \lambda = 1)$, $S4 = (\gamma = 0.4, \beta = 0.3, \alpha = 0.3 \text{ e } \lambda = 1)$, $S5 = (\gamma = 0.4, \beta = 0.3, \alpha = 0.3 \text{ e } \lambda = 10)$,$S6 = (\gamma = 0.4, \beta = 0.3, \alpha = 0.3 \text{ e } \lambda = 0.1)$. For $S1, S4$ *and* $S5$ the exponential curve presented best fit while for S2 and S3 the spherical curve was best. As the dataset for $S3$ *and* $S4$ were similar, we combined the two in only one regression was made for them.

With the semivariogram plotted and using the equation (11), we have the following levels of aggregation degree: $gc(S1) = 5.74$, $gc(S2) = 1.17$, $gc(S3\_S4) = 7.29$, $gc(S5) = 10.11$, $gc(S6) =$ 9.09, so $gc(S2)$ is the lowest value because β it will not carry any neighborhood influence, after that $gd(S1)$ do not have a high value because it is working only with γ that have some of the preference and neighborhood influence at the same time, besides this two value all the other stay close this happens when we added to the model some value to α.

Figure 4- a)Semivariogram S1 b)Semivariogram S2 c)Semivariogram S3 and S4 d)Semivariogram S5 e)Semivariogram S6



Conclusion

The cellular automata model presented herein contributes to the understanding of farmer behavior beyond profit maximization assumptions. By accounting for geographical proximity of influencers it is able to produce different patterns of spatial dependence, depending on the parameters set. The model can also be calibrated for speed of adoption. Future modeling work will focus on empirically calibrate the model to different regions of Brazil and on determining the economic drivers and psychological influencers of the behavior defined by the parameter values.

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