

A decision support system based on cellular automata to help the control of late blight in tomato cultures

Gizelle K. Vianna¹, Gustavo S. Oliveira², Gabriel V. Cunha^{3*}

1, 2, 3 – Universidade Federal Rural do Rio de Janeiro
Department of Mathematics

BR-465, Km 7, Seropédica, Brazil

¹gkupac@gmail.com, ²gustavo1071af@ufrj.br, ³gabrielvcunha@ufrj.br

Abstract. We designed and implemented a decision support system for small tomatoes producers that investigates ways to recognize the late blight disease from the analysis of digital images of tomatoes, using a pair of multilayer perceptron neural network. The networks outputs are used to calculate the damage level at each plant and to construct a situation map of a farm where a cellular automata simulates the outbreak evolution over the fields. The simulator can test different pesticides actions, helping in the decision on when to start the spraying and in the analysis of losses and gains of each choice of action.

1 Introduction

In Brazil, in 2015, the agribusiness corresponded to 21.46% of the Brazilian GDP, or more than US\$400.00 million [1, 2]. Particularly, the tomato (*Solanum lycopersicon*) crop occupies the seventh position in the rank of food plant tons produced per year, with more than 1.9 tons produced in 2014 [1, 3]. However, that plant is vulnerable to many diseases and it ranks the second position in pesticide consumption per planted area [4], and tomatoes require continuous monitoring from experts, which might be prohibitively expensive and time-consuming, especially for small producers.

The most common disease that affects tomato crops worldwide is the late blight, caused by *Phytophthora infestans*, a fungus that inhabits the soil and disseminates through spores. The disease could be visually recognized by the identification of dark brown lesions on leaves that vary from brown or gray to pale green, often situated at the edges of the leaves, that enlarge rapidly, developing into large brown necrotic areas [5, 6, 7]. It can spread quickly, specially under favorable climatic conditions consisting of a combination of relative humidity under 90% and temperature around 20°C (68°F). As a result, we have an epidemic that can lead to considerable losses in production [5, 8, 9].

Moreover, we are facing the emergence of resistant fungus variants, while a second generation of fungicides began to be used [10, 11, 12]. According to [13, 14, 15], with the aid of information technology for early detection of crop diseases, it was

* FAPERJ – Edital APQ1/2015, Processo nº 210.704/2016.

possible to delay the beginning of pesticides spraying to obtain an average reduction of 50% in total sprays, reaching rates of 80% reduction in some cases.

This paper presents a decision support system that generates simulations of spreading scenarios of contamination and tests alternatives for combating the disease, supported by meteorological data and a well-known prediction model of the late blight. This research is based on previous works [16, 17, 18] where we have measured the damage level at tomato plants by using digital images of their leaves and a neural network classifier that assigns, for each image, a status number among seven possible degrees of the scale from [6] that represents the health condition of tomato plants, as shown in Table 1.

Status	0	1	2	3	4	5	6
% of damage	0	0-3	3-12	12-22	22-40	40-76	≥ 77

Table 1: Status for each range of damage percentage [6].

We have used a combination of two ANN's to perform, for each pixel, its classification into one of three possible categories: healthy, injured or background. A JPEG image of a leaf, took in the open field, is processed into a text file that contains, for each pixel, its x and y coordinates, RGB values, and HSL values, linearly normalized. Each record is presented to both ANNs, already trained, where one ANN is trained to recognize green pixels and the other to recognize red pixels. A new schematic colored image is constructed, using the responses of the two ANNs, containing only green, red and black pixels. The damage level of each image is calculated based on the percentage of damage areas over the total number of leaf pixels, despising all background pixels.

2 The Decision Support System

The Integrated Pest Management Program of California University [19] enumerates several reputable prediction models of late blight propagation in tomato and potato crops. Among those, we have chosen the Hyre prediction model [20] that indicates that an initial outbreak of late blight will occur between 7 to 14 days after 10 consecutive favorable days. A favorable day, in turn, occurs after five consecutive days where the mean temperature stays between 7.0°C and 25.5°C (48°F and 78°F) and, at the same time, after 10 days with a total precipitation equal to, or higher than, 30 millimeters (1.2 inches).

1.1. The Forecasting Model

We have used historical data, obtained through the Brazilian National Institute of Meteorology [21], to calculate the mean of some meteorological variables in specific intervals of days, chosen by the system user during the simulation. We collected some meteorological data from the city of Paty do Alferes, one of the main tomato producer region in Brazil, from 01/01/1999 until 01/01/2015, which includes temperature, relative humidity, minimum temperature, maximum temperature and precipitation. The system user can also choose the size of the data window that will be used in the

historical average calculation, and it can be 5, 10 or 15 years, for all available variables. Those historical averages are used to estimate the meteorological variables, for each day of the period of simulation.

1.2. The Cellular Automata Model

A cellular automata (CA) was used to model the dynamics of late blight, defined in the two-dimensional domain, with Moore's neighborhood and a probabilistic transition function. The CA works over a matrix that represents a cultivated area of tomatoes where each cell corresponds to a plant that has a health condition value, or status, associated with it. The user defines the *wind direction* parameter, that controls the direction of the status changes. The status of any cell would only change if it can be reached by an infected cell in its neighborhood and if the wind direction allows this contact.

The next status of each cell $c(i,j)$, where i is the line and j is the column, depends on its current status, $E(c(i,j))$, and on the current status of all its neighbors, in a neighborhood of size 8. An infected cell could have its status worsened when there are infected cells in its neighbor, or improved, when a technique C for combating the disease is being used. Each neighbor can affect a cell $c(i,j)$ in a weighted way, according to the factors indicated by Hyre's model, shown in Table 2, which considered the number of outbreaks Qo , the number of favorable days Qf , and the current status E of cell $c(I, j)$. The combination of all changes would build the new status matrix.

		1	2	3	4	5	6
Qo > 1	Qf > = 10	0.1	0.8	1.4	1.6	1.8	2
	10 > Qf > = 7	0.1	0.5	1	1.1	1.2	1.4
Qo > 3	7 > Qf > = 5	0.2	0.4	0.6	0.7	0.8	0.9

Table 2: Rules for calculation of weight P.

We have tested two forms of combat and, according to the literature [22], the combat type 1, which uses Dimethimorph, could decrease the status of a cell by 30% of the current status. On the other hand, combat type 2, which uses Metalaxyl-M+Mancozeb, could decrease the status by 20%. Thus, when using a combat method, the CA dynamics can be summarized by (1).

$$E'(c(i, j)) = E(c(i, j)) + \sum_{n=1}^8 P(v_n(c(i, j))) - C * E(c(i, j)) \quad (1)$$

3 Results and Discussion

The simulation system is capable of mapping the streets and lines of a farm, where each tomato plant is placed in a matrix based on their real georeference information and the corresponding cell is painted with a different color that depends on the plant health status (Table 3). The resulting matrix thus conceptually represents a map of the

cultivated area being monitored by the system (Figure 1a). In the map, it is possible to select any cell and retrieve the corresponding sample information, including the original leaf image, the current health condition of the plant and the location of the plant in the field (Figure 1b).

Status	0	1	2	3	4	5	6
Cell color	Dark green	Green	Light green	Yellow	Orange	Dark Orange	Reddish orange

Table 3: Color correspondence of map cells for each possible status.

During the simulation, it is possible to visualize the spreading of the late blight in the conceptual map of the cultivated area and to analyze strategies to combat the disease (Figure 2). The simulation is interactive and simple, and the user can pause, resume or restart the simulation at any stage. It is also possible to stop the simulation at any time to choose a combat method for the disease. If a combat is tested during the simulation, a new dynamic could occur, reducing the status of tomatoes, depending on the contamination level of the field as a whole, the climatic factors, and the type of combat chosen. Figure 3 shows what happens when combat type 2 is used on the 12th day of simulation. Starting from the same situation of Figure 2a, it is possible to see that the losses could be minimized in the end of the 30th day of simulation.

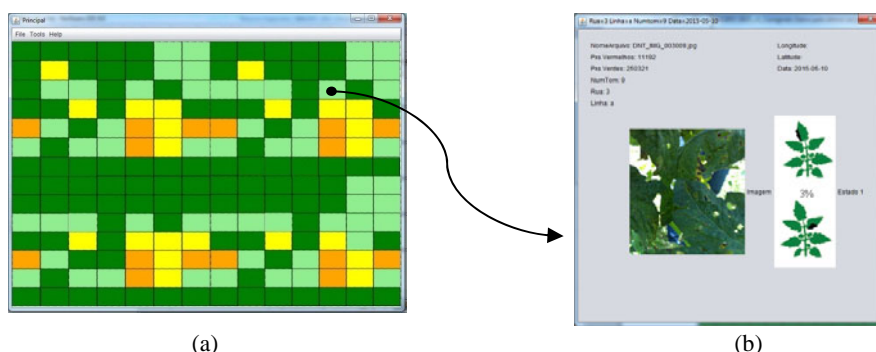


Fig. 1: (a) Conceptual map of a cultivated area of tomatoes from a monitored farm. (b) Details from a selected tomato on the map.

We are already working on a panel of statistics that will show the performance of the simulation, displaying the financial results obtained by chosen a specific combat strategy, and comparing the costs of using the pesticides against not using at all. We have modelled the dynamics of only two chemical fungicides to be available in this first version of our simulator because they are the most common in Brazil for tomato blight control. However, it is relatively simple to model new chemical control methods, and we are working on a tool that enables the user to do so.

We believe that this research is a suitable contribution to help small farmers in the early detection of late blight. The alternative we presented can accelerate the identification of the disease and help measuring the extension of the infestation. Plus, it can help small farmers to plan better the best time for spraying fungicides, protecting the environment while reducing the plantation costs.

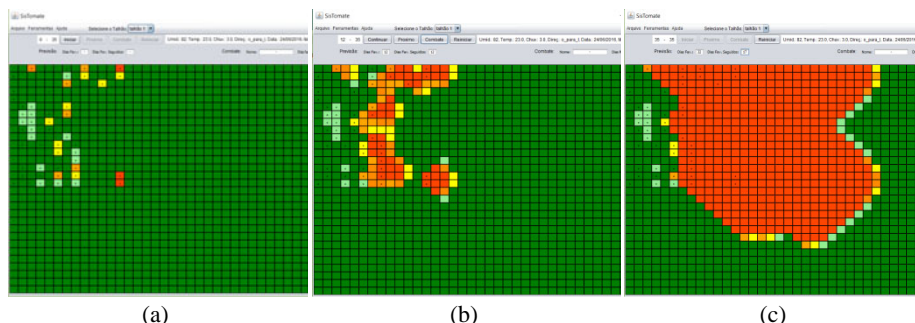


Fig. 2: A non-combat simulation starting at 06/24/2016, having wind direction from west to east and conducted during 35 iterations on a matrix with 1200 elements, where each cell represents one tomato plant. (a) At the beginning, before the simulation starts, with cells containing the original status of each plant, collected *in loco* (cells marked with an ‘*’ represents one photographed plant, while the others have their status all settled to 0=healy); (b) The map situation at iteration number 12, which means that the map represents the farm situation after 12 days from the initial day (c) The map situation at the 35th day, when the simulation ends.

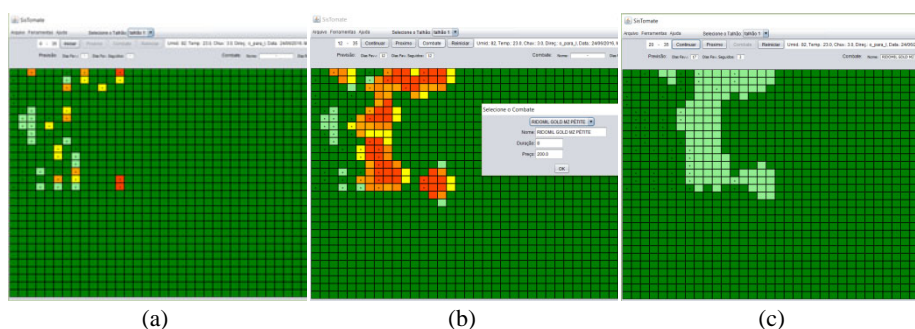


Fig. 3: A combat type 2 simulation starting at 06/24/2016, having wind direction from west to east and conducted during 35 iterations on a matrix with 1200 elements, where each cell represents one tomato plant. (a) On the 12th day of simulation, the combat type 2 was selected and the simulation was resumed; (b) The map situation at iteration number 35, when the simulation ends.

4 References

- [1] IBGE (Instituto Brasileiro de Geografia e Estatística). *Sistema IBGE de Recuperação Automática - SIDRA*, Retrieved from <http://www.sidra.ibge.gov.br/bda/agric/default.asp?z=t&o=11&i=P>, in October 18, 2016.
- [2] MAPA (Ministério da Agricultura Pecuária e Abastecimento), *Estatísticas e Dados Básicos de Economia Agrícola*, Retrieved from http://www.agricultura.gov.br/arq_editor/Pasta%20de%20Setembro%20-%202016.pdf, in October 10, 2016.
- [3] M. Rabelo, “Faeg participa do Congresso Brasileiro de Tomate Industrial”. Retrieved from: <http://sistemafaeg.com.br/noticias/10796-faeg-participa-do-congresso-brasileiro-de-tomate-industrial>, in May, 2015.

- [4] E. M. Neves, L. Rodrigues, M. Dayoub, and D. S. Dragone, "Bataticultura: dispêndios com defensivos agrícolas no quinquênio 1997-2001," *Batata Show*, vol. 6, pp. 22-23, 2003.
- [5] USDA (United States Department of Agriculture), *USABlight Project*, Retrieved from <https://usablight.org/node/29>, in October 4, 2016.
- [6] F.M. Correa, J.S.S. Bueno Filho, and M.G.F. Carmo, "Comparison of three diagrammatic keys for the quantification of late blight in tomato leaves," *Plant Pathology*, vol. 58, pp.:1128-1133,2009.
- [7] J.R. Macedo, C.L. Capeche, A. Melo da S., and S.B. Bhering, "Recomendações Técnicas para a Produção do Tomate Ecologicamente Cultivado," *Manejo do Solo - Circular Técnica*, vol. 33. Rio de Janeiro: Embrapa Solos, 2005.
- [8] E.S.G. Mizubuti, J.M.N. Maziero, L.A. Maffia, F. Haddad, and M.A Lima, "CGTE Program: Simulation, Epidemiology and Management of Late Blight," in *Global Initiative on Late Blight Conference*, Hamburg, Germany, 2002.
- [9] W.R. Stevenson, "An integrated program for managing potato late blight", *Plant Disease*, vol. 67, n.9, pp.:1047-1048, 1983.
- [10] A. Saxena, B.K. Sarma, and H.B. Singh, "Effect of Azoxystrobin Based Fungicides in Management of Chilli and Tomato Diseases," *Proced. National Academy of Sciences*, India:Springer, 2014.
- [11] C. Zhang, et al. "Fine mapping of the Ph-3 gene conferring resistance to late blight (*Phytophthora infestans*) in tomato," *Theor. Appl. Genet.*, vol. 126, Springer-Verlag, pp.:2643-2653, 2013.
- [12] D.H. Park, Y. Zhang, and B.S. Kim, "Improvement of resistance to late blight in hybrid tomato," *Hort. Environm. Biotechnol.*, vol. 55(2), Springer, pp.:120-124, 2014.
- [13] S. Sankaran, A. Mishraa, R. Ehsani, and C. Davis, "A review of advanced techniques for detecting plant diseases," *Computers and Electronics in Agriculture*, vol. 72, n.1, pp.:1-13, 2010.
- [14] A.K. Mahlein, E.-C. Oerke, U. Steiner, and H.-W. Dehne, "Recent advances in sensing plant diseases for precision crop protection," *European Journal of Plant Pathology*, vol. 133, n.1, pp.:197-209, 2012.
- [15] R. Bugiani, et al., "Monitoring airborne concentrations of sporangia of *Phytophthora infestans* in relation to tomato late blight in Emilia Romagna, Italy," *International Journal of Aerobiology*, vol. 11, , pp.:41-46, Elsevier Science, 1995.
- [16] G.K. Vianna and S.M.S. Cruz, "Análise inteligente de imagens digitais no monitoramento da requeima em tomateiros," *Anais do IX Congresso Brasileiro de Agroinformática*. Cuiabá, Brazil, 2013.
- [17] G.K. Vianna and S.M.S. Cruz, "Redes neurais artificiais aplicadas ao monitoramento da requeima em tomateiros," *Anais do X Encontro Nacional de Inteligência Artificial e Computacional (ENIAC)*, Fortaleza, Brazil, 2013.
- [18] D. Nunes, C. Werly, G.K. Vianna, and S.M.S. Cruz. "Early Discovery of Tomato Foliage Diseases Based on Data Provenance and Pattern Recognition," *5th International Provenance and Annotation Workshop (IPAW)*. Cologne, Germany, 2014.
- [19] UCIPM – Integrated Pest Management Program of California University, Retrieved from: <http://ipm.ucanr.edu/DISEASE/DATABASE/potatolateblight.html>, in June, 2016.
- [20] R.A. Hyre, "Progress in forecasting late blight of potato and tomato". *Plant Disease Reporter*, Illinois, vol. 38, n.4, pp.: 245-253, 1954.
- [21] INMET – Instituto Nacional de Meteorologia, Retrieved from: <http://www.inmet.gov.br/portal/>, in June 5th, 2016.
- [22] T.N.H. Rebouças, et al. "Potencialidade de Fungicida e Agente Biológico no Controle da Requeima do Tomateiro", *Horticultura Brasileira*, vol.32(01), 2014.