Revista Internacional de Investigación e Innovación Tecnológica

Página principal: www.riiit.com.mx

Simulation of fungal growth in papaya: an opportunity to enhance postharvest handling

Simulación del crecimiento fúngico en papaya: una oportunidad para mejorar el manejo postcosecha

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Technological innovation: Simulation of the growth of fruit spoilage fungi in postharvest.

Industrial Application Area: Application in agribusiness, in the management of the papaya supply chain.

Received: december 09th, 2020
Accepted: april 08th, 2021

Resumen

La papaya (*Carica papaya* L.) es un fruto climatérico que presenta una gran susceptibilidad al daño mecánico y a las pudriciones, causando grandes pérdidas económicas. La antracnosis causada por *Colletotrichum* es la más común de las enfermedades en la papaya, sin embargo, existen otros hongos que pueden causar deterioro. Con el fin de encontrar alternativas para el control de hongos en postcosecha de frutas, se han desarrollado métodos de micología predictiva. El uso de modelos matemáticos puede simular y predecir el comportamiento fúngico en función de las condiciones ambientales. Sin embargo, las simulaciones como herramienta para la toma de decisiones con el fin de asegurar la calidad de los frutos son escasas. El objetivo de este estudio fue simular la velocidad de crecimiento y el tiempo que tarda en aparecer la infección por cepas de *Colletotrichum gloeosporioides* y *Alternaria alternata* aislados de papaya en función de la temperatura. Se utilizaron cuatro cepas de *C. gloeosporioides* y dos cepas de *A. alternata* aisladas directamente de las pudriciones de la fruta. El crecimiento de los hongos se realizó en un medio natural realizado con pericarpio de papaya para evaluar sus tasas de crecimiento y fases lag. El modelo de Baranyi-Roberts fue utilizado para determinar la velocidad de crecimiento (μ_{max}) y la fase lag y la función

Solver (Microsoft Excel) fue usada para determinar el tiempo en que se hace visible el micelio (t_v) a partir del modelo de Baranyi-Roberts. El modelo cardinal con inflexión (CMI) fue utilizado para modelar t_v para *C. gloeosporioides* mientras que la función polinomial fue usada en *A. alternata*. Los modelos simulados fueron comparados con datos obtenidos del crecimiento de los hongos en frutos de papaya. Los modelos obtenidos proveen una percepción de la dinámica del crecimiento fúngico y es satisfactorio para describir el tiempo t_v comparado con los resultados obtenidos *in vivo*. Estos modelos pueden ser utilizados por transportistas con el propósito de establecer cuánto tiempo un producto fresco puede conservar su calidad antes de que las pudriciones aparezcan. Estos hallazgos pueden ser una herramienta muy útil en la toma de decisiones dentro de la cadena de suministro de la papaya.

Palabras clave: *Carica papaya*, micología predictiva, deterioro postcosecha, simulación del crecimiento, cadena de suministro.

Abstract

Papaya (*Carica papaya* L.) is a climacteric fruit with a high susceptibility to decay and mechanical damage, causing economic losses. Anthracnose caused by *Colletotrichum* species is the most common disease in papaya; however, many other fungi that cause damage. In order to find alternative methods to control postharvest fungi, predictive mycology methods have been developed. Mathematical models can simulate and predict fungal behavior as a function of environmental conditions. However, simulations as a tool for making decisions to assure fruit quality are scarce. This study's objective was to simulate the growth rate and the time to appearance of disease for *Colletotrichum gloeosporioides* and *Alternaria alternata* isolated from papaya as a function of temperature. Four *C. gloeosporioides* and two *A. alternata* isolates from decayed papaya were used. The isolates were cultured in a complex medium made with papaya pericarp to assess their growth rates and lag phases. The Baranyi-Roberts model was used to estimate the radial growth rates (μ_{max}) and Microsoft Excel's Solver feature was used to obtain the time for visible mycelium (t_v). The cardinal model with infletion (CMI) was used to model t_v for *C. gloeosporioides* whereas a polynomial function was used for *A. alternata*. The simulated models were compared with data obtained by growing the fungi on fresh papaya. The models obtained provide insight into the fungal growth dynamics and seem to be satisfactory for describing t_v compared to the data observed *in vivo*. Transporters could be use them to establish how much time a given crop can conserve its quality before decay begins. These findings could be a useful tool for making decisions in the papaya supply chain.

Keywords: *Carica papaya*, predictive mycology, postharvest decay, growth simulations, supply chain.

1. Introduction

Like other kind of fruit, papaya fruit (*Carica papaya* L) is an ecosystem that hosts different varieties of fungi (Droby & Wisniewski, 2018). Its high water content and low pH make this fruit more susceptible to fungal attacks (Marino et al., 2009). As a climacteric fruit, papaya has a short shelf life and high susceptibility to mechanical damage and disease that cause large economic losses. Quality control in handling, storage and transportation from the farm to the table is the most important issue for papaya and all kind of fruits in the fresh fruit industry (Sañudo-Barajas et al., 2009).

The postharvest disease of papaya becomes a problem when fruit start to ripen when the fruit has 25 % or more skin yellowing or more. Severity and incidence of disease increase after 4 weeks of storage at 10 °C, and chilling and mechanical injury can increase the development of postharvest disease (Ayón-Reyna et al., 2017). Anthracnose caused by *Colletotrichum gloeosporioides* is the most common postharvest disease of papaya throughout production areas (Zhou et al., 2014), although other species are also capable of causing decay. *Fusarium nivale, Botryodiploidia theobramae, Aspergillus* spp., *Alternaria alternata* and *Rhizopus stolonifer* have been reported frequently as a reoccurring disease in papaya storage in different countries (Helal et al., 2018).

Control of postharvest disease is generally based on application of fungicides due to their eradicative effects, low cost and easy application (Hernández-López et al., 2018). Nevertheless, the ongoing tendency to cut back on usage of synthetic fungicides and the emergence of fungal resistance has led to search non-chemical alternatives for postharvest fungal disease control (Bautista-Baños et al., 2013). Predictive mycology techniques have been developed in order to reduce economic losses and improve the quality and safety of fruit (Dantigny, 2016). Knowledge of fungal growth dynamics under different ambient conditions enables prediction of contamination starting or resumption and may be a decisive step in risk managing. This prediction is the objective of predictive mycology through mathematical models. It is based on the fact that fungi' response to the environmental factors is characterized in terms of identity and main growth-inducing factor, and reproducible for the microorganism in another similar environment. (Garcia et al., 2009). Several models have been reported to describe the growth of different microorganisms related to food safety and quality. The primary model shows how the microorganism changes over time, then it can be used to describe and fit for delay time, maximum specific growth rate, and microbial growth information. For example, Sandoval-Contreras et al. (2020) applied a predictive model for the effect of environmental conditions on *C. gloeosporioides* isolated from papaya. Sardella et al. (2018) simulated the growth kinetics of four postharvest fungal isolates from pear: *Penicillium expansum, A. alternata, Botrytis cinerea* and *R. stolonifer*. However, predictive models for fresh fruit are scarce, and these are much needed to improve the supply chain. The objective of this study was to assess the influence of temperature on mycelial growth rate and time to mycelial appearance for *A. alternata* and *C. gloeosporioides* isolated from papaya rots by predictive mathematical models and to evaluate the performance of the obtained models.

2. Methodology

Fungal strains. Two isolates of *A. alternata* (CpA-03 and CpA-04) and four isolates of *C. gloeosporioides* (CpC-01, CpC-02, CpC-03 and CpC-05), isolated from papaya rots and previously identified at molecular level, were used.

Culture media, inoculation, incubation conditions and growth assessment. The isolates were grown on PDA for up to 10 days at 25 °C. Spores suspension were prepared according to Iñiguez-Moreno et al. (2020)(Iñiguez-Moreno et al., 2020)(Iñiguez-Moreno et al., 2020) brief, spores were collected by flooding the surface with an aqueous solution of 0.05% Tween 80. Mycelium filaments were removed from the suspension by filtering with sterile medical tissue and suspensions were adjusted to 10^6 spores per mL using a hemocytometer. The study was carried out in vitro using papaya agar (PA) according to Sandoval-Contreras et

al. (2020) with 115 g of finely ground papaya pericarp and 16 g of agar per 1,000 mL. In triplicate, the papaya agar (PA) plates were inoculated centrally with 10 µl of the spore suspension and were sealed to prevent dehydration. Batches were incubated at different temperatures: 13, 18, 22, 25, 28, 30 and 35 °C for *A. alternata*, and 13, 16, 20, 25, 28, 30 and 35 °C for *C. gloeosporioides*. The water activity of papaya agar was measured at the beginning and at the end of the experiment for each treatment. It must be always near 1. The colonies were observed daily. Once the growth starts, the diameter of the colony was measured daily for up to 7 or 15 days. For data analysis, the diameter was converted to the radius (mm).

Data treatment. The Baranyi-Roberts primary model was used to fit the growth radius (mm) as a function of the time (d) (Baranyi & Roberts, 1994) using nonlinear regression of Centurion XV.II (Statgraphics, Warrenton, VA) with 95% confidence (Equations 1 and 2). The curve fitting procedure used Marquardt's algorithm and the obtained parameters were maximal growth rate (μ_{max}) and lag phase (λ).

$$R = R_0 + \mu A - \ln\{1 + \frac{[\exp(\mu_{max}A)-1]}{\exp(R_{max}-R_0)}\}$$

(Eq. 1)

$$A = t + \left(\frac{1}{\mu_{max}}\right)\ln[\exp(-\mu_{max}t) + \exp(-\mu_{max}\lambda) - \exp(-\mu_{max}t - \mu_{max}\lambda)]$$

(Eq. 2)

Where R_0 is the colony radius at time $t = 0$, R_{max} is the maximum colony radius in the plates, A is an integral variable running from 0 to t as a function of the curvature of the plot, λ (d) is the lag time, and t (d) is the time. The time t_v to develop visible mycelium of 2 mm of diameter at different temperatures was calculated using Excel's solver function (Microsoft, Redmond, WA) on the Baranyi-Roberts model.

The secondary cardinal model with infletion (CMI) developed by Rosso et al., (1993) was used to describe the effect of temperature on fungal growth rate (equation 3). The parameters μ_{max} at T temperature is calculated from cardinal values of temperatures (T_{min}, T_{opt} and, T_{max}), using the Marquardt's algorithm (95 % confidence).

$$\mu_{max} = \frac{\mu_{opt}(T-T_{max})(T-T_{min})^2}{(T_{opt}-T_{\min})\{(T_{opt}-T_{min})(T-T_{opt})-(T_{opt}-T_{max})(T_{opt}+T_{min}-2T)\}}$$

(Eq. 3)

The goodness of fit was evaluated by calculating the coefficient of determination R^2 and the root mean square errors (RMSE).

An alternative to describe the effect of temperature on time to develop visible mycelium (t_v), a polynomial function (equation 4) was used as a secondary model:

$$t_v = aT^2 + bT + c \qquad \textbf{(Eq. 4)}$$

Where t_v is the mycelium appearance time (d), T is the temperature (°C) and a, b and c are parameters to be calculated.

Validation. An external validation was performed on papaya fruit to evaluate the predictions of the models. Papaya fruits with commercial ripeness were disinfected (sodium hypochlorite 1 % v/v) for two minutes and rinsed with sterile distilled water. Suspensions of 10^6 spores per mL of each fungal isolates were prepared as previously described. Papaya fruits were then wounded with a 3 mm wide by 3 mm deep needle. Wounds were inoculated with 10 µL of spore suspension (one fruit per isolate, three wounds per fruit). The fruit were incubated at different temperatures inside the experiment in a saturated atmosphere (RH > 85 %). The

Baranyi-Roberts model was used to calculate the growth rate μ and lag phase after plotting the colony's radius against time. The time t_v was calculated using the Solver function (Excel) on the Baranyi-Roberts model. Finally, the obtained time of the mycelium appearance t_v on papaya fruit was compared with the corresponding t_v values estimated by the models *in vitro* using the bias (B_f) and the accuracy (A_f) factors (equations 5 and 6) (Ross, 1996).

$$B_f = 10^{[\Sigma \log(\frac{tv_{predicted}}{tv_{observed}})/n]} \quad \textbf{(Eq. 5)}$$

$$A_f = 10^{[\Sigma |\log(\frac{tv_{predicted}}{tv_{observed}})|/n]} \quad \textbf{(Eq. 6)}$$

3. Results

There were obtained the growth data consisting of the growth curves in triplicate of all isolates at different temperatures. In all cases no growth in PA was observed at 35 °C for any strain.

Primary model. The plotted curves obtained for all isolates were linear in shape with an initial lag time. No growth was observed at higher temperatures than 30 °C. The Baranyi-Roberts model was used to obtain the maximal radial growth rate μ_{max} and the lag time λ showing a good correlation ($R^2 > 0.95$; data not shown). The time t_v was calculated using Excel's Solver function on the Baranyi-Roberts model, inferring that the fungus's mycelium of is visible when it reaches two mm in diameter. Statistical analysis for μ_{max} and t_v (Tukey HSD test) showed two homogeneous groups for *C. gloeosporioides* isolates, and for *A. alternata* there were no significant differences between the strains ($P > 0.05$). Then, the sets of data were grouped as follow: the strains CpC-01 and CpC-05 formed the group CpC-g1; the strains CpC-02 and CpC-03 formed the group CpC-g2. The two strains of *A. alternata* formed the group CpA-g1. Tables 1 and 2 show the parameters obtained at each temperature assayed for the groups.

Table 1. Radial growth rate (μ)* (mm/d) and time for mycelium to become visible (t_v)* (d) as a function of temperature of *C. gloeosporioides* isolates using the Baranyi-Roberts models.

	C. gloeosporioides CpC-g1		*C. gloeosporioides* CpC-g2	
T(°C)	μ_{max} (mm/d)	t_v (d)	μ_{max} (mm/d)	t_v (d)
13	1.2±0.4	9.3±1.9	1.1±0.4	3.7±2.5
16	1.1±0.1	9.9±0.3	1.0±0.3	4.4±3.1
20	1.4±0.1	4.1±0.6	1.6 ±0.5	4.2±2.2
25	4.2±0.2	2.8±0.7	2.5±0.6	1.5±0.7
28	5.2±0.5	1.8±0.1	3.1±0.3	1.0±0.1
30	5.4±0.4	1.4±0.7	3.5±1.3	0.9±0.2
*35	-	-	-	-

*No growth was observed at this temperature.

Table 2. Radial growth rate (μ)* (mm/d) and time for the mycelium to become visible (t_v)* (d) as a function of temperature of *A. alternata* CpA-g1 using the Baranyi-Roberts models.

A. alternata CpA-g1		
T (°C)	μ_{max} (mm/d)	t_v (d)
13	1.7 ± 0.3	1.5 ± 0.4
18	2.8 ± 0.1	1.0 ± 0.04
22	3.0 ± 0.2	1.4 ± 0.2
25	4.3 ± 0.2	0.8 ± 0.3
28	4.0 ± 0.2	1.2 ± 0.4
30	3.6 ± 0.5	0.9 ± 0.4
*35	-	-

*No growth was observed at this temperature

Secondary Model. Rosso's cardinal model was used to evaluate the effect of temperature on μ_{max} for each group. Statistical analysis showed homoscedasticity of data and the CMI model provides a good fit. The parameters obtained are shown in Table 3. For the group CpC.g2 formed by the *C.*

gloeosporioides strains, T_{min} was negative indicating an under prediction of the model despite the goodness of fit. A good fit is considered with a $R^2 \geq 0.80$.

Table 3. Estimated coefficients for the growth of *A. alternata* and *C. gloeosporioides* isolated from papaya fruit on PA, fitted to the Rosso's model (equation 3).

	A. alternata	***C. gloeosporioides***	
Group	**CpA-g1**	**CpC-g1**	**CpC-g2**
μ_{opt} (mm/d)	3.9 ± 0.1	5.7 ± 1.3	3.1 ± 0.6
T_{max} (°C)	40.3 ± 2.1	30.2 ± 3.5	30.2 ± 2.6
T_{min} (°C)	12.1 ± 1.6	5.7 ± 2.3	-3.8 ± 4.8
T_{opt} (°C)	25.8 ± 0.8	29.6 ± 0.5	29.2 ± 1.5
R^2	0.80	0.92	0.80
RSME	0.2	0.34	0.2

The influence of temperature on μ_{max} is shown in figure 1 for all groups. The radial growth rate increases while temperature increases, reaching the optimal growth rate at optimum temperature. The lowest values for theoretical μ_{max} were reached at lower essayed temperature, while at upper temperatures variability was observed.

The effect of temperature on time t_v was estimated. There were negative correlations between t_v and T (CC =- 0.9, -0.8 and -0.5 for CpC-g1, CpC-g2 and CpA-g1 respectively), indicating that, as temperature increases, t_v is shorter. All strains appear early near the optimal temperature. The t_v obtained for CpC-g2 and CpA-g1 showed variability, being higher for CpA-g1, then, transformation of data (t_v for $1/t_v$) was done in order to stabilizing the variance. For the groups of *C. gloeosporioides* isolates, the polynomial function was the best choice for model due to their determination coefficient $R^2 > 0.78$ (Figure 2a and 2b). However, for the *A. alternata* it was not possible to fit the t_v data to any function despite the transformation of data. The Figure 2c shows only the obtained data with a general line of tendency and without equation.

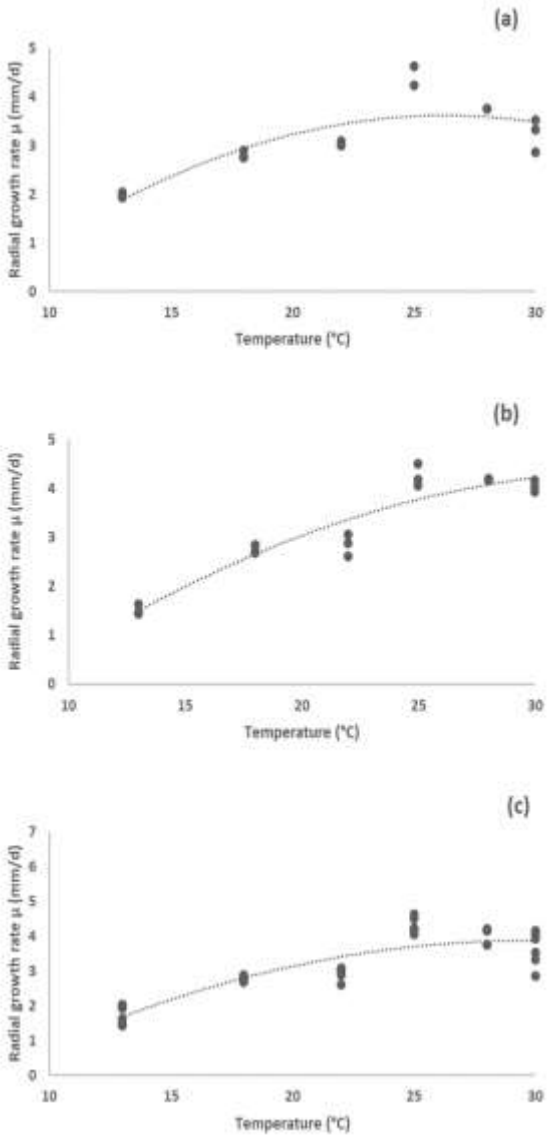

Figure 1. Radial growth rate (μ_{max}, mm/day) versus temperature (T, °C) for *C. gloeosporioides* and *A. alternata* isolated from papaya fruit. Points are observed data, and lines indicate the fit of the data to the CMI model a): group CpC-g1; b): group CpC-g2; c): group CpA-g1.

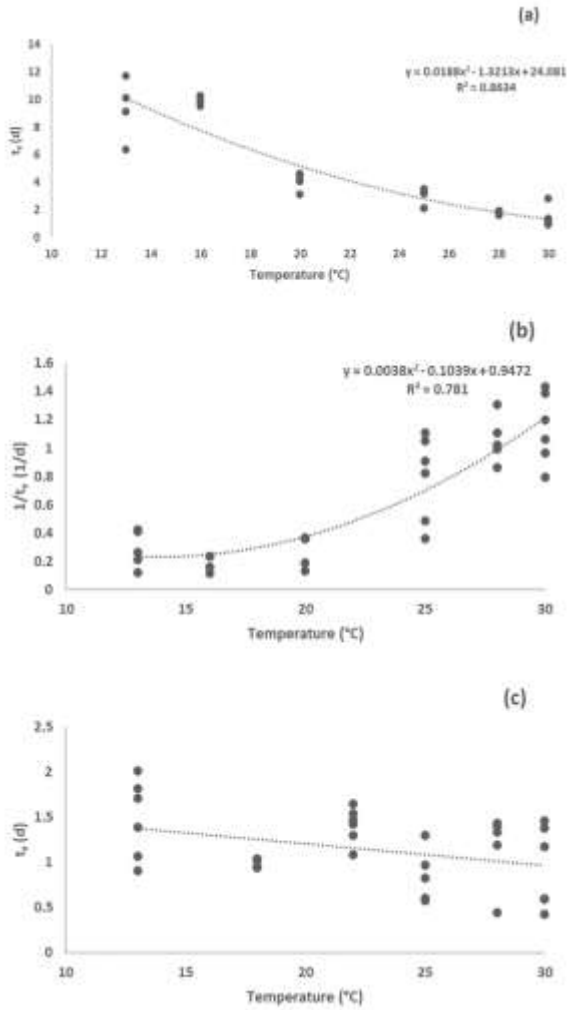

Figure 2. Time t_v as a function of temperature T for the isolates of papaya fruit. a): t_v against T for *C. gloeosporioides* CpC-g1 with no transformation of the data; b): 1/ t_v (transformed from t_v) against T for *C. gloeosporioides* CpC-g2 and c) t_v against T for *A. alternata* CA-g1. t_v indicates the time to become visible at naked eye of 2 mm of diameter. Points are observed data and lines indicate the fit data to the polynomial function, except for c), indicating the line of tendency.

Validation. Fresh papaya artificially infected and incubated at different temperatures were used to validate the models. To evaluate the perform of the model, the observed values were first plotted to calculate the time t_v. To evaluate numerically the prediction performance, B_f and A_f were calculated. The obtained values are shown in table 3.

Table 3. Bias (B_f) and accuracy factors (A_f) for each of the fungal predictive models.

Strain	*B_f	**A_f
C. gloeosporioides CpC-g1	1.05	1.71
C. gloeosporioides CpC-g2	0.82	1.91
A. alternata CA-g1.	1.87	1.87

*Bf < 1, under-prediction and Bf > 1, over-prediction. **Values close to 1 indicate small deviations.

According to the B_f obtained for the isolates, *A. alternata* showed over prediction but for *C. gloeosporioides* there were a good correlation between predicted and observed data. The A_f indicate a conservative correlation for all groups. In a perfect fit of the model, both the B_f and A_f factors would be 1.0.

4. Discussion

The infection of *C. gloeosporioides* can be in general divided into two steps: i) biotrophy when melanized appressoria are produced and penetrated host surface by mechanical forces and enzymatic degradation; and ii) necrotrophy when the hyphae are transformed and differentiated, thus destroying the host tissue (Wang et al., 2020). On the other hand, *A. alternata* is a fungus with high aggressiveness that penetrate membranes though appressoria germinated conidia, and the host-selective toxin (HST) is the responsible of the establishment of disease (Tsuge et al., 2016). Infection in a rot already indicates the presence of a pathogenic fungus, for these reasons the isolates used in this study were taken directly from the rots of fruit. The temperatures used in this work have been chosen to simulate the conditions that papaya fruits may encounter and may simulate the mismatches in temperatures during transport or in a non-certified papaya supply chain where conditions normally change. The fungal growth models have been developed to simulate the dynamics of growth for fungi to use it as a tool for making decisions at postharvest stage. It is important to note that fungi' germination time is an essential parameter of a model to estimate the

time remaining to fruit commercialization before a rot's appearance (Dutot et al., 2013). Mycelium becoming visible in fruit is one of most significant quality problems, because fruits with visible mycelium are discarded instead of being sold, causing economic losses (Sandoval-Contreras et al., 2017).

To our knowledge, a few models for fungal growth at postharvest stage have been developed. Belbahi et al. (2016) applied the CMI model on growth of *A. alternata* isolated from dates, finding the maximum and optimum temperature for growth at 39 and 26.1 °C respectively, similar value to our results, but the minimum temperature for growth was lower (1.6 °C). They found too a higher μ_{opt} than our research (12.1 mm/d). Using the CMI model, Sardella et al (2018) found 24, -4 and 35 °C for optimum, minimum, and maximum temperature for *A. alternata* isolated from pear and a μ_{opt} of 12.5 mm/d, showing discrepancy. The difference to our results may be due to de difference on the food matrix or pH level (Rychlik et al., 2014). They used agar with dates or pears, whereas we used papaya agar. Optimal temperature for growth of *A. alternata* have been reported between 25 – 35 °C, whereas at 37 °C there was no growth (Pose et al., 2009). Temperatures for *C. gloeosporioides* have been reported in a wide range. In general, it requires 25-28 °C temperature, pH 5.8-6.5 for better growth (Sharma & Kulshrestha, 2015). Previous studies in our laboratory showed an optimal temperature between 27.9 and 31.3 °C for the growth of *C. gloeosporioides* and a μ_{max} between 2.8 and 5.8 mm/d (Sandoval-Contreras et al., 2020). The under prediction of T_{min} of the model for the CpC-g2 group indicates that the fungus may grow after a longer time, beyond the period covered by the experiment (Sandoval-Contreras et al., 2017). Variability intraspecies exist in fungi that may be the cause of the wide range of values in the same way that has been reported. Studies on *A. carbonarius* at suboptimal environment conditions showed great variability on growth rate and ochratoxin production in a large number of isolates from different origin (Garcia et al., 2010). When spores are stressed, for example, if an inhibitory substance exist, variability can be observed. The rate of germination of *Penicillium corylophilum* in different concentrations of red cabbage seed extract, was affected by the extract concentration (Dagnas et al., 2015).

Papaya management is a complex process that implies an appropriate stage of maturity of fruit (green to ¼ yellow color), selection and protective treatment in packinghouse. Transportation temperature must remain at 12 – 13 °C to maintain their quality (Bautista-Baños et al., 2013). If these data were extrapolated to our results, it can be inferred that at these temperatures, *A. alternata* would grow in 2 – 3 days and *C. gloeosporioides* in 4 – 6 days, the maximum time on which papaya is free of rots. Papaya ripens slowly at 10 – 13 °C because is a climacteric fruit. If a mismatch in temperature transportation occurs, is time to react and make a decision in order to control the temperature, hence, avoid the infections (Zhou et al., 2014).

Our results showed that at temperatures between 25 – 30 °C all isolates grow faster than at extremes conditions. This is a useful information in the supply chain planning and logistic when the handling of papaya's handling is not made at optimal conditions. It is well known that good manufacturing practices (GMPs) are followed for papaya slated for export, but usually not on papaya for the domestic market. Out of the papaya production for national consumption, a high percentage lacks appropriate cold-storage and transportation. Papaya is packed in cartons to the distribution center, which increases their susceptibility to damage or infections (Bautista-Baños et al., 2013). The models

applied in this research could be used as we state previously.

Regarding the performance of the models, B_f indicates their structural deviation: whether the observed data are above or below the line of equivalence (Baert et al., 2007). A $B_f > 1$ indicates that fungi grows faster than the predicted by the model. *C. gloeosporioides* has a good prediction, contrary, *A. alternata* grows slower than the model. The B_f is not a value of accuracy because under and overestimations tend to cancel out. For these reasons, the A_f was performed to calculate how close are predictions to observations. The $A_f > 1$ indicates less accuracy (Ross, 1996). When differences exist between predictions model and real growth of fungi on the fruit, it would be probably be due to external factors or the fruit itself (Baert et al., 2007; Sandoval-Contreras et al., 2017). The differences may also be due to measurement error. An independent single measurement of growth will deviate from predictions by 20 %, and deviations are divided in environmental variability, experimental variability and the model error (Baranyi et al., 2014). An under or overestimation after the analysis of B_f and A_f, like a disagreement between predictions and single observations of growth may occur by different kinds of errors: a structural error, when variability is affected by the experimental or environmental conditions, or a model error which increases as the number of factors and studied region expands. Despite under or overestimations, an average like this is enough to represent the analysis. It can give us ideas for structure of the model to be fitted (Baranyi et al., 1999).

5. Conclusions

This work was one of the first approximation for modeling fungal growth at the postharvest stage and represents a good approximation to know the fungal performance at certain conditions. Although the information that exists regarding the development of fungal growth models is old, this is still valid because over time they have been shown to have the best performance (Garcia et al., 2009). Fungal growth models can help predict their behavior as a function of environmental factors. Then, they give useful information to manage the supply chain. Usage of these findings in the postharvest practices would help to decision-making to prevent economical losses due to decay of papaya fruit. That might be useful for the small-scale producer, which account for approximately 80% of papaya producers in Mexico, and exporters if they had problems with bin temperature or relative humidity during the distribution's steps.

6. Acknowledgements

We thank Acoyani Garrido Sandoval for editing the English language in this article, and the Mexican National Council of Science and Technology for the postdoctoral scholarship to T. Sandoval-Contreras (2018-000005-01NACV-00374).

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