ISSN 1392-3196
Žemdirbystė=Agriculture, vol. 98, No. 2 (2011), p. 195–204
UDK 632.937.14:578.76:631.8

The mathematical approach to the effect of potassium bicarbonate on mycelial growth of *Sclerotinia sclerotiorum* and *Rhizoctonia solani in vitro*

Ismail ERPER[1], Muharrem TURKKAN[2], Mehmet Serhat ODABAS[3]

[1]Ondokuz Mayis University
Samsun, Turkey
E-mail: ismailer@omu.edu.tr

[2]Ordu University
Ordu, Turkey

[3]Ondokuz Mayis University
Bafra Vocational School
Bafra, Samsun, Turkey

Abstract

In this study, we evaluated the effect of time (days of mycelial growth) and different doses of potassium bicarbonate ($KHCO_3$) on mycelial growth of *Sclerotinia sclerotiorum* and *Rhizoctonia solani* by multi regression analysis. All equations produced for mycelial growth of *S. sclerotiorum* and *R. solani* were derived as affected by doses and times. As a result of ANOVA and multi-regression analysis, it was found that there was close relationship between actual and predicted mycelial growth of *S. sclerotiorum* and *R. solani*. The produced prediction models in the present study are MGS = (a) − (b x dose) + (c x time), where MGS is mycelial growth of *S. sclerotiorum* and MGR = (a) + (b x dose) + (c x time), where MGR is mycelial growth of *R. solani*, a, b and c are coefficients. R^2 values were 0.81 for *S. sclerotiorum* and 0.75 for *R. solani*, standard errors were found to be significant at the $p < 0.001$ significance level.

Key words: modeling, growth rate, soilborne pathogens, $KHCO_3$.

Introduction

The soil borne fungi, agents of root rot and damping off diseases, cause important economic losses on various crops that often result in the death of plants every year. *Sclerotinia sclerotiorum* (Lib.) de Bary is an aggressive and destructive fungal pathogen that causes root rot and wilting on various host plants (Bolton et al., 2006), and is known to attack over 480 species of host plants worldwide in many different soil types and environmental conditions (Boland, 1990; Dillard, Cobb, 1995). The fungus survives in soil as sclerotia, which are hardened structures of fungal mycelium (Ben-Yephet et al., 1993) and a viable source of inoculum for long periods under unfavorable conditions (Wu, Subbarao, 2006; Bae, Knudsen, 2007). *Rhizoctonia solani* Kühn AG 4 is the major pathogen among anastomosis group (AG) worldwide, causing damping-off, stem rot and root rot on bean (*Phaseolus vulgaris* L.) (Sneh et al., 1991). AG 4 has been divided into AG 4 HG-I, AG 4 HG-II and AG 4 HG-III subgroups. Especially among *R. solani* anastomosis groups, AG 4 and AG 4 HG-I subgroups are the major fungal pathogens in bean plant growing areas in Black Sea Region in Turkey (Erper et al., 2003; Cebi, 2009; Erper et al., 2011).

Control of soil borne pathogens with chemicals is difficult because of their ecological behavior, their extremely broad host range and the high survival rate of resistant forms such as sclerotia under different environmental conditions (Yangui et al., 2008). In recent years, public demands to reduce pesticide use, stimulated by greater awareness of environmental and health issues as well as the development of fungicide resistant strains of pathogens, have created the need to find alternatives to pesticides. Natural substances such as bicarbonates

and their salts may be used to achieve this aim. The main advantages of using bicarbonates compared with fungicides include their relatively low mammalian toxicity, a broad spectrum of modes of action and relatively low cost (Olivier et al., 1998). They also have wide-spectrum antimicrobial properties. They have been shown to be effective growth inhibitors of some soil borne fungal pathogens (Punja, Grogan, 1982; Ricker, Punja, 1991; Arslan et al., 2009; Ordonez et al., 2009).

Developmental models are commonly explored using computational or simulation techniques (Odabas et al., 2009). The simulation software may be general-purpose, intended to capture a variety of developmental processes depending on the input files, or special-purpose, intended to capture a specific phenomenon. Input data range from a few parameters in models capturing a fundamental mechanism to thousands of measurements calibrated descriptive models of specific plants (species or individuals). Standard numerical outputs (i.e. numbers or plots) may be complemented by computer-generated images and animations (Prusinkiewicz, 2004). Most of the researchers have investigations focused on plant developmental periods from seed sowing to reproductive stages and from reproductive stages to harvest (Ellis et al., 1990). Environmental conditions affect the dry matter production rate, rooting percentage and the rooting degree of the plants. Different physiological processes occur in different periods of plant growth stage (Pearson et al., 1993; Cirak et al., 2005; Cirak et al., 2007; Odabas et al., 2005).

There are applied models relevant to epidemiological analyses of some soil borne pathogens. Quantifying the relationships and effects of pathogen, plant, and environmental factors on disease development by means of quantitative models can help in the design and efficient use of management strategies for soil borne pathogens (Wijetunga, Baker, 1979; Clarkson et al., 2004; Navas-Cortés et al., 2007). Clarkson et al. (2004) evaluated the feasibility of developing a prediction model for the carpogenic germination of *S. sclerotiorum* sclerotia in the field based on their response to temperature and soil water potential. Yang et al. (1990) investigated the effect of free moisture and plant growth stage on focus expansion of soybean aerial blight caused by *R. solani.* Simple linear regressions of the disease variables on days after inoculation showed increases in slopes as free moisture increased. In this study, models to predict the development of each disease variable were developed. Additionally, Navas-Cortés et al. (2007) quantified the combined effects of biotic (a range of virulence, inoculum density, and cultivar susceptibility) and abiotic (soil temperature) factors on development of *Fusarium* wilt in chickpea. They modeled the combined effects of soil temperature and inoculum density of *Foc*-0 and *Foc*-5 on disease developed in chickpea cvs. P-2245 and PV-61 differing in susceptibility to those races, using quantitative nonlinear models. Disease development over time in the temperature range of 10 to 30°C and inoculum densities between 6 and 8.000 chlamydospores g^{-1} of soil were described by the Weibull function. At optimum soil temperature, maximum disease intensity developed with *Foc*-5 and *Foc*-0 at 6 and 50 chlamydospores g^{-1} of soil respectively, in cv. P-2245, and with *Foc*-5 at 1.000 chlamydospores g^{-1} of soil in cv. PV- 61.

To our knowledge, there is not much study on mathematical modeling for mycelial growth of *S. sclerotiorum* and *R. solani* AG 4 HG-I. The objective of this study was to develop a model for estimating the mycelial growth of *S. sclerotiorum* and *R. solani* AG 4 HG-I *in vitro* exposure to increased doses of potassium bicarbonate ($KHCO_3$) at different times by multi linear regression.

Materials and methods

Fungal culture. Isolates of *S. sclerotiorum* Ss-5 and *R. solani* AG 4 HG-I M-62 used in the study were originally isolated from bean plants in bean growing area in Black Sea Region of Turkey, which was provided by Dr. Melike Cebi (Biology Department, Faculty of Arts and Science, Ondokuz Mayis University, Samsun, Turkey). Fungal cultures of *S. sclerotiorum* Ss-5 and *R. solani* AG 4 HG-I M-62 were maintained on potato dextrose agar (PDA: Oxoid). The PDA slants were stored at 4ºC and served as stock cultures for further use.

Assessment of mycelial growth. This study was conducted in the Mycology Laboratory of the Plant Protection Department of Faculty of Agriculture, Ondokuz Mayis University in 2010. Petri dishes PDA were prepared by adding different potassium bicarbonate ($KHCO_3$; Carlo Erba Reagenti (Milan, Italy) concentrations on the following basis: 0, 2, 4, 6, 8, 10, 25, 50, 75 and 100 mM for *S. sclerotiorum*. The pH of each $KHCO_3$ concentration was 6.0, 7.0, 7.1, 7.2, 7.3, 7.4, 8.0, 8.1, 8.1, and 8.2, respectively. Alike, different potassium bicarbonate concentrations (dose) on the following basis: 0, 10, 25, 50, 75, 100, 150, 200, 500, or 750 mM were added to PDA medium for *R. solani* AG 4 HG-I. The pH of each $KHCO_3$ concentration was 6.0, 7.4, 8.0, 8.1, 8.1, 8.2, 8.2, 8.3, 8.4, and 8.4, respectively. The medium was dispensed aseptically into 9 cm diameter Petri plates. A mycelial disc (5 mm diameter) taken from 7-day-old cultures that was grown on PDA, was placed in the centre of each potas-

sium bicarbonate-amended PDA for both fungi. The plates were then sealed with parafilm and incubated at 25ºC, for 6 days. Colony diameters were measured at two perpendicular points daily (Ordonez et al., 2009). All experiments were repeated twice.

Experimental design and data analyses. All experiments were conducted using completely randomized designs that included ten treatments with three replications. Analysis of variance was implemented using the program *Minitab* (version 12, "Minitab", USA) and Duncan at 0.05 significance level was used to compare treatment means.

Model construction. Regression problems start with a collection of potential predictors. Some of these are height or weight of an object. Other predictors can be categorical, like colour of flowers. These predictors can be useful in multiple regression analysis. Multiple regression analysis of the data obtained from *in vitro* study was performed for mycelial growth of *S. sclerotiorum* and *R. solani*. The general purpose of multiple regression is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable.

Given a data set $\{y_i, x_{i1}, \cdots, x_{ip}\}_{i=1}^{n}$ of n statistical units, a linear regression model assumes that the relationship between the dependent variable y_i and the p-vector of regressor's x_i is linear. This relationship is modelled through a so-called "disturbance term" ε_i – an unobserved random variable that adds noise to the linear relationship between the dependent variable and regressors. Thus the model takes form

$$y_i = \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i = x_i'\beta + \varepsilon_i, \; i = 1, \cdots, n,$$

where $'$ denotes the transpose, so that $x_i'\beta$ is the inner product between vectors x_i and β. Often these n equations are stacked together and written in vector form as $y = X\beta + \varepsilon$, where

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, x = \begin{pmatrix} x_1' \\ x_2' \\ \vdots \\ x_n' \end{pmatrix} = \begin{pmatrix} x_{11} \cdots x_{1p} \\ x_{21} \cdots x_{2p} \\ \vdots \ddots \vdots \\ x_{n1} \cdots x_{np} \end{pmatrix}, \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

Some remarks on terminology and general use:

y_i is called the *regressand*, *endogenous variable*, *response variable*, *measured variable*, or *dependent variable*. The decision as to which variable in a data set is modelled as the dependent variable and which are modelled as the independent variables may be based on a presumption that the value of one of the variables is caused by, or directly influenced by the other variables. Alternatively, there may be an operational reason to model one of the variables in terms of the others, in which case there need be no presumption of causality. x_i are called *regressors*, *exogenous variables*, *explanatory variables*, *covariates*, *input variables*, *predictor variables*, or *independent variables*. Usually a constant is included as one of the regressors. For example we can take $x_{i1} = 1$ for $i = 1, \cdots, n$. The corresponding element of β is called the *intercept*. Many statistical inference procedures for linear models require an intercept to be present, so it is often included even if theoretical considerations suggest that its value should be zero. Sometimes one of the regressors can be a non-linear function of another regressor or of the data, as in polynomial regression. The model remains linear as long as it is linear in the parameter vector β. The regressors x_i may be viewed either as random variables, which we simply observe, or they can be considered as predetermined fixed values which we can choose. Both interpretations may be appropriate in different cases, and they generally lead to the same estimation procedures; however different approaches to asymptotic analysis are used in these two situations. β is a p-dimensional *parameter vector*. Its elements are also called *effects*, or *regression coefficients*. Statistical estimation and inference in linear regression focuses on β. ε_i is called the *error term*, *disturbance term*, or *noise*. This variable captures all other factors which influence the dependent variable y_i other than the regressors x_i. The relationship between the error term and the regressors, for example whether they are correlated is a crucial step in formulating a linear regression model, as it will determine the method to use for estimation (Weisberg, 2005). A search for the best model to predict the mycelial growth was conducted with various subsets of the independent variables, namely, dose (mM) and time. The best estimating equation for the mycelial growth of *S. sclerotiorum* was determined with the R-program and formulized as MGS = (a) − (b x dose) + (c x time), where MG is mycelial growth of *S. sclerotiorum* and MGR = (a) + (b x dose) + (c x time), where MGR is mycelial growth of *R. solani*, a, b and c are coefficients of the produced equation (Tables 1 and 2). Multiple regression analysis was carried out until the least sum of square (R^2) was obtained. 3-D graphics were performed by *Slidewrite* program.

Results and discussion

Two experiments were performed for mathematical modeling for mycelial growth of *S. sclerotiorum* and *R. solani*.

Mycelial growth of Sclerotinia sclerotiorum. The mycelial growth of *S. sclerotiorum* started growing after 24 h. But, its growth signifi-

cantly reduced with the increasing concentrations of $KHCO_3$. At 48 h, *S. sclerotiorum* nearly covered the Petri dishes at 0 and 2 mM concentrations of bicarbonate, while it covered the Petri dishes after 48 h at 4 to 8 mM bicarbonate concentrations. Also, mycelial growth of the fungus was inhibited especially at concentrations greater than 25 mM. At 144 h, *S. sclerotiorum* completely covered the Petri dishes at all concentrations lower than 75 mM. However, the fungus did not show growth when exposed to 100 mM bicarbonate (Fig. 1).

As a result of the analysis, the effects of doses and times on mycelial growth of *S. sclerotiorum* have been found significant and an equation has been formed.

According to the regression statistics which is about the mycelial growth of *S. sclerotiorum*, it is observed that R^2 is 0.81. ANOVA significance F value has shown the validity of the model. As this value is below 1% in this study, the result of analysis has a significance of 1%. Following the determination of the importance level, mathematical equation has been obtained by using coefficients and corresponding independent x variable (MGS) and dependent *y* variables (dose and time).

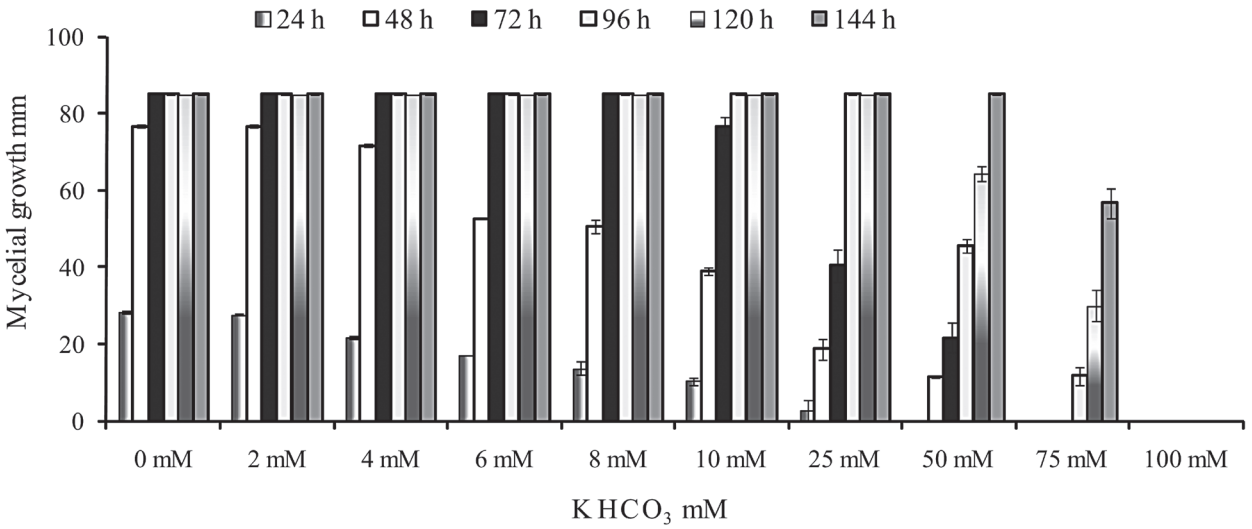

Figure 1. Mycelial growth of *Sclerotinia sclerotiorum* on Petri dishes exposure to increasing concentrations of potassium bicarbonate ($KHCO_3$) at different hours

Mathematical model which was developed by multi regression analysis, for mycelial growth of *S. sclerotiorum* has been formed as a + (b x dose) + (c x time). In this formula a, b and c symbolizes the coefficient obtained as a result of multi regression analysis. By taking into consideration the coefficient in the regression statistics, mycelial growth model of *S. sclerotiorum* has been formed:

mycelial growth (MGS) = (3.3069) − (0.0744 x dose) + (1.1547 x time),

standard error (SE) = 0.278*** $3.43E^{-3}$ *** 0.0669 ***,

regression coefficient (R^2) = 0.81.

The relation between the mycelial growth of *S. sclerotiorum* corresponding to the real values and the approximate mycelial growth of *S. sclerotiorum* obtained from mathematical equation has been shown in Figure 2.

The other points represent the mycelial growth of *S. sclerotiorum* obtained from the model. R^2, also known as the *coefficient of determination* is commonly used statistics to evaluate model fit. When the variability of the residual values around the regression line relative to the overall variability is small, the predictions from the regression equation are good. The regression line expresses the best prediction of the dependent variable (*y*), given the independent variables (*x*). However, nature is rarely perfectly predictable, and usually there is substantial variation of the observed points around the fitted regression line. The closer these values are to reality, the higher R^2 value of the mathematical model. In this study R^2 value obtained (0.81) shows that a model with 81% close to the reality has been formed. The effects of doses and times on mycelial growth of *S. sclerotiorum* are shown in Figure 3.

Mathematical equation has been benefited while showing this change caused by doses and times on the mycelial growth of *S. sclerotiorum*. In this graphic (Fig. 3) mesh part shows the change in the mycelial growth throughout *S. sclerotiorum* with times and doses of $KHCO_3$. It is drawn with the

help of mathematical equation obtained and *Slitewrite* graphic program. The most important feature of this program is to draw 3 dimension graphic by using not only the values entered but also the mathematical equation obtained. Figure 3 shows that the mycelial growth of *S. sclerotiorum* decreases and increases when the doses of potassium bicarbonate decrease and increase.

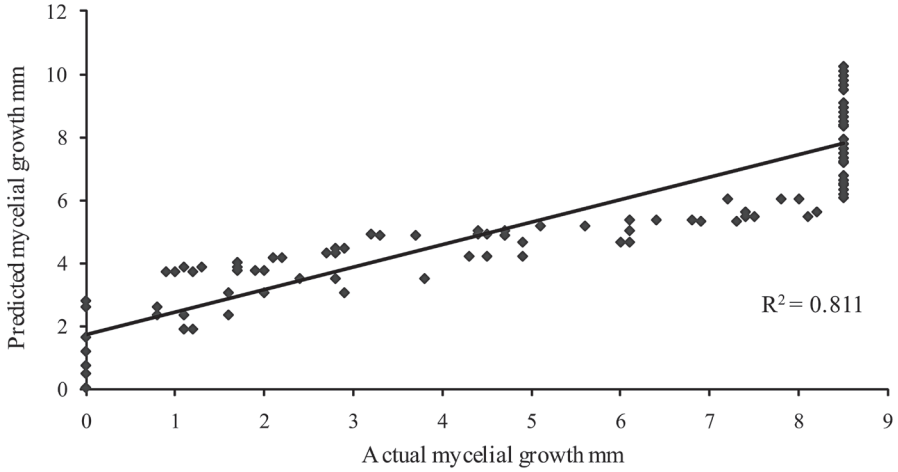

Figure 2. Relationship between actual and predicted the mycelial growth of *Sclerotinia sclerotiorum*

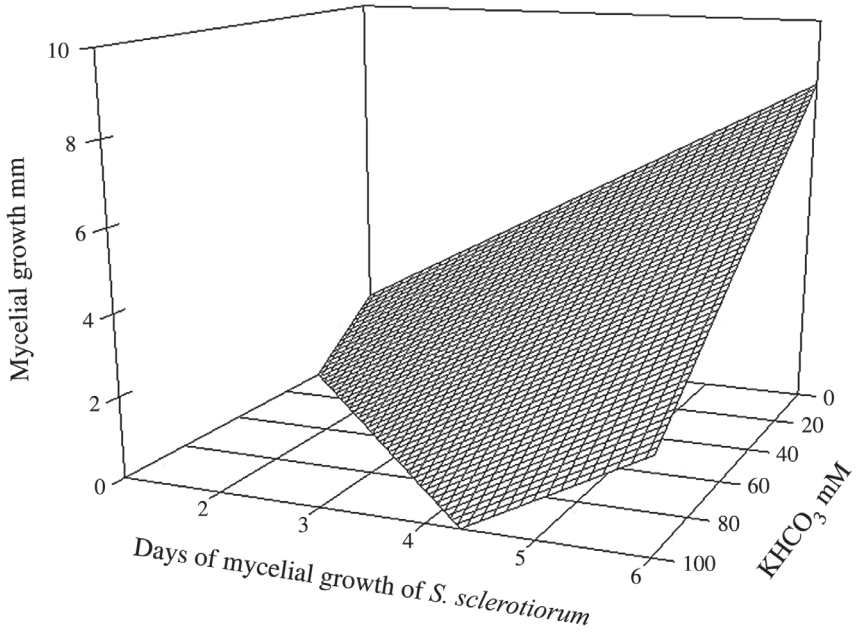

Figure 3. Mycelial growth of *Sclerotinia sclerotiorum* on Petri dishes exposure to increasing concentrations of potassium bicarbonate ($KHCO_3$) on different times (days of mycelial growth of *S. sclerotiorum*)

Mycelial growth of Rhizoctonia solani. Potassium bicarbonate used in the study significantly ($P < 0.05$) inhibited the growth of *R. solani*. The isolate started growing at 24 h, but the increasing concentrations of $KHCO_3$ significantly ($P < 0.05$) reduced its growth (Fig. 4), especially at concentrations greater than 100 mM. In addition, no mycelial growth was observed at a concentration 750 mM of $KHCO_3$.

As a result of the analysis, the effects of doses and times on mycelial growth of *R. solani* have been found significant and an equation has been formed.

With regard to the regression statistics belonging to the mycelial growth, it is observed that R^2 is 0.75. ANOVA significance F value has shown the validity of the model in other words whether or not the model can be formed. As this value is below 1% in this study, the result of analysis has a significance of 1%. Following the determination of the importance level, mathematical equation has been obtained by using co-efficients and corresponding independent x variable (MG) and dependent y variables (dose and time).

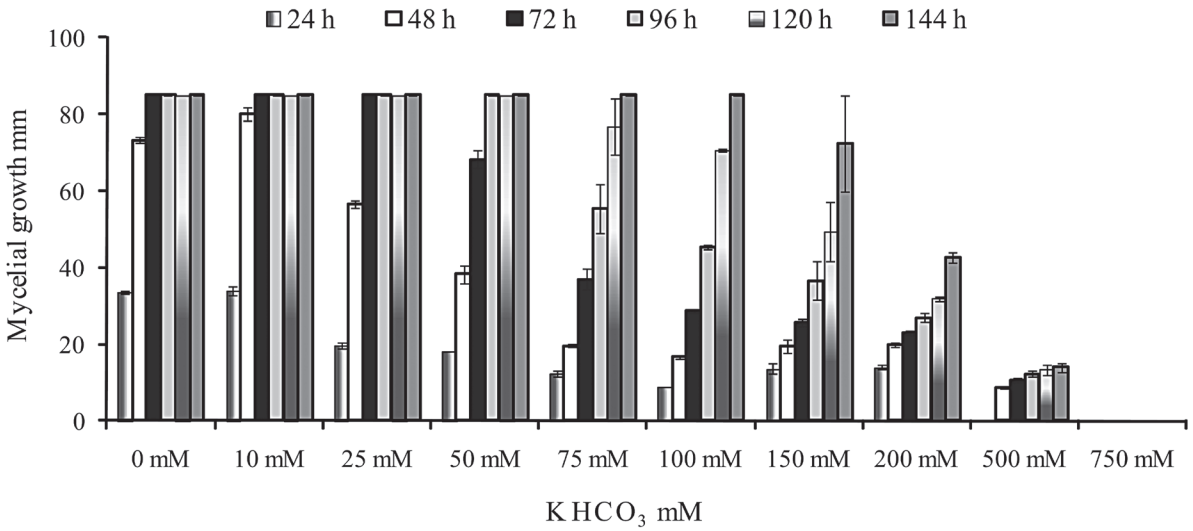

Figure 4. Mycelial growth of *Rhizoctonia solani* on Petri dishes exposure to increasing concentrations of potassium bicarbonate ($KHCO_3$) at different hours

Mathematical model for mycelial growth has been formed as a + (b x dose) + (c x time). In this formula a, b and c symbolizes the coefficient obtained as a result of multi regression analysis. By taking into consideration the coefficient in the regression statistics, mycelial growth model of *R. solani* has been formed:

mycelial growth (MGR) = (3.0399) + (−0.00981 x dose) + (0.9256 x time),

standard error (SE) = 0.302*** $5.26E^{-4}$ *** 0.0734 ***,

regression coefficient (R^2) = 0.75.

The relation between the mycelial growth of *R. solani* corresponding to the real values and the approximate mycelial growth of it obtained from mathematical equation is shown in Figure 5.

The other points represent the mycelial growth obtained from the model. The closer these values are to reality, the higher R^2 value of the mathematical model. In this study, R^2 value obtained (0.75) shows that a model with 75% close to the reality has been formed.

The effects of doses and times on mycelial growth of *R. solani* are shown in Figure 6. Mathematical equation has been benefited while showing this change caused by doses and times on the mycelial growth of *R. solani*. The regression line expresses the best prediction of the dependent variable (*y*), given the independent variables (*x*). However, nature is rarely perfectly predictable, and usually there is substantial variation of the observed points around the fitted regression line (as in the scatterplot shown earlier). In this graphic (Fig. 6) mesh part shows the change in the mycelial growth throughout *R. solani* with times and doses of $KHCO_3$. It is drawn with the help of mathematical equation obtained and *Slite-*

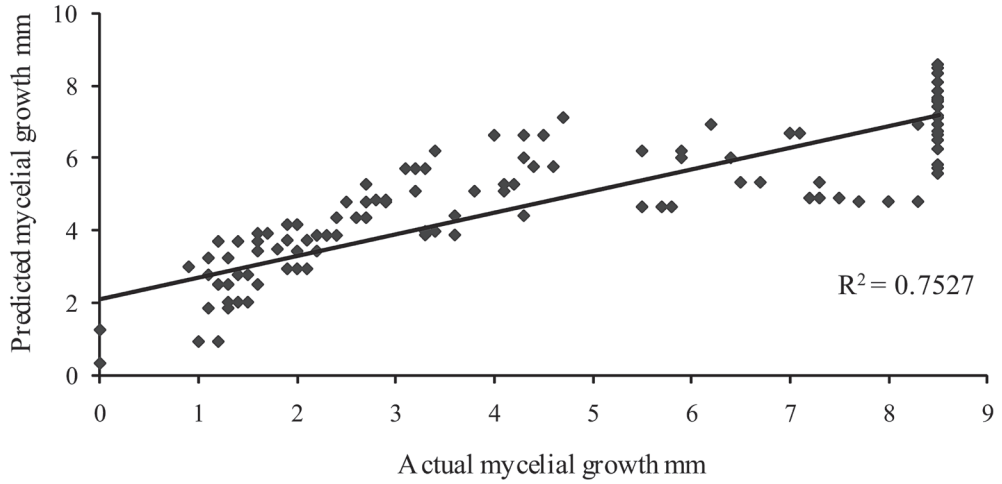

Figure 5. Relationship between actual and predicted the mycelial growth of *Rhizoctonia solani*

write graphic program. The most important feature of this program is to draw 3 dimension graphic by using not only the values entered but also the mathematical equation obtained. Figure 6 shows that the mycelial growth of *R. solani* increases as time's raises. In contrast, when the doses increase mycelial growth decreases.

Modeling of the epidemiology of some soilborne pathogens and pre-and-post-harvest pathogens was determined in the previous studies (Cuppers et al., 1997; McMeekin et al., 2002; Sautour et al., 2002; Clarkson et al., 2004; Lahlali et al., 2007; Judet-Correia et al., 2010). Clarkson et al. (2004) investigated the feasibility of developing a forecasting system for carpogenic germination of *S. sclerotiorum* sclerotia in the laboratory by determining key relationships among temperature, soil water potential, and carpogenic germination for sclerotia of two *S. sclerotiorum* isolates. As a result, it was determined that temperature showed a significant effect on both the rate of germination of sclerotia and the final number germinated. However, rate of germination related to temperature according to a probit model was correlated positively with temperature and final number of sclerotia germinated. In addition, quantifying the relationships and effects of pathogen, plant, and environmental factors on disease development by means of quantitative models could be of help in the design and efficient use of management strategies for root rot, wilt or damping-off disease caused by soil borne fungal pathogens. Navas-Cortés et al. (2007) examined the combined effects of biotic and abiotic factors on development of *Fusarium* wilt in chickpea. They modelled the combined effects of soil temperature and inoculum density of *Foc*-0 and *Foc*-5 on disease developed in chickpea cvs. P-2245 and PV-61 differing in susceptibility to those races, using quantitative nonlinear models.

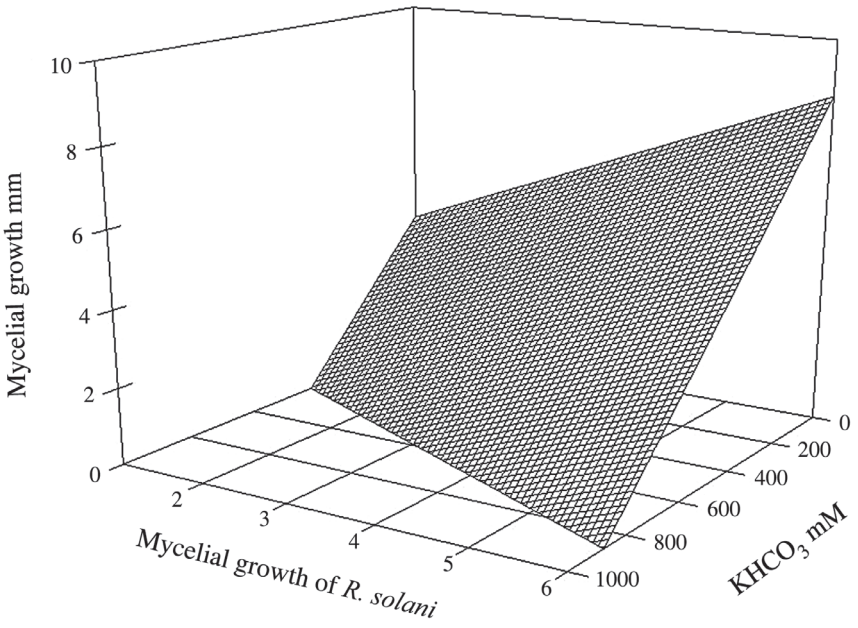

Figure 6. Mycelial growth of *Rhizoctonia solani* on Petri dishes exposed to increasing concentrations of potassium bicarbonate ($KHCO_3$) on different times (days of mycelial growth of *R. solani*)

Also, the studies on mathematical modeling evaluating the effect of times and different doses of potassium bicarbonate ($KHCO_3$) on mycelial growth of *S. sclerotiorum* and *R. solani* by multi regression analysis are limited. In the present study, models for estimating the mycelial growth of both the fungi *in vitro* exposure to increased doses of $KHCO_3$ at different times by multi linear regression were developed. As a result of ANOVA and multi-regression analysis, it was found that there was close relationship between actual and predicted mycelial growth of *S. sclerotiorum* and *R. solani*.

Mathematical modeling is an efficient tool for assessing how individual or combined environmental factors affect microorganisms that degrade processed foods. Different models have been developed in predictive microbiology for fitting growth curves and estimating biological parameters of foodborne and storage pathogens. Cuppers et al. (1997) modelled mold growth on a solid culture medium at various temperatures and NaCl concentrations by using five common food spoilage molds. In other study, Lahlali et al. (2007) validated models predicting the in vitro effect of water activity (a_w) and tem-

perature on the radial growth of *Botrytis cinerea*. It was determined that all models proved to be good predictors of the growth rates of *B. cinerea* within the limits of experiments. Also, it was determined that the results from modeling confirmed the general finding that a_w had a greater influence on fungal growth than temperature. Additionally, Judet-Correia et al. (2010) investigated a model for predicting the combined effect of temperature and a_w on the radial growth rate, μ, of *B. cinerea* and *Penicillium expansum* on grape berries. Ultimately, this study demonstrated the usefulness of the gamma concept for validating predictive models in foods or agricultural products. Contrary to the main values, it was shown that the optimum growth rates depended strongly on the strain and the medium. Also in this study, grape analogues were used to validate the combined effects of temperature and water activity on growth, then the optimum growth rate was determined on grape berries once the model had been validated. This approach allowed validation of the model over a wide range of variation of temperature and water activity, but also the estimation of the optimal growth rate on grape berries under non optimal conditions.

In other study, the effect of free moisture and plant growth stage on focus expansion of *R. solani* was quantified with soybeans planted in polyethylene chambers in a greenhouse. Simple linear regressions of the disease variables on days after inoculation showed increases in slopes as free moisture increased. Plant growth stage at inoculation also significantly affected the slopes. In this study, models to predict the development of each disease variable were developed, with accumulated free moisture hours as the forecaster. In addition to this, it was determined that severity of disease foci was less correlated with the other three disease variables (Yang et al., 1990). However, there is no much a quantitative modeling approach for *R. solani* which is one of the most important fungal pathogens. In our study, model for estimating the mycelial growth of *R. solani in vitro* exposure to increased doses of $KHCO_3$ at different times by multi linear regression was developed.

Conclusion

In the present study, the models for estimating the mycelial growth of *S. sclerotiorum* and *R. solani* exposure to different doses of $KHCO_3$ at different times by multi linear regression were developed. Close relationship between actual and predicted mycelial growth of *S. sclerotiorum* and *R. solani* was determined. Multi linear regression is an approach to modeling the relationship between dependent variable (y) and independent variables denoted (x). In our research, dependent variable was mycelial growth and independent variables were time and doses. This study concluded that the models are used as the parameter in mycelial growth of *S. sclerotiorum* and *R. solani*. Using multiple regression equations they are very much likely to predict the variation in mycelial growth of *S. sclerotiorum* and *R. solani* as related to doses and times with high probability. In this study, R^2 values obtained (0.81 and 0.75) show that models with 81% and 75% close to the reality have been formed for *S. sclerotiorum* and *R. solani*, respectively. There is a need to apply models studies for epidemiological analyses of other important fungal pathogens. Additionally, quantifying the effects of environmental factors on fungal disease development by means of quantitative models can help in the design and efficient use of management strategies for soilborne and post harvest pathogens.

Received 01 02 2011
Accepted 24 05 2011

References

Arslan U., Kadir I., Vardar C., Karabulut O. A. Evaluation of antifungal activity of food additives against soilborne phytopathogenic fungi // World Journal of Microbiology Biotechnology. – 2009, vol. 25, p. 537–543

Bae Y. S., Knudsen G. R. Effect of sclerotial distribution pattern of *Sclerotinia sclerotiorum* on biocontrol efficacy of *Trichoderma harzianum* // Applied Soil Ecology. – 2007, vol. 35, p. 21–24

Ben-Yephet Y., Genizi A., Siti E. Sclerotial survival and apothecial production by *Sclerotinia sclerotiorum* following outbreaks of lettuce drop // Phytopathology. – 1993, vol. 83, p. 509–513

Boland G. J. Biological control of plant diseases with fungal antagonists: challenges and opportunities // Canadian Journal of Plant Pathology. – 1990, vol. 12, p. 295–299

Bolton M. D., Thomma B. P. H. J., Nelson B. D. *Sclerotinia sclerotiorum* (Lib.) de Bary: biology and molecular traits of a cosmopolitan pathogen // Molecular Plant Pathology. – 2006, vol. 7, p. 1–16

Cebi M. Determination of genetic variation on multinucleate *Rhizoctonia* spp. isolates from common bean plants and their rhizosphere region in black sea coastal line: unpublished Ph. D. Thesis // Ondokuz Mayis University, Natural Sciences Institutes. – 2009. – 126 p.

Cirak C., Ayan A. K., Odabas M. S., Camas N. Modeling the effect of temperature on the days to germination in seeds of flue-cured and oriental tobacco (*Nico-*

tiana tabacum L.) // Journal of Plant Science. – 2007, vol. 2, iss. 3, p. 358–361

Cirak C., Odabas M. S., Ayan A. K. Leaf area prediction model for summer Snowflake (*Leucojum aestivum* L.) // International Journal of Botany. – 2005, vol. 1, iss. 1, p. 12–14

Clarkson J. P., Phelps K., Whipps J. M. et al. Forecasting *Sclerotinia* disease on lettuce: toward developing a prediction model for carpogenic germination of sclerotia // Phytopathology. – 2004, vol. 94, p. 268–279

Cuppers H. G., Oomes S., Brul S. A model for the combined effects of temperature and salt concentration on growth rate of food spoilage moulds // Applied and Environmental Microbiology. – 1997, vol. 63, p. 3764–3769

Dillard H. R., Cobb A. C. Relationship between leaf injury and colonization of cabbage by *Sclerotinia sclerotiorum* // Crop Protection. – 1995, vol. 14 iss. 8, p. 677–682

Ellis R. H., Hadley P., Roberts E. H., Summerfield R. J. Quantitative relations between temperature and crop development and growth // Climatic Change and Plant Genetic Resources. – London, New York, 1990, p. 89–128

Erper I., Karaca G., Balkaya A. Samsun ilinde üretimi yapılan bazı taze fasulye çeşitlerinin *Rhizoctonia solani*'ye duyarlılıklarının belirlenmesi // OMU Ziraat Fakültesi Dergisi. – 2003, vol. 18, iss. 3, p. 51–55 (in Turkish)

Erper I., Karaca G., Ozkoc I. Identification and pathogenicity of *Rhizoctonia* species isolated from bean and soybean plants in Samsun, Turkey // Archives of Phytopathology and Plant Protection. – 2011, vol. 44, iss. 1, p. 78–84

Judet-Correia D., Bollaert S., Duquenne A. et al. Validation of a predictive model for the growth of *Botrytis cinerea* and *Penicillium expansum* on grape berries // International Journal of Food Microbiology. – 2010, vol. 142, p. 106–113

Lahlali R., Serrhini M. N., Friel D., Jijakli M. H. Predictive modelling of temperature and water activity (solutes) on the in vitro radial growth of *B. cinerea* // International Journal of Food Microbiology. – 2007, vol. 114, p. 1–9

McMeekin T. A., Olley J. N., Ratkowsky D. A., Ross T. Predictive microbiology: towards the interface and beyond // International Journal of Food Microbiology. – 2002, vol. 73, p. 395–407

Navas-Cortés J. A., Landa B. B., Méndez-Rodríguez M. A., Jiménez-Díaz R. M. Quantitative modeling of the effects of temperature and inoculum density of *Fusarium oxysporum* f. sp. *ciceris* races 0 and 5 on development of *Fusarium* wilt in chickpea cultivars // Phytopathology. – 2007, vol. 97, p. 564–573

Odabas M. S., Kevseroglu K., Cirak C., Saglam B. Nondestructive estimation of leaf area in some medicinal plants // Turkish Journal of Field Crops. – 2005, vol. 10, iss. 1, p. 29–31

Odabas M. S., Radusiene J., Camas N. et al. The quantitative effects of temperature and light intensity on hyperforin and hypericins accumulation in *Hypericum perforatum* L. // Journal of Medicinal Plants Research. – 2009, vol. 3, iss. 7, p 519–525

Olivier C., Halseth D. E., Mizubuti S. G., Loria R. Postharvest application of organic and inorganic salts for suppression of silver scurf on potato tubers // Plant Disease. – 1998, vol. 82, p. 213–217

Ordonez C., Alarcón A., Ferrera R., Hernández L. V. *In vitro* antifungal effects of potassium bicarbonate on *Trichoderma* sp. and *Sclerotinia sclerotiorum* // Mycoscience. – 2009, vol. 50, p. 380–387

Pearson S., Hadley P., Wheldon A. E. A reanalysis of the effects of temperature and irradiance on time to flowering in chrysanthernum (*Dendranthema grandflora*) // Journal of Horticultural Science. – 1993, vol. 6, p. 89–97

Prusinkiewicz P. Modeling plant growth and development // Current Opinion in Plant Biology. – 2004, vol. 7, p. 79–83

Punja Z. K., Grogan G. Effects of inorganic salts, carbonate-bicarbonate anions, ammonia, and the modifying infl uence of pH on sclerotial germination of *Sclerotiorum rolfsii* // Phytopathology. – 1982, vol. 72, p. 635–639

Ricker M. D., Punja Z. Influence of fungicide and chemical salt dip treatments on crater rot caused by *Rhizoctonia carotae* in long-term storage // Plant Disease. – 1991, vol. 75, p. 470–474

Sautour M., Soares Mansur C., Divies C. et al. Comparison of the effects of temperature and water activity on growth rate of food spoilage moulds // Journal of Industrial Microbiology and Biotechnology. – 2002, vol. 28, p. 311–316

Sneh B., Burpee L., Ogoshi A. Identification of *Rhizoctonia* species. – St. Paul, USA, 1991. – 133 p.

Weisberg S. Applied linear regression. – New York, USA, 2005. – 310 p.

Wijetunga C., Baker R. Modeling of phenomena associated with soil suppressive to *Rhizoctonia solani* // Phytopathology. – 1979, vol. 69, p. 1287–1293

Wu B. M., Subbarao K. V. Analyses of lettuce drop incidence and population structure of *Sclerotinia sclerotiorum* and *S. minor* // Phytopathology. – 2006, vol. 96, p. 1322–1329

Yang X. B., Breggren G. T., Snow J. P. Effects of free moisture and soybean growth stage on focus expansion of Rhizoctonia aerial blight // Phytopathology. – 1990, vol. 80, p. 497–503

Yangui T., Rhouma A., Triki M. A. et al. Control of damping-off caused by *Rhizoctonia solani* and *Fusarium solani* using olive mill waste water and some of its indigenous bacterial strains // Crop Protection. – 2008, vol. 27, p. 189–197

ISSN 1392-3196
Žemdirbystė=Agriculture, vol. 98, No. 2 (2011), p. 195–204
UDK 632.937.14:578.76:631.8

Kalio bikarbonato poveikio *Sclerotinia sclerotiorum* ir *Rhizoctonia solani* grybienos augimui *in vitro* matematinis įvertinimas

I. Erper[1], M. Turkkan[2], M. S. Odabas[3]

[1]Turkijos Ondokuz Mayis universitetas
[2]Turkijos Ordu universitetas
[3]Turkijos Ondokuz Mayis universiteto Bafros profesinė mokykla

Santrauka

Tyrimų metu vertinta kalio bikarbonato ($KHCO_3$) įvairių normų įtaka *Sclerotinia sclerotiorum* ir *Rhizoctonia solani* grybienos augimui, priklausomai nuo grybienos augimo trukmės, taikant daugianarę regresinę analizę. Lygtys *S. sclerotiorum* ir *R. solani* grybienos augimui įvertinti buvo sudarytos atsižvelgiant į $KHCO_3$ dozę ir grybienos augimo trukmę. ANOVA ir daugianarė regresinė analizė parodė glaudų ryšį tarp faktinio ir prognozuojamo *S. sclerotiorum* bei *R. solani* grybienos augimo. Tyrimų metu buvo sukurti prognoziniai modeliai MGS = (a) − (b x dozė) + (c x laikas), kai MGS yra *S. sclerotiorum* grybienos augimas, ir MGR = (a) + (b x dozė) + (c x laikas), kai MGR yra *R. solani* grybienos augimas (a, b ir c – koeficientai). R^2 vertės *S. sclerotiorum* buvo 0,81, *R. solani* – 0,75, standartinės paklaidos buvo esminės esant $p < 0.001$ tikimybės lygiui.

Reikšminiai žodžiai: modeliavimas, augimo greitis, su dirva pernešami patogenai, $KHCO_3$.