Use of Bayesian Methods to Improve Prediction of Panicle and Shoot Blight Severity of Pistachio in California

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ABSTRACT

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Panicle and shoot blight, caused by a *Fusicoccum* sp., is one of the major aboveground diseases of pistachio in California. The effects of temperature, number of continuous rainy days in April and May, irrigation system, and incidence of latent infection of the *Fusicoccum* sp. on severity of panicle and shoot blight of pistachio leaves and fruit have been quantified previously, using data collected from 1999 through 2001. A predictive model for leaves and another model for fruit with good explanatory power were generated. In 2003 and 2004, newly collected data were used to evaluate the two models with non-Bayesian and Bayesian methods. The 95% credible (i.e., confidence) intervals of initial (before modification with non-Bayesian and Bayesian methods) and updated parameter estimates were used to investigate their prognostic validity. In 2003, the non-Bayesian analysis resulted in all parameter estimates, with the exception of cumulative daily mean temperature from 1 June until harvest, having different 95% confidence intervals than the parameter estimates of the original models. In addition, the parameter estimates for

drip irrigation for the leaf infection and the parameter estimates for drip irrigation and number of continuous rainy days in April and May for fruit infection were not statistically significant. With Bayesian methods, the re-estimated model parameters had overlapping 95% credible intervals with the initial estimated parameters, except for the number of continuous rainy days in April and May. When the two sets of modified parameter estimates were used to predict disease severity, statistically significant ($\alpha = 0.05$) differences between observed and predicted disease severities were found with non-Bayesian analysis for leaf infection in three locations and with Bayesian analysis for fruit infection in one orchard. The parameter estimates were modified again at the end of the 2004 season and were all statistically significant with both non-Bayesian and Bayesian methods. Both sets of parameter estimates gave predictions that were not significantly different from observed disease severity on leaves and fruit in all monitored orchards in 2004. In summary, Bayesian methods gave more consistent results when used to update parameter estimates with new information and yielded predictions not statistically different from observed disease severity in more cases than the non-Bayesian analysis.

Additional keywords: *Botryosphaeria dothidea*, *Pistacia vera*.

Panicle and shoot blight, caused by a *Fusicoccum* sp., anamorph of *Botryosphaeria dothidea* (Moug.:Fr.) Ces. & De Not., is one of the major aboveground diseases threatening the California pistachio industry. Buds, young blossoms, leaves, shoots, fruit, and entire fruit clusters can be infected throughout the season if environmental conditions are favorable (7). The pathogen produces pycnidia on buds, blighted rachises, fruit, leaf petioles, leaf lesions, and cankers of blighted shoots and panicles. Pycnidia are the main source of primary inoculum and can provide viable conidia for up to 6 years (7,10).

Temperature, rainfall, and wetness duration are of utmost importance for disease development (8). Pycnidiospores are dispersed by splashing or dripping water (9). On pistachio leaves, infections require continuous wetness duration of at least 9 to 12 h to develop symptoms (8). Irrigation with high-angle sprinklers is associated with high disease levels because fruit clusters and foliage are exposed to prolonged wetness (8). Spore germination on potato dextrose agar occurs in the range of 24 to 36°C, pycnidiospores fail to germinate when temperatures exceed 36°C, and the optimum range of temperatures for symptom development on fruit is 27 to 33°C (8).

In the northern and central valleys of California, pycnidiospores are dispersed and cause infection during rainy periods

from October (early fall) to March (early spring) (1). However, leaf and fruit are formed in spring and, thus, only spring rainfall is considered important for leaf and fruit infection. These early infections remain latent until temperatures from 25 to 27°C occur later in June to August (8).

Mila et al. (13) quantified the effects of temperature, precipitation pattern, irrigation system, and incidence of latent infection by a *Fusicoccum* sp. on panicle and shoot blight severity using a generalized linear model and disease severity data for leaves and fruit collected from 1999 through 2001. Two separate models with good explanatory power were generated, one for leaves and one for fruit (13). The models identify two important components for disease development; first, the effect of spring precipitation on incidence of latent infection and, second, the effect of summer temperatures on symptom development. If little precipitation occurs in spring, then low disease severity is predicted even if the temperature in summer is high, because the incidence of latent infection is low. However, if precipitation in spring is high, then the incidence of latent infection also is high and, therefore, disease severity is predicted to be high as the summer temperature increases.

Models are important tools for assessing or predicting disease risk. A vital aspect of prediction is to investigate whether a previously developed model is transportable (i.e., gives accurate results when it is applied in another period of time than that used to develop the model) (17). The concept often is referred to as validity of the model (2). Further, following the collection of additional data, models often are updated, such that the predictive model is

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adjusted to the new circumstances (17). The objectives of the present study were to use newly collected data to (i) investigate the prognostic validity of the parameter estimates of the disease models developed by Mila et al. (13) and (ii) evaluate the predictive power of the previously developed models. Non-Bayesian and Bayesian methodologies were applied and compared for this purpose.

MATERIALS AND METHODS

Description of prediction models. Full descriptions of the two models are given elsewhere (13). The models were developed using data collected in pistachio orchards from 1999 through 2001. Panicle and shoot blight severity on leaves and fruit was assessed six to eight times on the same trees in each orchard during the growing season. The factors that contribute to disease severity were analyzed and quantified using logistic regression (13). Significant factors were (i) incidence of latent infection of fruit by a *Fusicoccum* sp., (ii) use of drip irrigation (used as an indicator variable), (iii) the number of continuous rainy days (i.e., consecutive days with rain following a day with rain) in April and May, and (iv) the cumulative daily mean temperature (in °C) from 1 June until harvest (mid- to late September).

Model evaluation. Panicle and shoot blight development was monitored in seven orchards, one each in Butte, Colusa, Glenn, Placer, and Tulare counties and two in Madera County in 2003, and in six of the seven orchards in Butte, Colusa, Glenn, Madera, and Tulare counties in 2004. Trees were ≈ 20 years old in all orchards, and five female single-tree replicates that had not received any fungicide treatment were used to monitor panicle and shoot blight severity in each orchard. The trees were arranged in a randomized complete block design among 20 trees used for fungicide experiments. In each tree, four branches bearing leaves and fruit were tagged in mid- to late March, before symptom development, and were observed for disease severity at 12- to 22-day intervals from April to September. At each evaluation, the severity of panicle and shoot blight on each branch was visually assessed using the Horsfall-Barratt rating scale (5).

The overnight freezing incubation technique (ONFIT) (11) was used to determine the incidence of latent infection in pistachio leaves and fruit. Fifty symptomless leaves and fruit were collected from each orchard from the same trees on the dates that disease severity was recorded. Latent infection was defined as percentage of leaves or fruit on which mycelia and pycnidia of the *Fusicoccum* sp. were present.

Weather data were obtained from the California Irrigation Management Information System (CIMIS). Orchards in Butte, Colusa, Glenn, Madera, Placer, and Tulare counties were 4, 11, 7.5, 10, 15, and 6 km, respectively, from the closest CIMIS weather station. These were the same weather stations from which weather data were used for model development (13). CIMIS weather stations collect weather data on a minute-by-minute basis and calculate hourly and daily values.

Model modification with logistic regression. At the end of the 2003 and 2004 seasons, the parameter estimates of the previously developed models were modified using logistic regression (13) based on the observed disease severity data collected in that year. That is, data collected in 2003 and then in 2004 were combined together with the original data collected in 1999, 2000, and 2001 and reanalyzed. Model fit was assessed using deviance (i.e., the summation of differences between observations and their predictions based on the model) and the visual examination of residuals.

The modified parameter estimates were used to generate disease predictions in each orchard in 2003 and 2004. Parameter estimates at the end of 2004 were used to predict panicle and shoot blight severity in 2003. Calculations were made in an Excel spreadsheet. These predictions were compared with observed severity on leaves and fruit with a *t* test ($\alpha = 0.05$).

Model modification with Bayesian methods. In Bayesian analysis, parameters are treated as if they were random variables and described with probability distributions rather than point estimates (4). There are three key components associated with parameter estimation: prior distribution, likelihood function, and posterior distribution. These three components are formally combined by Bayes's rule: $f(\theta | y_{\text{obs}}) \propto g(\theta) \times L(y_{\text{obs}} | \theta)$, where the symbol $\propto$ denotes proportionality and θ is a set of parameters to be estimated (4). Currently collected data (y_{obs}) are used to form the likelihood function $L(y_{\text{obs}} | \theta)$; that is, the probability to observe y_{obs} given a set of parameters θ . Existing evidence on the parameters of interest θ can be summarized quantitatively via probability distributions called the prior distributions $g(\theta)$ (4). The posterior distribution $f(\theta | y_{\text{obs}})$ describes the new state of knowledge about the parameters in light of the experience gained. That is, posterior parameter estimates result from combining new knowledge about parameters θ deriving from empirical data y_{obs} with the past knowledge about parameter estimates. The posterior distribution can be used to estimate means and 2.5th and 97.5th percentile probability intervals (also known as 95% credible intervals [CI]) (4).

Depending on the level of existing knowledge, a prior parameter distribution may be noninformative (or vague) when no knowledge is available, informative when some knowledge is available, or very informative when considerable knowledge is available (4). In empirical terms, a noninformative prior is represented with a normal distribution with mean set at 0 and the 95% CI set at $-\infty$ and $+\infty$; an informative prior is represented with a normal distribution with mean set at the value the parameter estimate is believed or known to be and the 95% CI set at $-\infty$ and $+\infty$; and a very informative prior is represented with a normal distribution with mean and 95% CI set at the value the parameter estimate is believed or known to be (14).

When few empirical data are available and informative or very informative prior parameter estimates are used, it is common for the posterior parameter distributions to tend to be similar to the priors (i.e., mean and 95% posterior CIs very similar to the prior distribution). In this case, the prior distributions overwhelm the likelihood function (6); that is, the newly collected data do not significantly change what is already known about the parameter estimates. In some cases, however, the 95% posterior CIs tend to be narrower than those of the priors, which means that, although the available information did not change in general, more confidence was gained about what was already known (12).

In the present study, very informative prior parameter distributions, derived from our previous effort to quantify panicle and shoot blight severity on pistachio leaves and fruit (13), were applied. Specifically for leaves, the 95% CIs of prior distributions for parameters associated with intercept, drip irrigation, number of rainy days following a rainy day in April and May, and cumulative daily mean temperature from 1 June until harvest were (−7.5, −6.38), (−2.4, −1.78), (0.65, 0.78), and (0.0003, 0.0018), respectively (13). For fruit, the 95% CIs of prior distributions for intercept, drip irrigation, percentage of latent infection, number of continuous rainy days in April and May, and cumulative daily mean temperature from 1 June until harvest were (−9.4, −7.8), (−1.74, −0.57), (0.028, 0.05), (0.7, 0.9), and (0.001, 0.002), respectively (13). At the end of 2003, the mean of the posterior parameter distributions were used to predict disease severity in 2004 and used as prior distributions for modifying the parameter estimates at the end of the 2004 season.

A significant challenge in interpreting the results of the Bayesian methodology is to assess the relative differences, if any, between the prior and posterior parameter distributions. This assessment is important because it provides evidence for the level of prognostic validity of the estimated parameters and, eventually, of the prediction models. One way to compare prior and posterior distributions is to examine whether these distributions are over-

lapping (3). This can be done by comparing their 95% CIs. Using a classical statistical framework, if the 95% CIs for two distributions do not overlap, then there is at least a 95% likelihood that the distributions are distinct. A similar approach can be considered in the Bayesian framework (3).

The software Bayesian inference using Gibbs sampler (BUGS, version 1.3; freely available via the World Wide Web) was used for performing the Bayesian analysis. The models were constructed exactly as in the original logistic regression analysis, except that the parameters were estimated as a combination of the newly collected data in 2003 and 2004 (which form the likelihood function) and the prior distributions of the parameter estimates known by analyzing the data collected from 1999 to 2001.

BUGS software is based on an iterative simulation method called the Gibbs sampler (15,16), a particular Markov chain algorithm that calculates a parameter value conditional on the others and, thus, allows for the calculation of posterior distributions from a multidimensional parameter space (4). Simulation was performed with 10,000 iterations. The software includes summary statistics tools such as history, density, quantiles to see traces, kernel density distribution plots, and running quantiles of the parameter estimates (14). During the simulation, parameter estimates start from a value that may change significantly during the next iteration; however, as the simulation progresses, the parameter estimates converge to one value. The convergence can be inspected visually with the traces (14). Usually, a number of initial iterations are disposed as a "burn-in"; that is, an initial set of unstable parameter values, so that they do not interfere with the calculation of the posterior parameter distribution (i.e., mean and 95% CIs). In our analysis, the 1,000 initial iterations were disposed.

RESULTS

In 2003, precipitation in April and May was higher than precipitation in 1999, 2000, and 2001, when the original models were developed, and a high number of consecutive rainy days were recorded. Daily summer temperatures were similar to those recorded in the summers of 1999, 2000, and 2001; however, during the last 2 weeks of July, daily air temperatures ranged from 26 to 29°C. Most panicle and shoot blight symptoms were observed after this period. In 2004, the number of consecutive rainy days and daily temperatures between June and early September were similar to those recorded from 1999 to 2001.

Model parameter estimates were modified at the end of the 2003 season (Table 1) with non-Bayesian and Bayesian logistic regression. The non-Bayesian analysis showed that all parameter estimates, with the exception of cumulative daily mean temperatures from 1 June until harvest, had different 95% CIs than the

Fig. 1. Prior parameter estimates and parameter estimates after re-estimation with Bayesian methods (at the end of the 2003 and 2004 seasons) for A, cumulative daily mean temperature (°C) from 1 June until harvest and B, number of continuous rainy days in April and May for predicting panicle and shoot blight severity of pistachio fruit.

TABLE 1. Parameter estimates for predictive models of panicle and shoot blight severity on pistachio leaves and fruit at the end of the 2003 season re-estimated with non-Bayesian and Bayesian methods^a

		Non-Bayesian parameter estimates			Bayesian parameter estimates		
			95% CI ^b			95% CI ^b	
Model, risk factor	Init. mean ^c	Mean	2.5%	97.5%	Mean	2.5%	97.5%
Leaves							
Intercept	−6.9	−4.64*	−5.5	−3.8	−6.74	−7.12	−6.40
Drip irrigation	−2.1	−0.8*	−2.0	0.38	−1.57	−1.80	−1.36
No. consecutive ^d	0.72	0.21*	0.11	0.31	0.44*	0.41	0.48
Mean temp. (°C) ^e	0.0011	0.0008	0.0004	0.0012	0.0003	0.00018	0.00047
Fruit							
Intercept	−8.6	−5.1*	−5.8	−4.23	−5.30	−5.65	−5.0
Drip irrigation	−1.06	−0.88*	−1.97	0.21	−1.57	−1.86	−1.32
Latent infection (%) ^f	0.04	0.02	0.008	0.038	0.036	0.03	0.04
No. consecutive ^d	0.8	0.11*	−0.01	0.23	0.13*	0.10	0.16
Mean temp. (°C) ^e	0.0016	0.001	0.0008	0.0014	0.001	0.0009	0.0012

^a Re-estimates parameters marked with asterisks (*) are significantly different from the initial ones ($P < 0.05$).

^b 95% posterior credible intervals.

^c Mean initial parameters.

^d Number of consecutive rainy days (April through May).

^e Cumulative daily mean temperature (June through September).

^f Percentage of fruit with latent infections by a *Fusicoccum* sp.

parameter estimates of the original models. Furthermore, the parameter estimates for drip irrigation for leaf infection and the parameter estimates for drip irrigation and number of continuous rainy days in April and May for fruit infection were not statistically significant, as was the case in the original models. The estimated deviance (equal to 3.4) and the visual examination of residuals suggested good model fit.

When Bayesian methods were applied, all posterior parameter distributions, with the exception of the number of continuous rainy days in April and May, had overlapping 95% CIs with the prior parameter distributions. Nevertheless, the posterior 95% CIs were narrower than the prior ones (Fig. 1). The number of continuous rainy days was the only parameter estimate for which the posterior 95% CIs were distinct from the prior ones ([0.65, 0.78] for leaves and [0.7, 0.9] for fruit).

Panicle and shoot blight severities on leaves and fruit were predicted with parameter estimates recalculated with non-Bayesian and Bayesian methods. Both sets of parameter estimates gave pre-

dictions statistically not different ($\alpha = 0.05$) from the observed severity on leaves and fruit in the orchards of Madera, Placer, and Tulare counties (Fig. 2). Statistically significant differences between observed and predicted disease severities were found with non-Bayesian analysis for leaf infection in Glenn, Butte, and Colusa counties and with Bayesian analysis for fruit infection in Colusa County.

The parameter estimates were modified again at the end of the 2004 season (Table 2). The non-Bayesian analysis showed that all parameter estimates had overlapping 95% CIs with the parameter estimates after the 2003 season. The parameter estimates for drip irrigation and number of continuous rainy days in April and May were again statistically significant. The estimated deviance (equal to 4.2) and the visual examination of residuals suggested good model fit. When Bayesian methods were applied, all posterior parameter estimates had overlapping 95% CIs with the prior parameter estimates. Again, the posterior 95% CIs were narrower than the prior ones (before the 2003 modification) (Fig. 1).

Fig. 2. Observed and predicted (after parameter re-estimation with non-Bayesian and Bayesian methods) panicle and shoot blight severity at the end of the 2003 season on pistachio **A, C, E, and G**, leaves and **B, D, F, and H**, fruit in the orchards of **A and B**, Glenn, **C and D**, Placer, **E and F**, Madera, and **G and H**, Tulare counties.

TABLE 2. Parameter estimates for predictive models of panicle and shoot blight severity on pistachio leaves and fruit at the end of the 2004 season re-estimated with non-Bayesian and Bayesian methods^a

Model, risk factor	Non-Bayesian parameter estimates			Bayesian parameter estimates		
	Mean	95% CIs ^b		Mean	95% CIs ^b	
		2.5%	97.5%		2.5%	97.5%
Leaves						
Intercept	-4.83	-5.5	-4.1	-6.53	-6.82	-6.24
Drip irrigation	-1.0	-2.1	-0.07	-1.4	-1.61	-1.19
No. consecutive ^c	0.25	0.19	0.31	0.43	0.40	0.46
Mean temp (°C) ^d	0.0007	0.0003	0.0012	0.0003	0.00017	0.00044
Fruit						
Intercept	-5.2	-5.9	-4.56	-5.74	-6.0	-5.48
Drip irrigation	-1.22	-2.20	-0.24	-1.50	-1.77	-1.22
Latent infection (%) ^e	0.03	0.015	0.047	0.036	0.03	0.04
No. consecutive ^c	0.13	0.03	0.22	0.13	0.09	0.16
Mean temp (°C) ^d	0.001	0.0008	0.0015	0.001	0.0008	0.0012

^a Re-estimates parameters marked with asterisks (*) are significantly different from the initial ones ($P < 0.05$).

^b 95% posterior credible intervals.

^c Number of consecutive rainy days (April through May).

^d Cumulative daily mean temperature (June through September).

^e Percentage of fruit with latent infections by a *Fusicoccum* sp.

Fig. 3. Observed and predicted (after parameter re-estimation with non-Bayesian and Bayesian methods) panicle and shoot blight severity at the end of the 2004 season on pistachio A, C, E, and G, leaves and B, D, F, and H, fruit in the orchards of A and B, Glenn, C and D, Colusa, E and F, Madera, and G and H, Tulare counties.

Panicle and shoot blight severities on leaves and fruit were predicted with parameter estimates from non-Bayesian and Bayesian analyses. Both sets of parameter estimates gave predictions not significantly different from the observed severity in leaves and fruit in all monitored orchards (Fig. 3). Panicle and shoot blight severities on leaves and fruit in 2003 were predicted with parameter estimates derived with non-Bayesian and Bayesian methods after the 2004 season. Both sets of parameter estimates gave predictions that were not significantly different from the observed severity in leaves and fruit in 2003 in all monitored orchards.

DISCUSSION

The most remarkable result of this study was the pronounced difference between updated parameter estimates obtained with non-Bayesian and Bayesian methods in 2003. Re-analysis of the logistic regression with incorporation of the 2003 data yielded no statistically significant results for the parameter estimate for drip irrigation for leaf and fruit infection and the parameter estimate for continuous days with rain in April and May for fruit infection. Parameters re-estimated with the Bayesian approach provided better predictions than the non-Bayesian approach of disease severity on leaves and equally good ones on fruit.

The parameter estimates were modified again at the end of 2004, and the modified models performed well in predicting disease severity in 2004, a year with less-favorable weather conditions for disease development than 2003. Non-Bayesian and Bayesian approaches yielded statistically significant parameter estimates. When the 2004 parameter estimates were used to predict disease observed in 2003, both non-Bayesian and Bayesian estimates gave predictions not significantly different from observed disease severity. Although the models should be evaluated in a series of different weather conditions, this 2-year evaluation suggests that they have good potential to predict accurately years of low disease severity and allow for the modification of the models in years of high disease severity, such as in 2003.

The original models were developed under moderate weather conditions for the disease; that is, years with few consecutive days of rainfall (i.e., 2 to 6 days) during the critical period and summer air temperatures below or near the 50-year summer average (13). In none of the years from 1999 to 2001 in which panicle and shoot blight was monitored were the numbers of continuous rainy days in April and May as high as in 2003. For instance, the highest number (i.e., 8 days) of continuous rainy days in April and May was recorded in the Glenn County orchard in 2000 whereas, in 2003, the same orchard had 13 continuous rainy days in April and May.

In an ideal situation, a model, once developed, would be sufficient to predict disease risk in another circumstance. However, in most cases, models are highly dependent on the data used (2). Cross-validation often is implemented to validate a prediction model (2). That is, a subset of data is not used for the model development but is used for validating the model. In the present study, two different approaches of cross-validation were investigated. In the non-Bayesian approach, all the data were re-analyzed together; that is, averaging over all data, irrespective of the year (17). On the other hand, in the Bayesian approach, data were divided into two sets: data used in the original model and newly collected data. That is, the newly collected data were weighted against the originally collected data (3). The implications of this difference between the two approaches were obvious in 2003, when averaging over the data with non-Bayesian meth-

ods resulted in nonsignificance of two explanatory variables (drip irrigation and continuous days with rain) that were significant in the initial models.

Empirical disease warning systems usually are developed based on field observations or historical data. When these systems are quantitative, a serious limitation could be the generation of poor results because of a limited number of observations used in the statistical analysis. Bayesian methodology offers an interesting approach for evaluating and modifying the parameter estimates of explanatory variables of previously developed models.

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