Modeling the Effects of Cloudy Weather on Regional Epidemics of Soybean Rust

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Abstract

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This study simulated daily development of soybean rust (SBR), caused by *Phakopsora pachyrhizi*, based on cloud cover conditions. Results from a previous study that determined the relationship between shading and apparent infection rates were applied in this study to simulate SBR progress on a regional scale using a semi-empirical logistic model parameterized according to the observed cloud cover conditions. Depending on local weather data availability, cloudy days were assumed to be either (i) the days with less than 2 h of full sun or (ii) the days with complete cloud cover as measured by three daily observations. Estimated disease progress and final estimates of epidemic intensity

were verified by 30 reports of seasonal disease progress in 11 regions of Brazil and South Africa from 2002 to 2007. The model predicted final disease severity and the observed final severity fall into a linear relationship with correlation coefficient $r = 0.96$ and a slope close to 1. Severe SBR epidemics occurred when 19.5 or more cloudy days were recorded during the period from initial disease detection to the date of final disease assessment near the end of a growing season in Brazil and South Africa. Mild epidemics were observed with less than eight cloudy days in a season.

Soybean rust (SBR), caused by the fungus *Phakopsora pachyrhizi*, has been reported in most soybean (*Glycine max*)-growing regions worldwide (18,32,41). In Brazil, SBR was first observed during the 2001–02 season, and outbreaks have been observed in many regions of the country (41). Severe epidemics have also been reported frequently in the mist belt zone of KwaZulu-Natal province in South Africa (30). Although seasonal disease epidemics in these tropical regions have been managed with preventive fungicide sprays, severe yield losses were still observed in regions with favorable weather conditions for disease development (18,41).

Experimental results and field observations from various researchers have demonstrated that *P. pachyrhizi* is sensitive to light (1,6,13,15,17,20,23,27). Germination of urediniospores of *P. pachyrhizi* is inhibited by direct sunlight and germ tubes grow in the opposite direction to a light source (15,17). Sporulation is mostly on the abaxial side of soybean leaves and in the lower canopy, where exposure to direct sunlight is minimal (2,23,27). In field experiments with controlled shading conditions, SBR incidence and severity were greater in the shaded areas than that in plants under full sunlight (6).

In the tropics, severe epidemics of SBR are often observed in regions where prolonged rainfall periods occur (5,32). In addition to providing favorable humidity and temperature conditions, rain clouds may favor SBR epidemics by providing the shading that protects pathogen infection and development from direct sunlight. Similarly, SBR epidemics usually expand to temperate latitudes in Argentina, China, and United States in fall season, when reduced solar radiation intensity occurs (7,9,19,32).

Modeling approaches have employed weather variables to assess potential inoculum survival and epidemic development of SBR in previous studies (5,16,28,29,38,39). Weather factors such as temperatures, rain, and leaf wetness were used mostly as predictors to assess disease development. A few laboratory and field studies have addressed the effects of shading on SBR development as well.

However, sunlight-related weather variables have never been used as a model input at a regional scale.

We hypothesized that the apparent infection rate of SBR is influenced by solar radiation intensity, in addition to other factors mentioned above. Therefore, cloudiness, which affects sunlight intensity, may have the power to explain epidemics of SBR in field conditions. The objectives of this study were to (i) quantify the reduction in SBR apparent infection rates in unshaded environments, (ii) develop a simulation model to estimate seasonal disease progress from apparent infection rates regulated by cloud cover conditions, and (iii) validate our simulations with regional reports of seasonal epidemics in Brazil and South Africa.

Materials and Methods

Data collection and preliminary analysis. SBR development was simulated in eight regions of Brazil and three regions in South Africa during different growing seasons in 2002 to 2007, totaling 30 distinct rust epidemics, of which the disease monitoring data were collected in several studies (Table 1). Climate data were provided by Instituto Nacional de Meteorologia (Brazil) and the South African Weather Service (South Africa). Weather stations within 100 km to the disease reports in each soybean-growing region were selected to provide weather data.

Daily observations of rainfall, relative humidity, cloudiness, and temperature were summarized over the main soybean growing season in each region, which usually extends from November to March in both countries. Although most weather data were collected similarly in the two countries, cloudiness was estimated using different approaches. In Brazil, the number of hours of direct sunlight per day was recorded. For this study, days were arbitrarily assumed to be cloudy when less than 2 h of direct sunlight per day was observed. In South Africa, the fraction of the sky covered by clouds was recorded every day by a trained observer at 00, 12 and 18 h coordinated universal time. For this study, days were considered cloudy when the sky was more than 7/8 covered by clouds during all three observations.

Seasonal weather variables were compared, including total precipitation (Prp), number of rain days (Nrd), number of cloudy days (Ncd), average maximum and mean temperatures (Tx and Tm, respectively), and the proportion of days with high relative humidity allowing dew formation (Pdd). PROC CORR procedure in SAS (SAS Institute) was used to estimate Pearson's correlation at $P = 0.05$. The Ncd required for different epidemic intensities

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was estimated in SAS using the general linear model (PROC GLM) procedure.

Regional epidemics of SBR can be classified empirically as light, moderate, or severe based on average severity rating, yield losses, defoliation, and number of fungicide sprays (Table 2) (4,10,39). Plant pathologists in Brazil and South Africa estimated the intensity of SBR epidemics (Table 1) at the end of the main growing season based on one or more of these criteria. For specific locations in Brazil, more detailed seasonal SBR progress curves were also available (11,12,24–26,31,35,37).

Model parameter estimation. Results from a previous study (6) were used for the parameterization in our model development. In the previous study, the effect of shading on SBR infection and development was determined at the University of Florida in 2006 and 2007. Briefly, potted soybean plants (Mycogen 5N351RR, maturity group 3.5) inoculated with *P. pachyrhizi* were placed for 12 days in shade (provided by shade cloth allowing 20% solar radiation transmission) or in full sunlight until evaluation for incidence of SBR. Pots were placed on open ground covered by mowed turfgrass. Disease incidence rates were normalized to the largest values in each trial and treatment means were estimated and statistically compared at $P = 0.05$. Because a cloudy day was defined as a day with <2 h of direct sunlight in Brazil or with cloud coverage on the sky >7/8 in South Africa, the percentage of direct sunlight reaching the surface on a cloudy day would be close to or much less than the percentage of direct sunlight at 20% solar radiation transmission rate in the previous experiment. Therefore, we used this parameterization in simulation in this study based on the above approximation.

Disease development over the course of 12 days was treated as a monomolecular process in this previous study. The monomolecular model is appropriate when disease develops exclusively from pri-

mary inoculum sources (21). In these trials, there was no time for secondary infections to develop because disease assessment occurred 12 days after inoculation. Therefore, the observed variability in SBR incidence relied on the different monomolecular apparent infection rates (r_M) in the shaded treatment compared with the full sunlight. The monomolecular apparent infection rate is different from the apparent infection rate normally used in a model describing a polycyclic disease progress (e.g., a logistic model). In our study, we used the monomolecular infection rate derived from the previous study as a substitution of the apparent infection rate in the polycyclic disease development for regional SBR development based on field data. The substitution is on a daily basis, such as during disease development simulated by the logistic model in this study; on every day, the model used a new apparent infection rate which was based on a monomolecular infection rate derived according to the cloudiness on that given day.

To estimate the monomolecular apparent infection rates under different light treatments, SBR development in shade and full sunlight was assumed to follow the monomolecular model with all plants initially healthy ($Y_{M0} = 0$) and maximum possible disease intensity equal to 1 at time n (equation 1)

$$Y_{Mn} = 1 - (1 - Y_{M0}) \times \exp(-r_M \times t) \quad 1$$

in which Y_{Mn} = disease incidence after time $t = n$, Y_{M0} = disease incidence at time $t = 0$, and r_M = monomolecular apparent infection rate. In our case, $n = 12$ days and r_M represents infection rate under 20% sunlight.

Under the assumptions of zero initial incidence and uniform primary inoculum, we calculated the rate of change (α) in the monomolecular apparent infection rates (r_M) in full sunlight compared with the shaded conditions. The estimation was based on average final disease incidence observed in both environments within the

Table 1. Soybean-growing regions and seasons with the reported first detection dates and final soybean rust epidemic intensity at various locations in Brazil and South Africa

Country, region ^x	Growing season	First detection dates ^y	Observed final disease intensity ^z
Brazil			
Southeastern Mato Grosso	2004–05	16 December 2004	Severe
	2005–06	11 December 2005	Severe
	2006–07	6 December 2006	Moderate
Central Mato Grosso	2004–05	30 December 2004	Light
	2005–06	28 December 2005	Light
Western Bahia	2002–03	7 February 2003	Severe
	2003–04	15 January 2004	Light
	2005–06	16 January 2006	Light
	2006–07	22 December 2006	Moderate
Northern Rio Grande do Sul	2004–05	14 February 2005	Light
	2005–06	12 January 2007	Light
	2006–07	11 January 2007	Light
Southeastern Goiás	2002–03	15 December 2002	Severe*
	2003–04	9 December 2003	Severe
	2005–06	30 December 2006	Moderate
	2006–07	27 December 2006	Severe
Northwest São Paulo	2002–03	31 January 2003	Light*
	2003–04	18 December 2003	Severe
	2004–05	12 January 2005	Light
Triangle Minas Gerais	2003–04	9 December 2004	Severe
	2004–05	15 December 2004	Moderate
Mato Grosso do Sul	2004–05	28 December 2004	Light
	2005–06	30 November 2005	Severe
South Africa			
Mist Belt KwaZulu-Natal	2003–04	...	Severe
	2004–05	...	Severe
	2005–06	...	Severe
Mpumalanga Province	2003–04	...	Light
	2004–05	...	Moderate
	2005–06	...	Severe
Free State	2005–06	...	Light

^x Cloudy day definitions by the local weather service: less than 2 h of direct sunlight per day in Brazil locations; average observed cloud coverage on the sky >7/8 at 00, 12, and 18 h coordinated universal time in South African location. The cloudiness was observed at a local level within a range of 100 km.

^y First detection dates were reported by Embrapa, Brazil.

^z Asterisk (*) indicates that final disease intensity was slightly overestimated by model simulation in these cases.

time period of 12 days (equations 2 to 4). According to the previous study, r_M was approximately 0.2 under 20% sunlight, and approximately 0.05 under full sunlight (6).

$$Y_{M<SHADE>} = 1 - \exp(-r_M \times t) \quad 2$$

$$Y_{M<SUNLIGHT>} = 1 - \exp(-\alpha \times r_M \times t) \quad 3$$

$$\alpha = \text{Ln}(1 - Y_{M<SUNLIGHT>}) / \text{Ln}(1 - Y_{M<SHADE>}) \quad 4$$

Model development and validation. Development of SBR in natural conditions most likely follows a logistic pattern with maximum disease intensity at 1 (equation 5).

$$dY/dt = r_{Ln} \times Y_{Ln} \times (1 - Y_{Ln}) \quad 5$$

The logistic model has been used to describe epidemics of polycyclic diseases similar to SBR (21,36). In this model, increments of disease intensity (dY) in time dt are regulated by a constant logistic apparent infection rate (r_{Ln}) multiplied by the proportions of both diseased (Y_{Ln}) and healthy plants ($1 - Y_{Ln}$) at time $t = n$. The development of a polycyclic disease relies on secondary inoculum produced on the diseased plants during epidemics.

The logistic apparent infection rate (r_{Ln}) contains information on both infection efficiency and production of secondary inoculum (21,33). Environmental and host characteristics negatively affecting infection and sporulation reduce the apparent infection rate (14,21,33). In this study, we assumed that a logistic model explained disease development, and that other conditions such as temperatures were not limiting the disease development. The apparent infection rate was adjusted daily as a function of cloudiness on a given day so that it was not a constant. Greater apparent infection rates of SBR occur on cloudy days, while the infection rate was reduced by a fraction α (equation 4) on a clear day, as calculated from our experimental data. Based on equations 1 through 5, the assumptions led to $r_{Ln} = r_M$ on a cloudy day and $r_{Ln} = \alpha \times r_M$ on a clear day.

Unlike monomolecular models, logistic models increase from an established initial disease level. In this study, most of the simulations were set to start at the first detection date reported in the region at a severity level of one lesion per leaf (0.4 to 0.8% by area). This is the minimum detectable level for a trained observer previously reported for SBR (8). One exception was made for the 2002–03 growing season in Brazil, when SBR was observed for the first time in many regions that lacked trained disease observers. Therefore, the first detection dates in that season did not reflect the minimum detectable levels because the disease was noticed when premature defoliation occurred (40). In these cases, the epidemics of

SBR were considered to have started at least 1 month earlier than reported detections in those regions (40), and disease simulations were given a starting date 1 month before the reported detection dates. In South Africa, the detection dates of SBR were not regularly reported. Thus, model simulations were arbitrarily set to start on December 1 of each year because most soybean fields were usually established at that time and inoculum was locally present (3).

Starting on the detection dates, daily increments of disease severity were calculated from the current ratios of healthy to diseased plant tissue multiplied by the adjusted apparent infection rate according to the daily cloudiness condition for cloudy and non-clouded days (i.e., $r_{Ln} = r_M$ or $r_{Ln} = \alpha \times r_M$). Daily disease increments were integrated for estimation of disease progress curves and final epidemic intensity (Table 2) at the end of disease development. Modeled final disease intensities were compared with the reported intensity of epidemics observed at each location (Table 1). In several specific cases of disease progress from fungicide trials, the estimated disease progress curves were compared with the disease progress from untreated plots in which more detailed disease information was available (11,12,24–26,31,35,37).

Results

Disease severity only showed significant ($P = 0.01$) correlation with Ncd and Nrd (Table 3). Among the weather variables, Ncd had a significant ($P = 0.05$) positive correlation with Prcp and Nrd during the epidemics (Table 3). A negative correlation ($r = -0.48$) was observed between Ncd and average Tm, whereas the correlations between Ncd and Tx and Pdd were not significant at $P = 0.05$.

Analyses showed that severe SBR epidemics were reported in regions with more than 19.5 cloudy days between the first disease detection and the final disease assessment date (Table 4). Disease epidemics were much less severe, with minimum yield losses, in regions with less than eight cloudy days (Table 4).

Overall, the cloudiness-based model explained regional development of SBR in both regions, especially in the four cases shown in Figure 1 with more detailed disease progress information. In all, 94% of the epidemics had final intensity accurately estimated from cloud cover conditions over disease development. However, the model overpredicted the intensity of 2 in 30 epidemic cases. In this study, no final epidemic intensity was underestimated.

The joint correlation between predicted and observed disease severity was estimated to be 0.976, with a regression line slope of

Table 2. Criteria used to determine disease level: mean severity (MS), estimated yield losses (YL), defoliation (Defol), and average number of required fungicide sprays (Sprays) at different epidemic intensity levels (4,10,39)

Epidemic intensity	MS (%)	YL (%)	Defol (%)	Sprays
Light	<20	0–15	<10	0 to 1
Moderate	20–40	15–30	10–30	1 to 2
Severe	>40	30–70	30–60	>2

Table 3. Estimates of Pearson's correlation among weather variables and disease severity observed at 30 epidemic locations from disease detection to disease assessment date in Brazil and South Africa²

Variables	Ncd	Nrd	Prcp	Tx	Tm	Pdd
Nrd	0.560*	...	...	...	...	...
Prcp	0.396*	0.604**	...	...	...	...
Tx	–0.353	–0.616**	–0.596**	...	...	...
Tm	–0.487*	–0.567*	–0.572**	0.735	...	...
Pdd	0.090	0.664*	0.532	–0.378	–0.278	...
Severity	0.786**	0.413*	0.195	–0.104	–0.313	–0.022

² Ncd = number of cloudy days; Nrd = number of rainy days; Prcp = precipitation (mm); Tx = average maximum temperature (°C); Tm = average mean temperature (°C); Pdd = proportion of days with dew formation; * and ** indicate significant at $P = 0.05$ and 0.01 , respectively.

Table 4. Expected number of cloudy days to cause a certain level of disease severity based on the model simulation from 30 epidemic locations in Brazil and South Africa

Epidemic intensity ^y	LSM of cloudy days ^z	Standard error
Light	7.9 a	1.35
Moderate	13.6 b	1.91
Severe	19.5 c	1.23

^y Light = disease severity <20%, Moderate = disease severity of 20 to 40%, and Severe = disease severity >40%.

^z Least-square mean. Estimates followed by different letters differ at $P = 0.05$.

1.02 (Fig. 2). The residuals were randomly distributed over time of epidemic development and also over observed disease severity. Nonetheless, the model had a tendency to slightly overpredict disease severity at low disease severity levels.

Discussion

This model provides a simpler way to describe regional disease development compared with previously developed SBR models (5,16,38). Based on these results, cloud cover was an adequate estimator for modeling apparent infection rates of SBR in Brazil and South Africa, resulting in accurate predictions of the disease's temporal progress and final epidemic intensity. Results demonstrate that Ncd can be used to estimate overall disease develop-

ment. The three different Ncd resulting in different disease development levels (Table 4) identified from the analyses were consistent with previous field observations (32,41). In 2 of 30 epidemic cases, our model slightly overpredicted final disease intensity. Both cases were first-time disease outbreaks; therefore, evaluator inexperience may have influenced the ratings of actual disease severity (8,40). Nonetheless, our cloudiness-based model was robust over subjective variations in disease rating because most predictions of SBR severity were consistent with observations from different disease evaluators.

Our cloudiness-based model was successfully extrapolated over time and space. The model structure permitted simulations to be initiated at different times and crop stages (Fig. 1) over a number

Fig. 1. Estimated soybean rust progress curves using the cloudiness-based model and observed disease severities at four locations in Brazil: **A**, Uberaba, MG, 2003 (37); **B**, Barreiras, BA, 2004 (25); **C**, Mogi Mirim, SP, 2003 (11,12); and **D**, Itaberá, SP, 2003 (31).

of regions. However, the model had a strong assumption on disease severity levels at first detection time. Model estimates were based on daily epidemic buildup from initial disease levels. The initial severity values should reflect actual disease values at the starting time so that disease increments are accumulated over accurate initial levels. The success of this cloudiness-based modeling would depend on the presence of sufficient and accurate disease monitoring systems.

Clouds provide shading by blocking direct solar radiation and are also often associated with rainfall in tropical regions. Because both shade and rainfall favor SBR development, as a predictor, cloudiness incorporates both rainfall and shade effects in modeling. In addition to shading and rain, cloud cover may also influence other biologically important weather factors that impact regional SBR development. *P. pachyrhizi* requires specific ranges and time of leaf wetness (6 to 8 h) at certain temperatures (22 to 24°C optimal) for infection and development (22). In tropical regions, summer rain events provide moisture and prolonged shading by rain clouds, reducing average temperatures. At most locations in our study, the Ncd and Nrd were positively correlated, while the Ncd and average air temperature were negatively correlated. Thus, lower temperatures may lead to longer leaf wetness duration. Collectively, in these regions, cloudiness used in SBR modeling may serve as an integrated index reflecting multiple effects from other factors, including rainfall, leaf wetness, temperature, and solar radiation, negatively or positively related.

Rainfall, temperature, and leaf wetness have been employed alone or in combination to estimate SBR severity (5,16,38). However, previous models use only one of these factors to assess SBR development regionally. One example is a rainfall-based SBR regression model developed by Del Ponte et al. (5) using data from Brazil. In this study, the variables of accumulative rainfall and rain days (rainfall >1 or 5 mm/day) were observed in a fixed period of 30 days, whereas ours used a simulation model of daily cloudiness as a predictor of the apparent infection rate in disease development. Because rainfall, rain days, and cloudiness in tropical regions are highly correlated, it is not surprising that our cloudiness-based model yielded results similar to those of the rainfall-based model. Both models demonstrate a high ability to describe regional SBR development. However, a simulation model is more flexible than a regression model if daily data are available.

From a modeling perspective, cloud cover is an appropriate and advantageous estimator variable on a regional scale because it exhibits large spatial correlation within regions. Although data collection of a rainfall variable is straightforward, large variations are observed within relatively close locations; therefore, more observations are required to characterize these variables on a regional scale when using a rainfall-based model. In tropical regions of Brazil, similar cloud cover is observed over hundreds of kilometers (34). In this case, only a few observations in a fairly large region are needed to determine regional cloud cover conditions,

which simplifies data input of the cloud cover-based simulation model. In many locations of Brazil and South Africa, cloud cover is regularly observed and weather data are typically available to the public through the national weather service. Data accessibility makes this cloudiness-based model simple for growers to use for SBR management in these countries. In the future, the cloudiness-based model and the rainfall model approaches may be combined in order to achieve even more accurate results. The rainfall model could be used to predict general disease risk during early disease development. Once the initial disease level is determined by field surveys, the cloudiness-based simulation model can be incorporated to simulate daily disease progress for more accurate disease forecasts.

Regional risk for severe SBR outbreaks can be estimated in our simulation model from historical patterns of cloud cover. Backward model simulations would determine critical timing for disease onset leading to yield losses based on regional cloud cover patterns during soybean reproductive stages. In general, later SBR onset in a region results in shorter time for disease development. Accurate simulation results would give support for decision making of appropriate management strategies to avoid profit losses on a regional scale.

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Fig. 2. Predicted disease level versus observed soybean rust severity at seven locations in Brazil, linearized to LOGITS; that is, $\log(P/(1 - P))$, in which P is the disease severity in 0 to 1. The solid line represents the solution for the regression equation and the dotted line represents values of correlation equal to 1.

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