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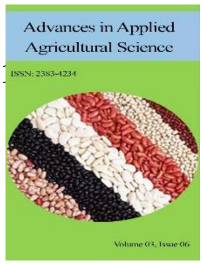

Research Article

Soybean frogeye leaf spot (*Cercospora sojina*): first weather-based prediction models developed from weather station and satellite data

Sepulcri Gabriela M.[1], Moschini Ricardo C.[1] and Carmona Marcelo A.*[2]

[1] *Instituto de Clima y Agua, Instituto Nacional de Tecnología Agropecuaria (INTA), Castelar, Argentina.*

[2] *Cátedra de Fitopatología, Facultad de Agronomía, Universidad de Buenos Aires, Av. San Martín 4453, C1417DSE, Buenos Aires, Argentina.*

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* Corresponding Author;
E. Mail: carmonam@agro.uba.ar

ABSTRACT

In Argentina, soybean frogeye leaf spot occurs sporadically. However, particularly in the Pampas Region, the incidence and severity of this fungal disease have significantly increased in the last years. In the present study, its epidemic progress was evaluated in six sites of the Pampas region during the 2009/2010 soybean season. Also, meteorological variables were calculated during the nine days previous to each field observation of disease occurrence for each site, using weather station and satellite data. Rain occurrence was obtained from the 3B42 TRMM product and temperature images were taken from NOAA-AVHRR. Then, logistic models were used to estimate probabilities of having severe or moderate to null disease. The stepwise procedure used to select the best model included the interaction (product) between wetness frequency (WF) and sum of days without precipitation (DwP) as a variable. Estimations from the resulting model agreed with the observed epidemiological curve for one of the sites studied (El Trébol, Santa Fe) during the 2010/2011 soybean season and coincided with the low disease presence recorded during the 2011/2012 soybean season. These new results could be useful as support for rational fungicide application.
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Abbreviations used: FLS (Frogeye leaf spot); total number of spots (NS); daily spot increase rate (DSiR); Daily maximum temperature (XT); Daily minimum temperature (MT); National Institute of Agricultural Technology (INTA); National Meteorological Service (SMN); advanced very high resolution radiometer images (NOAA-AVHRR); Daily Relative Humidity (RH); Precipitation (PR); Tropical Rainfall Measurement Mission (TRMM); severe (Sev); moderate to null (Mod); probability of having a severe outbreak (SevPr); probability of having a moderate to null epidemic (ModPr); wetness frequency (WF); dew-induced WF (DW); precipitation-induced WF (PW); product of days without precipitation (DwP) and WF (It1).

Frogeye leaf spot (FLS) is a disease caused by *Cercospora sojina* Hara. This disease is considered as explosive and with a high probability of unexpected occurrence epidemics, which generates great uncertainty. This fungus was firstly described in Japan in 1915 and then in the United States in 1924 (Melchers, 1925). In Brazil, this disease was identified by Yorinori in Paraná state in 1971 and by Reis and Kimati in Río Grande do Sul state in 1973 (Veiga & Kimati, 1974). Worldwide, average yield damage ranges between 10 and 50 % (Laviolette *et al.*, 1970; Bernaux, 1979; Mian *et al.*, 1998).

In Argentina, FLS was first cited in the central area of Córdoba province in 1983 (Giorda & Justh, 1983) and then found in Tucumán, Salta, Jujuy, Catamarca and Santiago del Estero provinces in the 1997/1998, 1998/1999 and 1999/2000 soybean seasons (Ploper *et al.*, 2000). During the following years, its occurrence was sporadic but its prevalence increased in other provinces such as Entre Ríos, Córdoba, Santa Fe and Buenos Aires. During the 2008/2009 soybean season, we recorded severe FLS attacks, mainly in Córdoba and Santa Fe provinces (Carmona *et al.*, 2009) and in the 2009/2010 soybean season, FLS prevalence, incidence and severity increased and expanded to relevant areas of the Pampas Region (Carmona *et al.*, 2010a). Leaf incidence of 100% and severity oscillating between 3 and 331 spots per leaf were recorded at Piamonte, Las Petacas, María Susana, El Trébol (Santa Fe province) and at Monte Buey and Bengolea (Córdoba province) (Carmona *et al.*, 2010a). Estimated losses caused by FLS during the 2009/2010 soybean season were about 2000 million dollars (Carmona, 2011).

FLS is mainly a leaf disease but also can develop on stems, pods and seeds. Infection can occur at any phenological stage but symptoms are usually observed after flowering, becoming more evident from the beginning-pod stage (R3 stage, Fehr & Caviness, 1977). Young tissues are the most vulnerable. In Argentina, during the 2009/2010 soybean growing season, FLS symptoms were found in fields planted with susceptible soybean varieties at vegetative growth stage and in voluntary plants with two or three leaves (Carmona *et al.*, 2010a). Sources of primary inoculum are infected seeds, stubble and voluntary soybean plants. Disease development is favored by a warm and humid environment, especially with temperatures between 25 and 30-35 ºC, precipitation occurrence, dew and relative humidity greater than 90% (Yorinori, 1989; Mian *et al.*, 2008).

Regarding FLS management, main control strategies include the use of tolerant or resistant cultivars, seed and foliage fungicide treatment and crop rotation. Use of resistant varieties is the prime control action. However, it is supposed that the existence of races could change the genotype reaction. In Argentina, race 11 predominates in Buenos Aires, Córdoba and Santa Fe provinces, whereas race 12 is mostly found in Santiago del Estero and Entre Ríos provinces (Scandani *et al.*, 2012). Knowledge that resistant cultivars have the Rcs3 gene, together with the identification of new sources of resistance to C. sojina, are key factors for future disease management. In Argentina, resistance genes were incorporated mainly in long-maturity groups because FLS initially developed in the northwest of the country (Carmona *et al.*, 2010a). Thus, varieties belonging to maturity groups VII and VIII are currently resistant. Approximately 50% of the Pampas Region is planted with maturity groups III, IV and V, which are mostly susceptible (Carmona *et al.*, 2010a). As a consequence, the only available strategy to avoid damages in these varieties is chemical control.

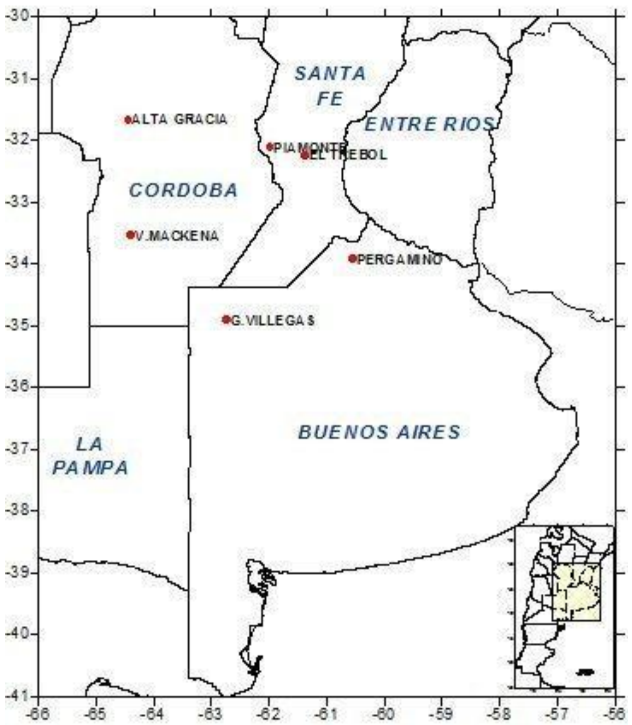

Fig. 1 Sites within the Argentine Pampas region where frogeye leaf spot was recorded

Since 2009, FLS has become more important because of its severity and affected crop surface.

Therefore, a thorough research is necessary and research projects that allow anticipating or minimizing the damage caused by FLS should be developed. An efficient and sustainable chemical control should be reached before resistant genotypes become widely available. Thus, it is essential to create a regional prediction system to operate together with chemical control so as to help reduce the potential crop losses.

Prediction models are used to estimate disease occurrence probability for a specific site or region, based on different sources of variables. Many prediction models use meteorological variables obtained from weather station data. Among these variables, precipitation is the one with most spatial variability (Hubbard, 1994). Hence, regional disease predictions depending on precipitation as the main variable are often uncertain because of the lack of spatial representation and irregular distribution of the weather station network (Levizzani *et al.*, 2002; Huffman *et al.*, 2007). The spatial resolution of model inputs affects the accuracy of regional predictions. Those using raster precipitation data (satellite images) are more accurate than those using irregular distributed punctual measurements (weather station data) (Guo *et al.*, 2004; Smith *et al.*, 2004). An alternative to weather station precipitation data are remote sensing estimations. Remote sensing is a high-technology and readily available tool that, among its numerous applications, provides precipitation estimates at regional scale (Fattorelli *et al.*, 1995). Therefore, lack of meteorological information distributed homogeneously in a region is one of the main constraints for plant disease models that depend on meteorological data as inputs (Workneh *et al.*, 2004).

The aim of this study was to generate exploratory models to estimate the occurrence probabilities of binary levels of FLS increasing rates based on weather station and satellite meteorological variables. According to the reviewed literature, there is no available background related to FLS prediction.

Materials and Methods

Monitoring and quantification of Frogeye Leaf Spot

FLS severity values were recorded in susceptible soybean varieties at different phenological stages assessed according to Fehr and Caviness (1977), where R3 = beginning pod, R4 = full pod, R5 = beginning seed, R6 = full seed, R7 = beginning maturity, and R8 = full maturity. Measures were performed from R3 in six sites within the Pampas region (Santa Fe, Córdoba and

Table 1. *FLS progress (NS, DSiR) observed in soybean fields. Details of site, soybean variety, phenological stage and observation date.*

Site	Soybean variety	Observation Date (Julian day)	Phenological stage	NS*	DSiR**
El Trébol (Santa Fe)	A4990	43	R3	11.40	0.76
		50	R4	13.60	0.31
		60	R5	19.40	0.58
		67	R5,5	21.30	0.27
		75	R6	22.30	0.13
		81	R6.5	37.10	2.47
		88	R7	65.60	4.10
Piamonte (Santa Fe)	DM3700	1	R4	64.00	4.30
		13	R5	64.00	0.00
		22	R5	148.50	16.5
		29	R5.6	236.00	12.5
Vicuña Mackenna (a) (Córdoba)	DM4670	9	R2	5.00	0.33
		22	R3	3,50	0.00
		29	R3	15.50	1.70
		36	R5	39.00	3.36
Vicuña Mackenna (b) (Córdoba)	DM4670	26	R2	1.00	0.07
		36	R3	0.80	0.00
		43	R4	3.50	0.39
		50	R5	7.40	0.56
		57	R5.2	15.60	1.17
		71	R5.8	93.50	5.56
		77	R6	136.20	7.12
Pergamino (Buenos Aires)	NA4613	75	R4	5.10	0.34
		85	R5.3	6.70	0.16
		97	R6	11.20	0.38
General Villegas (a) (Buenos Aires)	A4970	24	R3	4.00	0.27
		32	R4	10.00	0.75
		59	R5	25.00	0.56
General Villegas (b) (Buenos Aires)	5009	24	R2	2.00	0.13
		59	R5	22.00	1.54
		69	R6	24.00	0.20
Alta Gracia (Córdoba)	A4613	29	R3	3.60	0.24
		42	R4	7.80	0.32
		77	R6	62.00	1.55

* Number of spots: average of observed values in the lower and upper crop canopy.

** Daily spot increase rate: results from subtracting the NS observed at time t respect the NS observed at time t-1, divided by day interval between both consecutive dates. The first DsiR value for each site-soybean variety analyzed was calculated dividing the corresponding NS value by 15 days.

Buenos Aires provinces) in the 2009/2010 soybean season (Figure 1, Table 1). I n addition, observed data from one of those sites were obtained during 2010/2011.

For data collection, 30 plants were randomly extracted from each field. Only central leaflets from main stems were counted. Severity was calculated counting average number of lesions (spots) per leaflet. Only spots of at least 2 mm were considered. The total number of spots (NS) was divided by the total number of leaflets sampled. Then, to confirm *C. sojina* presence, plants with lesions were incubated in a wet chamber at a temperature range of 24-27ºC and alternating 12 hours of ultraviolet light and darkness.

For further analysis, observed data were expressed as daily spot increase rate (DSiR; N=34). DSiR results from dividing the difference between the NS observed at time *t* respect the NS at *t-1* by the day-interval between these two consecutive observation dates. The first DsiR value for each site-soybean variety analyzed was calculated dividing the corresponding NS value by 15 days. Table 1 shows the site, soybean variety, phenological stage, NS and DSiR for each observation date.

Meteorological input data

Maximum and Minimum Temperature

Daily maximum (XT) and minimum (MT) temperature data were obtained from 29 weather stations from the National Institute of Agricultural Technology (INTA) and National Meteorological Service (SMN) for the period b etween December 2009 and April 2010. These data were taken to 25-Km grids in all the study area based on a climatic temperature zoning of the region that was done using NOAA-AVHRR (advanced very high resolution radiometer) images that take land surface temperature information during clear sky days. Satellite overpasses coincident with the occurrence of XT and MT were taken from a five-year period (2004-2008). A semi-supervised classification was run over those images. This consists of a mixed technique that uses validation data for classification (supervised) and statistical methods (ISODATA) for class selection (unsupervised). Thus, homogeneous temperature areas within the study region were obtained. These areas served for grouping weather stations and then assigning a temperature value to each 25-Km pixel according to its closeness but within the same homogeneous area. This allowed giving spatial distribution to temperature data using the own temperature behavior rather than statistical interpolation methods. This method was also applied previously (Sepulcri, 2010).

Relative Humidity

Daily Relative Humidity (RH) data were obtained from the 29 weather stations cited above. Mean daily values (average of the three observations made at 9, 15 and 21 h) corresponding to the period between December 2009 and April 2010 were used. These values were taken to 25-Km grids through Krigging interpolation (Burgess and Webster 1980), which allowed obtaining daily RH matrixes for the whole study area.

Precipitation

Precipitation (PR) occurrence data were obtained from product 3B42 (Huffman *et al.* 2007) available from TRMM (Tropical Rainfall Measurement Mission), which provides three-hourly precipitation estimates (mm) at 25 Km of spatial resolution. These images were obtained for December 2009-April 2010 and December 2010-April 2011 and for the Pampas Region. Eight images per day were integrated from 9 am of a day to 9 am of the following day according to the SMN observation protocol. PR occurrence was defined for those cases where it exceeded the 0.8 mm threshold, giving a value of 1. Values below 0.8 mm were assigned a value of 0. It is worth mentioning that we have previously validated this product with weather station data from the Pampas Region (Sepulcri *et al.*, 2009) and obtained 85% of agreement between satellite and station data.

Logistic model development

Logistic regression is the most common method used to model binary or categorical response data (Agresti, 2002). These types of models are useful to predict events and several authors have used them for disease prediction (De Wolf *et al.*, 2002; Moschini *et al.*, 2006; Carmona *et al.*, 2010b). This method adjusts non-linear regression

Table 2. *Description of meteorological variables*

Variable	Description
DwP	Days without precipitation (PR < 0.8 mm)
PW	Precipitation wetness (days with simultaneously occurrence of PR ≥ 0.8 mm and RH>83%, within a temperature range of MT > 15ºC and XT < 30ºC)
DW	Dew wetness (days without precipitation (PR < 0.8 mm) and RH > 85%, within a temperature range of MT > 15ºC and XT < 30ºC)
WF	Wetness frequency (sum of PW + DW)
DRHT	Days with simultaneous occurrence of RH > 83% and temperature ranging between MT > 15ºC and XT < 30ºC)
AcPR	Accumulated PR (mm)
mXT	Mean maximum temperature (ºC)
mMT	Mean minimum temperature (ºC)
It1	WF * DwP
It2	DRHT * DwP

models for binary response data by the maximum likelihood method. Functions like Logit establish a link between a stochastic component and meteorological regression variables.

In the present study, the dependent variable was defined as the probability of having severe or moderate to null levels of DSiR of FLS, either above or below a certain threshold. To define that threshold, a statistical criterion was considered based on the median or 50% percentile value. For our dataset, the median value was: DSiR = 0.475. Therefore, observations with DSiR greater than or equal to 0.475 were considered as severe (Sev) and those below that threshold were moderate to null (Mod).

Besides, independent meteorological variables were calculated from daily XT, MT, RH and PR values, over the nine-day periods prior to each DSiR observation. The period length was also defined by statistical criteria (maximizing the non-parametric Kendall Tau-b correlation coefficient, Sprent & Smeeton, 2001) but considering that leaf lesions do not appear until 7 to 14 days after host tissue invasion (Mian *et al.*, 2009). The meteorological variables analyzed are detailed in Table 2.

Finally, logistic regression models were run using SAS Logistic procedure (Proc LOGISTIC SAS 1994), which fits models for binary response data by the maximum likelihood method. The probability of having a severe outbreak (SevPr) implies exceeding the 0.475 threshold of DSiR. A logit function provides the link function between the stochastic component and meteorological variables. The logistic model output is a probable DSiR value that can be severe (SevPr) or moderate to null (ModPr). The relationship can be written as:

$$\ln(SevPr / 1\text{-}SevPr) = \beta_0 + \beta_1 X_1$$

where X_1 is a weather predictor and β_0 and β_1 are parameter estimators. SevPr is obtained by solving:

$$1 / (1+Exp^{-(\ln(SevPr/1\text{-}SevPr))})$$

The probability of having a moderate to null epidemic (ModPr) results from subtracting SevPr to 1. For final model assessment, the critical P_c value (probability value to classify a case as severe that provides the most accurate prediction) was taken into consideration. The stepwise logistic regression procedure was run with all meteorological variables and then the most appropriate model was selected. The significant levels to enter and stay in the model were specified as 0.05.

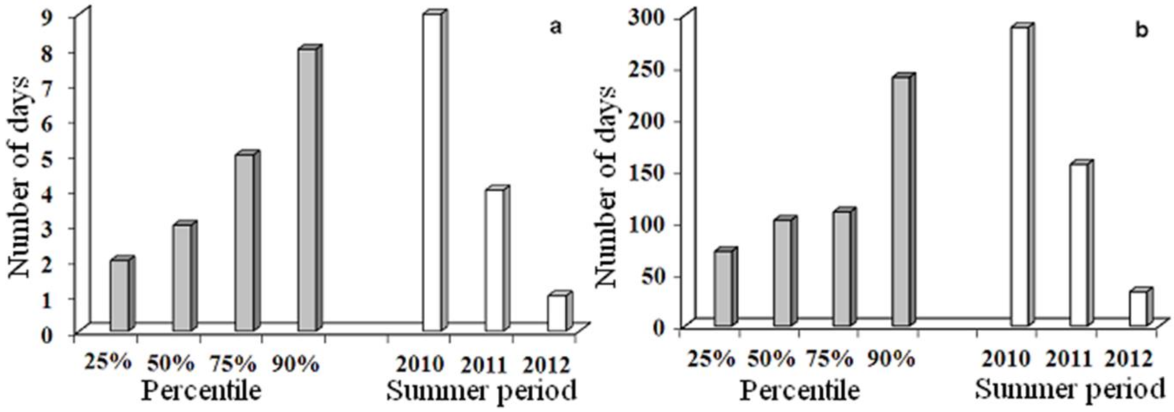

Fig 2. Number of days of a. WF and b. WF * DwP (It1) during summer (46 days) recorded at Marcos Juárez weather station. Dark bars: historical percentiles (1971-2012 series). Clear bars: summer period values (2010, 2011 and 2012). WF: wetness frequency. DwP: days without precipitation.

Comparisons between model outputs and field data

Predictions resulted from the selected logistic model were compared with FLS observations obtained from a soybean field located at El Trébol (Santa Fe province) during 2010/2011. Weather data used for model running were PR occurrence obtained from TRMM 3B42 product and daily XT, MT and RH values recorded at Marcos Juarez INTA weather station (Córdoba province), located 70 km southwest from the observation site. Also, during the 2011/2012 soybean season, the same model was run using all data from Marcos Juarez INTA weather station. During this last season, no severe epidemics were reported in the area. Hence, we evaluated whether the model estimates followed the same observed trend.

It is important to mention that the observed data were poor because FLS was either hardly or broadly expressed during the 2008/2009 and 2009/2010 soybean seasons respectively. However, no new observations of severe FLS were later recorded at the sites where it was most frequently observed.

Annual values of the main independent variables were calculated for the summer period (45 days, approximately) in which phenological stages R3 and R5 are concentrated. For the study area's latitude, this period comprises from January 20th to March 6th. For this, a 42-year (1971-2012) time series of daily XT, MT, RH and PR from Mar cos Juárez INTA weather station was used. Percentile values 25%, 50%, 75% and 90% were contrasted with model variable values obtained during the summer periods of 2010, 2011 and 2012.

Results

Monitoring and quantification of Frogeye Leaf Spot

The monitoring method proposed was very useful to quantify FLS severity. NS ranged from 1 to 236 according to the growing stage and soybean variety (Table 1). Maximum NS values corresponded to the varieties DM 3700 and DM 4670, which are susceptible to FLS (Carmona *et al.*, 2010a). Also, incubation of plant material with lesions confirmed the presence of the pathogen.

Table 3. *Resulting model based on meteorological variables to estimate probabilities of having severe or moderate to null DSiR*

Model*	Parameter	Estimator	Standard Error	Probab > $\chi 2$	P_c**
I	Intercept	- 1.5752	0.65	0.015	0.51
	It1	0.2297	0.08	0.006	

* **It1=** WF * DwP, being WF: wetness frequency (sum of PW + DW) and DwP: days without precipitation (PR < 0.8 mm). PW: Precipitation wetness (days with simultaneously occurrence of PR ≥ 0.8 mm and RH>83%, within a temperature range of MT > 15ºC and XT < 30ºC). DW: Dew wetness (days without precipitation (PR < 0.8 mm) and RH > 85%, within a temperature range of MT > 15ºC and XT < 30ºC)

**** P_c:** critical predicted probability value to classify a case as severe that provides the most accurate prediction

Meteorological variables and logistic model development

Meteorological variables were calculated during nine-day periods prior to each DSiR observation. The most significant variables were wetness frequency (WF), which simulates dew-induced (DW) and precipitation-induced (PW) WF within a favorable daily temperature range, and It1, which results from the product of days without precipitation (DwP) and WF. Kendall's correlation coefficients of these two variables with DSiR values were 0.51 and 0.54 respectively. Also, WF and It1 were calculated for 46-day periods from January 20th to March 6th for 42-year (1971-2012) time series and for each study year (2010, 2011 and 2012) using Marcos Juárez weather station data. During summer 2010, both WF and It1 showed the third highest values (9 for WF and 288 for It1) in 42 years, exceeding the 90% percentile (Figure 2). In 2011 and 2012, those variables showed lower values (4 for WF and 156 for It1 and 1 for WF and 33 for It1, respectively). The values of these weather variables coincided with FLS observed data for those seasons, which that were mostly severe during 2010, moderate to null in 2011 and with no disease reports during 2012. Simple variables that were only related to PR occurrence (accumulated PR and DwP) had weak correlation coefficients with FLS occurrence and severity.

The stepwise logistic regression run with all meteorological variables selected model I as the most appropriate (Table 3), with a P_c value of 0.51 and It1 as the selected variable. It1 combines by multiplication WF (days) with DwP. This model correctly classified 79.4% of DSiR observations (27 out of 34 cases). Model I was selected for having the best performance and being the most simplified. Bivariate models that integrated the variable mXT with It1 or It2 showed not enough influence on disease response. Figure 3 shows the results of model I, the independent variable evolution during the period analyzed and observed data in El Trébol (Santa Fe province), during the 2009/10 soybean season.

Comparisons between model outputs and field data

Estimates obtained from the selected model (I) run with 2011 and 2012 summer periods meteorological data were

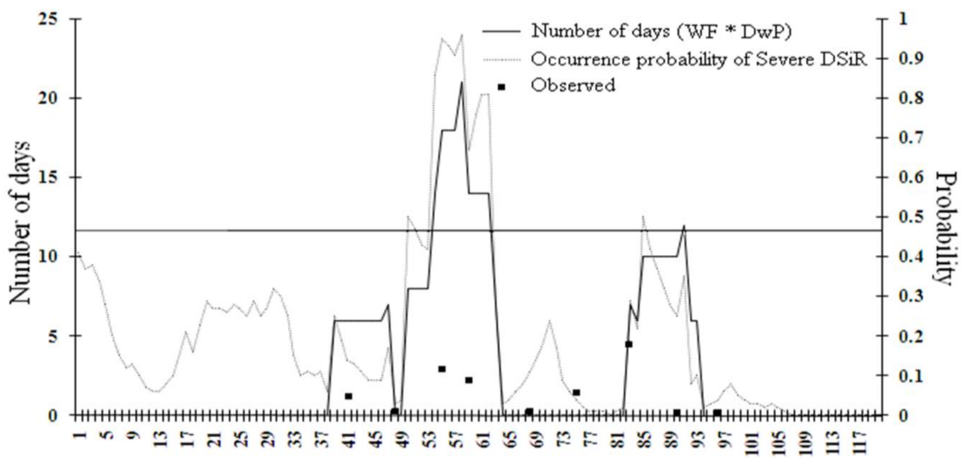

Fig 3. Evolution of severe FLS occurrence probability expressed as DSiR estimated from model I (Table 3), independent variable It1 (WF*DwP) and observed FLS data during the 2009/2010 soybean season in El Trébol (Santa Fe province). DSiR: daily spot increase rate. WF: wetness frequency. DwP: days without precipitation.

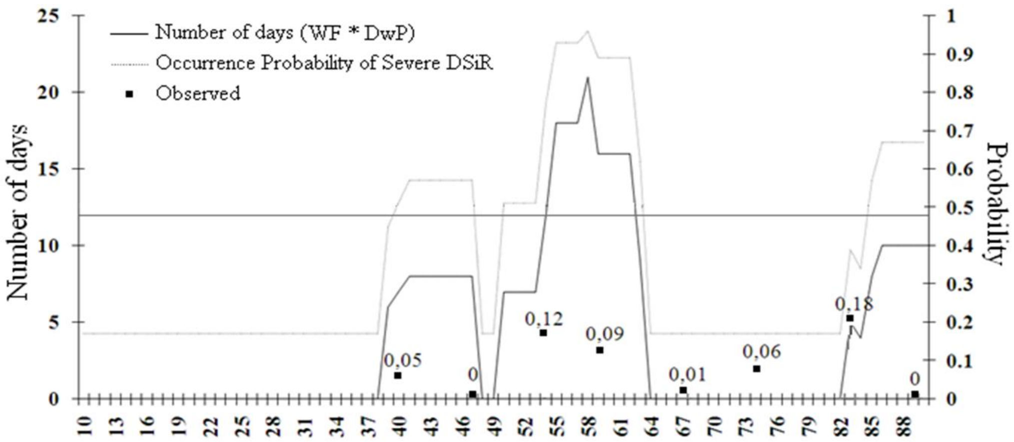

Fig 4. Evolution of severe FLS occurrence probability expressed as DSiR estimated from model I, independent variable It1 (WF*DwP) and observed data during the 2010/2011 soybean season in El Trébol (Santa Fe province). DSiR: daily spot increase rate. WF: wetness frequency. DwP: days without precipitation.

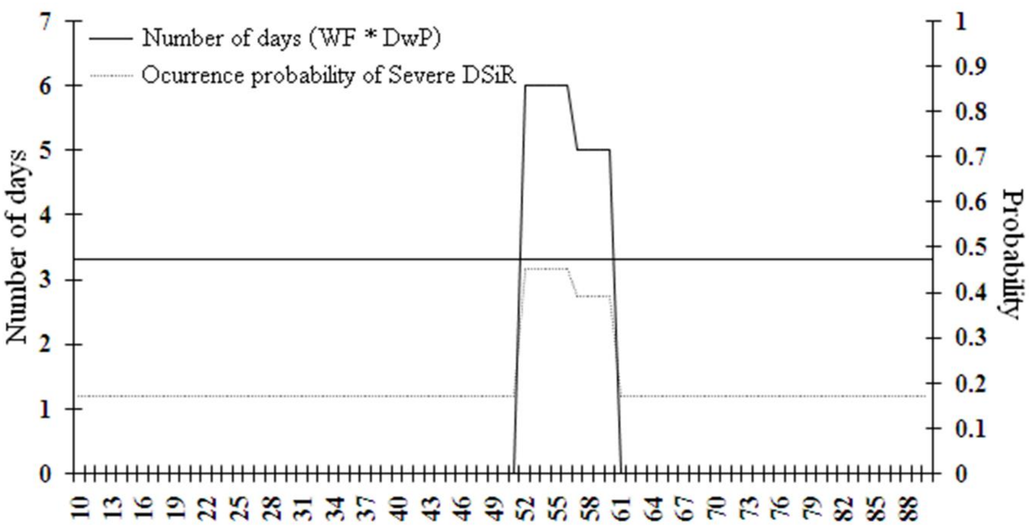

Fig 5. Evolution of severe FLS occurrence probability expressed as DSiR estimated from model I and independent variable It1 (WF*DwP) during the 2011/2012 soybean season in El Trébol (Santa Fe province). DSiR: daily spot increase rate. WF: wetness frequency. DwP: days without precipitation.

contrasted with FLS DSiR observations derived from a soybean field situated at El Trébol (Santa Fe province). These results were plotted together with the independent variable throughout the period analyzed. In 2011, predictions of model I followed DSiR observed trend with a slight trend towards overestimation in a 10-day period within the timeline analyzed (Figure 4). In 2012, the meteorological conditions were not favorable for disease development (Figure 5). Hence, there were only mild to null FLS reports, which coincides with model I estimates, which gave no severe alarms in all the period analyzed. These results could be some kind of first validation for this model which is in exploratory phase.

Discussion

During the 2009/2010 growing season, soybean FLS

was widely expressed in all the Pampas Region, especially over the most susceptible genotypes such as variety DM 3700, which showed the maximum number of observed lesions at Piamonte. Particularly, this field was not harvested because losses and damages were so high that the harvesting cost and poor quality of grains did not outweigh such work.

Among the meteorological variables identified, WF had a direct relation with the binary response variable. This weather variable estimates wetness duration (total wet days) by considering high RH for days without rain or combining high RH with PR occurrence, both within a favorable daily temperature range. Conversely, variables related only to PR (millimeters or PR occurrence) reached very weak or negative correlation coefficients with disease observations. Hence, WF seems to have greater incidence on disease development than PR occurrence. Also, it is worth considering that *C. sojina* does not need rain for dispersion. Wind can spread dry and free conidia to neighboring areas. Then, conidia require WF for germination and tissue penetration, as observed in other *Cercospora* species (Lartey *et al.*, 2010). This is probably why rain as simple variable did not reach high correlation coefficients with FLS occurrence, in contrast to that observed in other diseases such as those caused by *Glomerella glycines*, *Colletotrichum truncatum*, *Septoria glycines*, and *Phomopsis sojae*.

It1, which resulted from the product between WF and DwP, calculated for nine-day periods before symptoms manifestation, reached the highest correlation value with DSiR observations. This result allows us to associate days without rain with greater sunlight duration, which is favorable for sporulation. This is consistent with that found by Veiga and Kimati (1974), who stated that long sunlight duration and alternation of night darkness are related to greater *C. sojina* sporulation. Hence, It1 and WF could simplify the meteorological conditions observed during the 2009/2010 soybean growing season that favored the occurrence of a severe FLS attack. Both variables exceeded the 90% percentile of the 42-year time series in Marcos Juárez (Córdoba province). Extreme values recorded for the main independent variables during this growing season could justify the sporadic nature of this disease.

The fact that variables were processed within nine-day periods prior to each DSiR observation could help in future disease prevention and management, planning in advance a monitoring and/or timely chemical control. Since this procedure could be performed daily starting from the last vegetative soybean stages, it is expected to help in planning monitoring and giving risk alarms. Although a recommendation based on economic damage threshold for susceptible varieties already exists

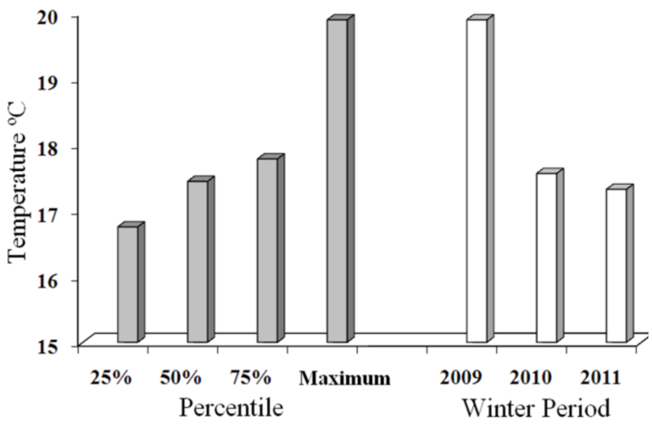

Fig 6. Mean maximum temperature (mXT) from winter (192 days) at Marcos Juárez. Dark bars: 1971-2011 time series (percentiles 25%, 50%, 70% and historical maximum). Clear bars: values reached during the winter periods of 2009, 2010 and 2011.

(Carmona, 2011; Carmona *et al.*, 2010a), results obtained in this study could improve chemical control decisions and allow obtaining a better economic and sustainable performance.

In addition, it should be emphasized that this work included remote sensing meteorological data to estimate PR occurrence and temperature. The aim is to establish some kind of regional alarm system which allows having an accurate FLS risk assessment in each site and thus improve management efficiency. This method has been previously proposed and applied to estimate wheat *Fusarium* head blight spatial distribution (Sepulcri, 2010). The main advantages resulting from precipitation remote sensing estimates were better spatial coverage and no need of data interpolation for sites where meteorological weather stations were not available. The main disadvantage observed from using this kind of data was the uncertainty about the real precision of datasets and its relation with conventional weather station measurements (Workneh *et al.*, 2004).

Another aspect to consider is the inoculum availability associated with its winter survival. According to this, we proposed to analyze winter temperature conditions previous to each summer season. In this case, we analyzed the 2009, 2010 and 2011 winter seasons and then compared them to winter temperature time series (1971-2011) for Marcos Juárez (Córdoba province). The 2009 winter period was characterized by having the highest mean maximum temperature, compared with the 41 seasons analyzed (Figure 6). We believe that this higher than normal temperature favored winter survival in stubble and thus the occurrence of such a severe attack during the 2009/2010 soybean crop season. During 2010 and 2011, winter conditions were close to normal and hence no severe attacks were recorded.

Finally, the results obtained in this work could provide useful information at regional level that would help, in conjunction with other tools, to generate risk alarms and create an efficient monitoring system and a sustainable disease chemical control.

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