Weather-Based Predictive Modeling of Orange Rust of Sugarcane in Florida

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ABSTRACT

Epidemics of sugarcane orange rust (caused by *Puccinia kuehnii*) in Florida are largely influenced by prevailing weather conditions. In this study, we attempted to model the relationship between weather conditions and rust epidemics as a first step toward development of a decision aid for disease management. For this purpose, rust severity data were collected from 2014 through 2016 at the Everglades Research and Education Center, Belle Glade, Florida, by recording percentage of rust-affected area of the top visible dewlap leaf every 2 weeks from three orange rust susceptible cultivars. Hourly weather data for 10- to 40-day periods prior to each orange rust assessment were evaluated as potential predictors of rust severity under field conditions. Correlation and stepwise regression analyses resulted in the identification of nighttime (8 PM to 8 AM) accumulation of hours

with average temperature 20 to 22°C as a key predictor explaining orange rust severity. The five best regression models for a 30-day period prior to disease assessment explained 65.3 to 76.2% of variation of orange rust severity. Prediction accuracy of these models was tested using a case control approach with disease observations collected in 2017 and 2018. Based on receiver operator characteristic curve analysis of these two seasons of test data, a single-variable model with the nighttime temperature predictor mentioned above gave the highest prediction accuracy of disease severity. These models have potential for use in quantitative risk assessment of sugarcane rust epidemics.

Keywords: ecology and epidemiology, mycology

Incited by the fungal pathogen *Puccinia kuehnii*, orange rust of sugarcane was long considered to be a disease of minor economic importance prior to 2000, when its range was limited to only Asia and Australia (Magarey 2000). However, between 1999 and 2001, the Australian sugarcane industry experienced severe epidemics of orange rust on the cultivar Q124. The predominant cultivar at the time (Q124) accounted for nearly 45% of the country's sugarcane hectareage. Attributed to the emergence of a new rust variant (race), yield losses were reported to exceed 200 million Australian dollars (Magarey et al. 2011). In the western hemisphere, orange rust was not reported on sugarcane (*Saccharum* interspecific hybrids) until 2007, when it was first observed in Florida attacking two major cultivars, CP80-1743 and CP72-2086 (Comstock et al. 2008). Together, these cultivars accounted for nearly one-third of the state's sugarcane hectareage. Within 2 to 3 years, orange rust was reported throughout North, Central, and South America (Barbasso et al. 2010; Chavarría et al. 2009; Comstock et al. 2008; Flores et al. 2009; Ovalle et al. 2008; Pérez-Vicente et al. 2010). Total sugar losses >50% have been reported in countries throughout the world, with yield components, such as stalk density, stalk biomass, and sucrose content, all being negatively impacted (Comstock et al.

2010; Raid et al. 2011; Rott et al. 2016). Although its exact pathway of introduction into the western hemisphere is not known, it has been hypothesized that urediniospores of *P. kuehnii* were carried by upper-level atmospheric currents from Africa to America (Rott et al. 2016).

Host–plant resistance is the preferred and usual method of managing orange rust in locations where sugarcane is grown commercially (Rott et al. 2016). However, because the genome of sugarcane is very complex, breeding for resistance to orange rust is a challenging and long process (Jackson 2018; Yang et al. 2018). Starting from an annual pool of approximately 150,000 seedlings, typically only one or two cultivars are released per year by the U.S. Department of Agriculture Sugar Cane Field Station at Canal Point, Florida, which leads the Florida sugarcane breeding effort. The process has been further complicated by the adaptability of *P. kuehnii*, limiting the durability of cultivar resistance (Sanjel et al. 2019). In 2007, when orange rust was first found in Florida, a majority of commercial sugarcane cultivars proved to be susceptible to the disease, and >40% of the germplasm was also affected (Comstock et al. 2010). Furthermore, several cultivars that were resistant to orange rust in 2007 became susceptible to the disease within 3 to 5 years (Rott et al. 2016). Similar to the situation that has occurred repeatedly with cereal rusts, this change in reaction to the disease was associated with the selection of new physiological races of *P. kuehnii* (Rott et al. 2016). For this reason, management of orange rust in Florida currently relies on foliar fungicide applications, a practice first enabled in 2008 by the authority of an emergency quarantine exemption (Raid 2010).

As with many fungal pathogens, RH and temperature are considered key factors influencing orange rust epidemics. Magarey et al. (2004) reported that temperatures from 17 to 24°C associated with a minimum of 97% RH were the best conditions for in vitro spore germination of *P. kuehnii* from Australia. More than 50% of *P. kuehnii* urediniospores from Florida germinated at temperatures

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*The e-Xtra logo stands for “electronic extra” and indicates that one supplementary table is published online.

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between 20 and 29°C, but spore germination was only 18% at 30°C and nonexistent at 31°C (Sanjel et al. 2019). Likewise, using Florida isolates of the pathogen and sugarcane grown in controlled conditions, Martins et al. (2010) reported that temperatures from 20 to 25°C associated with >8 h of leaf wetness resulted in appearance of orange rust symptoms. These studies using controlled conditions provided important background information regarding the epidemiological understanding of orange rust; however, information regarding weather variables affecting the development of orange rust epidemics under field conditions is limited. Orange rust epidemics in the field are generally considered to be favored by warm and humid conditions (Magarey 2000; Rott et al. 2016). More specifically, in a 2-year study in Florida reported in 2019, Sanjel et al. (2019) reported that temperatures between 20 and 22.2°C from 8 PM to 8 AM were conducive to appearance of severe disease symptoms in the field.

The modeling of temporal development of epidemics by Van der Planck during the 1960s formed the basis for plant disease modeling (van Maanen and Xu 2003). During the intervening decades, various disease-forecasting models were developed and implemented successfully to aid growers in assessing the risk of outbreaks of different plant diseases and their management (Audsley et al. 2005; Coakley et al. 1988; De Wolf et al. 2003; Del Ponte et al. 2006; Madden et al. 1978; Pavan et al. 2011; Small et al. 2015). Data related to spore germination only were used in the 2000s in Australia to predict the occurrence of orange rust (Staier et al. 2004). Predictive models for orange rust were also developed based on epidemics and weather data from different growing locations but single cropping seasons in Australia (1999/2000) and Brazil (2009/2010) (Sentelhas et al. 2016). This work resulted in identification of agroclimatic favorability zones for orange rust. The objective of our work was to develop weather-based models that could be used to predict orange rust development on susceptible sugarcane cultivars based on 3 years of disease and weather data from a location (Belle Glade, Florida) known to be conducive for orange rust.

MATERIALS AND METHODS

Disease severity data. Three orange rust susceptible cultivars were monitored under natural infection conditions for 5 years during the 2014 to 2018 crop seasons (plant cane or first ratoon crop) at Belle Glade, Florida. In 2014, 2016, and 2018, disease severity was monitored in plant cane on three susceptible cultivars (CP80-1743, CL85-1040, and CP88-1762), which had been planted using a randomized complete block design in 2013, 2015, and 2017, respectively. An additional sugarcane cultivar planted in 2013, cultivar CP89-2143, was also monitored for rust severity but only in 2014. In 2015 and 2017, plants from the 2013 and 2015 plantings were monitored in the first ratoon crop after harvest of plant cane. Additionally, in 2015 and 2017, commercial fields of CL85-1040 and CP88-1762 were also monitored in the plant cane crop. Planting dates varied from early October to mid-December, and cultivation practices followed the local production recommendations (Anderson 1990). Within each block and for a single cultivar, individual experimental plots were formed by four rows of sugarcane bordered by one row of CL85-1040 on one side and one row of cultivar CL90-4725 (susceptible to brown rust caused by *Puccinia melanocephala*) on the other side. These six rows were 10.7-m long each and had a 1.5-m interrow spacing. All experimental plots were surrounded by a 3-m alley on each side. Commercial fields included 27 to 36 rows that were each 274-m long. For each growing season, severity data of orange rust (percentage area of leaf affected by rust) were collected every 2 weeks, with few exceptions, from the date of first rust symptom detection until sugarcane harvest (Supplementary Table S1).

Rust symptoms on the upper third leaf portion of the top visible dewlap (TVD) leaf were assessed using a diagrammatic scale described by Purdy and Dean (1981). This scale represents simulated percentage of disease leaf surface (1, 5, 10, 25, and

50%) as a result of rust infection. The upper third leaf portion of the TVD leaf was considered for assessment, because rust lesions tend to appear mostly within this area. Because of sugarcane's indeterminate growth, sugarcane stalks produce new leaves continuously. The TVD leaf of a sugarcane stalk is the highest unfolded leaf with a visible dewlap, and new TVD leaves emerge every 7 to 10 days (Van Dillewijn 1952). Therefore, at a given date of observation, rust lesions on TVD leaves are symptoms that appeared most recently. A total of 32 stalks per cultivar were scored (8 stalks in each of four blocks or in four different commercial field locations) at each assessment date in each growing season, and values were averaged as described by Sanjel et al. (2019). At each assessment date, the mean disease severity value from the cultivar with the highest disease level was used to determine temporal disease progress of orange rust in each growing season. Data would, therefore, not be biased (lower disease severity owing to a cultivar that was not yet or no longer susceptible to the disease), although conditions were favorable for disease development on another cultivar.

Meteorological data and weather variables. Previously described weather predictors from published modeling efforts for different crop diseases were used to develop a set of potential predictors for modeling of orange rust epidemics (Audsley et al. 2005; Coakley et al. 1988; De Wolf et al. 2003; Del Ponte et al. 2006). Based on these studies, weather variables, such as hourly and daily minima, maxima, averages, sums, ratios, indices, and the number of hours of specific conditions, were calculated using R statistical software (R version 3.2.3) (R Core Team 2016). Hourly and daily weather data from 2014 through 2018 were retrieved from the South Florida Water Management District (SFWMD) weather station (<https://www.sfwmd.gov/weather-radar/current-weather-conditions>) at Belle Glade, Florida, located within 1.6 km of the experimental plots.

Data of daily and hourly minimum, maximum, and average temperature (degrees Celsius), RH (percentage), rainfall (millimeters), and wind speed (meters second⁻¹) were analyzed. Leaf wetness was estimated using an empirical method based on a threshold of RH ≥ 90% as described in other studies (Kim et al. 2002; Rowlandson et al. 2015). Two indices, humid thermal ratio (HTR) and afternoon humid thermal ratio (AHTR), were calculated in an attempt to overcome the problem of multicollinearity. HTR was calculated as the ratio of daily average RH and daily average temperature. AHTR was calculated as the ratio of daily afternoon RH (3 to 5 PM local standard time) and maximum temperature. Thermal time accumulation with base temperature 16°C was calculated from the date of planting to each disease assessment date as described by Zhou et al. (2003).

The concept of windowpane analysis was used to construct weather-based predictor variables for different window periods as explained by Kriss et al. (2010). A total of 250 weather variables were created for four different time periods: 7 to 17, 7 to 27, 7 to 37, and 7 to 47 days prior to disease assessment. These selected window lengths (10 to 40 days) consisted of analysis of weather variables prior to disease assessment. The rationale for using time periods up to 7 days before disease assessment was because it is unlikely that any infections initiated in the last 7 days would be visible on the TVD leaf at the day of disease assessment, because sugarcane rust has a latent period of 9 to 14 days (Martins et al. 2010).

Model development and validation. Disease severity data collected for the first 3 years (2014 to 2016) were used in model development. The combined dataset used for model development consisted of 32 observations collected during the period of active sugarcane growth of each crop season (Supplementary Table S1). This period started when maximum tiller population was reached and lasted until the end of the period of rapid stalk elongation that was determined based on thermal time requirement as explained by Zhou et al. (2003). Using JMP Pro 13 (SAS Institute Inc.), a correlation matrix was created using the TVD highest (across cultivars) mean rust severity value at each assessment date with all

weather variables for each time point to identify the variables associated with orange rust epidemics in Florida. Only weather variables with absolute value of Pearson's correlation coefficient ≥ 0.3 and with significance level < 0.05 were used for inclusion in the modeling process. Additionally, variables considered to have biological significance and that were not already represented among the variables that met the inclusion criteria were used. For highly intercorrelated weather variables (as indicated by the variance inflation factor [VIF] of the multicollinearity test; $VIF > 10$), only variables having the highest correlation coefficient with disease severity and assumed to capture information of the other collinear variables were used in the modeling process.

Disease severity data (percentage) were converted into proportions and logit transformed, and regression analysis was performed using the R statistical package. The regression model can, therefore, be written as follows:

$$\ln(Y/[1 - Y]) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$$

in which $\ln(Y/[1 - Y])$ is the logit of disease severity Y , β_0 to β_k are parameters, and X_1 to X_k are predictor variables.

Stepwise regression and regression subset procedures were used as a guide to develop single-variable and multiple-variable regression models using the "MASS" and "leaps" packages in R version 3.2.3 (Lumley 2017; R Core Team 2016; Ripley et al. 2019). Logit weight ($Y \times [1 - Y]$) was used for each regression model to minimize the sum of weighted squared residuals and produce residuals with constant variance. Regression models were evaluated based on graphical appraisal of the randomness and normality of the residuals, coefficient of determination (R^2) or adjusted coefficient of multiple determination (R^2_{adj}), residual squared error (RSE), Akaike information criterion (AIC), and Bayesian information criterion (BIC). AIC and BIC are both penalized likelihood criteria used for candidate model selection.

For model selection, models with the lowest AIC and BIC values are considered closer to the true model (Aho et al. 2014). A multicollinearity test with VIFs was carried out to assess the correlation among the independent variables in multiple-variable regression models (Draper and Smith 1981; Kutner et al. 2005). The leave one out cross-validation (LOOCV) approach, which provides an average of estimates of prediction error for each model, was used

for model validation as described by Del Ponte et al. (2006). The best-fitting model should have the lowest predicted error sum of squares value (Draper and Smith 1981; Kutner et al. 2005). The value for cross-validated statistics (CVSs) obtained by the LOOCV procedure for each model was compared with the average RSE.

The predictive capacity of single- and multiple-variable models for disease severity on the TVD leaf was tested using the case/control approach (Yuen and Hughes 2002). Observed orange rust severity data collected for the 2017 and 2018 crop seasons ($n = 44$) were classified as cases (disease severity proportion > 0.1) and controls (disease severity proportion ≤ 0.1). The predicted disease severity proportions for two crop seasons (2017 to 2018) from each of the models as a case or control were then compared with their actual case ($n = 9$) and control ($n = 35$) status by plotting a receiver characteristics curve (ROC) using the "pROC" package in R version 3.2.3 (R Core Team 2016; Robin et al. 2019). Areas under the receiver characteristics curve (AUCs) at a given disease threshold were used to determine the overall prediction capacity of these models for future disease severity. An AUC value > 0.5 indicates that a model has class separation capacity, because the predictor is different from the line of no discrimination.

RESULTS

Disease progress. Orange rust symptoms were first evident on the TVD leaf by 15 January during the midwinter season in Florida over the 5 years of disease observation in the field at the Everglades Research and Education Center (EREC) in Belle Glade (2014 to 2018). Disease severity did not begin to increase rapidly until mid-March or early April for the 2015 to 2017 epidemics (Fig. 1). In 2018, the epidemic started to peak only from the end of April. Orange rust progress was quite different in 2014 compared with disease progress during the other 4 years because the disease severity on the TVD leaf increased rapidly from the end of January until the end of February and remained at 11 to 13% until mid-May when it increased again. Lowest overall disease progress was observed in 2018 compared with the other years of disease observation.

Across all 5 years of disease observation, rust severity on the TVD leaf reached maximum values of 12 to 35% from the end of May to the beginning of July. Progressive reductions of disease severity on the TVD leaf were observed after this period, dropping to $< 5\%$ between the end of August and the end of September. Rapid increase in disease severity started when sugarcane plants reached maximum tiller population and canopy closure, regardless of the crop season. Canopy closure was observed approximately 180 to 190 days after planting depending on the month of planting of the plant cane crop and 130 to 160 days in the ratoon crop depending on the harvest month of the plant cane crop. Orange rust severity started to increase again from mid-September and was $> 10\%$ by early December in 2014 and 2015 (Fig. 1).

Weather variables correlated with orange rust severity.

Preliminary correlation analyses indicated that weather variables from a 30-day window prior to disease assessment ($t - 7$ to $t - 37$ prior to disease assessment at time t) were consistently associated with disease severity for all years of disease observation. For this period, correlation analysis and stepwise regression procedures allowed us to identify 10 variables that were individually correlated with disease severity (Table 1). Pearson correlation coefficients ranged from -0.43 to 0.89 for these 10 variables. Most of the variables that were significantly correlated with orange rust severity were based on temperature and RH. Among those, four were duration variables: DT20_N (number of hours at night with an average temperature of 20 to 22°C), DT20_W (number of hours per day with an average temperature of 20 to 22°C), DT20RH90_N (number of hours at night with an average temperature of 20 to 22°C and RH $\geq 90\%$), and DT20RH90_W (number of hours per day with an average temperature of 20 to 22°C and RH $\geq 90\%$). These

Fig. 1. Temporal progress of sugarcane orange rust during 5 years (2014 to 2018). Each point at each assessment date represents the mean disease severity value of four sets of eight stalks (32 leaves) across three different cultivars (cultivars CP80-1743, CL85-1040, and CP88-1762), with data from the most affected cultivar presented. Disease severity (percentage of rust-affected area) was assessed on the upper third leaf portion of the top visible dewlap leaf using the schematic scale described by Purdy and Dean (1981).

variables were calculated from the same basic weather elements, and they were intercorrelated; thus, they could not be used together in modeling. The same intercorrelation was also found for the two average (RH and RH_N) variables calculated from RH (Table 1). The hours with average temperature between 20 and 22°C during the night period from 8 PM to 8 AM accumulated for 30 days (DT20_N) had the highest correlation coefficient of the 10 significantly correlated variables ($r = 0.89$, $P < 0.0001$). The correlation coefficient for DT20RH90_N ($r = 0.86$, $P < 0.0001$), when RH $\geq 90\%$ was also considered, was lower than the correlation coefficient obtained for DT20_N ($r = 0.89$, $P < 0.0001$) without RH. The two other temperature-based duration variables, DT20_W and DT20RH90_W, had a similar correlation coefficient: $r = 0.85$ (DT20_W) and $r = 0.85$ (DT20RH90_W), $P < 0.0001$. These variables were also observed to be the most significant variables when used in the single-variable regression models (Table 2).

Similar correlation coefficients were obtained for two indices, AHTR and TT16 (-0.52 versus -0.53 , respectively). Similarly, the correlation for number of hours with maximum temperature $>32^\circ\text{C}$ was also significant ($r = -0.62$, $P = 0.004$). No significant correlation with orange rust severity was obtained with other temperature-based and precipitation-based variables at a significance threshold level of 5% (Table 1). Nevertheless, average temperature at night (AT_N) was also included in the modeling process because of its presumed biological significance.

Model development. Single-variable models developed based on several weather variables explained different amounts of variation in orange rust severity. However, only those models with relatively high R^2 values and low CVS values were selected. Given the high correlation of orange rust severity with the temperature duration-based variables, three single-variable regression models were developed (Table 2). These single-variable models explained different amounts of variation in TVD rust severity with R^2 values ranging from 0.653 to 0.762 (Table 2). Among the three single-variable models, OR1 described the most orange rust severity variation ($R^2 = 0.748$) (Table 2). For these three single-variable models, AIC and BIC values ranged from 6.29 to 17.3 and from 11.4 to 21.7, respectively (Table 2).

Stepwise regression and regression subset procedures were performed using all of the significantly correlated variables to select

the model with the best combination of variables. Two (OR4) and three (OR5) independent variable models were identified after the stepwise regression and regression subset analysis process (Table 2). These multiple regression models were able to explain 3% additional variation in orange rust severity compared with the best single-variable model (OR4 and OR5 versus OR1) (Table 2). Additionally, AIC and BIC values for these models ranged from 6.29 to 6.94 and from 12.2 to 14.3, respectively. VIF values among the weather variables used in multiple regression models showed lack of multicollinearity (OR4 and OR5) (Table 2).

Model validation. All regression models were validated using cross-validation statistics as calculated from LOOCV and cross-validated residual distributions (Fig. 2 and Table 2). Predictive capacity of each model for future disease severity was tested using ROC analysis. OR1 had the lowest prediction error (CVS = 0.08) among the single-variable regression models. Lower prediction error (CVS = 0.07) was observed for multiple-variable regression model OR5 compared with OR4 (CVS = 0.08) (Table 2). Cross-validated residuals for orange rust severity estimations by the single-variable models and multiple-variable models indicated better fit when residuals were scattered closer around the line (difference between predicted and observed) at zero (Fig. 2). Results from ROC analysis suggested that all models are able to predict disease severity at a given disease severity threshold of 0.1 (Fig. 3). Highest overall predictive accuracy was observed with single-variable model OR1 with an AUC value of 0.795 followed by model OR3 (also a single-variable model) with an AUC value of 0.793. Among the multiple-variable models, OR5 had a slightly lower predictive accuracy (AUC = 0.765) compared with OR4 (AUC = 0.781) (Fig. 3).

DISCUSSION

Florida's sugarcane production is largely concentrated south of Lake Okeechobee in a region known as the Everglades Agricultural Area (EAA). Cultivated on about 160,000 ha, this area produced a crop valued at $>\$2$ billion during the 2017 to 2018 growing season. Historically, 80 to 90% of the state's sugarcane hectareage is planted to <12 cultivars, with 2 to 4 major cultivars commonly accounting for $>50\%$ of the total. Because of sugarcane's perennial nature, with a typical field being planted

TABLE 1. Pearson's correlation coefficients (r) between 21 weather variables and mean disease severity of sugarcane orange rust (caused by *Puccinia kuehnii*) observed on top visible dewlap leaves on the most affected cultivar at Belle Glade, Florida during three consecutive growing seasons (2014 to 2016)

Variable	Description ^a	r	P value
DT20_N	Duration (h) $20 \leq$ average $T \leq 22^\circ\text{C}$ at night (8 PM to 8 AM)	0.89	<0.0001
DT20_W	Duration (h) $20 \leq$ average $T \leq 22^\circ\text{C}$	0.85	<0.0001
DT20RH90_N	Duration (h) $20 \leq$ average $T \leq 22^\circ\text{C}$ at night (8 PM to 8 AM) while RH $\geq 90\%$	0.86	<0.0001
DT20RH90_W	Duration (h) $20 \leq$ average $T \leq 22^\circ\text{C}$ while RH $\geq 90\%$	0.85	<0.0001
TT16	Thermal time accumulation with base T 16°C (degrees Celsius per day)	-0.53	<0.002
DMA32	Duration (h) maximum $T \geq 32^\circ\text{C}$	-0.62	0.0001
RH	Average RH (%)	-0.47	0.0065
RH_N	Average RH (%) at night (8 PM to 8 AM)	-0.43	0.013
AHTR	Afternoon humid thermal ratio	-0.52	0.0023
DRH90	Duration (h) RH $\geq 90\%$	-0.43	0.0003
HTR	Humid thermal ratio	-0.12	0.501
SAT	Sum of average T	-0.22	0.222
SAT_N	Sum of average T at night (8 PM to 8 AM)	-0.30	0.0935
AT	Average T	-0.22	0.2223
AT_N	Average T at night (8 PM to 8 AM)	-0.30	0.0926
MT	Average hourly minimum T ($^\circ\text{C}$)	-0.22	0.2343
MaT	Average hourly maximum T ($^\circ\text{C}$)	-0.23	0.2125
PPT	Sum of precipitation (mm)	-0.14	0.4261
DPPT0	Duration (h) precipitation > 0 mm	-0.19	0.2858
DPPT1	Duration (h) precipitation > 1 mm	-0.08	0.6525
DPPPT5	Duration (h) precipitation > 5 mm	-0.04	0.8239

^a Disease severity was assessed at 2-week intervals, and weather variables were calculated for a period of 30 days (7 to 37 days prior to each disease assessment) except for TT_16, which was calculated from the day of planting to each assessment day. T indicates temperature. Humid thermal ratio is the ratio of average RH to the average temperature, and afternoon humid thermal ratio is the ratio of afternoon average RH (3 PM to 5 PM) to the maximum temperature.

and then harvested annually for 3 to 4 years, major cultivar shifts occur more slowly with sugarcane than with annual crops. Complicating matters further, sugarcane is vegetatively propagated by placement of entire sugarcane stalks, referred to as seed cane, in widely spaced furrows. This practice requires tons of “seed” per hectare rather than mere kilograms, and it greatly extends the length of time required for a cultivar to build up to a significant proportion of the total hectareage. Given these limitations and the propensity for new pathogen races to arise, Florida’s sugarcane hectareage has ranged between 24 and 70% orange rust susceptible (Raid et al., *unpublished data*). Such vulnerability necessitates management with fungicides to prevent significant economic yield losses.

Located in the southern part of the humid subtropical climate zone of the northern hemisphere (Pavan et al. 2011), Florida is reputed for summers that are long, humid, and hot and for winters that are dry and mild. Large variations in temperature occur in south Florida from January through December starting as low as average temperatures of 10 to 15°C for a couple of months early in the year followed by average daily temperatures of 19 to 27°C in spring and very warm summer temperatures (average weekly maximum summer temperatures of 32 to 34°C). Precipitation in south Florida occurs predominately in the warmer months. The amount of precipitation can vary both temporally and spatially during these months (Winsberg 2003).

Weather variables associated with the occurrence and progress of orange rust epidemics in Florida were identified through correlation analyses between weather variables and mean disease severity of the most affected cultivar recorded on the TVD leaf over 3 years (2014 to 2016); 250 weather-based predictors were created for each of four different time periods (7 to 17, 7 to 27, 7 to 37, and 7 to 47 days prior to each disease assessment day). The duration of hours with average temperature between 20 and 22°C during the overnight period (8 PM to 8 AM) accumulated for 30 days (DT20_N) was the single most important variable of the 10 significant variables associated with orange rust epidemics in Florida. The same variable calculated while RH was ≥90% (DT20RH90_N) and the cumulative hours within the same temperature range calculated for a 24-h period (DT20RH90_W) also showed strong relationships with orange rust severity, but the correlation coefficients were slightly lower compared with DT20_N. This is likely owing to the fact that most nighttime periods (8 PM to 8 AM) in Florida have an RH > 90%. Therefore, the minimum duration of leaf wetness required for infection occurs frequently, assuming that RH > 90% is a good proxy of leaf wetness

(Rowlandson et al. 2015). This indicated that high numbers of accumulated overnight hours with temperatures between 20 and 22°C were the best environmental conditions for development of orange rust in Florida.

Leaf wetness and temperature are essential factors for appearance and progress of rust diseases of sugarcane (Barrera et al. 2012, 2013; Magarey et al. 2004). Temperature is recognized to impact inoculum availability, time of disease onset, rate of disease progress, and eventual decline of the epidemic (Barrera et al. 2013). Highest rates of spore germination of Australian isolates of

Fig. 2. Plot of cross-validated residuals of mean sugarcane orange rust severity data observed on the top visible dewlap leaf estimated by regression models using weather variables for a period of 30 days (7 to 37 days prior to disease assessment) from 3 years of disease observation (2014 to 2016) at Belle Glade, Florida. All five models (OR1 to OR5) are described in Table 2. Y is disease severity expressed as a proportion. LOOCV, leave one out cross-validation.

TABLE 2. Single-variable and multiple-variable models obtained through stepwise and best-subset regression analyses for predicting sugarcane orange rust severity at Belle Glade, Florida during three consecutive growing seasons (2014 to 2016)

Models ^a	P value	VIF ^b	R ² or R ² _{adj} ^c	PRESS ^d	RSE ^e	CVS ^f	AIC ^g	BIC ^h
Single-variable models								
OR1: $\ln(Y/[1 - Y]) = -2.67 + 0.00913 \times \text{DT20_N}$	<0.0001		0.74	2.58	0.08	0.08	7.02	11.4
OR2: $\ln(Y/[1 - Y]) = -2.54 + 0.00928 \times \text{DT20RH90_N}$	<0.0001		0.67	3.49	0.09	0.10	15.4	19.8
OR3: $\ln(Y/[1 - Y]) = -2.53 + 0.00884 \times \text{DT20RH90_W}$	<0.0001		0.65	3.66	0.09	0.11	17.3	21.7
Multiple-variable models								
OR4: $\ln(Y/[1 - Y]) = -2.51 - 0.00622 \times \text{DMaT32} + 0.0081 \times \text{DT20_N}$	<0.0001	1.49 DT20_N 1.49 DMaT32	0.76	2.51	0.08	0.08	6.29	12.2
OR5: $\ln(Y/[1 - Y]) = 1.1 + 0.152 \times \text{AT_N} - 0.0878 \times \text{RH} + 0.0082 \times \text{DT20_N}$	<0.0001	4.72 AT_N 4.95 RH 1.24 DT20_N	0.76	2.50	0.08	0.07	6.94	14.3

^a Regression models developed using disease severity values collected at 2-week intervals for 3 years (2014 to 2016) of disease observation on the top visible dewlap leaf. Weather variables are defined in Table 1. OR1 to OR5 refer to the various orange rust models. Y is disease severity expressed as a proportion.

^b VIF, variance inflation factor.

^c R², coefficient of determination for single-variable models; R²_{adj}, adjusted coefficient of multiple determination for multiple-variable models.

^d PRESS, prediction sum of squares.

^e RSE, residual squared error.

^f CVS, cross-validated statistic.

^g AIC, Akaike information criterion.

^h BIC, Bayesian information criterion.

P. kuehnii were obtained around 20°C (17 to 23°C), with at least 97% RH (Magarey et al. 2004). Spores of this pathogen from Florida germinated well at temperatures between 20 and 29°C (Sanjel et al. 2019), and temperatures from 20 to 25°C associated with a leaf wetness period >8 h were found to be necessary for appearance of orange rust symptoms in controlled conditions (Martins et al. 2010). Thus, it is not surprising that the temperatures best associated with severity of orange rust in our study were within the range of temperatures previously reported in the literature. Duration of overnight leaf wetness is sufficient all year round for the development of rust epidemics in south Florida (C. Fraisse, *unpublished data*). In contrast to other geographical locations where orange rust occurs, development of disease epidemics in Florida is not limited by leaf wetness. This is supported by the high correlation values obtained in our study between rust severity and night temperatures without a criterion of RH $\geq$ 90%.

Over the 3 years (2014 to 2016) of study, the correlation between orange rust severity and night temperatures was highest and most consistent when cumulative hours of conducive conditions over a 30-day period (7 to 37 days before disease assessment) were used. These disease-conducive conditions included high humidity at night and temperatures between 20 and 22°C. The incubation period from the infection of the sugarcane leaf by *P. kuehnii* to pathogen sporulation ranges from 9 to 14 days (Irey 1987; Martins et al.

2010). Therefore, a 30-day period includes at least two to three rust infection cycles for inoculum buildup.

Our objective was to develop predictive models for orange rust severity on TVD leaves based on weather variables in Florida. This was accomplished by developing three single-variable and two multiple-variable regression models. All of the models explained >65% of variation in disease severity, but three models, namely OR1 (the single-variable model), OR4 (a multiple-variable model), and OR5 (a multiple-variable model) had the lowest prediction errors. Incorporating other variables, such as DMat32, AT_N, and RH (OR4 and OR5), in addition to a temperature-based duration variable improved the overall fit of the models compared with the single-variable model (OR1). Based on penalized likelihood criteria AIC and BIC calculated for each candidate model, OR1 and OR4 had the lowest AIC and BIC values, indicating that these were the best-fit models when compared with the other models presented in this study.

ROC analysis suggested that the highest overall predictive accuracy for future disease severity can be obtained with OR1, which is a single-variable model. Although model fit statistics indicated that best-fit models use multiple variables (OR4 and OR5), their prediction accuracy was slightly lower compared with single-variable models (OR1 and OR3) according to ROC analysis with test data. This might have been owing to overfitting of the OR4 and OR5 models.

In the EAA, fungicide applications to control orange rust in commercial fields are presently scheduled pertaining to disease scouting that is performed every 2 weeks in untreated sugarcane fields. Scouting begins in early spring when the first symptoms of orange rust are found in the plant cane crop, and scouting finishes in the fall when sugarcane harvest begins (C. Mellinger, *personal communication*). We developed weather-based predictive models for orange rust severity in Florida in hopes of alerting growers when the disease is expected to develop on susceptible varieties. This would help growers to be prepared for the management of orange rust epidemics. Weather-based models developed by Sentelhas et al. (2016) were used to define agroclimatic favorability zones for orange rust occurrence in the state of Queensland, Australia and the state of Sao Paulo, Brazil. This information is expected to help growers to make rational decisions on planting sugarcane varieties susceptible to orange rust and chemical control strategies. The application of the models developed in our study will largely depend on the availability, resolution, and reliability of weather data. Regional weather data are available from three Florida Agriculture Weather Network (FAWN) stations located in or near the EAA (Wellington, Belle Glade, and Clewiston). The Belle Glade FAWN site is colocated with the SFWMD station site used in this study. It should be noted that, because these models were developed based on field studies in Florida, they should not be generalized across other sugarcane-producing regions without validation.

The models developed herein could be used to estimate favorability/rust severity using the preceding 30-day period. They could be the groundwork for the development of a disease advisory system to help growers to manage orange rust epidemics by optimizing the timing of fungicide applications. There is also potential for use of these models in mapping the agroclimatic favorability zones for orange rust occurrence and epidemic development.

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Fig. 3. Receiver operating characteristics curves for five different models to predict sugarcane orange rust severity based on weather variables. Diagonal lines represent the line of no discrimination. All five models (OR1 to OR5) are described in Table 2. Sensitivity indicates the true positive proportion, and 1 – specificity indicates false-positive proportion. AUC, area under the receiver operating characteristics curve.

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