Modeling the airborne inoculum of *Polystigma amygdalinum* to optimize fungicide programs against almond red leaf blotch

Gemma Pons-Solé[1,2], Laura Torguet[3], Neus Marimon[3], Xavier Miarnau[3], Elena Lázaro[4], Antonio Vicent[4], and Jordi Luque[1]*

[1]*Sustainable Plant Protection, Institut de Recerca i Tecnologia Agroalimentàries (IRTA) Cabrils, Ctra. de Cabrils km 2, E-08348 Cabrils, Spain*

[2]*Plant Physiology Laboratory, Universitat Autònoma de Barcelona (UAB), 08193 Bellaterra, Spain*

[3]*Fruit Production Program, Institut de Recerca i Tecnologia Agroalimentàries (IRTA) Fruitcentre, PCiTAL, Park of Gardeny, Fruitcentre Building, E-25003 Lleida, Spain*

[4]*Centre de Protecció Vegetal i Biotecnologia, Institut Valencià d'Investigacions Agràries (IVIA), Ctra. CV-315 km 10.7, 46113 Moncada, Spain*

*Corresponding author: Jordi Luque; E-mail: jordi.luque@irta.cat

Keywords: decision support system, disease control, epidemiology, modeling, *Polystigma amygdalinum*, *Prunus dulcis*, red leaf blotch

Funding: Instituto Nacional de Investigación y Tecnología Agraria y Alimentaria (INIA, Spain); Grant Number: RTA2017-00009-C04-01, and Agencia Estatal de Investigación (AEI, Spain); Grant Number: PID2020-114648RR-C31 (MCIN/AEI/10.13039/501100011033). G.P.-S. is supported by a predoctoral grant from AEI; Grant Number: PRE2018-085207. J.L., L.T., and X.M. are supported by the CERCA Program, Generalitat de Catalunya.

ABSTRACT

Red leaf blotch (RLB) of almond, caused by the ascomycete *Polystigma amygdalinum*, is a severe foliar disease endemic in the Mediterranean Basin and Middle East. Airborne ascospores of *P. amygdalinum* were monitored from 2019 to 2021 in two almond orchards in Lleida, Spain, and a Bayesian beta regression was used to model its seasonal dynamics. The selected model incorporated accumulated degree-days (ADD) and ADD considering both vapor pressure deficit and rainfall as fixed effects, and a random effect for the year and location. The performance of the model was evaluated in 2022 to optimize RLB fungicide programs, by comparing the use of model predictions and action thresholds with the standard program. Two variants were additionally considered in each program to set the frequency between applications, based on: i) a fixed frequency of 21 days, or ii) specific meteorological criteria (spraying within seven days after rainfalls greater than 10 mm, with daily mean temperatures between 10 and 20°C, and with minimum 21 days between applications). Programs were evaluated in terms of RLB incidence and number of applications. The program based on the model with periodic fungicide applications was similarly effective as the standard, resulting only in a 2.6% higher RLB incidence but with fewer applications (three to four, compared with seven in the standard). When setting the frequency between applications by using the meteorological criteria, a higher reduction in the number of applications (two to three) was observed, while RLB incidence increased by roughly 16% in both programs. Therefore, the model developed in this study may represent a valuable tool towards a more sustainable fungicide schedule for the control of almond RLB in northeast Spain.

INTRODUCTION

Red leaf blotch (RLB) is one of the most important foliar diseases affecting almond (*Prunus dulcis* (Mill.) D.A. Webb) in the Mediterranean Basin and Middle East (Cannon 1996; Farr and Rossman 2022). The disease is endemic in these regions and to date has not been reported as occurring in other almond-growing areas in the world such as the USA or Australia (Farr and Rossman 2022). RLB is caused by the ascomycete *Polystigma amygdalinum* P.F. Cannon. The pathogen overwinters in almond leaf litter where the sexual stage is developed and ascospores are produced in perithecia. In spring, under favorable temperature and humidity conditions, and especially after rain events, mature ascospores are released and air-spread to eventually infect new almond leaves (Banihashemi 1990; Pons-Solé et al. 2023; Suzuki et al. 2008). Banihashemi (1990) showed that ascospore release in Iran begins at bloom (early March) and reaches the maximum at petal fall and the beginning of fruit set (late March to early April), whereas in Lebanon ascospore release can occur between February and mid-May (Saad and Masannat 1997). Similarly, the main infection period in Spain has been reported to be from March to mid-June (Zúñiga et al. 2020). Following infections, fungal stromata develop and RLB symptoms appear after a relatively long incubation period of 30 to 40 days in Iran and Lebanon (Banihashemi 1990; Saad and Masannat 1997), and from 35 to 70 days in Spain (Zúñiga et al. 2020). First symptoms appear as pale yellowish spots on both leaf sides, turning into orange-reddish and finally dark brown. Lesion size increases with time and in late summer they may cover almost entirely the leaf surface. When disease severity is high, premature defoliation can be observed in summer (Cannon 1996; Habibi and Banihashemi

2016; Miarnau et al. 2021; Shabi 1997), with a subsequent decrease in tree photosynthetic activity and thus possibly affecting yield (López-López et al. 2016). The occurrence of secondary infection cycles during the cropping season has not been confirmed, as conidia formed during summer in pycnidia are not infective and are thought to act as spermatia in the sexual reproduction of the pathogen (Cannon 1996; Habibi and Banihashemi 2016). Therefore, RLB is considered a monocyclic disease with a single inoculum source consisting of the perithecia formed in infected leaves fallen in the previous year.

Concerning the effect of meteorological conditions on the life cycle of *P. amygdalinum*, in Iran Ghazanfari and Banihashemi (1976) reported on the importance of winter temperatures below 10°C for perithecia maturation. More recently in Spain, Zúñiga et al. (2020) found that the meteorological conditions from October to January influence the total available ascospore amount for the next season. The authors found positive correlations between the total seasonal ascospore amounts and the mean relative humidity, the accumulated rainfall, the number of rainy days, and the number of days with mean temperature higher than 20°C recorded within this period. Recently, Pons-Solé et al. (2023) suggested that *P. amygdalinum* ascospore release may benefit from concurrent mild temperatures (between 10°C and 20°C) and the hydration of fallen leaves through humidity or rain. Regarding the relationships between meteorological variables and RLB disease development in Catalonia, Spain, Miarnau et al. (2021) observed that annual RLB incidence was positively correlated with the accumulated rainfall in spring (especially in April), while it was negatively correlated with high temperatures in spring (especially in May) and summer.

There are no known almond cultivars completely resistant to RLB, although several authors have observed differential levels of RLB susceptibility among cultivars (Heydarian and Moradi 2005; Miarnau et al. 2021; Ollero-Lara et al. 2019). This means that effective control strategies against RLB mainly rely on the protection of trees with fungicides. Regarding RLB control with fungicides, experiments on the efficacy of various plant protection products have been conducted in Iran (Amanifar 2017; Banihashemi 1990; Bayt Tork et al. 2014), reporting triforine and mancozeb as the most effective fungicides against RLB. Recently in Spain, Torguet et al. (2022) observed that, in general, systemic fungicides performed better than contact ones. Currently registered fungicides for RLB control in Spain are included in FRAC groups 3 (sterol biosynthesis inhibitors, i.e., difenoconazole), 7 (succinate dehydrogenase inhibitors, i.e., boscalid), and 11 (quinone outside inhibitors, i.e., pyraclostrobin and kresoxim-methyl) (FRAC 2022; MAPA 2022). To get effective disease control, five to nine fungicide applications are usually timed on a calendar basis each season, starting at petal fall and ending in summer (July to August) (Torguet et al. 2022). However, little research has been done on optimizing fungicide programs. Torguet et al. (2022) compared calendar-based programs (every 14, 21, or 31 days from petal fall) with meteorological-based programs (15 days after rainfalls over 15 mm and with 10 to 15°C as mean minimum temperature), proving that programs following those meteorological criteria were just as effective as those calendar-based but with fewer number of applications.

To be effective, fungicide applications against RLB must coincide with the infection period, defined by the presence of airborne ascospores, susceptible host leaves, and favorable conditions for infection. Epidemiological models are a useful tool to predict the periods of higher risk of infection based on meteorological variables (De Wolf and Isard 2007), thus avoiding the direct quantification of inoculum in real-time conditions, which is methodologically and logistically difficult to achieve. Modeling approaches can be used together with action thresholds to develop decision support systems (DSSs) and optimize the management of plant diseases (Gent et al. 2013; Knight 1997). DSSs can serve as decision aids to schedule fungicide applications based on disease risk, so that the number of fungicide applications can be reduced without compromising disease control efficacy (Lázaro et al. 2021; Marimon et al. 2020). Reducing fungicide application frequency and overall use is desirable as it reduces the environmental impact and the economic cost of crop protection. In the European Union, this has been promoted by the European Commission through the European Green Deal and specifically the 'from farm to fork' strategy, which targets a reduction in the use of chemical pesticides by half in 2030 (European Commission 2020).

To our knowledge, no epidemiological models to predict RLB risk of infection are available. Therefore, we aimed to develop an epidemiological model for *P. amygdalinum* airborne inoculum dynamics under the cropping conditions in Catalonia, Northeast Spain, to optimize fungicide programs and contribute towards a more sustainable disease control. The specific objectives of this work were: i) to develop an epidemiological model to predict *P. amygdalinum* airborne ascospore availability based on meteorological variables, and ii) to evaluate the performance of the model in a DSS to schedule optimized fungicide programs for RLB management.

MATERIALS AND METHODS

Experimental orchards

The model was developed with data collected from 2019 to 2021 in an experimental almond orchard owned by IRTA (Institut de Recerca i Tecnologia Agroalimentàries) (orchard 1) and a commercial one (orchard 2). Model evaluation was carried out in 2022 in orchard 2 and three additional commercial orchards of similar characteristics (orchards 3 to 5). All orchards were located in Lleida province, Catalonia, NE Spain, within a radius of 26 km area (Table 1). RLB occurs naturally in all orchards, as it is a widespread disease in the study region (Miarnau et al. 2021). Orchards 1 to 3 were planted in alternating rows with various earlier and later-flowering cultivars, as it is common in this almond-growing region. All orchards were drip irrigated, and pruning, soil management, and fertilization were based on the Spanish Integrated Production Management practices (BOE 2002). Leaf litter was present in all orchards, and no products (e.g., urea) were applied to promote its decomposition. Weeds were controlled by mechanical methods since no herbicides were used during the experimental period. No fungicide treatments were applied in any of the orchards during the experiments, besides the applications corresponding to the model evaluation carried out in 2022 in orchards 2 to 5.

RLB airborne inoculum dynamics

A Hirst 7-day recording volumetric spore trap (Burkard Manufacturing Co. Ltd, Rickmansworth, Hertfordshire, UK) was placed in a central position in orchards 1 and 2, operating continuously from mid-February to mid-September in 2019, 2020, and 2021. The airflow was set at 10 L min^{-1}, **with the intake orifice located at 0.45 m above the ground.** Airborne particles were captured on a Melinex® 200 gauge (TEKRA, New Berlin, WI, USA) plastic tape, rotating at 2 mm h^{-1} and previously coated with a layer of silicone solution (Lanzoni, Bologna, Italy). Tapes were processed to estimate the daily airborne ascospore concentration of *P. amygdalinum* according to the molecular methods described by Zúñiga et al. (2018). DNA was extracted using the E.Z.N.A® Plant DNA Kit (Omega Bio-Tek, Norcross, GA, USA), and real-time quantitative PCR (qPCR) was conducted in a Stepone™ Real-Time PCR System thermal cycler (Life Technologies, Carlsbad, CA, USA), using the *P. amygdalinum* specific primer pair Pamyl2F4/Pamyl2R2 (Zúñiga et al. 2018). Daily concentration of ascospores (ascospores m^{-3}) was calculated considering the daily air volume sunk by the spore trap. The yearly cumulative concentration of trapped ascospores was calculated for each orchard, as the total of daily ascospore concentrations. For the statistical analyses, the cumulative proportion of ascospores on a 0 to 1 scale was calculated on a daily basis, based on the daily concentration of ascospores and the yearly cumulative concentration of ascospores, for each orchard and year.

Weather data

For model development, daily accumulated rainfall, mean relative humidity (RH), and mean temperature were monitored from 2019 to 2021 in orchards 1 and 2 by automatic weather stations of the Meteorological Service of Catalonia (MeteoCat, https://ruralcat.gencat.cat/web/guest/agrometeo.estacions). The weather station in orchard 1 was located about 250 m away, while the closest weather station to orchard 2 was located in Tàrrega (UTM 31T X = 347015, Y = 4614430), about 6 km away. From weather data, three new variables were calculated following Rossi et al. (2009), based on the sums of the daily mean temperatures above 0°C. These variables were: accumulated degree-days (ADD), ADD considering vapor pressure deficit (ADDvpd), and ADD considering vapor pressure deficit and rainfall (ADDwet), computed as follows:

$$ADD_i = \sum_{j=biofix}^{N_i} T_j$$

$$ADDvpd_i = \sum_{j=biofix}^{N_i} T_j \cdot VPD_j$$

$$ADDwet_i = \sum_{j=biofix}^{N_i} T_j \cdot WET_j$$

where i and j are the subscripts for observations and days, respectively, ranging between the biofix (January 1st each year) and the number of days until time i, N_i. T_j is the mean daily air temperature (°C) when $T_j > 0$, otherwise $T_j = 0$. VPD_j is a binary variable calculated as follows: when vapor pressure deficit (vpd) ≤ 4 hPa, $VPD_j = 1$; otherwise, $VPD_j = 0$, with vpd calculated from temperature and relative humidity (rh, %) as shown:

$$vpd_j = \left(1 - \frac{rh_j}{100}\right) \cdot 6.11 \cdot exp\left(\frac{17.47 \cdot T_j}{239 + T_j}\right)$$

Finally, WET_j is a binary variable calculated as follows: when rainfall ≥ 2 mm and vpd ≤ 4 hPa, $WET_j = 1$, otherwise, $WET_j = 0$.

For the model evaluation in 2022, the same weather station in orchard 2 was used, while an additional wireless cellular data logger with rain, RH, and temperature sensors (Em50, Decagon Devices, Pullman, WA, USA) was installed in each of orchards 3 to 5.

Modeling the dynamics of airborne ascospores

Beta regression was used to relate the cumulative proportion of captured *P. amygdalinum* ascospores to the fixed factors ADD, ADDvpd, and ADDwet due to the nature of the response variable, which assumes values in the open interval (0,1). The model was fitted using the data collected from 2019 to 2021 in orchards 1 and 2 and it was parametrized in terms of the mean μ and a dispersion parameter Φ whereby the variance

$$\sigma^2 = \frac{\mu(1-\mu)}{1+\Phi}$$

is dependent on the mean (Ferrari and Cribari-Neto 2004). Let Y_{ilk} (i = 1, …, n; l = 1, …, L; k = 1, …, K) be the cumulative proportion of ascospores for the ith observation in location l and year k, with mean μ_{ilk} and unknown precision Φ. The mean (μ_{ilk}) was linked to the linear predictor using the logit function:

$$logit\ (\mu_{ilk}) = \beta_0 + \sum_{j=1}^{N_\beta} \beta_j\, x_{jilk} + v_{lk}$$

where β_0 is the intercept of the model, x_{jilk} are the fixed factors (i.e., ADD, ADDvpd, and ADDwet), β_j are the parameters for the fixed factors, and v_{lk} represents an independent structured random effect for the year and orchard location. This random effect captures the heterogeneity and the variability that may exist between the l locations and the k years. To avoid zeros and ones, the response data were transformed as $y_i^{new} = \frac{y_i \cdot (n-1) + 1/2}{n}$ where n is the sample size, as proposed by Smithson and Verkuilen (2006).

DSS evaluation

Fungicide application programs. According to Magarey and Sutton (2007), a commercial evaluation of a given model should test how well the model output can be used to predict the appropriate deployment of disease management measures. Usually, disease incidence and/or severity and the number of fungicide applications are compared between calendar-based and model-driven fungicide programs. In our case, different fungicide application programs were evaluated in 2022 in orchards 2 to 5 (Table 1). In orchards 2 and 3, programs were assessed on cultivar 'Marinada' trees, whereas 'Guara' was the assessed cultivar in orchards 4 and 5. In each orchard, the trial had a randomized block design, with four experimental blocks and four-tree plots per evaluated program as experimental units. Five programs were evaluated: i) CAL: standard calendar-based program, with applications initiating at petal fall and repeated every 21 days to the end of July; ii) CAL+MET: like CAL, but applications were repeated with meteorological criteria (until seven days after rain episodes greater than 10 mm and with daily mean temperatures between 10ºC and 20ºC; with a minimum frequency of 21 days between applications), as adapted from Torguet et al. (2022); iii) MOD: the model selected in this study was implemented in this program. Action thresholds of 10% and 65% predicted cumulative ascospores were chosen to start and finish fungicide applications, respectively, with a frequency between applications of 21 days; iv) MOD+MET: like MOD, but applications were repeated with the same meteorological criteria used in CAL+MET; and v) UTC: non-treated control. **The 10% initial threshold was chosen considering the selected model's potential for overprediction at lower values, and to ensure that treatments would be initiated when new leaves were present. The 65% threshold was chosen to conclude**

fungicide applications considering that the main infection period of *P. amygdalinum* in Spain has been reported to be from March to mid-June (Zúñiga et al. 2020), though airborne ascospores might be less present until the end of August.

The product used for all fungicide applications was Signum® (from BASF; active ingredients: Pyraclostrobin 6.7% + Boscalid 26.7%), applied at the label concentration of 1.0 kg ha^{-1} (MAPA 2022). This fungicide was chosen because it was the only registered product for the control of RLB in 2022 in Spain (MAPA 2022) which showed good performance to control RLB in previous studies (Torguet et al. 2022). The fungicide was applied using a single nozzle sprayer Turbo 400 (Sirfran, Alicante, Spain) at 2 bars. The application volume was calibrated to approximately 1,000 L ha^{-1}, which is a common commercial rate used in most Spanish almond-growing regions.

To evaluate the fungicide programs, we considered both the seasonal number of applications and the resulting RLB incidence at the end of the experimental period. RLB incidence was assessed in early August 2022 as described by Miarnau et al. (2021). In each experimental unit, 100 leaves (50 per each of the two central trees) were arbitrarily selected from new shoots at different heights and orientations located in the outer canopy. RLB incidence was recorded as the number of diseased leaves (i.e., leaves showing at least one identifiable RLB lesion) out of the total evaluated leaves.

Model definition. Binomial logistic regression was used to estimate the RLB incidence for each of the considered fungicide programs (CAL, CAL+MET, MOD, MOD+MET, and UTC). Additionally, the almond cultivar ('Guara' (GUA) vs 'Marinada' (MAR)) was also included in the model as a fixed effect. The model was fitted using the data collected in 2022 in orchards 2 to 5. The number of diseased leaves, Z_{ilk} (i = 1, ..., n; l = 1, ..., L; k = 1, ..., K) for the ith observation within the block l of the orchard k, out of a total of n_{ilk} leaves analyzed, was assumed to follow a binomial distribution with unknown probability of disease, θ_{ilkm} (i.e., RLB incidence).

$$Z_{ilkm} \sim Binomial\ (n_{ilkm}, \theta_{ilkm})$$

RLB incidence (θ_{ilk}) was linked to the linear predictor using the logit function:

$$logit\ (\ \theta_{ilk}) = \alpha_0 + \sum_{j=1}^{N_\alpha} \alpha_j\, x_{jilk} + u_k + w_{l:k}$$

where α_0 is the intercept of the model, which captures the effect of the untreated control-cultivar 'Guara' (UTC-GUA), x_{jilk} are the fixed factors (i.e., CAL, CAL+MET, MOD, MOD+MET, MAR), α_j are the parameters for the fixed factors. In addition, the model includes two random effects: u_k as an independent random effect to capture the variability between the k orchards, and $w_{l:k}$ as a nested random effect between the block l within the orchard k, which captures variability between the l blocks distinguishing blocks within the same orchard.

Model inference

For both models (i.e., the beta regression and the binomial regression) inference was carried out using Bayesian statistics with integrated nested Laplace approximations (INLA) by means of the 'R-INLA' package for R (Rue et al. 2009). For the beta regression model, the R code provided by Martínez-Minaya et al. (2021) was adapted. All statistical analyses were implemented in R software version 4.2.0 (R Core Team 2022).

Both inference processes were set under weakly independent prior scenarios. Specifically, for the beta regression model, parameters associated to the fixed effects were defined considering vague Gaussian prior distributions $\beta_j \sim N(0, \tau_\beta = 10^{-3})$, and an independent Gaussian distribution for the random effect location-year $\nu_{lk} \sim N(0, \tau_\nu = 1/\sigma_v^2)$. In this model, τ_ν and Φ were considered hyperparameters and their corresponding priors were defined as $\tau_\nu \sim \mathrm{PC-prior}\ (5,0.01)$ and $\Phi \sim \mathrm{Ga}(1,0.1)$ respectively. Pearson correlation coefficients between fixed factors were calculated, and those models considering fixed factors with $|r| > 0.7$ were not further considered to avoid potential problems of multicollinearity (Dormann et al. 2013). For the binomial regression, parameters associated to the fixed effects were also defined considering vague Gaussian prior distributions $\alpha_j \sim N(0, \tau_\alpha = 10^{-3})$, and two independent Gaussian distributions for the two random effects, $u_k \sim N(0, \tau_u = 1/\sigma_u^2)$ and $w_{l:k} \sim N(0, \tau_w = 1/\sigma_w^2)$. In this model, τ_u and τ_w were considered hyperparameters and their corresponding priors were defined as $\tau_u \sim \mathrm{Ga}\ (0.001,0.001)$ and $\tau_w \sim \mathrm{Ga}(0.001,0.001)$, respectively.

For both the beta regression and the binomial regression analysis, all possible combinations of their respective initial components were evaluated. The total number of combinations was 2^k, with k denoting the number of components in the linear predictor, including random effects. The main objective was to identify the most parsimonious model that offered optimal explanatory and predictive performance. The best model was selected according to the deviance information criterion (DIC) (Spiegelhalter et al. 2002), the widely applicable information criterion (WAIC) (Watanabe 2010), and the mean logarithmic conditional predictive ordinate

(LCPO) (Roos and Held 2011), by selecting the model with the lowest values of DIC, WAIC, and LCPO. As a rule of thumb, if two models differed in DIC by more than 3, the one with the smaller DIC was preferred (Spiegelhalter et al. 2002). In the case of WAIC and LCPO, there is no rule of thumb about how much this difference should be. When no meaningful differences were observed between models, the parsimony criterion was applied and the model with fewer covariates was finally selected.

For the beta regression selected model, median values of the posterior predictive distribution were linearly regressed against the observed values, and the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) were further calculated.

RESULTS

RLB airborne inoculum dynamics and weather summary

In orchard 1, yearly cumulative concentration of ascospores in 2019, 2020, and 2021 were estimated by qPCR to be 1043, 506, and 30 ascospores m^{-3}, respectively. In orchard 2, the corresponding cumulative concentration of ascospores were 6044, 581, and 111 ascospores m^{-3}, respectively. In orchard 1, 90% of ascospore detection was reached between mid-August and mid-September in 2019 and 2020, but in early May in 2021. In orchard 2, 90% of ascospore detection was reached between late May and early July in all monitored years.

During the study period in orchard 1, annual mean temperature ranged from 14.6°C in 2021 to 14.9°C in 2019, the number of days with VPD ≤ 4 hPa ranged from 131 in 2019 to 164 in 2020 and 2021, and the number of days with rainfall ≥ 0.2 mm ranged from 60 in 2019 to 90 in 2020. In orchard 2, annual mean temperature ranged from 14.3°C in 2021 to 14.6°C in 2019 and 2020, the number of days with VPD ≤ 4 hPa ranged from 132 in 2019 to 168 in 2020, and the number of days with rainfall ≥ 0.2 mm ranged from 76 in 2019 and 2021 to 92 in 2020. Regarding the ADD-derived variables (Fig. 1), annual ADD in orchard 1 ranged from 5324°C-days to 5448°C-days (in 2021 and 2019, respectively); annual ADDvpd ranged from 1051°C-days to 1433°C-days (in 2019 and 2021, respectively); and ADDwet ranged from 389°C-days to 605°C-days (in 2019 and 2020, respectively). In orchard 2, annual ADD ranged from 5242°C-days to 5358°C-days (in 2021 and 2020, respectively); annual ADDvpd ranged from 979°C-days to 1417°C-days (in 2019 and 2020, respectively); and ADDwet ranged from 389°C-days to 557.0°C-days (in 2021 and 2020, respectively).

Modeling the dynamics of airborne ascospores

The explored models for the cumulative proportion of ascospores of *P. amygdalinum* are ranked in Table 2 based on their DIC, WAIC, and LCPO values. Considering that the Pearson correlation coefficient between ADDvpd and ADDwet in the ascospore monitoring period was $|r| = 0.92$, models including both variables were not considered. Thus, the selected model included the fixed effects ADD and ADDwet, and the random effect for the year-location (ν).

In the selected model, the parameter for the fixed effect ADD had a median posterior distribution of 0.086 with a 95% credible interval (CrI) (0.077, 0.094), while the parameter for the fixed effect ADDwet had a median posterior distribution of 1.107 with a 95% CrI (0.982, 1.235). None of the credible intervals were overlapping with zero (Table 3). Therefore, the two fixed effects had positive effects on the expected cumulative proportion of *P. amygdalinum* airborne ascospores. The posterior distribution of the two hyperparameters was also computed (Table 3). The median posterior distribution of the dispersion parameter Φ was 3.048, while in the case of the precision of the random effect τ_v it was 0.993. This indicates that it is important to consider the random effect in the model, as it explains some of the variability that fixed effects cannot explain. When computing the linear regression of the observed values against the median posterior predictive distribution, it accounted for 78% of the total variance (R^2 = 0.78), with a slope of 0.736 and an intercept of 0.143 (Fig. 2). The MAE for this model was 0.141, and the RMSE was 0.180.

Considering the median posterior distribution (Fig. 3), 10% of *P. amygdalinum* ascospores were captured from 465 to 920 ADD and from 60 to 105 ADDwet, corresponding from 3 March to 19 April. At the other extreme, 90% of ascospores were captured from 1790 to 3745 ADD and from 155 to 305 ADDwet, corresponding from 6 June to 29 August.

DSS evaluation

The explored models for the RLB incidence are ranked in Supplementary Table S1 based on their DIC, WAIC, and LCPO values. The selected model included as fixed effects only those related to the fungicide programs, and the nested random effect (w) block:orchard. The covariate associated with the cultivar did not significantly improve the explanatory behavior of the model (Supplementary Table S1).

From the posterior distribution of the fixed parameters (Supplementary Table S2) of the selected model, the expected RLB disease incidence for each of the evaluated fungicide programs across all the experimental orchards was computed. The median RLB incidence for the UTC was 82.8%, 95% CrI (75.3%, 88.3%). On the other extreme, the median RLB incidence in the CAL program was 2.4%, 95% CrI (1.4%, 4.0%), whereas in the rest of assessed programs it ranged from 5.0%, 95% CrI (3.1%, 8.1%) in MOD to 19.0%, 95% CrI (12.6%, 27.7%) in CAL+MET (Fig. 4).

The posterior distributions of the estimated differences in RLB incidence between the fungicide programs (Table 4) showed that all programs led to a substantial reduction in RLB incidence compared to the UTC with probabilities of these differences as being negative equal to one ($P(<0) = 1$). Specifically, on average over all orchards, the CAL program led to a reduction in RLB incidence of −80.4%, 95% CrI (−84.7%, −73.8%) while the CAL+MET program showed a reduction of − 63.3%, 95% CrI (− 66.2%, −73.8%), compared to UTC. Similarly, the MOD program showed a reduction in RLB incidence of −77.6%, 95% CrI (−81.0%, −72.0%) while the MOD+MET led to a reduction of − 64.4%, 95% CrI (− 66.9%, −60.2%), also compared to UTC.

All the programs including the model and/or the meteorological criteria (CAL+MET, MOD, MOD+MET) when compared with CAL, resulted in RLB incidence increases as follows: +16.6%, 95% CrI (11.0%, +24.2%) in CAL+MET; +2.6%, 95% CrI (+1.20%, +4.9%) in MOD; and +16.0%, 95% CrI (10.5%, +23.4%) in MOD+MET (Table 4). Hence, the levels of disease incidence between MOD and CAL programs were those that differed the lowest (+2.6%). The credible interval for the estimated difference between MOD+MET and CAL+MET overlapped zero, thus indicating that no substantial difference on RLB incidence was detected between these programs.

Concerning the total number of fungicide applications, information is summarized in Table 5. The first application was carried out between 17 March and 4 April, while the last was between 21 April and 29 July, depending on the fungicide program. On average, 7.00 ± 0.0 (mean ± std. error) seasonal applications were made with the CAL standard fungicide program, 3.75 ± 0.5 applications with the MOD program (a 46% reduction compared to CAL), and 2.25 ± 0.5 applications with the MOD+MET and CAL+MET fungicide programs (a 68% reduction).

DISCUSSION

In this study, a Bayesian beta regression framework was implemented to model the dynamics of *P. amygdalinum* airborne ascospores in Lleida region, NE Spain. The beta regression avoids traditional data transformations as it assumes that the response variable follows a beta distribution, which is flexible for modeling proportions as it is defined by only two parameters (Ferrari and Cribari-Neto 2004). This modeling approach was proposed by Martínez-Minaya et al. (2021) to describe ascospore dynamics of *Plurivorosphaerella nawae*. To our knowledge, the beta regression model reported here is the first epidemiological model developed to predict the airborne inoculum dynamics of *P. amygdalinum*. The model was further used to design and evaluate a DSS to optimize fungicide application programs for RLB management.

Modeling was performed using the combination of three types of accumulated degree-days variables (ADD, ADDvpd, and ADDwet) since several biological systems, such as ascospore maturation and release, have been reported to be dependent on thermal time accumulation (Lovell et al. 2004;

Martínez-Minaya et al. 2021; Rossi et al. 2009; Spotts and Cervantes 1994). January 1 was chosen as the biofix to start degree-days accumulation for being a fixed date in which, in our conditions, almond leaf fall is completed and mature perithecia stages are still not present in infected leaf litter (Zúñiga et al. 2020). In our selected model, ADD and ADDwet were the variables driving *P. amygdalinum* airborne ascospore availability. Both variables had a continuous positive effect on the predicted variable, **with the coefficient of ADDwet being greater.** The inability to consider both ADDvpd and ADDwet variables in the same model because of their high correlation showed that ADDwet was more relevant in the model than ADDvpd, thus highlighting the importance of water availability on the *P. amygdalinum* ascospore development and release along the season. This is consistent with previous findings reported in Spain by Zúñiga et al. (2020), who found that the seasonal amount of available ascospores was positively correlated with the accumulated rainfall in January. Moreover, Miarnau et al. (2021) reported a positive correlation between annual RLB incidence and accumulated spring rainfall, which would also support the findings of this study. More recently, Pons-Solé et al. (2023) suggested that *P. amygdalinum* inoculum release may benefit from concurrent mild temperatures (between 10 and 20°C) and the hydration of fallen leaves, associated with humidity and rain variables. Torguet et al. (2022) also found that it was efficient to program RLB fungicide **applications** after rain events over 15 mm with 10 to 15°C as minimum temperature, thus suggesting a relationship between these meteorological conditions and airborne inoculum availability and subsequent infections. Similarly, wetness and temperature have been noted as drivers for ascospore development and dispersal in other ascomycete pathogens with an overwintering stage in leaf litter. Rossi et al. (2009) regressed the cumulative proportion of *Venturia pyrina* trapped ascospores against physiological time and found the best fit when using ADDwet. For *P. nawae*, ADD and ADDvpd were useful to model the dynamics of ascospore production in leaf litter, also suggesting that dew resulting from low VPD may favor ascospore development in the absence of rain (Martínez-Minaya et al. 2021).

Additionally, our selected model **incorporated** a random effect associated with the year and the location suggesting that, as expected, there were additional unmeasured sources of variability determining the availability of *P. amygdalinum* airborne ascospores. These variability sources may be related to several factors, such as infection dynamics among years or intrinsic characteristics of the locations and the almond cultivars present there or nearby. Nevertheless, the model showed high goodness of fit and accounted for 78% of the total variance of the observed values, which is relevant considering the above-mentioned sources of variability, as well as the high variability observed between the yearly cumulative concentration of ascospores across the studied orchards and years. **Also, it is worth noting the model's potential for overprediction at lower values and underprediction at higher values, traits that were considered when defining the DSS action thresholds.**

The performance of the predictive model in a DSS was evaluated to optimize fungicide programs against RLB **in 2022**. The model was used to predict the beginning and the end of the airborne ascospore availability period, thus avoiding the time- and resource-consuming quantification of ascospores through molecular or microscopy tools, and thus determining the period in which trees must be protected. Thresholds of 10% and 65% of predicted cumulative proportion of ascospores were proposed to start and finish fungicide **applications**, respectively, considering the median posterior predictive distribution of the model. In addition, we compared repeating **applications** every 21 days (as label recommended) or following specific meteorological criteria (until 7 days after rain episodes greater than 10 mm and with daily mean temperatures between 10 and 20ºC, with a minimum frequency of 21 days). This second criterion, included in the CAL+MET and MOD+MET programs tested here, was adapted from that reported in Torguet et al. (2022), and additionally considering the recent findings obtained by Pons-Solé et al. (2023). In short, this criterion considers that *P. amygdalinum* ascospore release benefits from mild temperatures and the hydration of fallen leaves.

A single fungicide was used during the evaluation of fungicide programs, as the aim of our work was to determine the program-associated efficacies rather than the efficacy of the product itself. Signum® is a systemic product with preventive activity that showed good performance (75-95% efficacy) in a previous study (Torguet et al. 2022). Nevertheless, fungicide alternation should be rigorously observed when implementing DSSs in commercial orchards for RLB control, to limit the risk of developing pathogen resistance (Brent and Hollomon 2007). **Further research would be necessary to validate our findings when using other fungicide products including their alternation.**

Regarding the duration of the fungicide programs, it was observed that the main difference between the standard calendar-based program and the other evaluated programs was the timing of the last **applications**. Our results suggest that extending the protection period until mid-summer, as has been recommended for decades (Torguet et al. 2022), was not essential to show good efficacy against RLB in 2022. The predictive model and action thresholds proposed here, as discussed below, can help to narrow the duration of fungicide programs which, in turn, would coincide with the RLB infection period previously described in Catalonia (Zúñiga et al. 2020). Additional research should be done to validate or adapt the proposed thresholds in different geographical contexts.

The efficiency of the tested programs was compared in terms of RLB control and number of seasonal applications. The observed levels of RLB incidence in the UTC during the experimental period were high, comparable to previous studies in the same region (Miarnau et al. 2021; Torguet et al. 2022), thus allowing the comparison between the four tested fungicide programs regarding RLB control. All the tested programs substantially reduced disease incidence as compared to the UTC. The standard CAL resulted in the lowest RLB incidence (median value of 2.4%), followed by the fungicide program that includes the predictive model (MOD) (median value of 5.0%) to establish the period in which trees must be protected. For the programs in which applications were repeated following specific meteorological criteria (CAL+MET and MOD+MET), the estimated RLB incidences were higher (median values of 19.0% and 18.4%, respectively). Nevertheless, the RLB control obtained with the CAL+MET and MOD+MET fungicide programs was still high and comparable to those reported by Torguet et al. (2022) with calendar-based applications (10% to 40% incidence in their study).

Besides, we observed great differences in the seasonal number of fungicide applications. We found that higher levels of disease control were associated with higher number of fungicide applications. On average, 7 applications were applied in the CAL standard program, whereas only 3.75 applications in the MOD, and 2.25 applications in the CAL+MET and MOD+MET fungicide programs. When evaluating CAL+MET and MOD+MET fungicide programs, the 68% reduction in the number of applications led to an increase in RLB incidence of +16.6% and +16.0%, respectively, compared with the CAL standard program. However, the 46% reduction in the number of applications obtained with the MOD program resulted only in a RLB incidence increase of +2.6%. Hence, despite this relatively low increase in RLB incidence, we consider that the resulting reduction in the number of fungicide applications described in this work is noteworthy. Further research would be needed to untangle and quantify the relationship between low RLB levels and nut yield, to determine which disease thresholds farmers can assume without compromising almond production, and therefore decide the optimal fungicide strategy.

The results of the current research contribute towards the use of more sustainable fungicide programs against almond RLB disease in northeast Spain, and specifically the European Green Deal target of reducing by half the use of chemical pesticides by 2030 (European Commission 2020).

ACKNOWLEDGEMENTS

The authors acknowledge the technical support from IRTA staff: Guillem Martínez, Robert Oró, Jesús Ortiz, Sílvia Burillo, and Lourdes Zazurca.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in CORA (Catalan Open Research Area – Repositori de Dades de Recerca) at https://doi.org/10.34810/data237.

CONFLICT OF INTERESTS

The authors declare no potential conflict of interests.

LITERATURE CITED

Amanifar, N. 2017. Evaluation of the efficiency of two fungicides on the control of almond leaf blotch disease on two cultivars in along Zayanderood. J. Plant Prot. 31:166-171.

Banihashemi, Z. 1990. Biology and control of *Polystigma ochraceum*, the cause of almond red leaf blotch. Plant Pathol. 39:309-315.

Bayt Tork, D., Taherian, M., and Divan, R. 2014. Evaluation of some fungicides for controlling almond red leaf blotch (*Polystigma amygdalinum*). Int. J. Adv. Biol. Biomed. Res. 4:1011-1016.

BOE. 2002. Real decreto 1201/2002, de 20 de noviembre, por el que se regula la producción integrada de productos agrícolas. Boletín Oficial del Estado, Madrid, Spain. https://www.boe.es/eli/es/rd/2002/11/20/1201

Brent, K. J., and Hollomon, D. W. 2007. Fungicide resistance in crop pathogens: how can it be managed? 2nd ed. Fungicide Resistance Action Committee, Brussels, Belgium.

Cannon, P. F. 1996. Systematics and diversity of the Phyllachoraceae associated with Rosaceae, with a monograph of *Polystigma*. Mycol. Res. 100:1409-1427.

De Wolf, E. D., and Isard, S. A. 2007. Disease cycle approach to plant disease prediction. Annu. Rev. Phytopathol. 45:203-220.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R., Gruber, B., Lafourcade, B., Leitão, P. J., Münkemüller, T., McClean, C., Osborne, P. E., Reineking, B., Schröder, B., Skidmore, A. K., Zurell, D., and Lautenbach, S. 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36:27-46.

European Commission. 2020. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system. E. Commission, ed., COM(2020) 381 final. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0381

Farr, D. F., and Rossman, A. Y. 2022. Fungal Databases, U.S. National Fungus Collections, ARS, USDA.

Felipe, A. J. 1977. Almendro: estados fenológicos. Inf. Téc. Econ. Agrar. 27:8-9.

Ferrari, S. L. P., and Cribari-Neto, F. 2004. Beta regression for modelling rates and proportions. J. Appl. Stat. 31:799-815.

Fungicide Resistance Action Committee (FRAC) 2022. FRAC Code List ©*2022: Fungal control agents sorted by cross resistance pattern and mode of action (including coding for FRAC Groups on product labels). https://www.frac.info/docs/default-source/publications/frac-code-list/frac-code-list-2022--final.pdf?sfvrsn=b6024e9a_2

Gent, D. H., Mahaffee, W. F., McRoberts, N., and Pfender, W. F. 2013. The use and role of predictive systems in disease management. Annu. Rev. Phytopathol. 51:267-289.

Ghazanfari, J., and Banihashemi, Z. 1976. Factors influencing ascocarp formation in *Polystigma ochraceum*. Trans. Br. Mycol. Soc. 66:401-406.

Habibi, A., and Banihashemi, Z. 2016. Mating system and role of pycnidiospores in biology of *Polystigma amygdalinum*, the causal agent of almond red leaf blotch. Phytopathol. Mediterr. 55:98-108.

Heydarian, A., and Moradi, H. 2005. Relative resistance of selected almond cultivras to the causal agent of red leaf blotch disease, in Chahar mahal-va-Bakhtiari province. Iran. J. Plant Pathol. 41:157-169.

Knight, J. D. 1997. The role of decision support systems in integrated crop protection. Agric. Ecosyst. Environ. 64:157-163.

Lázaro, E., Makowski, D., and Vicent, A. 2021. Decision support systems halve fungicide use compared to calendar-based strategies without increasing disease risk. Commun. Earth Environ. 2:224.

López-López, M., Calderón, R., González-Dugo, V., Zarco-Tejada, P., and Fereres, E. 2016. Early detection and quantification of almond red leaf blotch using high-resolution hyperspectral and thermal imagery. Remote Sens. 8:276.

Lovell, D. J., Powers, S. J., Welham, S. J., and Parker, S. R. 2004. A perspective on the measurement of time in plant disease epidemiology. Plant Pathol. 53:705-712.

Magarey, R. D., and Sutton, T. B. 2007. How to create and deploy infection models for plant pathogens. Pages 3-25 in: General concepts in integrated pest and disease management. A. Ciancio and K. G. Mukerji, eds. Springer, Dordrecht, The Netherlands.

MAPA. 2022. Registro de Productos Fitosanitarios. https://www.mapa.gob.es/es/agricultura/temas/sanidad-vegetal/productos-fitosanitarios/fitos.asp

Marimon, N., Eduardo, I., Martínez-Minaya, J., Vicent, A., and Luque, J. 2020. A decision support system based on degree-days to initiate fungicide spray programs for peach powdery mildew in Catalonia, Spain. Plant Dis. 104:2418-2425.

Martínez-Minaya, J., Conesa, D., López-Quílez, A., Mira, J. L., and Vicent, A. 2021. Modeling inoculum availability of *Plurivorosphaerella nawae* in persimmon leaf litter with Bayesian beta regression. Phytopathology 111:1184-1192.

Miarnau, X., Zazurca, L., Torguet, L., Zúñiga, E., Batlle, I., Alegre, S., and Luque, J. 2021. Cultivar susceptibility and environmental parameters affecting symptom expression of red leaf blotch of almond in Spain. Plant Dis. 105:940-947.

Ollero-Lara, A., Agustí-Brisach, C., Lovera, M., Roca, L. F., Arquero, O., and Trapero, A. 2019. Field susceptibility of almond cultivars to the four most common aerial fungal diseases in southern Spain. Crop Protect. 121:18-27.

Pons-Solé, G., Miarnau, X., Torguet, L., Lázaro, E., Vicent, A., and Luque, J. 2023. Airborne inoculum dynamics of *Polystigma amygdalinum* and progression of almond red leaf blotch disease in Catalonia, NE Spain. Ann. Appl. Biol. DOI: https://www.doi.org/10.1111/aab.12831

R Core Team. 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Roos, M., and Held, L. 2011. Sensitivity analysis in Bayesian generalized linear mixed models for binary data. Bayesian Anal. 6:259–278.

Rossi, V., Salinari, F., Pattori, E., Giosuè, S., and Bugiani, R. 2009. Predicting the dynamics of ascospore maturation of *Venturia pirina* based on environmental factors. Phytopathology 99:453-461.

Rue, H., Martino, S., and Chopin, N. 2009. Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. J. R. Statist. Soc. B 71:319-392.

Saad, A. T., and Masannat, K. 1997. Economic importance and cycle of *Polystigma ochraceum*, causing red leaf blotch disease of almond, in Lebanon. EPPO Bulletin 27:481-485.

Sakar, E. H., El Yamani, M., Boussakouran, A., and Rharrabti, Y. 2019. Codification and description of almond (*Prunus dulcis*) vegetative and reproductive phenology according to the extended BBCH scale. Sci. Hortic. 247:224-234.

Shabi, E. 1997. Disease management of the almond pathogens *Glomerella cingulata*, *Polystigma ochraceum* and *Tranzschelia pruni-spinosae.* EPPO Bulletin 27:479-480.

Smithson, M., and Verkuilen, J. 2006. A better lemon squeezer? Maximum-likelihood regression with beta-distributed dependent variables. Psychol. Methods 11:54–71.

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., and Van der Linde, A. 2002. Bayesian measures of model complexity and fit. J. R. Statist. Soc. B 64:583–639.

Spotts, R. A., and Cervantes, L. A. 1994. Factors affecting maturation and release of ascospores of *Venturia pirina* in Oregon. Phytopathology 88:260-264.

Suzuki, Y., Tanaka, K., Hatakeyama, S., and Harada, Y. 2008. *Polystigma fulvum*, a red leaf blotch pathogen on leaves of *Prunus* spp., has the *Polystigmina pallescens* anamorph/andromorph. Mycoscience 49:395-398.

Torguet, L., Zazurca, L., Martínez, G., Pons-Solé, G., Luque, J., and Miarnau, X. 2022. Evaluation of fungicides and application strategies for the management of the red leaf blotch disease of almond. Horticulturae 8:501.

Watanabe, S. 2010. Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. J. Mach. Learn. Res. 11:3571-3594.

Zúñiga, E., León, M., Berbegal, M., Armengol, J., and Luque, J. 2018. A qPCR-based method for detection and quantification of *Polystigma amygdalinum*, the cause of red leaf blotch of almond. Phytopathol. Mediterr. 57:257-268.

Zúñiga, E., Romero, J., Ollero-Lara, A., Lovera, M., Arquero, O., Miarnau, X., Torguet, L., Trapero, A., and Luque, J. 2020. Inoculum and infection dynamics of *Polystigma amygdalinum* in almond orchards in Spain. Plant Dis. 104:1239-1246.

TABLES

Table 1. Characteristics of the almond orchards included in this study, and years corresponding to *Polystigma amygdalinum* ascospore monitoring and model development and evaluation

Orchard	Location	UTM coordinates (WGS 84, 31 T)		Plantation year	Cultivar	Rootstock	Tree spacing	Model development (ascospore monitoring)	Model evaluation
		X	*Y*						
1	Les Borges Blanques	320870	4597530	2009	Tarraco, Marinada[a]	GF-677	4 x 2 m	2019-2021	-
2	Vilagrassa	341313	4612125	2007	Tarraco, Marinada, Vairo, Belona[a]	GF-677	7 x 6 m	2019-2021	2022
3	Lleida	294423	4613174	2007	Tarraco, Marinada[a]	GF-677	7 x 6 m	-	2022
4	Alcarràs	283296	4608633	2000	Guara	GF-677	5 x 5 m	-	2022
5	Soses	288321	4601766	2008	Guara	GF-677	5 x 3 m	-	2022

[a] Orchards with multiple cultivars, usually in alternating rows.

Table 2. Models for the cumulative proportion of *Polystigma amygdalinum* airborne ascospores

Model no.	Model[a]	DIC[b]	WAIC[c]	LCPO[d]
1	ADD + ADDwet + ADDvpd + *v*	-3856.11	-3857.62	-1.53
2	ADD + ADDwet + *v*	-3852.24	-3853.60	-1.53
3	ADD + ADDvpd + *v*	-3773.02	-3774.08	-1.50
4	ADD + ADDwet + ADDvpd	-3607.86	-3608.60	-1.43
5	ADD + ADDwet	-3563.35	-3564.24	-1.41
6	ADD + *v*	-3551.87	-3552.87	-1.41
7	ADD + ADDvpd	-3501.95	-3502.55	-1.39
8	ADD	-3466.70	-3467.30	-1.37
9	ADDwet + *v*	-3456.59	-3457.40	-1.37
10	ADDwet + ADDvpd + *v*	-3456.22	-3457.13	-1.37
11	ADDvpd + *v*	-3130.64	-3130.82	-1.24
12	ADDwet + ADDvpd	-3028.19	-3028.82	-1.20
13	ADDwet	-2822.90	-2823.54	-1.12
14	ADDvpd	-2520.92	-2521.19	-1.00
15	*v*	-2289.07	-2289.66	-0.91
16	Null model	-2244.23	-2244.51	-0.89

[a] ADD: accumulated degree-days; ADDvpd: ADD considering vapor pressure deficit; ADDwet: ADD considering vapor pressure deficit and rainfall; *v*: random effect associated to the year and location. All models include intercept, biofix = 1st January, T_{base} = 0°C.

[b] DIC: deviance information criterion.

[c] WAIC: widely applicable information criterion.

[d] LCPO: logarithmic conditional predictive ordinate.

Table 3. Mean, standard deviation (SD), quantiles (Q), and mode for the parameters and hyperparameters of the selected model for the cumulative proportion of *Polystigma amygdalinum* airborne ascospores

Parameters[a]	**Mean**	**SD**	**$Q_{0.025}$**[c]	**$Q_{0.5}$**	**$Q_{0.975}$**[c]	**Mode**
Intercept	-3.213	0.748	-4.756	-3.212	-1.677	-3.207
ADD	0.086	0.004	0.077	0.086	0.094	0.085
ADDwet	1.108	0.064	0.982	1.107	1.235	1.107
Hyperparameters[b]						
Φ	3.051	0.136	2.791	3.048	3.325	3.044
τ_v	1.365	1.299	0.130	0.993	4.813	0.372

[a] ADD: accumulated degree-days; ADDwet: ADD considering vapor pressure deficit and rainfall.

[b] Φ: dispersion parameter of the likelihood; τ_v: precision of the random effect.

[c] 95% credible interval is defined by $Q_{0.025}$ and $Q_{0.975}$.

Table 4. Summary of the posterior distributions of the estimated differences in red leaf blotch incidence between the evaluated fungicide programs in 2022 in four almond orchards in Lleida region, Spain

Reference level	Fungicide program	Median of estimated differences (95% credible interval)	*P*(<0)[a]
UTC	CAL	-0.804 (-0.847, -0.738)	1
	CAL+MET	-0.633 (-0.662, -0.738)	1
	MOD	-0.776 (-0.810, -0.720)	1
	MOD+MET	-0.640 (-0.669, -0.602)	1
CAL	CAL+MET	0.166 (0.110, 0.242)	0
	MOD	0.026 (0.012, 0.049)	0
	MOD+MET	0.160 (0.105, 0.234)	0
CAL+MET	MOD	-0.139 (-0.205, -0.090)	1
	MOD+MET	-0.007 (-0.049, 0.035)	0.625
MOD	MOD+MET	0.133 (0.086, 0.197)	0

[a] *P*(<0) indicates the probability of the differences being negative.

Table 5. Relevant dates and number of applications of the fungicide programs evaluated for almond red leaf blotch control in 2022 in four almond orchards in Lleida region, Spain

Orchard	Open flower[a]	Petal fall[a]	Fungicide program[b]	First application	Last application	Number of applications
2	17 March	22 March	CAL	24 March	25 July	7
			CAL+MET	24 March	31 May	3
			MOD	4 April	7 June	4
			MOD+MET	4 April	31 May	3
3	15 March	22 March	CAL	23 March	29 July	7
			CAL+MET	23 March	21 April	2
			MOD	23 March	5 May	3
			MOD+MET	23 March	21 April	2
4	8 March	15 March	CAL	17 March	20 July	7
			CAL+MET	17 March	21 April	2
			MOD	22 March	26 May	4
			MOD+MET	22 March	21 April	2
5	8 March	15 March	CAL	17 March	20 July	7
			CAL+MET	17 March	21 April	2
			MOD	17 March	19 May	4
			MOD+MET	17 March	21 April	2

[a] Phenological stages according to Felipe (1977). Equivalent stages in BBCH scale (Sakar et al. 2019) were 65 and 67, respectively for each column.

[b] A fifth untreated control program (UTC) was included in all orchards.

FIGURE LEGENDS

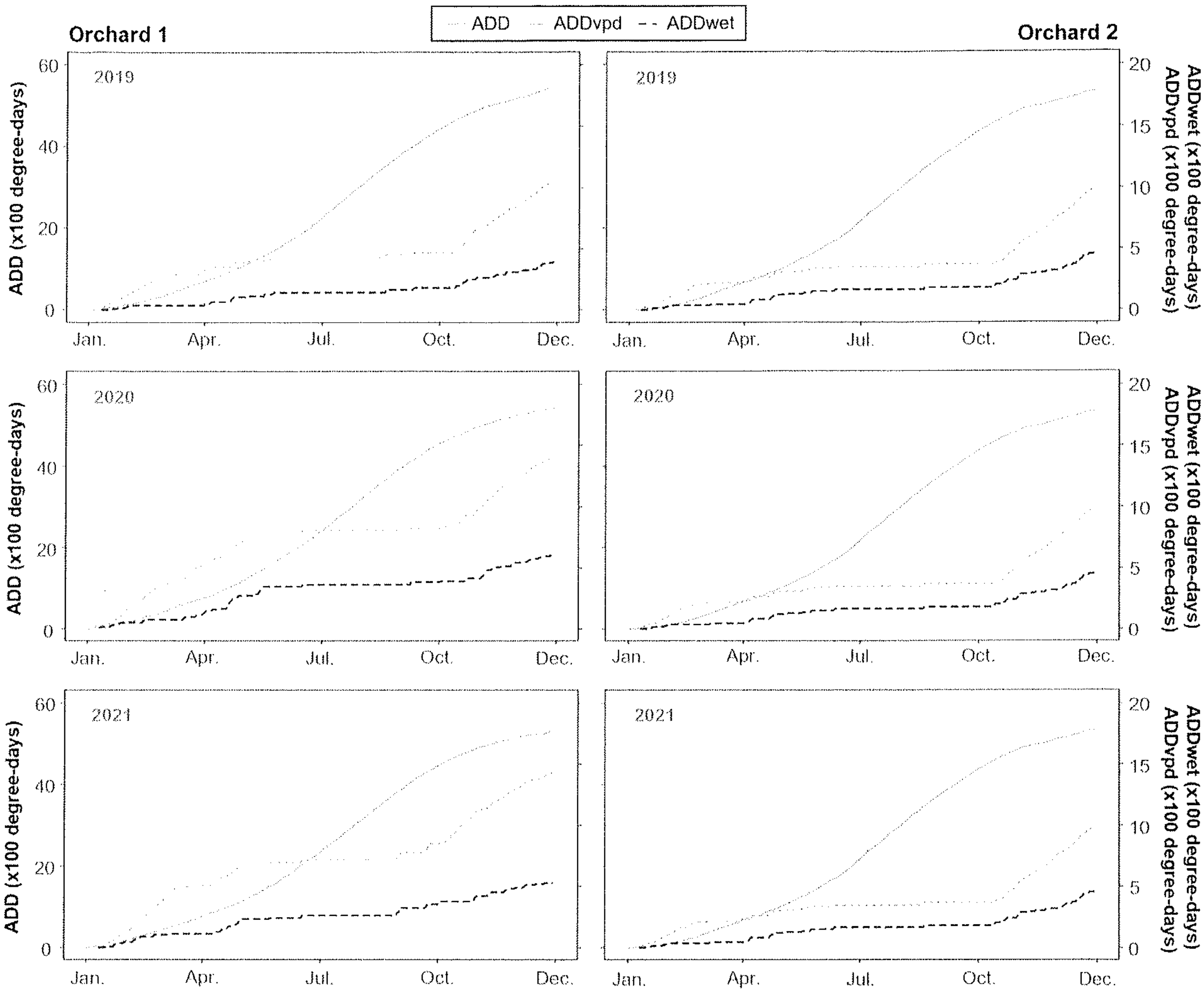
Fig. 1. Accumulated degree-days (ADD), ADD considering vapor pressure deficit (ADDvpd), and ADD considering vapor pressure deficit and rainfall (ADDwet) in orchards 1 and 2 from 2019 to 2021.

Fig. 2. Linear regression (solid line) between observed values and the median of the posterior predictive distribution of the selected model for the cumulative proportion of *Polystigma amygdalinum* airborne ascospores, including the fixed effects ADD (accumulated degree-days), ADDwet (ADD considering vapor pressure deficit and rainfall), and the random effect (v) associated to the year and the location. The dashed line represents the 1:1 relationship.

Fig. 3. Data (**A**) and median posterior predictive distribution (**B**) for the model of cumulative proportion of *Polystigma amygdalinum* airborne ascospores, based on the fixed effects ADD (accumulated degree-days), ADDwet (ADD considering vapor pressure deficit and rainfall), and the random effect (v) associated to the year and the location.

Fig. 4. Estimated posterior distributions of red leaf blotch incidence for the fungicide programs evaluated in 2022 in four almond orchards in Lleida region, Spain. UTC: untreated control; MOD+MET: model-based program + meteorological criteria; MOD: model-based program; CAL+MET: calendar-based program + meteorological criteria; CAL: calendar-based program.

Fig. 1


ADD
ADDvpd
ADDwet
Orchard 1
Orchard 2
2019
2020
2021
ADD (x100 degree-days)
ADDwet (x100 degree-days)
ADDvpd (x100 degree-days)
0
20
40
60
0
5
10
15
20
Jan.
Apr.
Jul.
Oct.
Dec.

787 **Fig. 2**

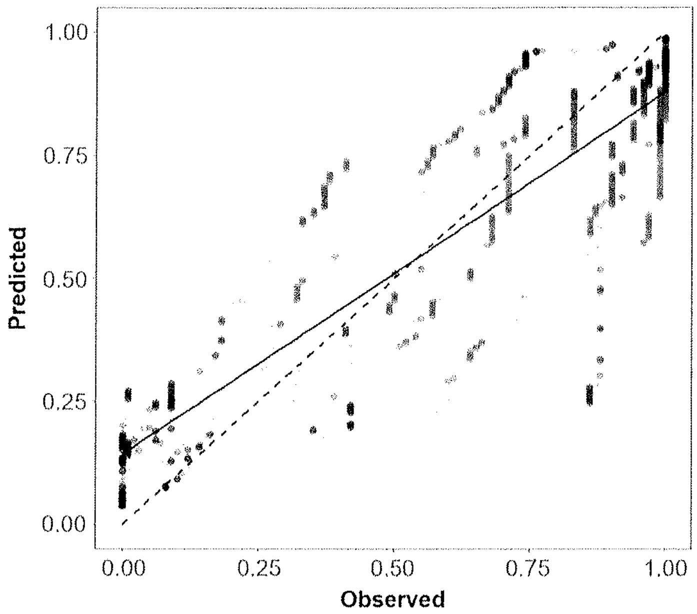
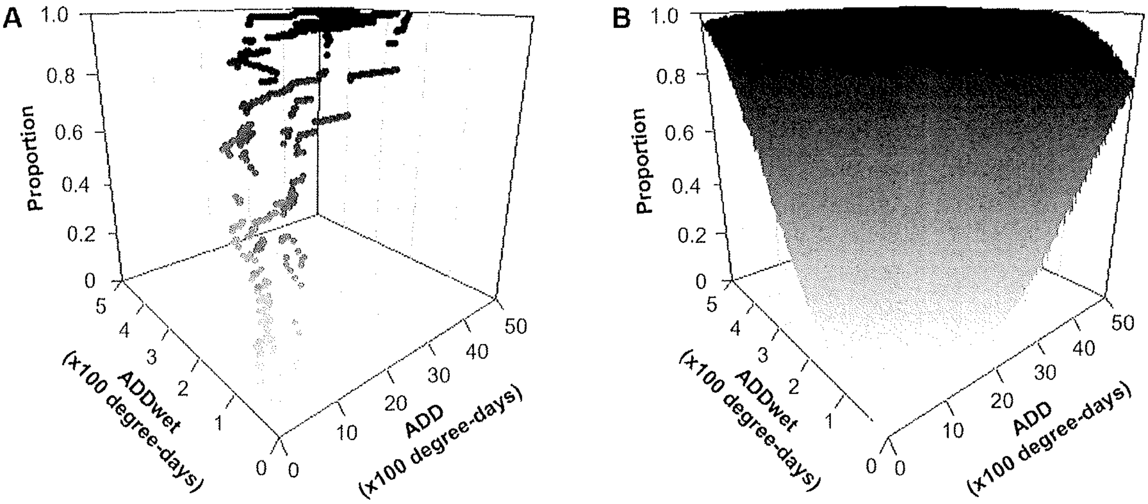
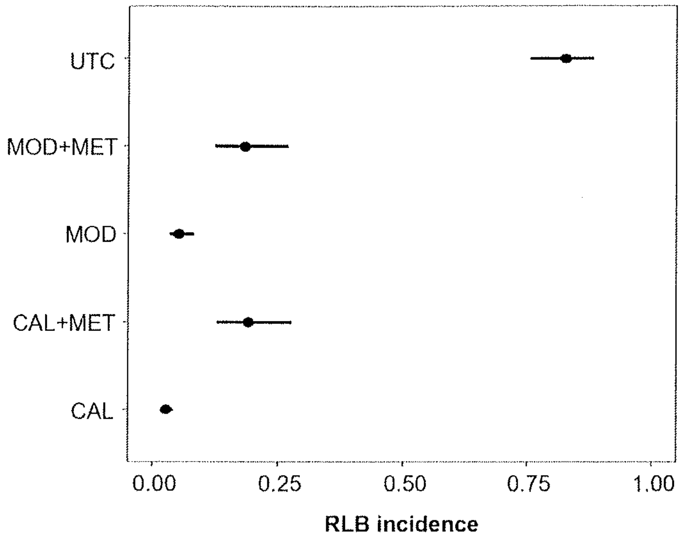


Fig. 3


A
B
Proportion
1.0
0.8
0.6
0.4
0.2
0
ADDwet
(x100 degree-days)
5
4
3
2
1
0
ADD
(x100 degree-days)
10
20
30
40
50

789 **Fig. 4**



Supplementary Table S1. Models for the red leaf blotch incidence

Model no.	Model [a]	DIC [b]	WAIC [c]	LCPO [d]
1	$\alpha_{0^{*}}$ + CAL+ [CAL+MET] + MOD + [MOD+MET] + MAR + u + w	902.69	938.47	2.94
2	$\alpha_{0^{**}}$ + CAL+ [CAL+MET] + MOD + [MOD+MET] + u + w	902.71	938.45	2.94
3	$\alpha_{0^{**}}$ + CAL+ [CAL+MET] + MOD + [MOD+MET] + w	903.44	941.34	2.95
4	$\alpha_{0^{*}}$ + CAL + [CAL+MET] + MOD + [MOD+MET] + MAR + w	903.46	941.74	2.95
5	$\alpha_{0^{*}}$ + CAL+ [CAL+MET] + MOD + [MOD+MET] + MAR + u	969.91	988.69	3.09
6	$\alpha_{0^{**}}$ + CAL+ [CAL+MET] + MOD + [MOD+MET] + u	969.91	988.65	3.09
7	$\alpha_{0^{*}}$ + CAL+ [CAL+MET] + MOD + [MOD+MET] + MAR	1363.89	1392.61	4.35
8	$\alpha_{0^{**}}$ + CAL+ [CAL+MET] + MOD + [MOD+MET]	1375.01	1397.94	4.37
9	$\alpha_{0^{***}}$ + MAR + w	2819.84	17918.60	14.35
10	α_0 + w	2838.42	17858.08	14.34
11	$\alpha_{0^{***}}$ + MAR + u + w	3265.09	16264.38	14.20
12	α_0 + u + w	3266.29	16260.31	14.20
13	$\alpha_{0^{***}}$ + MAR + u	4246.75	4088.01	13.55
14	α_0 + u	4246.75	4088.44	13.55
15	$\alpha_{0^{***}}$ + MAR + w	4475.94	4131.50	14.13
16	α_0 (Null model)	4481.85	4078.36	14.08

[a] α_0: intercept; $\alpha_{0^{*}}$: intercept (UTC-GUA); $\alpha_{0^{**}}$: intercept (UTC); $\alpha_{0^{***}}$: intercept (GUA); CAL: calendar-based program; [CAL+MET]: calendar-based program + meteorological criteria; MOD: model-based program; [MOD+MET]: model-based program + meteorological criteria; MAR: 'Marinada' cultivar; u: random effect associated to the orchard; w: nested random effect associated to the block:orchard interaction.

[b] DIC: deviance information criterion.

[c] WAIC: widely applicable information criterion.

[d] LCPO: logarithmic conditional predictive ordinate.

Supplementary Table S2. Mean, standard deviation (SD), quantiles (Q), and mode for the parameters and hyperparameters of the selected model for the red leaf blotch incidence

Parameters	Mean	SD	$Q_{0.025}$ [b]	$Q_{0.5}$	$Q_{0.975}$ [b]	Mode
B_{0}**(UTC)	1.569	0.228	1.120	1.568	2.023	1.567
CAL	-5.294	0.165	-5.619	-5.294	-4.970	-5.294
CAL+MET	-3.016	0.098	-3.207	-3.016	-2.825	-3.016
MOD	-4.507	0.129	-4.760	-4.507	-4.253	-4.507
MOD+MET	-3.060	0.098	-3.253	-3.060	-2.868	-3.060
Hyperparameters [a]						
τ_W	1.490	0.568	0.607	1.415	2.808	1.266

[a] τ_W: precision of the nested random effect block:orchard.

[b] 95% credible interval is defined by $Q_{0.025}$ and $Q_{0.975}$.