



# BotRisk: simulating the annual bunch rot risk on grapevines (*Vitis vinifera* L. cv. Riesling) based on meteorological data

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## Abstract

The aim of the present investigations was to simulate the annual risk of bunch rot (*Botrytis cinerea*) on *Vitis vinifera* L. cv. Riesling grapes based on three long-term ( $n = 3 \times 7 = 21$  cases) assessment data sets originating from three Central European grape-growing regions. Periods when meteorological parameters were significantly ( $p < 0.01$ ) correlated with the cumulative degree day ( $CDD_{7;18;24}$ ) reaching 5% disease severity were determined by Window Pane analysis. Analyses revealed five critical weather constellations (“events”) influencing annual epidemics: relatively low temperatures after bud break, dry conditions during flowering, high temperatures after flowering, and low temperatures and high precipitation sums during/after veraison were all associated with thermal-temporal early epidemics. Meteorological data in each of the five events served as input for the bunch rot risk model “BotRisk.” The multiple linear regression model resulted in an adjusted coefficient of determination ( $R^2_{adj.}$ ) of 0.63. BotRisk enables (i) the simulation of the thermal-temporal position of the annual epidemic and, based on this, (ii) the classification of the annual bunch rot risk into three classes: low, medium, or high risk. According to leave-one-out cross-validation, 11 of 21 case studies were correctly classified. No systematic bias caused by location was observed, indicating that the transfer of the model into other locations with comparable climatic conditions could be possible. BotRisk (i) represents a novel viticultural decision support tool for crop cultural and chemical measures against bunch rot and (ii) enables an estimation of the bunch rot risk under changing environmental conditions.

**Keywords** *Botrytis cinerea* · Bunch rot risk · Climate change · Decision support tool · Cumulative degree days · Epidemiology · Window Pane analysis

## Introduction

Grape bunch rot caused by *Botrytis cinerea* is a major fungal disease on grapevines (*Vitis vinifera* L.) worldwide, threatening both grape yield and wine quality (Kassemeyer and Berkelmann-Löhnertz 2009; Smart and Robinson 1991).

Under the climatic conditions of many traditional grape-growing regions, grape bunch rot appears virtually every season (Molitor et al. 2016).

Recent statistical investigations into the epidemics of *B. cinerea* in the *Vitis vinifera* cultivar Riesling recorded in Geisenheim/Germany enabled (i) the simulation of the epidemic disease progress and (ii) the identification of weather conditions with predictive value for annual grape bunch rot epidemics (Molitor et al. 2016). Here, the annual disease progress as a function of thermal time (summation of the physiologically effective temperature (Trudgill et al. 2005) reflecting the phenological development) turned out to be well described by sigmoidal curves ( $0.97 < R^2$ ) with comparable slope factors in all years, while the thermal-temporal position of the epidemic strongly varied (Molitor et al. 2016). Window Pane analysis carried out according to Coakley and Line (1982) showed that annual weather conditions greatly affected the timing of the annual bunch rot epidemic, which is linked to the potential wine quality (Molitor et al. 2016).

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Grape bunch rot models have already been developed under different climatic conditions in the past, such as in the models of Broome et al. (1995), Nair and Allen (1993), and the “Bacchus” model (Agnew et al. 2004). Common to all of them is that they advise botryticide applications based on the interactions between temperature and wetness duration. All three models assume that the effects of temperature-dependent wetness durations on the infection level are constant during berry development. However, recent results (Molitor et al. 2016) demonstrated that wetness-based models might not be suitable to guide botryticide treatments in the case of the cultivar Riesling and in cool climate viticulture conditions.

The significant links established between annual weather conditions in specific periods of grape development and the seasonal bunch rot risk (Molitor et al. 2016) provide an excellent starting point to model the annual thermal-temporal position of the bunch rot epidemic (i) to quantify the annual bunch rot risk and (ii) to potentially support grape growers’ decisions concerning bunch rot control measures.

To broaden the database for such a bunch rot risk model and make it more robust for local conditions or effects, in the present investigations, we analyzed a data set of 21 cases of annual bunch rot assessment series originating from three Central European grape-growing regions and their corresponding daily meteorological records.

The investigation aimed to (i) develop a bunch rot risk model simulating the annual risk in terms of the annual position of the bunch rot epidemic on the cultivar Riesling based on the output of Window Pane analysis and (ii) validate the model output to test its general suitability as a decision support tool for practical viticulture.

## Materials and methods

### Assessment and meteorological data

The progress of the grape bunch rot disease on the white *Vitis vinifera* L. cultivar Riesling was monitored between 2007 and 2013 (Geisenheim, Germany) and between 2010 and 2016 (Remich, Luxembourg; Deidesheim, Germany) at weekly to bi-weekly intervals between veraison and harvest. The Riesling vineyards under observation were trained in a vertical shoot positioning system and are described in detail in Table 1. No fungicides with known activity against *B. cinerea* (botryticides) were applied.

In the case of Geisenheim and Remich, visually observed disease severities were classified into seven classes (0%; 1–5%; 6–10%; 11–25%; 26–50%; 51–75%; 76–100%) following the EPPO guideline PP1/17. In Deidesheim, visually observed disease severities were classified into four classes (0%, 0.1–5%, 5.1–25%, 25.1–100%). One hundred randomly selected clusters were assessed in three (Deidesheim) or four

(Geisenheim, Remich) replicated plots of the experimental vineyards. Average disease severities per plot were generally calculated by summing up the number of observations per class multiplied by the arithmetic mean of the class interval and dividing this sum by the total number of observations ( $n = 100$ ). Overall averages (whole observation vineyard) are the averages of the three or four plots, respectively.

For all locations, the daily average air temperatures (measured 2 m above the ground) and precipitation sums (measured 1 m above the ground) of the closest weather station were used. Distances between experimental vineyards and respective weather stations are given in Table 1. In the case of Deidesheim, weather data originated from Neustadt-Mussbach (Table 1). Key meteorological data from the three locations in the respective observation years are shown in Table 2.

### Disease progress curves

Sigmoidal curves have been demonstrated to be well adapted to the annual bunch rot epidemic under Central European conditions (Molitor et al. 2015, 2016, 2017, 2018, 2019; Porsche et al. 2018). Such sigmoidal curves were fitted to the disease severity data of each year and for each location plotted against the thermal time (summation of the physiologically effective temperature (Trudgill et al. 2005)) reflecting the phenological development using SigmaPlot 13 (Systat Software Inc., San Jose, CA, USA). This thermal time is expressed as the cumulative degree days  $CDD_{7;18;24}$  after BBCH 65 (Molitor et al. 2016; Molitor et al. 2014b) using Eq. (1) following Molitor et al. (2016):

$$y = \frac{100}{1 + e^{-((x-x_0)/a)}} \quad (1)$$

where  $y$  is the disease severity,  $x$  the cumulative degree day  $CDD_{7;18;24}$ ,  $x_0$  the inflection point of the curve, and  $a$  the slope factor of the curve in the inflection point.

For each of the year-location combination, parameters describing the disease progress curve were determined. Coefficients of determination ( $R^2$ ) and significance levels ( $p$ ) were determined to quantify the adaptation of the fitted curves to the observation data.

Based on Eq. (1), the cumulative degree day  $CDD_{7;18;24}$ , reaching a disease severity of 5% ( $x_{5\%}$ ), was computed for every season. The threshold of 5% was selected following Beresford et al. (2006) and Evers et al. (2010).

### Window Pane analysis

To detect critical periods during the season (relative to the date of BBCH 65), when environmental variables were related

**Table 1** Features of the experimental vineyards

Location	Geisenheim, Germany	Remich, Luxembourg	Deidesheim, Germany
Coordinates	49.98 N, 7.95 E	49.54 N, 6.35 E	49.42 N, 8.19 E
Year of plantation	1982	1994	1980
Cultivar	Riesling	Riesling	Riesling
Clone	Gm 239	unknown	N 90
Rootstock	5C	SO4	5C
Weather station	Geisenheim	Remich	Neustadt-Mussbach
Distance to weather station (km)	0.1	0.1	5.1
Observation years	7 (2007–2013)	7 (2010–2016)	7 (2010–2016)

with the thermal-temporal position of the epidemic, Window Pane analysis was conducted following the approach of Coakley and Line (1982), as described by Kriss et al. (2010). Window Pane analyses determine the length and the starting time of temporal windows during which average values of environmental variables are significantly correlated with plant disease levels at a specific time point (target) such as at the end of a season (Kriss et al. 2010; Molitor et al. 2016). In the present study, the impact of the environmental variables, i.e., the daily average air temperature and daily precipitation sum, on the cumulative degree day  $CDD_{7;18;24}$

reaching a disease severity of 5%, was examined based on all 21 cases. Linear correlations between the summary environmental variables (average values of environmental variables in the different time windows) and the cumulative degree day  $CDD_{7;18;24}$  reaching a disease severity of 5% (target) were calculated for the window widths 5, 10, 20, 30, 50, and 100 days. Pearson correlation coefficients ( $r$  values) and significance levels ( $p$  values) were determined for each summary environmental variable. Significant correlations were declared when individual  $p$  values were below 0.05 and highly significant correlations when  $p < 0.01$ .

**Table 2** Key annual and growing season (April–October) meteorological variables in the three observation locations

Location	Year	Mean annual temperature (°C)	Mean growing season temperature (°C)	Annual precipitation sum (mm)	Growing season precipitation sum (mm)
Geisenheim	2007	11.5	15.7	509	274
	2008	10.9	15.2	535	339
	2009	10.8	16.1	583	311
	2010	9.7	14.9	658	426
	2011	11.3	16.0	469	305
	2012	10.8	15.3	531	330
	2013	10.4	15.5	557	397
	Average	10.8	15.5	549	340
Remich	2010	10.0	15.0	695	388
	2011	11.4	15.5	533	287
	2012	10.3	14.4	700	449
	2013	9.9	14.7	813	576
	2014	11.8	15.9	722	444
	2015	11.5	15.6	540	347
	2016	10.9	15.9	760	462
	Average	10.8	15.3	680	422
Deidesheim	2010	10.1	15.3	742	462
	2011	11.7	16.4	566	379
	2012	11.3	15.9	593	377
	2013	10.4	15.6	644	465
	2014	12.2	16.4	524	350
	2015	11.8	16.2	400	216
	2016	11.3	16.1	582	383
	Average	11.3	16.0	578	376

## Model development and validation

Window Pane analysis identified five critical meteorological constellations, hereafter referred to as “events,” with highly significant correlations between the summary environmental variables and the  $CDD_{7;18;24}$  values when reaching 5% disease severity ( $x_{5\%}$ ). A multiple linear regression model based on one summary environmental variable in each of the five events was developed to simulate the  $x_{5\%}$  value using the open access software tool R. The selection of potential input variables for the novel bunch rot risk model—hereafter referred to as “BotRisk”—took place in the following order:

1. Summary environmental variables causing a local maximum of the absolute  $r$  values in a series of highly significant Pearson correlation coefficients ( $p < 0.01$ ) in Window Pane analysis were selected in the different window widths.
2. Of these selected potential input variables, one summary environmental variable per event was included in the multiple linear regression model. The best model was selected based on the highest adjusted  $R^2$  value of the model.

According to their calculated  $CDD_{7;18;24}$  values, annual bunch rot risk classes were declared as follows:

- Class 1—“low” annual bunch rot risk:

predicted  $CDD_{7;18;24}$  values reaching 5% disease severity  $> 1000$

- Class 2—“medium” annual bunch rot risk:

predicted  $CDD_{7;18;24}$  values reaching 5% disease severity  $> 900$  and  $\leq 1000$

- Class 3—“high” annual bunch rot risk:

predicted  $CDD_{7;18;24}$  values reaching 5% disease severity were  $\leq 900$ .

Class ranges were defined to achieve (i) approximately equal numbers of observed cases in each of the three classes as well as (ii) class boundaries that were as round as possible for practical applications.

The predictive value was tested by leave-one-out cross-validation according to Ladenbruch and Mickey (1968). Predicted  $CDD_{7;18;24}$  values reaching 5% disease severity values (as simulated by BotRisk) were calculated by averaging all but one ( $n - 1$ ) data sets and compared with observed  $CDD_{7;18;24}$  values (retrieved from disease progress curves). Coefficients of determination

( $R^2_{adj.}$ ), mean bias errors (MBE), and mean absolute errors (MAE) of the cross-validated model were calculated. The validation of correct risk classification in the cross-validated model took place based on observed and predicted  $CDD_{7;18;24}$  values reaching 5% disease severity.

## Results

### Disease progress as a function of thermal time

Disease severities at the different assessment dates and locations are shown in Table 3.

Sigmoidal curves of the type  $y = \frac{100}{1 + e^{-((x-x_0)/a)}}$  fitted the disease progress curves precisely ( $r^2 \geq 0.87$ ,  $p \leq 0.069$ ) (Supplementary Table 1; Fig. 1).

Disease severities of 5% were reached between 781 (Geisenheim 2010) and 1112 (Deidesheim 2012) cumulative degree days  $CDD_{7;18;24}$ . The average  $CDD_{7;18;24}$  reaching 5% disease severity were 972 (Geisenheim), 931 (Remich), and 961 (Deidesheim) with no significant differences between locations according to the analysis of variance ( $p = 0.05$ ) (Supplementary Table 1).

### Impact of environmental conditions

Supplementary Figs. 1 and Fig. 2 show the results of Window Pane analysis for the summary environmental variables’ daily average temperatures and daily precipitation sum using all six tested window widths (5, 10, 20, 30, 50, 100 days). Pearson correlation coefficients as result of the Window Pane analysis are (as defined by Kriss et al. (2010)) generally depicted at the end of the respective summary period.

The following summary environmental variables were highly significantly ( $p \leq 0.01$ ) and positively (high value  $\rightarrow$  late epidemic) correlated with the thermal-temporal position of the epidemic ( $x_{5\%}$  value):

- Summary environmental variable daily average air temperature
- Bbetween  $-42$  and  $-39$ , between 72 and 76 days as well as 91 days after BBCH 65 (D65) (window width:, 5 days),
- Bbetween  $-39$  and  $-35$  as well as between 75 and 80 D65 (window width:, 10 days),
- Bbetween  $-30$  and  $-28$  as well as between 75 and 90 D65 (window width:, 20 days),
- aAt  $-19$  and  $-18$ , between 73 and 85 as well as between 88 and 99 D65 (window width:, 30 days),
- Bbetween 88 and 108 D65 (window width:, 50 days)

**Table 3** *Botrytis cinerea* disease severities at the different assessment dates in the different observation years in Geisenheim, Remich, and Deidesheim

	Year	Date	DOY *	D <sub>65</sub>	CDD <sub>7;18;24</sub> after BBCH 65	Disease severity
Geisenheim	2007	22.08.	234	86	850.9	0.4
	2007	28.08.	240	92	914.4	0.6
	2007	04.09.	247	99	975.5	3.3
	2007	24.09.	267	119	1120.5	9.6
	2007	09.10.	282	134	1211.5	44.4
	2008	27.08.	239	81	829.9	0.2
	2008	10.09.	253	95	967.9	1.7
	2008	09.10.	282	124	1111	32.3
	2009	15.09.	258	98	999.4	0.5
	2009	22.09.	265	105	1074.4	6.7
	2009	01.10.	274	114	1149.6	12.1
	2009	08.10.	281	121	1200	38.0
	2010	31.08.	243	70	724.2	2.2
	2010	10.09.	253	80	801	4.1
	2010	14.09.	257	84	836.4	18.6
	2010	23.09.	266	93	894.1	41.7
	2010	29.09.	272	99	921.4	48.2
	2010	07.10.	280	107	980.5	80.8
	2010	14.10.	287	114	1009.5	92.4
	2011	29.08.	241	89	884.5	7.7
	2011	05.09.	248	96	952.9	19.2
	2011	13.09.	256	104	1034.4	60.7
	2011	19.09.	262	110	1077.1	82.3
	2012	05.09.	248	83	862.2	0.8
	2012	12.09.	255	90	929.1	1.0
	2012	18.09.	261	96	973.6	2.7
	2012	25.09.	268	103	1012.7	6.8
	2012	02.10.	275	110	1048.6	11.9
	2012	08.10.	281	116	1080.2	20.9
	2012	12.10.	285	120	1090.5	25.0
	2013	09.09.	252	77	791.9	0.2
	2013	16.09.	259	84	842.4	0.7
	2013	23.09.	266	91	886.1	2.9
2013	30.09.	273	98	932	7.1	
2013	08.10.	281	106	975	13.1	
2013	14.10.	287	112	988.7	37.0	
2013	21.10.	294	119	1029.1	65.7	
Remich	2010	09.09.	252	74	743.8	0.6
	2010	21.09.	264	86	830.0	1.4
	2010	28.09.	271	93	869.9	2.9
	2010	06.10.	279	101	935.9	12.3
	2010	13.10.	286	108	980.2	30.9
	2011	10.08.	222	67	623.1	0.0
	2011	24.08.	236	81	775.4	0.1
	2011	06.09.	249	94	890.8	1.6
	2011	14.09.	257	102	965.5	3.1
	2011	22.09.	265	110	1020.4	7.7
	2011	28.09.	271	116	1075.9	13.1
	2012	17.09.	260	88	865.7	0.0

**Table 3** (continued)

	Year	Date	DOY *	D <sub>65</sub>	CDD <sub>7;18;24</sub> after BBCH 65	Disease severity
	2012	01.10.	274	102	929.1	0.4
	2012	08.10.	281	109	959.5	2.3
	2012	15.10.	288	116	974.6	5.8
	2012	24.10.	297	125	1038.8	20.4
	2013	17.09.	260	75	726.1	0.5
	2013	01.10.	274	89	816.2	4.9
	2013	08.10.	281	96	858.4	7.0
	2013	14.10.	287	102	869.5	14.7
	2014	01.09.	244	79	779.0	1.1
	2014	16.09.	259	94	928.4	3.1
	2014	22.09.	265	100	988.9	5.1
	2014	30.09.	273	108	1047.1	10.3
	2014	07.10.	280	115	1105.2	22.8
	2015	31.08.	243	76	738.1	0.0
	2015	17.09.	260	93	871.5	5.5
	2015	23.09.	266	99	910.8	23.6
	2015	30.09.	273	106	956.3	38.8
	2016	05.09.	248	71	733.2	0.4
	2016	19.09.	262	85	879.1	0.6
	2016	28.09.	271	94	956.0	2.8
	2016	05.10.	278	101	1000.4	5.9
	2016	12.10.	285	108	1017.0	17.1
	2016	18.10.	291	114	1039.6	22.1
Deidesheim**	2010	16.09.	259	92	907.1	2.3
	2010	23.09.	266	99	950.8	4.7
	2010	01.10.	274	107	990.6	8.6
	2011	05.09.	248	99	1001.9	9.7
	2011	12.09.	255	106	1075.1	20.0
	2012	03.09.	246	82	862.9	0.0
	2012	10.09.	253	89	937.0	0.1
	2012	17.09.	260	96	993.2	0.4
	2012	24.09.	267	103	1041.1	1.1
	2012	01.10.	274	110	1078.8	2.4
	2013	26.08.	238	60	629.8	0.2
	2013	02.09.	245	67	703.2	0.4
	2013	09.09.	252	74	777.3	0.4
	2013	16.09.	259	81	827.4	1.1
	2013	23.09.	266	88	871.8	6.2
	2013	30.09.	273	95	918.4	13.3
	2013	07.10.	280	102	949.6	24.6
	2014	18.08.	230	71	746.9	0.0
	2014	25.08.	237	78	801.0	0.4
	2014	01.09.	244	85	869.5	1.5
	2014	08.09.	251	92	942.4	3.2
	2014	15.09.	258	99	1004.9	7.1
	2014	22.09.	265	106	1072.5	13.5
	2015	17.08.	229	69	676.5	0.0
	2015	24.08.	236	76	748.4	0.1
	2015	31.08.	243	83	819.3	0.9



**Table 3** (continued)

Year	Date	DOY *	D <sub>65</sub>	CDD <sub>7;18;24</sub> after BBCH 65	Disease severity
2015	07.09.	250	90	876.9	8.6
2015	14.09.	257	97	938.6	14.0
2016	22.08.	234	71	740.8	0.0
2016	29.08.	241	78	813.7	0.0
2016	05.09.	248	85	890.7	0.7
2016	12.09.	255	92	967.6	2.3
2016	19.09.	262	99	1038.3	7.9
2016	26.09.	269	106	1093.3	12.4

DOY, day of the year; D<sub>65</sub>, days after BBCH 65; CDD<sub>7;18;24</sub>, cumulative degree days according to Molitor et al. (2016). Assessment data from Geisenheim were originally published in Molitor et al. (2016)

\*29 February was not considered in leap years

\*\*Assessment data from Deidesheim were kindly provided by DLR Rheinpfalz, Neustadt/Weinstraße

- Summary environmental variable daily precipitation sum
- Between 100 and 108 as well as between 110 and 123 D<sub>65</sub> (window width, 50 days) (Supplementary Fig. 1, Fig. 2)
- At 4 D<sub>65</sub> (window width, 5 days)
- Between 6 and 8 D<sub>65</sub> (window width, 10 days)
- At 17 D<sub>65</sub> (window width, 20 days)
- At 38, 47 as well as between 41 and 44 D<sub>65</sub> (window width, 50 days)

On the other hand, the following summary environmental variables were significantly and negatively (low value → late epidemic) correlated with the thermal-temporal position of the epidemic ( $x_{5\%}$  value):

- Summary environmental variable daily average air temperature
- Between 32 and 34 D<sub>65</sub> (window width, 5 days)
- Between 38 and 40 D<sub>65</sub> (window width, 50 days)
- Summary environmental variable daily precipitation sum
- At 77 as well as between 80 and 87 D<sub>65</sub> (window width, 20 days)
- Between 81 and 87 D<sub>65</sub> (window width, 30 days)

Analyses revealed five critical meteorological “events” where summary environmental variables were highly significantly ( $p \leq 0.01$ ) correlated with the thermal-temporal position of the epidemic ( $x_{5\%}$  value) in different window widths:

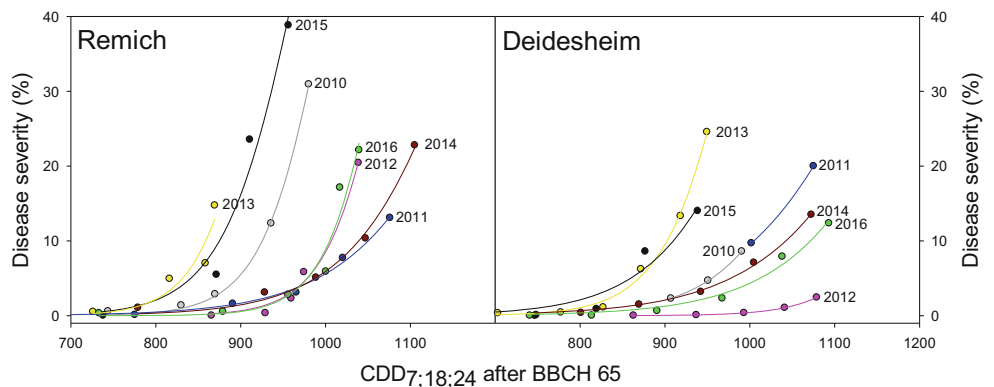
- Temperatures around 40 days prior to flowering (event 1)
- Temperatures around 30 days after flowering (event 2)
- Temperatures around 70 days after flowering (event 3)
- Precipitation around flowering (event 4)
- Precipitation around 70 days after flowering (precipitation) (event 5)

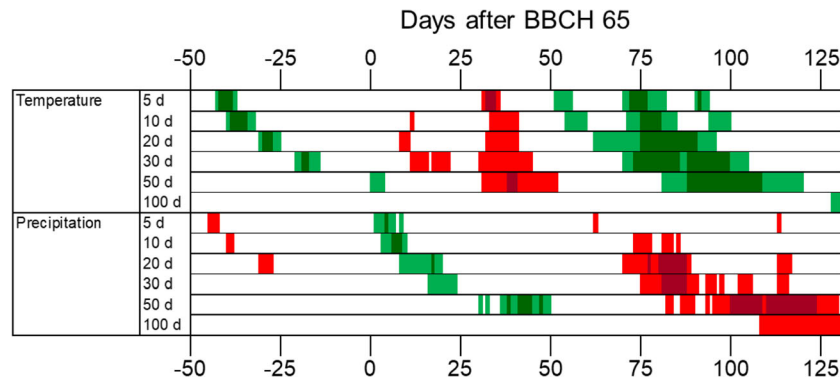
**BotRisk model to simulate the position of the annual bunch rot (*Botrytis cinerea*) epidemic**

Multiple linear regression kept the following input variables for the BotRisk model:

- Event 1: summary environmental variable temperature on day – 38 D<sub>65</sub> (window width, 10 days) = variable a

**Fig. 1** Disease progress curves in Remich and Deidesheim in the different seasons as functions of the thermal time (CDD<sub>7;18;24</sub> after BBCH 65). Disease progress curves of Geisenheim are illustrated in Molitor et al. (2016)





**Fig. 2** Significant (significance level:  $p \leq 0.05$ ) positive (green), highly significant ( $p \leq 0.01$ ) positive (dark green), significant ( $p \leq 0.05$ ) negative (red), or highly significant ( $p \leq 0.01$ ) negative (dark red) correlations between the summary environmental variables of daily average temperatures (temperature) and daily precipitation sums (precipitation)

- Event 2: summary environmental variable temperature on day 33  $D_{65}$  (window width, 5 days) = variable b
- Event 3: summary environmental variable temperature on day 74  $D_{65}$  (window width, 5 days) = variable c
- Event 4: summary environmental variable precipitation on day 17  $D_{65}$  (window width, 20 days) = variable d
- Event 5: summary environmental variable precipitation on day 87  $D_{65}$  (window width, 30 days) = variable e

Based on this model, the  $CDD_{7;18;24}$  reaching 5% disease severity can be calculated as follows:

$$\begin{aligned}
 &951.476 \\
 &+ 7.2173 * \text{summary environmental variable temperature} \\
 &\text{on day } -38 D_{65} \text{ (window width, 10 days)} \\
 &- 16.317 * \text{summary environmental variable temperature} \\
 &\text{on day } 33 D_{65} \text{ (window width, 5 days)} \\
 &+ 10.793 * \text{summary environmental variable temperature} \\
 &\text{on day } 74 D_{65} \text{ (window width, 5 days)} \\
 &+ 21.986 * \text{summary environmental variable precipitation} \\
 &\text{on day } 17 D_{65} \text{ (window width, 20 days)} \\
 &+ 2.512 * \text{summary environmental variable precipitation on} \\
 &\text{day } 87 D_{65} \text{ (window width, 30 days)}
 \end{aligned}$$

$R^2$  of the model is 0.7244,  $R^2_{adj}$  (model accuracy) 0.6325, and the  $p$  value of the model 0.0008.

Leave-one-out cross-validation resulted in a coefficient of determination ( $R^2_{cv}$ ) of 0.51. The mean bias errors (MBE) in the leave-one-out cross-validation were  $-10.8 CDD_{7;18;24}$  for Geisenheim,  $-1.5 CDD_{7;18;24}$  for Remich, and  $14.4 CDD_{7;18;24}$  for Deidesheim (overall average MBE,  $0.7 CDD_{7;18;24}$ ) with mean absolute errors (MAE) of 61.5 (Geisenheim), 45.6 (Remich), and 54.6  $CDD_{7;18;24}$  (Deidesheim) (overall average MAE,  $53.9 CDD_{7;18;24}$ ). The leave-one-out cross-validation of the classification of annual bunch rot risk classes demonstrated that in 11 of 21 cases, the predicted classification matched the observed classification. In four cases, observed classes were one class higher than the predicted classes and in six cases, one class lower than

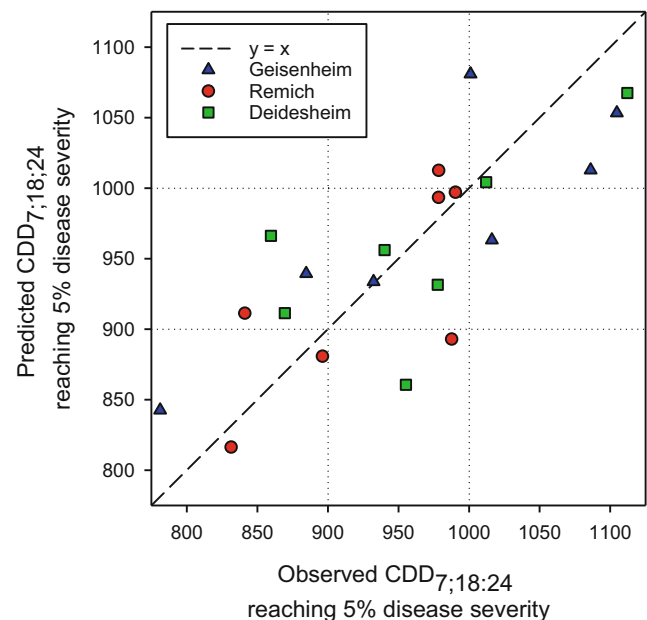
and the cumulative degree days  $CDD_{7;18;24}$  reaching a disease severity of 5% depending on (i) the starting date of a window (relative to the date of BBCH 65) and (ii) the window width according to Window Pane analysis. Correlation coefficients are depicted on the last day of each temporal window

the predicted classes. No cases were observed in which the prediction indicated a high risk, but a low risk was observed in practice and vice versa (Fig. 3, Table 4).

## Discussion

### Impact of meteorological conditions on the annual epidemic

Window Pane analysis demonstrated that the annual thermal-temporal position of the bunch rot epidemic was independent



**Fig. 3** Leave-one-out cross-validation: Predicted plotted versus the observed cumulative degree days  $CDD_{7;18;24}$  after BBCH 65 reaching a disease severity of 5% in Geisenheim (blue triangles), Remich (red circles), and Deidesheim (green squares). The dashed line represents the 1:1 relationship. The dotted lines represent the frontiers of the risk classes according to the bunch rot risk model BotRisk



**Table 4** Cross-validation of the classification of annual bunch rot risk classes

		Observed			
		Class 3 “high risk”	Class 2 “medium risk”	Class 1 “low risk”	Sum
Predicted	Class 1 “low risk”	0	2	4	6
	Class 2	4	4	2	10
	“medium risk”				
	Class 3	3	2	0	5
	“high risk”				
Sum		7	8	6	21

The predicted number of cases according to leave-one-out cross-validation in classes 1 to 3 is plotted against the observed number of cases in the respective classes. Class 1, “low” annual bunch rot risk: predicted CDD7;18;24 values reaching 5% disease severity > 1000; class 2, “medium” annual bunch rot risk: predicted CDD7;18;24 values reaching 5% diseases severity > 900 and < = 1000; class 3, “high” annual bunch rot risk: predicted CDD7;18;24 values reaching 5% diseases severity were < = 900

of the location and significantly correlated with the meteorological conditions in specific periods of grape phenology.

Five distinct periods (referred to as critical “events”) were identified when meteorological conditions were of high prognostic value for the annual thermal-temporal position of the epidemic:

Event 1: Post-bud break period (temperatures)

Obviously, high temperatures in the period around – 40 days  $D_{65}$  are linked to a thermal-temporal late annual bunch rot epidemic. For the years 1993 to 2015, BBCH 63 was reached in Luxembourg on average 56 days after BBCH 09 (bud break) (Molitor and Keller 2016). Hence, the critical event identified here represents the period of approximately 16 days after bud break. Warm conditions during the initial shoot development and flower formation period in spring are leading to increased flower sizes (Keller 2015). Interestingly, studies with the cultivar Sauvignon blanc in 2010 showed that the elongation effects of gibberellic acid applications on the cluster stem length were most pronounced where the treatment was applied 14 to 36 days after budburst (Molitor et al. 2012b), which indicates that this period might be the most crucial period for inflorescence stem growth. Potentially, the effect of warm post-bud break temperatures on the epidemic might be explained by an elongation of the cluster stems leading to a looser cluster structure. The latter has been demonstrated several times to be strongly correlated with a lower predisposition to bunch rot (e.g., Molitor et al. (2012a, 2015); Hed et al. (2009); Intrigliolo et al. (2014); Tello and Ibanez (2017)).

Event 2: Post-flowering period (temperatures)

The present investigation demonstrated that high temperatures in a period of approximately 30 days after flowering were significantly correlated with an early epidemic. We suppose that this effect might be explained by intensified cell division and cell expansion processes under warm conditions in this period (Keller 2015), leading to more compact grape clusters.

Events 3 and 5: Period between veraison and harvest (temperatures + precipitation)

While the effects of meteorological conditions on the annual bunch rot epidemic in events 1 and 2 can supposedly be explained by indirect effects on the cluster structure, the link between high precipitation sums between veraison and harvest and the thermal-temporal position of the epidemic might be caused by the following direct effect of moist conditions on the epidemiology of the disease:

- (i) The availability of water promotes the development of fungal pathogens.
- (ii) High post-veraison water availability facilitates the water uptake into the berries, resulting in larger berries, compact clusters, and a high risk of the fruit cracking (Keller et al. 2003).
- (iii) Rain events after veraison re-activate latent *B. cinerea* infections, which often lead to direct infections of ripening berries (Evans and Emmett 2011).

Most likely, the inverse influence of air temperature and precipitation between veraison and harvest on bunch rot epidemics is related to the frequently observed negative association between precipitation and temperature during the summer months under Central European conditions.

However, especially under changing environmental conditions, extreme events such as severe rain events in combination with high air temperatures or combinations of both are becoming more likely (IPCC 2012), and those conditions are highly favorable for fungal infections. Consequently, to keep the model robust against those non-steady environmental factors, both variables remained in the model even though some collinearity between them exists.

Event 4: Flowering period (precipitation)

Furthermore, there was a strong link between the amount of precipitation during the flowering process and the thermal-temporal position of the annual epidemic. As described before

(Molitor et al. 2016), wet weather conditions around grape bloom are associated with a (thermal-temporal) late annual bunch rot epidemic. This supports the hypothesis that during grape flowering, in particular, adverse weather conditions are reducing the degree of the fruit set—as described by Kliewer (1977), Nesbitt et al. (2016), and Mosedale et al. (2015)—and, consequently, are loosening the bunch structure and reducing the predisposition to bunch rot.

The observed phenomena demonstrated that the same environmental factor can have both, a positive or a negative effect on the thermal-temporal position of the epidemic depending on the phenological stage of the host plants.

### The bunch rot risk model BotRisk

Based on the highly significant correlations between the meteorological conditions and the  $CDD_{7;18;24}$  reaching a disease severity of 5% in the five critical events identified above, the novel bunch rot risk model BotRisk was developed using a multiple linear regression approach with five input variables.

Model validation showed that the model did not markedly over- or underestimate the time point reaching 5% disease severity in any of the three locations. On average, the overall mean absolute error (MAE) of the cross-validated model was 53.9  $CDD_{7;18;24}$ , which reflects a time frame of 6 days (assuming an average daily temperature of 16.0 °C; average (2000–2009) September temperatures in Geisenheim/Germany, 15.6 °C, in Remich/Luxembourg, 15.6 °C).

Observed adjusted coefficients of determination show an adequate level of goodness of fit for the model to simulate the cumulative degree days reaching 5% disease severity ( $R^2_{adj.} = 0.633$ ). Obviously, there are other factors besides air temperature and precipitation that influence the thermal-temporal position of the epidemic. Potentially, unexplained variance between the different years might be due to crop cultural practices changing from year to year: e.g., the moment of first shoot topping has been demonstrated to influence the annual epidemic in a significant manner (Molitor et al. 2015).

Furthermore, the annual epidemic might have been influenced by grape pests, such as the grape berry moth (*Lobesia botrana* (Denis & Schiffermüller), *Eupoecilia ambiguella* (Hübner)), or fungal diseases, such as powdery mildew (*Erysiphe necator* Schwein.), which are able to wound berry skin and create entry points for *Botrytis cinerea*. Furthermore, frequently observed fluctuations in the annual yield level (Molitor and Keller 2016) and, in consequence, differences in the pace of grape maturation after veraison might have influenced the epidemic.

Interestingly, in the present model, the influence of the location (potentially including differences in soil type, soil fertility or soil management, fertilization, grape vigor, age of plants, rootstock, clone, planting density, canopy management regime) turned out to be of minor importance. This is

demonstrated by the fact that the differences in the mean bias errors of the model caused by the location are negligible (MBE,  $-10.8$  to  $14.4$   $CDD_{7;18;24} = -1.2$  to  $1.6$  days (assuming a daily average temperature of 16 °C)). Potential location differences caused by generally higher or generally lower temperatures at specific sites may have been adjusted for during the calculation of the  $CDD_{7;18;24}$ . Furthermore, validation indicates that model transfer to other locations with comparable climatic conditions might be possible. However, keeping in mind that Geisenheim, Remich, and Deidesheim are located in cool climate viticulture regions with comparable climatic conditions, the present model should not be directly transferred to regions with markedly deviating climatic conditions without previous validation with local data sets.

The predicted risk class differed by a maximum of one class compared with the observation class. I.e., in none of the 21 studied cases did the model predict a low bunch rot risk while a high bunch rot risk was observed or vice versa.

### Potential BotRisk applications

BotRisk enables a simulation of the thermal-temporal position of the annual bunch rot epidemic in the Riesling cultivar in the past or (based on climate projections) in the future even if only the basic, most frequently recorded environmental variables, temperatures, and precipitation, are available. Here, the calculated  $CDD_{7;18;24}$  reaching a disease severity of 5% functions as the annual risk indicator. The lower the simulated annual value of the  $CDD_{7;18;24}$  reaching a disease severity of 5%, the higher the annual risk for an early bunch rot epidemic. Based on this, three bunch rot risk classes have been defined indicating years with low, medium, or high bunch rot risk.

Founded on observation data from the three first critical events coupled with long-term average data for the two missing critical events 3 and 5 in the period between veraison and harvest, an estimation of the annual bunch rot risk of the present season can be realized around 1 month after flowering, and this information can then be integrated into the bunch rot control strategy. This might, under practical conditions, support the decisions, if botrycide applications (e.g., at bunch closure or veraison) or crop cultural measures are necessary or (monetarily as well as environmentally) meaningful. In the past, practical bunch rot control strategies were mainly based on routine fungicide applications (Shtienberg 2007). However, excessive chemical bunch rot control measures are becoming increasingly criticized and restricted (Elmer and Michailides 2007; Shtienberg 2007). Consequently, the classification of the annual bunch rot risk might be efficiently implemented in the fungicide regime as a measure of Integrated Pest Management enabling either (i) a reduction of the number of botrycide applications and thus a reduction in pesticide use in years with a lower bunch rot risk or (ii) a

higher bunch rot control efficiency due to the targeted application of botryticides in years with a high bunch rot risk.

The annual thermal-temporal position of the epidemic has been demonstrated to be significantly correlated with annual wine quality (Molitor et al. 2016) as the presence of *B. cinerea* at early (unripe) stages of berry development negatively affects wine composition (because of berry decay) and hinders further grape maturation (Molitor et al. 2012a). BotRisk might be combined with phenological models (Molitor et al. 2014b, 2016, 2020) as well as regional or local climate change projections (Molitor et al. 2014a; Molitor and Junk 2019) aiming for a simulation of the bunch rot disease progress in relation to the progress of the grape phenology/maturity. This study might reveal if the risk of vintages with an early bunch rot epidemic at stages of incomplete grape maturity (leading to low potential wine quality) is supposed to increase or decrease in the future and if specific adaptation strategies might become necessary.

## Conclusions

The annual meteorological conditions during specific periods of grape development are significantly correlated with the thermal-temporal position of the bunch rot epidemic on *Vitis vinifera* L. cv. Riesling. Based on periods of highly significant correlations between meteorological data and the thermal-temporal position of the epidemic, the bunch rot risk model BotRisk was developed based on a multiple linear regression approach. BotRisk allows for a simulation of the annual thermal-temporal position of the bunch rot epidemic in Riesling based on temperature and precipitation records in different periods of grape development with an accuracy ( $R^2_{adj}$ ) of 0.63 and classifies the annual bunch rot risk in three risk classes. The observed minor influence of the location on model robustness indicates that a transfer into other locations of comparable climatic conditions might be possible. Presently, BotRisk represents a bunch rot risk model for the grape cultivar Riesling. However, the approach of BotRisk is open for parameterization for other cultivars based on respective long-term observation data sets.

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