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Simulation of oat yield through biological and environmental variables for reducing fungicide application and increasing interval from application to grain harvest

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Abstract

Simulation models based on biological and environmental variables allow the analysis of scenarios in proposing more sustainable management. The objectives is to identify potential biological and environmental variables for inclusion and validation of multiple linear regression model for yield simulation and analyze scenarios that promote yield and satisfactory control of foliar diseases, with longer intervals between the last fungicide application and the grain harvest. The study was conducted in 2015, 2016, 2017, in Augusto Pestana, RS, Brazil. The soil is classified as Oxisol and the climate of the region as Cfa type, by the Köppen classification. The experimental design was randomized blocks, with three replications, in a 22 x 4 factorial, for 22 oat cultivars (10 recommended and 12 no longer recommended) and 4 fungicide use conditions (no application; one application 60 days after emergence (DAE); two applications, 60, 75 DAE; and three applications, 60, 75, 90 DAE. In 2015 and 2016, the fungicide FOLICUR® CE was used, and in 2017 PRIMO®, at a dosage 0.75 and 0.3 liters ha^{-1}, respectively. Necrotic leaf area, rainfall depth, mean minimum and maximum temperatures, thermal sum, and crop cycle period (days) are potential variables by the Stepwise technique in the simulation of oat yield, validating the use of the multiple linear regression. The condition with three fungicide applications, at 60, 75, 90 DAE, resulted in satisfactory foliar disease control and grain yield, while maintaining a long interval between the last fungicide application and the grain harvest, thus improving the safety of the product obtained.

Keywords: *Avena sativa*; multiple linear regression; zero hunger; food security.

Abbreviations: NLA_necrotic leaf area; R_rainfall depth; T_{min}_minimum temperature; T_{mean}_mean temperature; T_{max}_maximum temperature; TS_thermal sum; DAE_days after emergence; FY_ favorable year; UY_unfavorable year; IY_intermediate year; GY_grain yield; GYo_observed grain yield; GYs_simulated grain yield; WF_without fungicide; CF_1_one fungicide application at 60 days after emergence; CF_2_two fungicide applications, at 60 and 75 days after emergence; CF_3_three fungicide applications, at 60, 75, and 90 days after emergence.

Introduction

White oat (*Avena sativa* L.) is a multipurpose species that stands out as human food due to the high nutritional quality of its grains (Marolli et al., 2017a; Silva et al., 2020). It has high protein quality, adequate lipid and carbohydrate contents, and a high proportion of dietary fiber, mainly -glucan, which is related to reduction of cholesterol, diabetes, and obesity (Mantai et al., 2020; Basso et al., 2022).

Oat crops are highly susceptible to fungal pathogens that cause foliar diseases that can completely compromise grain yield, under favorable conditions (Oliveira et al., 2014; Silva et al., 2015). Leaf rust (*Puccinia coronata Cda. f.sd.avenae*) and helminthosporiosis [*Dreschslera avenae (Eidam) El Sharif*] are among the most important oat foliar diseases (Dietz et., 2019; Pereira et al., 2020). Breeding programs have been developing more resistant cultivars to mitigate damages caused by these diseases (Silva et al., 2015; Nazareno et al., 2018). However, diseases are not satisfactorily controlled by genetic resistance due to the rapid evolution of pathogens (Bhardwaj et al., 2021). The rapid evolution of a disease is dependent on the susceptibility of the cultivar, production systems without crop rotation, rapid evolution and reproduction rate of fungi, and meteorological conditions favorable to the disease progress (Silva et al., 2015; Basso et al., 2022).

The intensive use of fungicides for controlling these diseases is still the most efficient way to ensure grain yield and quality (May et al., 2020; Pereira et al., 2020). However, most oat grains are used for preparation of foods, often used fresh, denoting the need for a careful management to avoid agrochemical residues in the grains (Silva et al., 2015; Da Luz et al., 2017). In addition, the irresponsible use of fungicides can cause serious damages to the environment, such as contamination of soil, water, and air, and death of animals, mainly birds, fish, and pollinating insects (Pereira et al. 2020; Rani et al., 2021). These conditions reinforce the need for more efficient managements to ensure food security and environmental preservation (Coelho et al., 2020; Basso et al., 2022). In this perspective, managements that anticipate or even extend the time between the last application and the grain harvest can assist in reducing the number of applications, thus ensuring a satisfactory control of diseases with food security. In this context, models for analyzing simulated scenarios involving biological and environmental variables and considering the disease progress and grain yield are important.

Therefore, agricultural prediction models should involve biological and environmental variables (De Mamann et al., 2020; Alessi et al., 2021a). Multiple linear regressions are among prediction models involving biological and environmental variables. It enables the combination of controlled and uncontrolled variables in the simulations (Mantai et al., 2016; Alessi et al., 2021a). Increasing efficiency of these models depends on the choice of more expressive independent variables over the dependent variable (Prunzel et al., 2016; Alessi et al., 2021b). The Stepwise technique is one of the most used methods for selection of variables, as it iteratively selects variables that have the most effect on the output set, excluding possible redundancies (Mantai et al., 2016; Marolli et al., 2017a). Multiple linear regression models combined with selection of variables using the Stepwise technique enables to extract important information when searching for simulation and management optimization, exploring variables that significantly affect crop yield (Silva, et al., 2016; Trautmann et al., 2017).

The objective of this work was to identify potential biological and environmental variables for inclusion and validation of multiple linear regression models for yield simulation and analyze scenarios that promote yield and satisfactory control of foliar diseases, with longer intervals between the last fungicide application and the grain harvest.

Results and discussion

Agricultural year conditions and fungicide use in the expression of grain yield

The air temperatures were higher in 2017 (Table 1), compared to those in 2015 and 2016, with a strong instability in the oat vegetative stage. The highest rainfall depths occurred during the grain filling stage (Fig 1A). The low soil moisture at the nitrogen application time, combined with the high air temperature during the cycle (Fig 1A.), was decisive for compromising the expected yield of 4000 kg ha^{-1}. The overall mean grain yield under these conditions was 1861 kg ha^{-1} (Table 1), regardless of the fungicide application condition, making 2017 an unfavorable year (UY) for oat crops.

The lowest air temperatures were observed in 2016 (Table 1), with a stability throughout the crop cycle. Although the rainfall depths were lower than the historical mean, they were adequately distributed (Fig 1B); and although more expressive during the grain filling stage, the temperatures were mild, which is a condition that hindered the development of foliar diseases. Nitrogen was applied under adequate conditions of soil moisture due to rainfall in previous days. The overall mean yield was close to that expected (4000 kg ha^{-1}), making 2016 a favorable year (FY) for oat crops.

Medium to high temperatures were observed in 2015 (Table 1), with a greater stability than that in 2017. The rainfall depth was similar to the historical mean of the last 25 years, however, with a high rainfall volume during the crop cycle. Regarding the soil moisture when nitrogen was applied, a rainfall occurred soon before the application of the nutrient. Medium to high air temperatures and high rainfall volumes throughout the cycle are favorable environmental conditions for the development of foliar diseases. The yield obtained was lower than that expected, although the nitrogen application conditions were favorable (Fig 1C). Considering the obtained yield, 2015 was an intermediate year (IY) for oat crops.

Meteorological conditions directly affect oat grain yields (Marolli et al., 2017b; Rother et al., 2019). Considering winter crops, the conditions in the agricultural year are defined by the amplitude and stability of air temperature and intensity and distribution of rainfall throughout the crop cycle (Cordeiro et al., 2015; Arenhardt et al., 2015). Mild temperatures are desirable at the beginning of the oat cycle, with no occurrence of very low temperatures or frost formation at the crop flowering stage (Leonard and Martinelli, 2005). Moreover, high temperatures can accelerate the cycle, reducing the quality of production components, and can increase respiration rates, reducing the photosynthesis efficiency, negatively affecting grain yield (Rodrigues et al., 2011; Castro et al., 2012). Water stress is one of the main environmental factors that directly affect crop yield (Santos et al., 2016; Scremin et al., 2017). High rainfall depths can favor the occurrence of diseases and loss of grain quality (Klein et al., 2019). The lack of rains induces stomatal closure in plants, resulting in low transpiration and photosynthesis rates, compromising the crop production (Souza et al., 2019; De Mamann et al., 2019). Favorable conditions for oat crops are those with mild temperatures and radiation to favor tillering and grain filling, without occurrence of high rainfall volume and intensity, but with a sufficient rainfall quantity to favor an adequate water supply and soil moisture (Mantai et al., 2015; Marolli et al., 2018).

Descriptive statistics of real data obtained under experimental conditions

Table 2 shows the descriptive statistics of minimum, mean, and maximum necrotic leaf areas, meteorological indicators, and grain yield for all cultivars and crop conditions (unfavorable, favorable, and intermediate). The yield and necrotic leaf area were obtained considering different fungicide use conditions, but under similar meteorological conditions. The most significant evolution of necrotic leaf area at 90 and 105 DAE showed significant reductions along the fungicide applications. These results are consistent with the yield obtained, as a greater control of leaf necrosis is obtained when increasing the number of fungicide applications. The conditions with two and three applications tended to approximate yield values, denoting that the use of fungicide after 90 days can provide satisfactory control, maintaining a long interval between application and harvest for a greater food security.

Potential variables for composition and simulation via multiple linear regressions

Table 3 shows the mean squares for identifying potential variables by the partial regression model using the Stepwise technique, serving as a reference for the selection of variables for developing multiple linear regression models. All meteorological variables, days after emergence, and necrotic leaf areas were significant, regardless of the analyzed cultivar, denoting perennializations of simulation quality by the joint use of these variables.

According to Leal et al. (2015), identifying the main components is essential for an efficient estimate of grain yield. The stepwise method selects potential variables for

Table 1. Temperatures and rainfall depths during the oat crop cycle and oat grain yield in 2015, 2016, and 2017.

Month	Temperature °C			Rainfall (mm)		Fungicide / GY (kg ha^{-1})				$\bar{x}$	Class
	Min	Max	Mean	25years*	Occurred	WF	CF_1	CF_2	CF_3		
2017											
May	14.0	22.4	18.2	149.7	434.3						
June	10.7	21.8	16.2	162.5	146.3						
July	8.3	24.4	16.3	135.1	10.75	1149	1869	2116	2310	1861C	UY
August	11.4	23.7	17.5	138.2	117.8						
September	15.3	27.0	21.2	167.4	161.5						
October	13.7	26.8	20.2	156.5	304.0						
Total	-	-	-	909.4	1174.6						
2016											
May	11.0	20.7	15.9	149.7	55.8						
June	4.7	19.3	12.0	162.5	9.8						
July	8.5	21.5	15.0	135.1	80.5	3200	3814	4072	4331	3854A	FY
August	9.4	22.5	15.9	138.2	160.0						
September	8.4	22.8	15.6	167.4	56.3						
October	12.3	24.8	18.5	156.5	325.8						
Total	-	-	-	909.4	688.2						
2015											
May	13.1	22.7	17.9	149.7	181.3						
June	9.5	21.4	15.5	162.5	228.3						
July	10.5	20.5	15.5	135.1	211.5	1229	2086	3055	3406	2444B	IY
August	13.3	24.8	19.0	138.2	86.8						
September	12.7	20.9	16.8	167.4	127.3						
October	14.7	25.2	19.9	156.5	161.8						
Total	-	-	-	909.4	997.0						

GY: grain yield; FY: favorable year for cultivation; IY: intermediate year for cultivation; UY: unfavorable year for cultivation; WF: without fungicide; CF_1: one fungicide application at 60 days after emergence (DAE); CF_2: two fungicide applications, at 60 and 75 DAE; CF_3: three fungicide applications, at 60, 75, 90 DAE; Min: mean minimum temperature; Max: mean maximum temperature; *: historical rainfall depth from May to October of the last 25 years; means followed by the same letters in the columns are not statistically different from each other by the Skott-Knott model at 5% error probability.

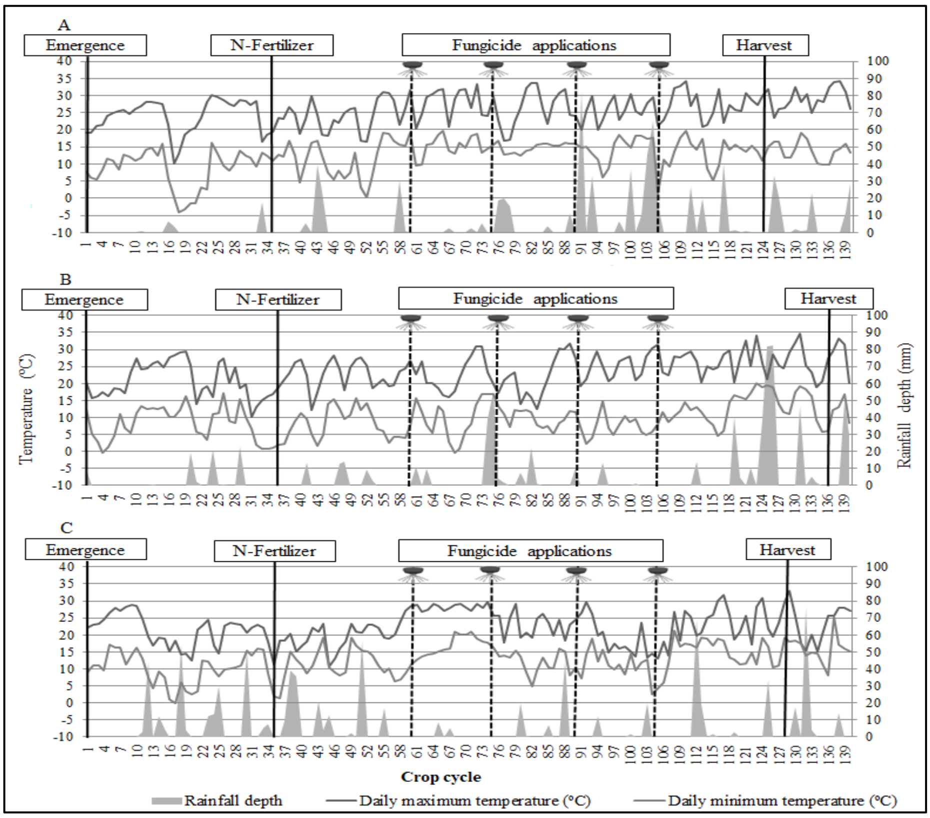

Fig 1. Rainfall and daily minimum and maximum temperatures in the experiment area during the oat crop cycle, in 2015, 2016, and 2017.

Table 3. Mean square values for identifying potential variables using the Stepwise technique for developing multiple regression models to estimate grain yield.

Cultivar	Mean Square / Stepwise Model						
	R (mm)	T_{min} (°C)	T_{mean} (°C)	T_{max} (°C)	TS (°C)	Cycle (DAE)	NLA (%)
Joint Analysis [2017(UY), 2016(FY), 2015(IY)]							
URS Altiva	615214*	10618239*	1212657*	21063160*	8022634*	62137929*	16255910*
URS Brava	518611*	5718415*	2879882*	5341338*	19830963*	16974347*	28078610*
URS Guará	170448*	3951223*	1894435*	3458150*	13587363*	10779019*	21365684*
URS Estampa	326142*	1468615*	11944502*	156548*	4121875*	2958305*	61199020*
URS Corona	4623011*	14160970*	1226841*	1817263*	21019788*	6018703*	21140882*
URS Torena	393321*	3228255*	1570927*	2980820*	12223989*	9975016*	18146267*
URS Charrua	194329*	4285030*	2298389*	4014042*	11577929*	9153214*	17380260*
URS Guria	1151625*	9224358*	534895*	21380706*	7858480*	1285491*	10759833*
URS Tarimba	267326*	4961290*	2322930*	4213891*	14823227*	11926447*	17741658*
URS Taura	278008*	46692217*	1832541*	3512581*	9354821*	16843291*	10399869*
URS 21	379356*	16520831*	431680*	14374486*	9254332*	7562819*	13708430*
FAEM 007	507495*	122152541*	264832*	5611354*	31187111*	3546891*	15926205*
FAEM 006	468412*	31885036*	1025504*	19046428*	16939321*	13113933*	35219709*
FAEM 5 Chiarasul	107114*	32313969*	223664*	2422963*	22374877*	18373660*	43633799*
FAEM 4 Carlasul	1588189*	33781370*	6248672*	1244131*	4081213*	14080120*	11406144*
Brisasul	989468*	10168594*	6059842*	9494986*	23097111*	20159263*	28482102*
Barbarasul	829222*	8827394*	2186611*	4408616*	22090905*	17240994*	41507214*
URS Fapa Slava	523531*	9772140*	17582816*	135462*	13311204*	10735993*	25837768*
IPR Afrodite	46845*	8211889*	4150134*	6335573*	22265600*	17162853*	37296506*
UPFPS Farroupilha	134907*	4718849*	2254348*	3968430*	17792499*	15138901*	25745628*
UPFA Ouro	545412*	9421208*	5717775*	9924173*	7364193*	6449470*	9617580*
UPFA Gaudéria	2540867*	2313156*	51297614*	795237*	7742123*	4821461*	1825859*
Geral	1774526*	75417408*	36197508*	60089140*	307038323*	261383674*	479545367*

R: accumulated rainfall; T_{min}: minimum temperature; T_{max}: maximum temperature; T_{mean}: mean temperature; TS: thermal sum; NLA: necrotic leaf area; DAE: days after emergence; UY: unfavorable year for cultivation; IY: intermediate year of cultivation; FY: favorable year for cultivation; *: significant by F-test at 5% probability of error.

Table 4. Multiple linear regression equations and estimation of oat grain yield.

Cultivars	$GY=b_0±b_{1NLA}±b_{2R}±b_{3Tmin}±b_{4Tmean}±b_{5Tmax}±b_{6TS}±b_{7DAE}$	GY_O (kg ha^{-1})	GY_E (kg ha^{-1})
Joint Analysis [2017(AD). 2016(AF). 2015(AI)]			
URS Altiva	$GY=34581-30_{NLA}+0.65_{R}-2699_{Tmin}+3618_{Tmean}-2908_{Tmax}+17.49_{TS}-187_{DAE}$	2909	2954
URS Brava	$GY=45134-46_{NLA}+1.62_{R}-4210_{Tmin}+5143_{Tmean}-3839_{Tmax}+29.23_{TS}-326_{DAE}$	2744	2876
URS Guará	$GY=40176-29_{NLA}-0.88_{R}-4312_{Tmin}+6140_{Tmean}-4275_{Tmax}+22.12_{TS}-234_{DAE}$	2813	2944
URS ETSampa	$GY=36453-26_{NLA}-0.76_{R}-4347_{Tmin}+6749_{Tmean}-4536_{Tmax}+18.33_{TS}-191_{DAE}$	2489	2652
URS Corona	$GY=49344-27_{NLA}-3.21_{R}-6074_{Tmin}+9274_{Tmean}-6182_{Tmax}+26.05_{TS}-264_{DAE}$	2975	3176
URS Torena	$GY=37112-30_{NLA}-0.42_{R}-3733_{Tmin}+5214_{Tmean}-3734_{Tmax}+21.63_{TS}-231_{DAE}$	2576	2712
URS Charrua	$GY=38495-31_{NLA}+0.1_{R}-4141_{Tmin}+5862_{Tmean}-4081_{Tmax}+20.65_{TS}-219_{DAE}$	2757	2868
URS Guria	$GY=30413-32_{NLA}+0.98_{R}-1987_{Tmin}+2224_{Tmean}-2025_{Tmax}+19.57_{TS}-219_{DAE}$	2660	2768
URS Tarimba	$GY=45804-33_{NLA}-1.57_{R}-5099_{Tmin}+7365_{Tmean}-5089_{Tmax}+25.89_{TS}-270_{DAE}$	2575	2774
URS Taura	$GY=35337-27_{NLA}-0.86_{R}-4907_{Tmin}+7416_{Tmean}-4725_{Tmax}+20.41_{TS}-215_{DAE}$	2447	2622
URS 21	$GY=35295-25_{NLA}-0.87_{R}-2743_{Tmin}+3403_{Tmean}-2776_{Tmax}+20.33_{TS}-217_{DAE}$	2606	2660
FAEM 007	$GY=51555-36_{NLA}-3.1_{R}-5391_{Tmin}+7263_{Tmean}-5149_{Tmax}+32.91_{TS}-345_{DAE}$	2839	2987
FAEM 006	$GY=40005-32_{NLA}-1.17_{R}-3826_{Tmin}+5075_{Tmean}-3728_{Tmax}+24.08_{TS}-252_{DAE}$	2847	2988
FAEM 5 Chiarasul	$GY=42028-37_{NLA}-0.83_{R}-2665_{Tmin}+2679_{Tmean}-2612_{Tmax}+27.76_{TS}-299_{DAE}$	2646	2734
FAEM 4 Carlasul	$GY=35821-33_{NLA}+0.29_{R}-4375_{Tmin}+6150_{Tmean}-4043_{Tmax}+22.39_{TS}-244_{DAE}$	3065	3251
Brisasul	$GY=53267-58_{NLA}+2.33_{R}-6092_{Tmin}+8173_{Tmean}-5569_{Tmax}+35.58_{TS}-400_{DAE}$	2811	2946
Barbarasul	$GY=50401-35_{NLA}-1.91_{R}-5201_{Tmin}+7589_{Tmean}-5411_{Tmax}+28.05_{TS}-293_{DAE}$	2780	2955
URS Fapa Slava	$GY=32891-44_{NLA}+1.51_{R}-2635_{Tmin}+2855_{Tmean}-2355_{Tmax}+23.66_{TS}-257_{DAE}$	2423	2505
IPR Afrodite	$GY=48081-31_{NLA}-1.89_{R}-6510_{Tmin}+9701_{Tmean}-6238_{Tmax}+26.68_{TS}-280_{DAE}$	2908	3019
UPFPS Farroupilha	$GY=39083-39_{NLA}+0.82_{R}-3981_{Tmin}+4999_{Tmean}-3548_{Tmax}+25.86_{TS}-286_{DAE}$	2916	3024
UPFA Ouro	$GY=30449-29_{NLA}+0.84_{R}-2381_{Tmin}+2449_{Tmean}-2020_{Tmax}+20.62_{TS}-232_{DAE}$	2531	2641
UPFA Gaudéria	$GY=37014-30_{NLA}-0.45_{R}-3313_{Tmin}+4100_{Tmean}-3099_{Tmax}+24.17_{TS}-268_{DAE}$	2521	2586
Geral	$GY=39499-31_{NLA}-0.61_{R}-4065_{Tmin}+5613_{Tmean}-3979_{Tmax}+23.22_{TS}-248_{DAE}$	2720	2879

GY: grain yield (kg ha-1); NLA: necrotic leaf area (%); R: accumulated rainfall; T_{min}: minimum temperature (ºC); T_{max}: maximum temperature (ºC); T_{mean}: mean temperature (°C); TS: thermal sum (ºC); DAE: days after emergence; GY_O: observed grain yield; GY_E: grain yield estimated by multiple regression equation; UY: unfavorable year for cultivation; IY: intermediate year of cultivation; FY: favorable year for cultivation; b1, b2, b3, b4, b5, b6 and b7: regression coefficients.

Table 5. Necrotic leaf area data of oat cultivars and meteorological variables.

Cultivars	Fungicide/NLA				Meteorological Data					DAE
	WF	CF_1	CF_2	CF_3	R	T_{min}	T_{mean}	T_{max}	TS	
URS Altiva	58	33	22	20	457	10.7	16.9	23.1	1355	105
URS Brava	53	30	24	21	457	10.7	16.9	23.1	1355	105
URS Guará	60	32	25	20	457	10.7	16.9	23.1	1355	105
URS Estampa	47	33	31	22	457	10.7	16.9	23.1	1355	105
URS Corona	69	51	23	27	457	10.7	16.9	23.1	1355	105
URS Torena	57	37	28	24	457	10.7	16.9	23.1	1355	105
URS Charrua	60	30	24	20	457	10.7	16.9	23.1	1355	105
URS Guria	56	31	27	22	457	10.7	16.9	23.1	1355	105
URS Tarimba	58	36	29	27	457	10.7	16.9	23.1	1355	105
URS Taura	67	32	24	22	457	10.7	16.9	23.1	1355	105
URS 21	60	38	28	24	457	10.7	16.9	23.1	1355	105
FAEM 007	66	49	27	30	457	10.7	16.9	23.1	1355	105
FAEM 006	72	47	26	21	457	10.7	16.9	23.1	1355	105
FAEM 5 Chiarasul	66	44	26	27	457	10.7	16.9	23.1	1355	105
FAEM 4 Carlasul	59	33	21	20	457	10.7	16.9	23.1	1355	105
Brisasul	47	34	24	22	457	10.7	16.9	23.1	1355	105
Barbarasul	63	51	25	20	457	10.7	16.9	23.1	1355	105
URS Fapa Slava	60	42	32	26	457	10.7	16.9	23.1	1355	105
IPR Afrodite	66	33	21	16	457	10.7	16.9	23.1	1355	105
UPFPS Farroupilha	56	34	24	20	457	10.7	16.9	23.1	1355	105
UPFA Ouro	46	30	27	22	457	10.7	16.9	23.1	1355	105
UPFA Gaudéria	44	31	29	26	457	10.7	16.9	23.1	1355	105

NLA: necrotic leaf area (%); WF: without fungicide; CF_1: one fungicide application at 60 days after emergence (DAE); CF_2: two fungicide applications, at 60 and 75 DAE; CF_3: three fungicide applications, at 60, 75, and 90 DAE; R: accumulated rainfall (mm); T_{min}: minimum temperature (°C); T_{max}: maximum temperature (°C); T_{mean}: mean temperature (°C); TS: thermal sum (°C).

Table 6. Simulation of oat yield by the general multiple linear regression model.

Cultivares	$GY=39499-31_{NLA}-0.61_{R}-4065_{Tmin}+5613_{Tmean}-3979_{Tmax}+23.22_{TS}-248_{DAE}$							
	WF_S	WF_O	CF_{1S}	CF_{1O}	CF_{2S}	CF_{2O}	CF_{3S}	CF_{3O}
URS Altiva	2295	2105	3070	2655	3411	3273	3473	3604
URS Brava	2450	1850	3163	2643	3349	3084	3442	3399
URS Guará	2233	2059	3101	2629	3318	3135	3473	3430
URS Estampa	2636	1870	3070	2477	3132	2684	3411	2924
URS Corona	1954	1888	2512	2978	3380	3410	3256	3622
URS Torena	2326	1689	2946	2483	3225	2962	3349	3172
URS Charrua	2233	2061	3163	2770	3349	3097	3473	3102
URS Guria	2357	1803	3132	2464	3256	2991	3411	3282
URS Tarimba	2295	1871	2977	2295	3194	2821	3256	3313
URS Taura	2016	1387	3101	2347	3349	2757	3411	3296
URS 21	2233	1963	2915	2561	3225	2894	3349	3005
FAEM 007	2047	1889	2574	2609	3256	3410	3163	3449
FAEM 006	1861	1850	2636	2696	3287	3248	3442	3595
FAEM 5 Chiarasul	2047	1714	2729	2332	3287	3103	3256	3433
FAEM 4 Carlasul	2264	2258	3070	2920	3442	3467	3473	3617
Brisasul	2636	1819	3039	2583	3349	3248	3411	3593
Barbarasul	2140	1753	2512	2586	3318	3278	3473	3504
URS Fapa Slava	2233	1408	2791	2328	3101	2891	3287	3065
IPR Afrodite	2047	1954	3070	2671	3442	3298	3597	3710
UPFPS Farroupilha	2357	2045	3039	2892	3349	3254	3473	3474
UPFA Ouro	2667	1786	3163	2440	3256	2772	3411	3127
UPFA Gaudéria	2729	1887	3132	2522	3194	2707	3287	2970

GY: grain yield (kg ha^{-1}); NLA: necrotic leaf area (%); R: accumulated rainfall (mm); T_{min}: minimum temperature (ºC); T_{max}: maximum temperature (ºC); T_{mean}: mean temperature (°C); TS: thermal sum (ºC); DAE: days after emergence; WF_S: without simulated fungicide application (kg ha^{-1}); WF_O: no observed fungicide application (kg ha^{-1}); $CF1_S$: one simulated fungicide application (kg ha^{-1}); $CF1_O$: with one observed fungicide application (kg ha^{-1}); CF_{2S}: two simulated fungicide applications (kg ha^{-1}); CF_{2O}: two observed fungicide applications (kg ha^{-1}); CF_{3S}: with three simulated fungicide applications (kg ha^{-1}); CF_{3O}: with three observed fungicide applications (kg ha^{-1}).

simulation models. In this method, a variable is considered explanatory due to the increase in the coefficient of determination resulting from its inclusion in the multiple linear regression model (Mantai et al., 2016). The Stepwise technique was used by Trautmann et al. (2017) to define variables for a multiple regression model for simulating wheat biomass. Mantai et al. (2016) used the model to define variables for developing a simulation model for estimating oat grain yield by multiple linear regression; by Marolli et al. (2017a) to select panicle variables to compose a multiple linear regression model for simulating grain yield of oat crops grown under different conditions of use of growth regulator and nitrogen fertilization; and by Alessi et al. (2021a) to define potential variables for developing a simulation model for estimating wheat grain yield.

Table 4 shows the multiple linear regression models developed for each oat cultivar tested, considering the joint analysis of unfavorable (UY), favorable (FY), and intermediate (IY) years, to ensure efficient simulation processes, regardless of the agricultural year conditions. In this perspective, the obtained and simulated data found for this cultivar, as well as for the other cultivars, presented great similarity. The general model obtained denoted the possibility of simulating grain yield, regardless of information on the cultivar. Table 5 presents the meteorological data and the necrotic leaf area of each oat cultivar, under the fungicide use conditions, in the evaluation at 105 DAE. These values were used to simulate the oat grain yield using the general model of multiple linear regression (Table 4).

The simulation by the general grain yield model showed similarity between simulated and observed values for all cultivars (Table 6). Therefore, proper identification of variables and use of multiple regression model, considering meteorological components, necrotic leaf area, and development cycle (DAE), result in satisfactory information for estimating grain yield and predict scenarios, with high similarity between simulated and observed values. Conditions that enable the generation of elements for formulation of a more qualified management of fungicides can be based on this database structure. Thus, increasing the number of years of study can generate elements to qualify the parameters of the model, expanding its range of action to a greater number of scenarios for simulation.

The observed and simulated values for the condition with three fungicide applications were higher than those in the other conditions, denoting that this fungicide management results in great productive potential than the other conditions, in addition to have a long interval before harvest. In this way, the management with three fungicide application, at 60, 75, and 90 DAE, provides disease control and a satisfactory yield, with a lower risk of pesticide residues in the oat grains, due to the long interval between the last application and the grain harvest, or even before the grain filling stage; this condition does not allow for mobilization of agrochemical residues to oat grains.

The use of multiple linear regression models to estimate yield of agricultural crops provides important information about factors that act throughout the crop cycle (Silva et al., 2016). In this context, the use of models developed by multiple linear regression enables the optimization of agricultural managements, making systems more productive, with predictable results according to the conditions presented (Pereira et al., 2013). The multiple linear regression method was also used by Prabhu et al. (2003) to develop simulation models for predicting rice yield, considering the severity of rice blast (brusone) in leaves and panicles; and by Steinmetz et al., (2013) to develop a simulation and prediction model for rice grain production, considering global solar radiation and minimum air temperature. According to Marolli et al. (2017a), multiple linear regression equations are efficient for simulating oat grain yield under the conditions of use of growth regulators, regardless of the N fertilizer rate used. In addition, (Trautmann et al., 2017) reported that multiple linear regression models are efficient for simulating wheat biomass yield for silage during the crop cycle in rotation systems; and Alessi et al. (2021a) used multiple linear regression to develop a wheat yield simulation model involving nitrogen management and ear components.

Materials and methods

Study area and experimental design

The work was carried out in 2015, 2016, and 2017, in Augusto Pestana, RS, Brazil (28°26'30''S and 54°00'58''W). The soil of the experimental area was classified as a Typic Hapludox (Latossolo Vermelho distroferrico tipico; Santos et al., 2018). The climate of the region is humid subtropical, according to the Köppen classification. The soil was analyzed before sowing and presented the following chemical characteristics: pH = 6.3; P = 34.1 mg dm^{-3}; K = 198 mg dm^{-3}; organic matter = 3.2%; Al= 0 cmolc dm^{-3}; Ca = 6.5 cmolc dm^{-3}; and Mg = 2.5 cmolc dm^{-3}.

The experimental plot consisted of five 5-meter rows spaced 0.2 m apart, resulting in an experimental unit of 5 m^2. The population density used was 400 viable seeds m^{-2}, according to the technical recommendation. Nitrogen was applied at sowing, using 10 kg ha^{-1}, and as topdressing at the fourth expanded leaf stage, considering an expected grain yield of 4 Mg ha^{-1}. Based on the soil P and K contents, 45 kg ha^{-1} of P_2O_5 and 30 kg ha^{-1} of K_2O were applied at sowing.

A randomized block experimental design with three replications was used, in a 22×4 factorial arrangement consisted of 22 oat cultivars and 4 fungicide use conditions. The analyzed oat cultivars included those currently recommended and those no longer recommended for crops in Brazil, namely: URS Altiva, URS Brava, URS Guará, URS Estampa, URS Corona, URS Torena, URS Charrua, URS Guria, URS Tarimba, URS Taura, URS 21, URS Fapa Slava, FAEM 007, FAEM 006, FAEM 5 Chiarasul, FAEM 4 Carlasul, Brisasul, Barbarasul, IPR Aphrodite, UPFPS Farroupilha, UPFA Ouro, and UPFA Gaudéria. The fungicide use conditions were: control (without application); one application at 60 days after emergence (DAE); two applications, at 60 and 75 DAE; and three applications, at 60, 75, and 90 DAE. The fungicide use conditions were proposed for analyzing the intervals between the last fungicide application and the harvest, considering protection periods of 15 to 20 days after application, as indicated in the product label. The last application (90 DAE) was chosen to ensure a considerable interval between the fungicide application and the grain maturity (around 30 days), and the absence of application in the grain filling stage. The fungicides used to control foliar diseases were Folicur® CE in 2015 and 2016 and PRIMO® in 2017 at the rate of 0.75 and 0.3 L ha^{-1}, respectively. The 3 central rows of each plot were considered for estimating grain yield; they were manually harvested when the grain moisture was approximately 15%. The plants were threshed using a stationary harvester and taken to the laboratory for correcting grain moisture to 13% and determining grain yield, which was converted to kg ha^{-1}.

Variables analyzed

The development of the grain yield simulation model for the oat cultivars was carried out considering the following variables: necrotic leaf area, rainfall depth (R), minimum temperature (T_{min}), mean temperature (T_{mean}), maximum temperature (T_{max}), thermal sum (TS), and days after emergence (DAE). Three plants were randomly collected from each plot for determining necrotic leaf area. Plants were collected from all plots at 60, 75, 90, and 105 DAE. The three upper leaves of each plant were removed to evaluate leaf area; the leaves were scanned using a leaf area reader and the WinDIAS software (Copyright 2012, Delta-T Devices Limited), and the necrotic area over the total leaf area was determined. The variables R, T_{min}, T_{mean}, and T_{max} during the cycle were obtained from a total automatic station installed at 500 meters from the experiment area.
The thermal sum was obtained by the equation:

$$TS = \sum_{i=1}^{n} \left(\frac{T_{max} + T_{min}}{2}\right) - TB$$

where:
n = number of days from emergence to harvest;
TB = basal temperature; the base temperature of oats used in the study was 4 °C (Pedro Júnior et al., 2004).

Statistical analysis and multiple linear regression

The Stepwise technique was used for defining potential variables to compose the multiple linear regression models. This technique enables to select variables with greater explanatory capacity, resulting in a simpler model with an efficient simulation (Marolli et al., 2017a; Alessi et al., 2021a). The addition and removal of variables were carried out using partial F statistics, according to the model:

$$F_j = \frac{QS_R(\beta_j \mid \beta}{QM_E\left(X_j,\right.}$$

where:
QS_R = sum of squares of the regression;
$QM_E(X_j, X_1)$ = mean square of the error that contains the variables X_j and X_1.

The variables selected by the Stepwise technique were used to compose the multiple linear regression models for the simulation of oat grain yield. This equation is composed of two or more variables for generating an equation, as follows (Cruz, 2006):

$$Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_p X_{pi} + \varepsilon_i$$

where:
X_p = the p-th observed variable;
b_p = the coefficient associated with the p-th variable;
$\varepsilon = Y - \hat{Y} = Y - b_0 - b_1 X_1 - \cdots - b_p X_p$ is the error.
This equation can be described as matrix:

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_n \end{bmatrix}; X = \begin{bmatrix} 1 & X_{11} & X_{21} & \ldots & X_{p1} \\ 1 & X_{12} & X_{22} & \ldots & X_{p2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & X_{1n} & X_{2n} & \ldots & X_{pn} \end{bmatrix}; \ b = \begin{bmatrix} b_0 \\ b_1 \\ \cdots \\ b_p \end{bmatrix} \ e \ \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdots \\ \varepsilon_n \end{bmatrix}$$

These matrices were used to obtain the regression coefficients:

$$\hat{b} = (X'X)^1 X'Y$$

and the variance of the coefficients was obtained by the covariance matrix of the vector of the regression coefficients:

$$C\hat{o}v(\hat{b}) = (X'X)^{-1}\hat{\sigma}^2$$

$$\hat{\sigma}^2 = \frac{(Y - X\hat{b})'(Y - X\hat{b})}{n - p - 1}$$

where:
n = number of equations;
p = number of parameters.
The hypothesis test was checked, $H_0: \beta_i = 0; vs\ H_a: \beta_i \neq 0$, and expressed by:

$$t = \frac{\hat{\beta}_i - \beta_i}{\sqrt{\hat{V}(\hat{\beta}_i)}}$$

The analyses were carried out using the GENES computer program (Cruz, 2013).

Conclusion

Necrotic leaf area, rainfall depth, minimum, mean, and maximum temperatures, thermal sum, and days of crop cycle are potential variables to be included in oat yield simulation models. The use of the multiple linear regression technique with these variables allows to obtain efficient models for grain yield simulations.
The condition with three fungicide applications, at 60, 75, and 90 days after emergence, results in satisfactory foliar disease control and grain yield, maintaining a long interval between the last fungicide application and the grain harvest, thus improving the safety of the product obtained.

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