PAB
Pesquisa Agropecuária Brasileira

Agrometeorology/ Original Article

ISSN 1678-3921

Journal homepage: www.embrapa.br/pab

For manuscript submission and journal contents, access: www.scielo.br/pab

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Received
June 08, 2020

Accepted
January 17, 2022

How to cite
SILVA, M.R. da; STREK, N.A.; CERA, J.C.; DUARTE JUNIOR, A.J.; RIBAS, G.G.; ROSSATO, I.G.; MEUS, L.D.; PEREIRA, V.F.; PILECCO, I.B.; BENEDETTI, R.P.; TONETTO, F.; ZANON, A.J. Forecasting rice yield in Rio Grande do Sul using the SimulArroz model. **Pesquisa Agropecuária Brasileira**, v.57, e02069, 2022. DOI: https://doi.org/10.1590/S1678-3921.pab2022.v57.02069.

Forecasting the rice yield in Rio Grande do Sul using the SimulArroz model

Abstract – The objective of this work was to evaluate a flooded-rice yield forecasting method for the state of Rio Grande do Sul, Brazil, using the SimulArroz model. Version 1.1 of this model and historical meteorological data were used, with six different scenarios composed of the following levels of field information: number of sowing dates (1 to 4) and number of cultivars and/or development cycles (1 to 3) during four growing seasons (2014/2015 to 2017/2018). The root mean square error (RMSE) for comparing the actual yield with the simulated yield for Rio Grande do Sul was of 618.3 and 1,024.8 kg ha^{-1}, i.e., of 8 and 13%, respectively. The forecast of rice yield by applying the SimulArroz model and historic meteorological data for Rio Grande do Sul shows a good predictability, and the recommended scenario is complex 1, using three sowing dates per site and the three most representative rice cultivars per region.

Index terms: *Oryza sativa*, crop modeling, decision-support systems, supply balance.

Previsão de safra de arroz irrigado para o Rio Grande do Sul pelo modelo SimulArroz

Resumo – O objetivo deste trabalho foi avaliar um método de previsão de safra para arroz irrigado por inundação no estado do Rio Grande do Sul, Brasil, por meio do modelo SimulArroz. Utilizou-se a versão 1.1 desse modelo e dados meteorológicos históricos, com seis cenários compostos pelos seguintes níveis de informação em campo: datas de semeadura (1 a 4) e número de cultivares e/ou ciclos de desenvolvimento (1 a 3) durante quatro safras (2014/2015 a 2017/2018). A raiz quadrada média do erro (RQME), para comparação da produtividade real com a produtividade simulada para o Rio Grande do Sul, foi de 618,3 e 1.024,8 kg ha^{-1}, isto é, de 8 e 13%, respectivamente. A previsão de safra de arroz com aplicação do modelo SimulArroz e dados meteorológicos históricos para o Rio Grande do Sul apresenta boa capacidade preditiva quanto à produtividade, e o cenário recomendado para a previsão é o complex 1, com uso de três épocas de semeadura por local e das três cultivares mais representativas por região.

Termos para indexação: *Oryza sativa*, modelagem de culturas, sistemas de apoio à decisão, saldo de fornecimento.

Introduction

The largest rice producer outside Asia is Brazil, where the state of Rio Grande do Sul stands out producing 70% of Brazilian rice in 1 million ha (FAO, 2018; Acompanhamento…, 2019). The Brazilian rice

market is very sensible about the rice yield forecast for this state as it impacts over Brazil and South America rice prices. An actual method for rice forecast relies on interviewing agronomists and extensionists about area and yield (Silva et al., 2016). This method is widely used, but it also presents weaknesses, as it depends on the extensionists' knowledge and experience; it shows also a high demand on time and maintenance costs, besides showing difficulty for defining a pattern among institutions (Monteiro et al., 2013; Morell et al., 2016). Yield forecasts based on crop models are a possible way to mitigate these weaknesses.

There are models developed for many crops such as Canegro for sugarcane growth (Inman-Bamber & Thompson, 1989), Hybrid-maize for maize (Yang et al., 2004), SoySim for soybean (Setiyono et al., 2010), and SimulArroz for rice (Duarte Junior et al., 2021). Once crop model parameters are calibrated, the model is able to capture the G×E×M interactions, and to predict yield across a wide range of weather and management conditions (Van Ittersum et al., 2013). During the last two decades, the use of crop models for yield forecast have been increasing. In Europe, the complex MARS-Crop Yield Forecasting System (M-CYFS) uses crop models, statistic-based models, remote sensing, and soil maps, for the yield forecast of wheat, barley, maize, rye, triticale, sugar-beet, potato, and sunflower, at very high spatial resolution (Baruth et al., 2017). M-CYFS is the most complex yield forecast in operation nowadays (Bussay et al., 2015). In the United States, peanut and maize forecasts rely on crop models for yield estimation (Shin et al., 2006, 2010). More specifically, in the US Corn Belt, a crop model-based yield forecast was developed for maize, using the Hybrid-maize model (Yang et al., 2004), in-season and historic weather data. This approach was capable to catch yield anomalies at different spatial scales, in years with highly favorable weather, or severe drought (Morell et al., 2016).

The Brazilian yield forecasting system is based on simple yet robust five steps approach, as follows: yield estimation based on a statistical model and historical yield data; technological level and production costs are determined for actual growing season; production area is based on remote sensing and on monitoring vegetation index anomalies along the season; monitoring is carried out for in season precipitation, temperature anomalies, and extreme climatic events; and validation is performed through interviewing agronomists and extensionists about area and yield (Acompanhamento…, 2019). Although robust, the Brazilian method could be improved by adding mechanistic crop-model to capture G×E× M interactions that drive the crop growth, development and yield (Van Ittersum et al., 2013). The required conditions to evaluate a crop model-based yield forecast were available for rice in Rio Grande do Sul, since the national institute of meteorology (Instituto Nacional de Meteorologia, INMET) provided daily weather data in high gridded resolution, and the SimulArroz model has been calibrated and validated since 2013 for rice in Rio Grande do Sul (Rosa et al., 2015; Ribas et al., 2017; Duarte Junior et al., 2021).

The objective of this work was to evaluate a flooded-rice yield forecasting method for the state of Rio Grande do Sul, Brazil, using the SimulArroz model.

Materials and Methods

The study comprised the state of Rio Grande do Sul rice area (Figure 1) that is classified in six regions bases for soil and climate characteristics: Fronteira Oeste (WB), Campanha (CA), Zona Sul (SO), Planície Costeira Interna (ICP), Planície Costeira Externa (ECP), and Central (CE), which represents 23, 11, 12, 9, 7, and 9% of the Brazilian rice production, respectively (Acompanhamento…, 2019). The climate is Cfa, subtropical humid, according to the Köppen-Geiger's classification, with some variability across regions that directly influence rice growth and development. Temperature increases from South to North, solar radiation increases from East to West, and relative humidity increases from West to East. During the winter (June to August), there is no rice growing in the paddy fields. The rice sowing period spans from September to December. Usually, cultivars are sown as follows: late ones (136 to 150 days), in September/October; medium cultivars (121 to 135 days), from September to December; and early cultivars (106 to 120 days), from October to December (Steinmetz et al., 2019). Rice harvest occurs from February to early May.

Long-term (1980-2019) and actual daily minimum (Tmin) and maximum (Tmax) air temperature and solar radiation (SRad) were used, which comprehends the interannual weather variability for Rio Grande do

Sul. Data were obtained from the INMET and from the weather database estimated by Xavier et al. (2016), which are both free and available on internet. Xavier et al. (2016) developed high-resolution grids (0.25° x 0.25°) of daily weather composed by Tmin, Tmax and SRad, using a cross-validation approach that compared an observed data point to an interpolated estimate point, to select the best interpolation scheme for each climate variable. The database by Xavier et al. (2016) was used to fill missing data of INMET database and of locations where long-term INMET database was not available. Twenty weather stations spread across

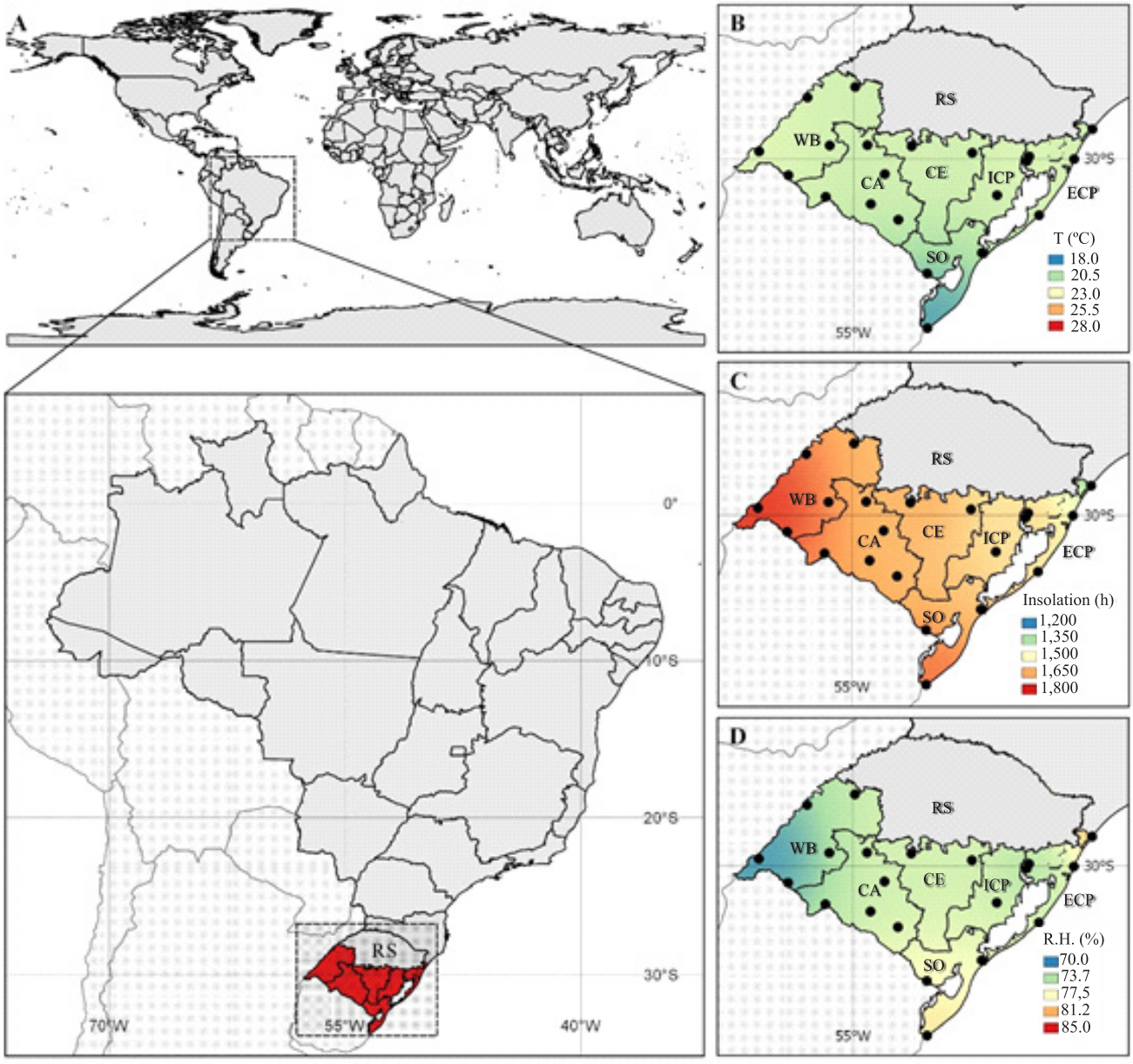

Figure 1. (A) Geographical location of the study area; (B) climatology of air temperature (°C); (C) accumulated sunshine duration (hours per season); and (D) relative humidity (%) during the rice growing season (from September to April) in the state of Rio Grande do Sul, Brazil. This state is divided into six regions of flooded-rice cultivation: Fronteira Oeste (WB), Campanha (CA), Zona Sul (SO), Planície Costeira Interna (ICP), Planície Costeira Externa (ECP) and Central (CE). Black dots (B, C and D) refer to weather stations.

the Rio Grande do Sul (Figure 1, Table 1) were used for rice yield forecast.

The crop model used for rice yield forecast was the SimulArroz, version 1.1, a process-based model developed to simulate rice growth, development, and yield in South Brazil (Duarte Junior et al., 2021). SimulArroz calculates phenology, dry matter production, and yield for flooded-rice on a daily time step. Phenology is calculated with the thermal time approach (°C per day), with the emergence, vegetative, reproductive, and development stages, and grain filling. The dry matter production is calculated through the radiation use efficiency and the leaf area index, that is a classic and robust approach in ecophysiology. Grain yield and yield components are calculated by equations described in the InfoCrop and ORYZA2000 models, with specific calibrations for cultivars in Southern Brazil (Rosa et al., 2015; Ribas et al., 2017; Duarte Junior et al., 2021). Four rice growing seasons were used for the rice forecast evaluation (2014/2015, 2015/2016, 2016/22017, and 2017/2018). Field information as rice area, percentage of sown area per week, and most important cultivars per growing season were obtained from the Instituto Rio Grandense do Arroz (IRGA) website. Alegrete (2014/2015 and 2016/2017), Santana do Livramento (2014/2015, 2015/2016, and 2016/2017), São Vicente do Sul (2014/2015 and 2016/2017), Rio Pardo (2016/2017), Jaguarão (2016/2017), Tramandaí (2017/2018), and Torres (2016/2017 and 2017/2018) were excluded from rice yield forecast, due to a large amount of missing weather data at these year/site combinations (Table 1).

Different scenarios considering different levels of field information were used for rice yield forecast. Simple 1 scenario (S1) was based on one sowing date per region (defined when 50% of rice area were sown) and on the most representative rice cycle per region. Simple 2 scenario (S2) was based on one sowing date per site (defined when 50% of rice area were sown) and on the most representative rice cycle per region. S2 is the equivalent scenario to that used in the US Corn Belt for maize forecast (Morell et al., 2016). Intermediate 1 scenario (I1) was based on three sowing dates per site (the most representative ones for percentage of sown area evolution, during the growing season) and on the three most representative rice cycles per region.

Table 1. Sites (weather stations) used for the flooded-rice yield forecast for each growing season and rice region in the state of Rio Grande do Sul, Brazil.

Rice region	Rice growing season			
	2014/2015	2015/2016	2016/2017	2017/2018
Fronteira Oeste (WB)	-[(1)]	Alegrete	-	Alegrete
	Quaraí	Quaraí	Quaraí	Quaraí
	São Borja	São Borja	São Borja	São Borja
	São Luiz Gonzaga	São Luiz Gonzaga	São Luiz Gonzaga	São Luiz Gonzaga
	Uruguaiana	Uruguaiana	Uruguaiana	Uruguaiana
Campanha (CA)	Bagé	Bagé	Bagé	Bagé
	Dom Pedrito	Dom Pedrito	Dom Pedrito	Dom Pedrito
	-	-	-	Santana do Livramento
	São Gabriel	São Gabriel	São Gabriel	São Gabriel
	-	-	São Vicente do Sul	São Vicente do Sul
Central (CE)	Rio Pardo	Rio Pardo	-	Rio Pardo
	Santa Maria	Santa Maria	Santa Maria	Santa Maria
Zona Sul (SO)	Jaguarão	Jaguarão	-	Jaguarão
	Rio Grande	Rio Grande	Rio Grande	Rio Grande
Planície Costeira Interna (ICP)	Camaquã	Camaquã	Camaquã	Camaquã
	Porto Alegre	Porto Alegre	Porto Alegre	Porto Alegre
Planície Costeira Externa (ECP)	Mostardas	Mostardas	Mostardas	Mostardas
	Tramandaí	Tramandaí	Tramandaí	-
	Torres	Torres	-	-

[(1)]Did not use.

Intermediate 2 scenario (I2) was based on four sowing dates per site (the most representative ones for the percentage of sown area evolution, during the growing season) and on the three most representative rice cycles per region. Complex 1 scenario (C1) was based on three sowing dates per site (the most representative ones for percentage of sown area evolution, during the growing season) and on the three most representative rice cultivars per region. Complex 2 scenario (C2) was based on four sowing dates per site (the most representative ones for percentage of sown area evolution, during the growing season) and on the three most representative rice cultivars per region.

For each site/scenario/growing season, the SimulArroz was ran at medium technologic level, and the simulated rice yields were compared against actual yields as reported by IRGA (2022). Seed density and atmospheric CO_2 concentration were settled as 200 plants ha^{-1} and 400 ppm, respectively. Comparisons were performed for each site, and weighted average was applied for upscale yield from site to rice region, and from rice region to Rio Grande do Sul state, using the relative contribution of harvested rice area (equation 1) as parameter. Both simulated and actual yield were reported at the standard 130 g kg^{-1} grain moisture content. Absolute (equation 2) and relative root mean square error (RMSE) (equation 3), BIAS index (equation 4), agreement index (dw) (equation 5), and Pearson correlation coefficient (r) (equation 6) were calculated to analyze the agreement between simulated and actual rice yields, as follows:

$$Yield = \sum_{i=1,...n} (Yield_{site\ i} x\ Area_{site\ i}) / \sum_{i=1,...n} (Area_{site\ i}) \quad (1)$$

$$RMSE = (\sum_{i=1,...n} (Y_i - O_i)^2)^{0.5} / n \quad (2)$$

$$RMSE(\%) = 100\ ((\sum_{i=1,...n} (Y_i - O_i)^2 / n)^{0.5} / \bar{O} \quad (3)$$

$$BIAS = (\sum Y_i - \sum O_i) / \sum O_i \quad (4)$$

$$dw = 1 - \sum (Y_i - O_i)^2 / [\sum (|Y_i - \bar{O}| + |O_i - \bar{O}|)]^2 \quad (5)$$

$$r = \sum (O_i - Om_i)\ x\ (Y_i - Ym_i) / \{[\sum (O_i - Om_i)^2]\ x\ [\sum (Y_i - Ym_i)2]\}^{0.5} \quad (6)$$

in which: Yield is the simulated rice yield for a rice region; $Yield_{site\ i}$ is the simulated rice yield for site i; $Area_{site\ i}$ is the actual rice area for site i; Y_i is the simulated yield; Ym_i is the average simulated yield; O_i is the observed yield; Om_i is the average observed yield; $\bar{O}$ is the average of all data; and n is the number of combinations (complex level-site-year).

Results e Discussion

Site-to-site simulated yield showed a greater yield variation than the site-to-site actual yield (Figure 2). Actual yield variation ranged from 5,766 kg ha^{-1} in Rio Pardo (2015/2016) to 9,634 kg ha^{-1} in Uruguaiana (2017/2018). S1 ranged from 2,189 kg ha^{-1} in Tramandaí (2015/2016) to 11,360 kg ha^{-1} in Santana do Livramento (2017/2018). S2 ranged from 1,859 kg ha^{-1} in Torres (2015/2016) to 11,473 kg ha^{-1} in Uruguaiana (2017/2018). I1 ranged from 3,507 kg ha^{-1} in Tramandaí (2015/2016) to 11,331 kg ha^{-1} in Uruguaiana (2017/2018). I2 ranged from 3,403 kg ha^{-1} in Tramandaí (2015/2016) to 10,982 kg ha^{-1} in Uruguaiana (2017/2018). C1 ranged from 3,896 kg ha^{-1} in Tramandaí (2015/2016) to 11,858 kg ha^{-1} in Bagé (2017/2018). C2 ranged from 4,052 kg ha^{-1} in Tramandaí (2015/2016) to 12,547 kg ha^{-1} in Uruguaiana (2017/2018). The rice growing seasons 2015/2016 and 2017/2018 showed the lower and higher yields, respectively, for both actual and simulated scenarios. Simulated site-to-site scenarios S1, S2, I1, and I2 underestimated the actual yields of -0.07 (S1, S2, I1) and -0.08 (I2); and scenarios C1 and C2 overestimated the actual yields of 0.03 and 0.06, respectively. RMSE (% mean) ranged from 21% (I1 and I2), 22% (C1), 24% (S2 and C2) to 25% (S1) (Figure 2). Studies comparing simulated and actual yields found RMSE (% mean) from about 14% to 79% for rice at field scale, in South Brazil, and 34% for maize, at county scale, in the US Corn Belt (Morell et al., 2016; Silva et al., 2016).

The best performance on simulated Rio Grande do Sul rice yield was attained in the C2 for 2014/2015 and 2015/2016, C1 for 2016/2017, and S1 for 2017/2018. In 2014/2015, the actual yield was 7,780 kg ha^{-1}, and C2 simulated yield was 6,746 kg ha^{-1}. In 2015/2016, actual yield was 6,928 kg ha^{-1}, and C2 simulated yield was 6,992 kg ha^{-1}. In 2016/2017, actual yield was 7,908 kg ha^{-1}, and C1 simulated yield was 7,961 kg ha^{-1}. In 2017/2018, actual yield was 7,936 kg ha^{-1}, and S1 simulated yield was 7,901 kg ha^{-1}. Considering the four yield simulation years from lower to higher RMSE, C1 showed 618.3 kg ha^{-1} (8%), C2 (RMSE = 10%), and S2, I1, S1, and I2 (RMSE = 13%) (Figure 3). Differences among S2, I1, S1, and I2 were about 50 kg ha^{-1} for absolute RMSE. For maize forecast in the

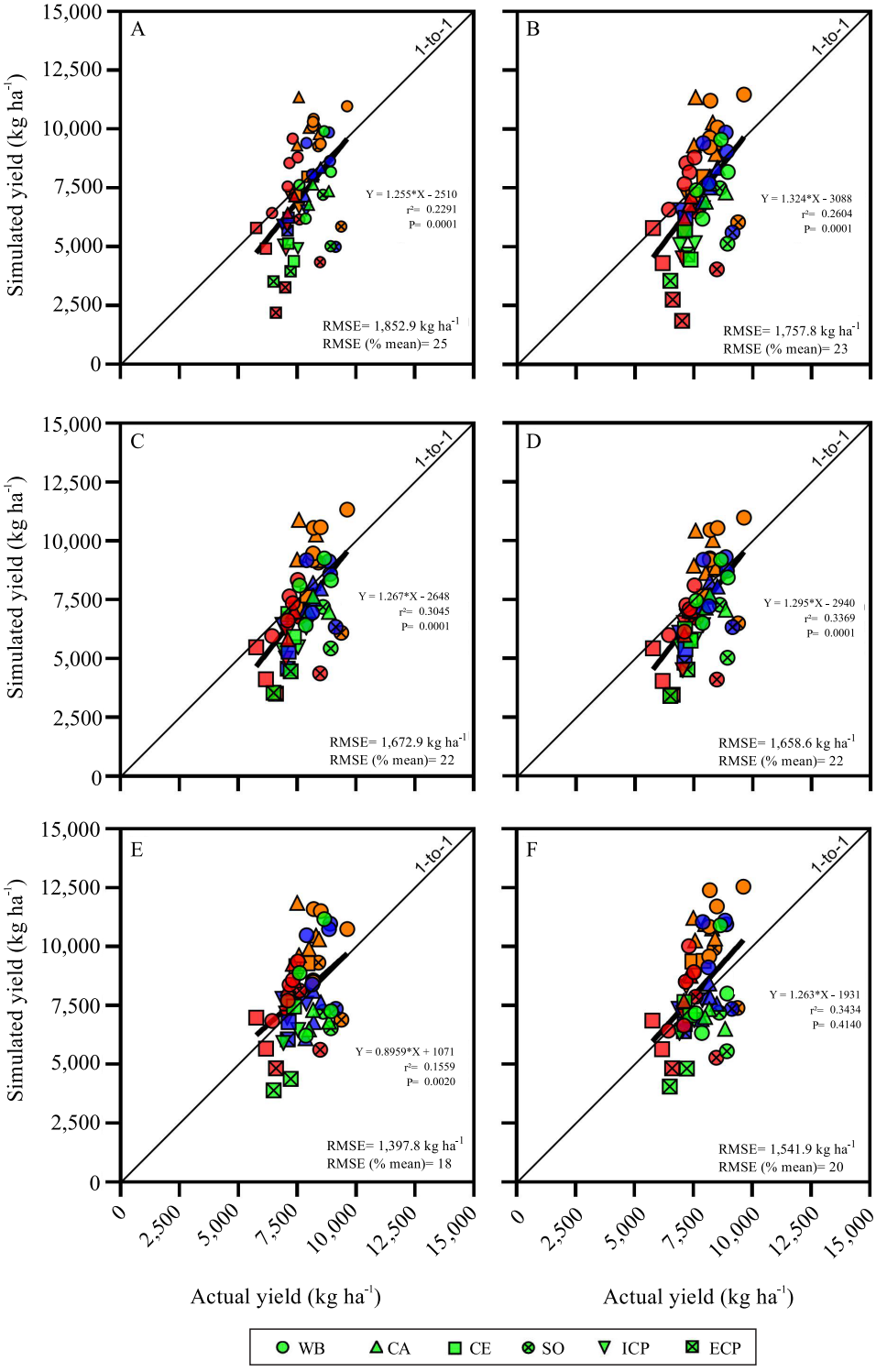

Figure 2. Comparison of simulated and actual flooded-rice yields, using six field information levels: A, simple 1; B, simple 2; C, intermediate 1; D, intermediate 2; E, complex 1; and F, complex 2. Each symbol represents a rice region in the state of Rio Grande do Sul, Brazil, for each growing season 2014/2015 (green), 2015/2016 (red), 2016/2017 (blue) and 2017/2018 (orange). The black line represents the 1:1 line; and the solid black line represents the fitted regression models. Root mean square error (RMSE) is expressed in both absolute and relative (% of actual mean yield) terms. WB, CA, CE, SO, ICP, and ECP, see Table 1.

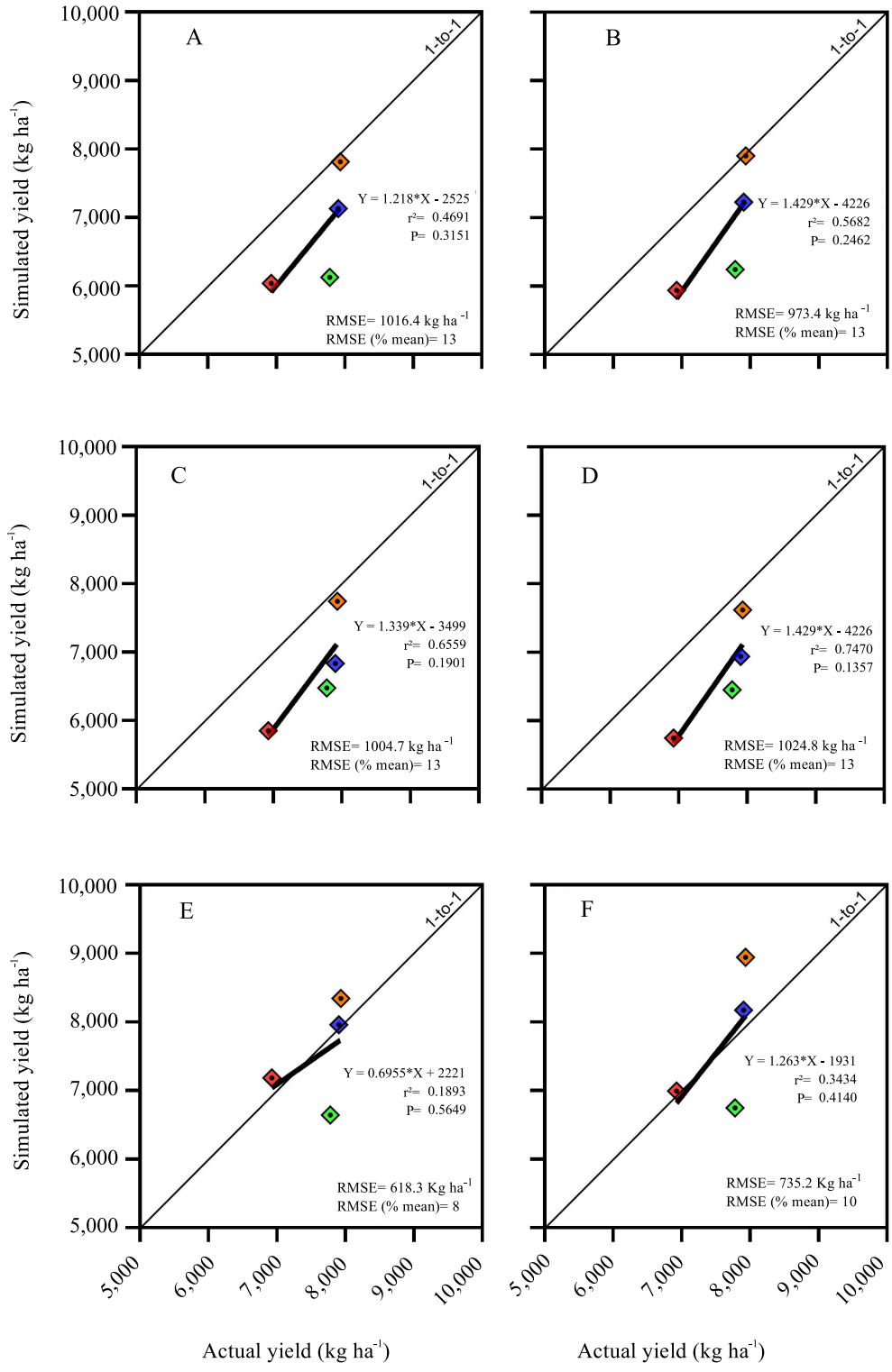

Figure 3. Comparison of simulated and actual flooded-rice yields for the state of Rio Grande do Sul, Brazil, using six field information levels: A, simple 1; B, simple 2; C, intermediate 1; D, intermediate 2; E, complex 1; and F, complex 2. Growing seasons: 2014/2015 (green), 2015/2016 (red), 2016/2017 (blue) and 2017/2018 (orange). The black line represents the 1:1 line; and the solid black line represents the fitted regression models. Root mean square error (RMSE) is expressed in both absolute and relative (% of actual mean yield) terms.

US Corn Belt, some authors observed 2,100 kg ha^{-1} (20%) RMSE (Morell et al., 2016). Using the same approach (S2 in our study), we observed 973.4 kg ha^{-1} (13%) RMSE. By improving field information (C1), it was possible to reduce RMSE to 618.3 kg ha^{-1} (8%), which means that the method by Morell et al. (2016) is applicable for rice in Rio Grande do Sul; and, it is also possible to improve accuracy through additional sowing dates and cultivar information. Besides, these results are indicative that SimulArroz 1.1 improved the simulation accuracy, in comparison to SimulArroz 1.0 that was previously used for rice yield estimation in Rio Grande do Sul by Rosa et al. (2015), with RMSE values ranging from 1,022 to 2,134 kg ha^{-1}, and by Silva et al. (2016) with RMSE (%) ranging from 12.7% to 79.7%, both above 618.3 kg ha^{-1} (8%) observed RMSE in the present study.

Comparing the scenarios that used generic parameters *vs* cultivar-specific parameters (I1 vs C1, and I2 vs C2), it was possible to quantify the RMSE reduction of about 5% on those that used cultivar-specific parameters, which endorses the importance of studies on calibrate new cultivars (Ribas et al., 2020). Scenario C1 was considered the best one for rice forecast. The agreement between simulated and actual yield increased, as comparisons moved from municipality level (RMSEn, 22.0%; BIAS, 0.03; dw, 0.53; and r, 0.39), to region level (RMSEn, 18.5%; BIAS, -0.01; dw, 0.62; and r, 0.58) and to state level (RMSEn, 8.1%; BIAS, -0.01; dw, 0.62; and r, 0.39) (Table 2). Considering the four growing seasons, the average for actual yield and scenario C1 were 7,743 kg ha^{-1} and 7,979 kg ha^{-1}, respectively (Figure 4).

The approach used in the present study, which relies on a calibrated process-based model, is capable to improve the Brazilian rice forecast, as it considers the environmental influence on yield, reducing the empiricism and the dependence on the knowledge of field extensionists and agronomists for yield estimation (Monteiro et al., 2013; Silva et al., 2016).

Table 2. Statistics RMSE, RMSEn, BIAS, dw, and r for municipality, region, and state levels for the simple 1 (S1), simple 2 (S2), intermediate 1 (I1), intermediate 2 (I2), complex 1 (C1) and complex 2 (C2) scenarios, for flooded-rice yield forecasts of four growing seasons (2014/2015, 2015/2016, 2016/2017, and 2017/2018) in the state of Rio Grande do Sul, Brazil.

Scenario	N	RMSE (kg ha^{-1})	RMSEn (%)	BIAS	dw	r
			Municipality			
S1	60	1,926.7	25.0	-0.07	0.54	0.48
S2	60	1,892.1	24.0	-0.07	0.55	0.51
I1	60	1,648.5	21.0	-0.07	0.55	0.55
I2	60	1,606.9	21.0	-0.08	0.62	0.58
C1	60	1,691.0	22.0	0.03	0.53	0.39
C2	60	1,834.7	24.0	0.06	0.53	0.45
			Region			
S1	23	1,852.9	24.5	-0.13	0.55	0.63
S2	23	1,757.8	23.3	-0.12	0.58	0.68
I1	23	1,672.9	22.1	-0.13	0.60	0.73
I2	23	1,658.7	22.0	-0.14	0.60	0.75
C1	23	1,397.8	18.5	-0.01	0.62	0.58
C2	23	1,541.9	20.4	0.01	0.60	0.60
			State			
S1	4	1,016.5	13.3	-0.11	0.53	0.68
S2	4	973.4	12.7	-0.11	0.58	0.75
I1	4	1,004.8	13.2	-0.12	0.47	0.81
I2	4	1,024.8	13.4	-0.12	0.56	0.86
C1	4	618.3	8.1	-0.01	0.62	0.44
C2	4	735.2	9.6	0.01	0.65	0.59

RMSE, root mean square error; RMSEn, normalized root mean square error; dw, agreement index; BIAS, bias index; r, Pearson's correlation coefficient; N, number of analyzed yields for municipality, region, or state levels, during four growing seasons.

It is possible to simulate crop development and dry matter production, using in-season weather data and historical weather data, from the date of the forecast to the end of the growing season, creating a wide range of simulated yields to derive a probabilistic distribution of yield anomalies for the actual growing season (Morell et al., 2016). The use of another calibrated rice model or SimulArroz calibration for tropical rice cultivars allows of the expansion of this yield forecast method for tropical Brazilian rice area. As an example of the MARS project in Europe, it is possible to couple this method, as a new tool to predict rice yield, and helps the national supply company (Companhia Nacional de Abastecimento – Conab), to improve the actual rice monitoring and forecast (Bussay et al., 2015).

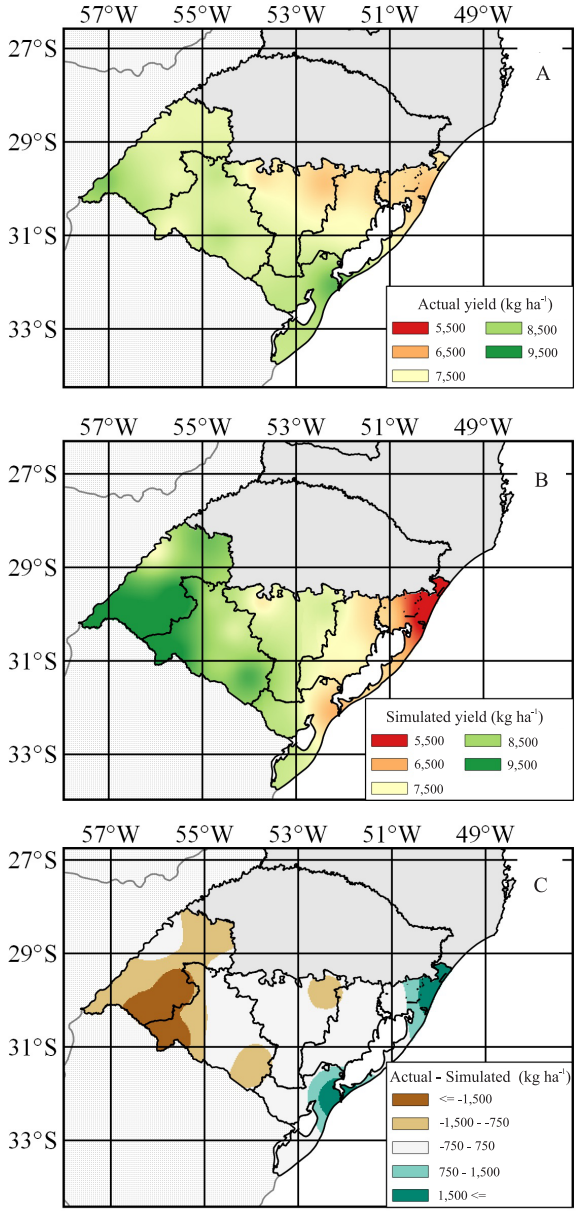

Figure 4. Comparison of simulated and actual flooded-rice yields for the state of Rio Grande do Sul, Brazil, using the complex I field information level, in four growing seasons (2014/2015, 2015/2016, 2016/2017, 2017/2018).

Crop models are powerful tools that can be used to generate information for management by farmers, government policy makers, and as a teaching tool (Streck et al., 2011). Here, we validated an easy method to improve the national forecasting system through the SimulArroz rice model application. Moreover, it is also possible to monitor the regional environmental footprint and climate change impacts, and to help Brazilian politics on decision-making (Streck et al., 2012; Supit et al., 2012). As Brazil is one of the most important food suppliers for the world, it is necessary to present reliable and technology-based solutions, to generate more accurate information on yield forecast. More research on yield forecast needs to be done, improving the interaction between remote sensing, field information, crop modeling, and machine learning.

Conclusions

1. Flooded-rice (*Oryza sativa*) yield forecasts using the SimulArroz version 1.1 and historic weather data for Rio Grande do Sul state, Brazil, shows good predictability (RMSE = 618.3 kg ha^{-1} or RMSE = 8 %).

2. The recommended scenario for flooded-rice yield forecasts is complex 1 (C1) composed of three sowing dates per site, and the three most representative rice cultivars per region.

Acknowledgments

To Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (Capes, Finance Code 1), for providing a fellowship (Project no. 88882.427646/2019-01) and supporting a 6-month internship (Project no. 88887.351533/2019-00) at the University of Nebraska-Lincoln to Michel Rocha da Silva; and to Fundação de Amparo à Pesquisa do Estado do Rio Grande do Sul (Fapergs, Project no. 17/2551-0000937-1), for funding part of the data collection for this project.

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