1 Original Article

2 **Modeling the effect of El Niño Southern Oscillation on the onset** 3 **of soybean rust in Southern Brazil**

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8 **ABSTRACT**

9 The onset of soybean rust (SBR) epidemics, caused by the fungus *Phakopsora pachyrhizi*,
10 in Brazil is mainly driven by the availability of inoculum and weather conditions that prevail
11 during the pre- or early-season. The effect of the El Niño-southern oscillation (ENSO) on
12 weather patterns of certain regions is well known. In Southern Brazil, rainfall levels are
13 increased above normal in spring and summer during the warm (El Niño) phase, which in
14 turn may affect epidemic patterns in summer crops. In this study, data on the first report
15 of SBR in a municipality recorded during 17 growing seasons (2004/05 to 2020/21) were
16 gathered from the Brazilian anti-rust consortium (*Consórcio Antiferrugem*). The Oceanic
17 Niño Index (ONI), or the average anomaly on the sea surface temperature in the El Niño
18 3.4 region for three consecutive months, was gathered from two trimesters prior to the
19 growing season [January, February, and March (JFM) and May, June, and July (MJJ)]
20 and one trimester from within-growing season [October, November, and December
21 (OND)]. A spatially structured Bayesian Cox proportional model suggested that the
22 increase in the probability of early SBR onset is associated with the increase in ONI from
23 MJJ and OND. No association was found for the ONI from JFM on disease onset. Our
24 results provide novel insights into the large-scale risk of SBR outbreaks in Southern Brazil,
25 whose knowledge may be useful for early-planning of disease management strategies.

26
27 **Keywords:** *Phakopsora pachyrhizi* | outbreaks | teleconnections | survival analysis | climate
28

29 **INTRODUCTION**

30 Soybean rust (SBR), a fungal disease caused by *Phakopsora pachyrhizi*, was first reported
31 in South America in 2001 (Yorinori et al., 2005). The disease has spread to the major
32 soybean (*Glycine max*) areas in the Americas and is currently a major concern for soybean
33 growers due to its potential to severely reduce crop yield, particularly in Brazil where
34 conditions are favorable for epidemic onset and development (Del Ponte et al., 2006a;
35 Dalla Lana et al., 2015; Godoy et al., 2016). Since the early years of dealing with the
36 disease, major actions were taken to understand the disease, prevent its further spread,
37 predict disease risk, and establish effective control measures, more notably in Brazil
38 (Godoy et al. 2016) and the United States (Allen et al., 2014; Sikora et al., 2014). In Brazil,
39 a national "anti-rust" consortium named "Consórcio Antiferrugem" was established in
40 2004, when efforts focused on monitoring the seasonal disease spread across the country
41 as well as testing fungicides for disease control (Barro et al., 2021; Dalla Lana et al., 2018;
42 Godoy et al., 2016; Machado et al., 2021). The initiative has been responsible for

collecting, curating, and sharing data on the first SBR detections at the municipality level every growing season (<http://www.consorcioantiferrugem.net>).

In general, the main soybean growing season in Brazil starts with the onset of the Spring season. In the tropics, sowing time is strongly dependent on the onset of the rainy season (usually by mid-September). Hence, delays in sowing time are not uncommon due to early-season droughts, which are responsible for moving sowing one or two months further. Prior to the introduction of the soybean rust pathogen into Brazil, winter (June-September) soybean cropping was a common practice targeting seed production. However, these crops were found to serve as an efficient 'green bridge' that allowed the movement of soybean rust inoculum across seasons (Godoy et al., 2016). Since 2005, it has become mandatory to establish a 90-day soybean-free period in 14 Brazilian states, with the goal of reducing airborne inoculum during the early season (Godoy et al., 2016). Indeed, the sowing period is allowed from mid-September up to December 31st in six states. The adoption of a soybean-free period has helped to decrease the disease risk (Godoy et al., 2016), but volunteer soybean plants and alternative hosts, which are impossible to eliminate completely, allow the fungus to survive between seasons (Yorinori et al., 2005). Once established, SBR epidemics may spread rapidly throughout the country/continent via transportation of the rust spores by air currents (Isard et al. 2011; Pan et al. 2006), which favors disease occurrence in every season (Del Ponte et al. 2006a).

Studies to elucidate factors (mainly weather-based) affecting the components of the disease cycle, as well as of observed epidemics, have been conducted to deepen the understanding of the fungal biology and epidemiology, as well as to develop and improve disease warning systems (Alves et al., 2011; Beruski et al., 2020; Del Ponte and Esker, 2008; Del Ponte et al., 2006b; Del Ponte et al., 2011; Koch and Hoppe, 1987; Marchetti, 1976). The most important weather-related variables that drive the development of SBR epidemics include rainfall (frequency and amount), leaf wetness duration, and temperature, which are critical for infection and further inoculum production during the successive cycles (Del Ponte et al., 2006a; Del Ponte et al., 2006b; Del Ponte and Esker, 2008).

In Brazil, the seasonal weather of some regions is under the influence of the El Niño–Southern Oscillation (ENSO) (Cirino et al., 2015). ENSO phases (El Niño, neutral, or La Niña) are determined by the Oceanic Niño Index (ONI), which is calculated based on anomalies in the normal sea surface temperature (SST) in the El Niño 3.4 region in the central Pacific, a region known to influence climate at the global scale (Grimm, 2003). In South America, the warm phase (El Niño) usually leads to an increase in rainfall levels in the south of the country (subtropics) and droughts in the tropics during the spring and summer months. The pattern is reversed during the cold phase (La Niña) (Cai et al., 2020; Cirino et al., 2015; Grimm, 2003).

The effects of the ENSO phases, or the ONI directly, have been investigated previously for human and plant diseases. Studies have linked El Niño events to outbreaks of malaria, cholera, plague, and dengue (Anyamba et al., 2019; Kovats et al., 2003; Rosenzweig et al., 2001). Fewer examples exist linking plant diseases and ENSO. In the United States, spectral and cross-spectral analysis was used to link a few oceanic indices (ONI, Pacific-North American pattern, or the North Atlantic Oscillation) to fluctuations of *Fusarium* head blight of wheat (Kriss et al., 2012) and wheat rust (Scherm and Yang, 1995). In Brazil, the apparent infection rates of coffee leaf rust epidemics were predicted to be greatest during El Niño seasons in most locations of the subtropical region (Hinnah et al.,

2020). For soybean rust, three studies conducted in Brazil used weather-based models, which were linked to a long series of historical weather and crop models, to predict SBR risk and investigate its association with the ENSO phases (Del Ponte et al., 2011; Fattori et al., 2021; Radons et al., 2021). The effect of SST in the El Niño 3.4 region on the SBR final seasonal prevalence (cumulative number of reports) was investigated for two states: Paraná and Mato Grosso during 11 growing seasons (2004 to 2014) (Minchio et al., 2018).

Because ENSO is known to trigger early rainfall in Southern Brazil (Cai et al., 2020; Cirino et al., 2015; Grimm, 2003) and soybean rust epidemics are highly dependent on rainfall (Del Ponte et al., 2006b), we hypothesize that ENSO also plays an important role in the time to outbreak onset on a regional basis. Therefore, in this study, we gathered data from soybean monitoring in Southern Brazil from 2005 to 2021 growing seasons to model the effect of anomalies in the SST (ONI) on the timing of regional epidemic onset.

MATERIAL AND METHODS

Data on soybean rust presence

The data on SBR onset in commercial fields in Southern Brazil were provided by the Brazilian national anti-rust consortium. The monitoring of SBR in Brazilian national territory is mandatory (by federal law) and it is done by agricultural specialists from state plant health defense agencies. Whenever soybean rust-like symptoms are spotted in commercial fields, samples are sent to an official laboratory, which is responsible for the confirmation and reporting to the national anti-rust consortium. The disease occurrence is given at the municipality level, therefore, whenever SBR is found in a commercial soybean field, the respective municipality is set as SBR-positive. The frequency in which fields are monitored is not provided. Data on the date of SBR occurrence within 17 growing seasons (2004/05 to 2020/21) were gathered for the three southernmost states (Paraná, Santa Catarina, and Rio Grande do Sul) of Brazil. Data on the planting date of the commercial field in which SBR was found were also retrieved. The time for disease onset was calculated as the difference between occurrence and planting date. Hereafter the notation for growing seasons displays the year in which the season has ended or harvested, e.g. the 2004/05 growing season will be denoted as 2005.

Data on Oceanic Niño Index (ONI)

Data ranging from 2004 to 2021 on the Oceanic Niño Index (ONI) were obtained from the National Oceanic Atmospheric Administration (NOAA) website (NOAA (National Oceanic and Atmospheric Administration), 2022). ONI is a measurement of the ENSO, which tracks the anomaly on the sea surface temperature (SST) at an area in the east-central tropical Pacific Ocean located specifically at the 5°N-5°S latitude and 120°-170°W longitude (Huang et al., 2017). ONI is calculated as a 3-month running average of the anomaly on SST from its climatic normal (30 years average, updated every 5 years). ONI data were retrieved from three trimesters: January, February, and March (ONI_{JFM}, prior to the growing season); May, June, and July (ONI_{MJJ}, prior to the growing season); and October, November, and December (ONI_{OND}, within the growing season).

The effect of ONI on the disease onset

The effect of ONI_{JFM}, ONI_{MJJ}, and ONI_{OND} on the disease onset was estimated through survival analysis using a Bayesian Cox proportional hazards (CPM) model. Survival

analysis estimates the probability of a certain event occurring (here is the SBR occurrence after the planting date). In this sense, survival analysis is used to estimate survival functions (equation 1).

$$S(t) = P(T > t) = 1 - F(t) \quad (4)$$

Where T is the random variable that measures the time to event, or in our case, the time to SBR report; the survival function $S(t)$ is the probability that T is higher than a given time t , therefore $S(t) = P(T > t)$. It gives the probability of disease occurrence for each time t , or yet, the probability of no occurrence of an outbreak over time. $F(t)$ is the cumulative probability distribution function of T . The distribution of $S(t)$ along all values of t gives the survival curve.

The hazard function $h(t)$ gives the conditional failure rate, which is defined as the probability of failure (or disease occurrence) in a small time interval (Lee and Wang, 2003). Its mathematical definition is given by equation 2, where $f(t)$ is the probability density function of T :

$$h(t) = \frac{f(t)}{S(t)} \quad (2)$$

The Cox proportional hazard (CPM) model is a product of the baseline hazard function $h_0(t)$, and a term accounting for a set of covariates x , which effects are regulated by their associated coefficients β .

$$h(t) = h_0(t)exp(\beta x) \quad (6)$$

The CPM was implemented under the Bayesian framework using the Integrated Nested Laplace Approximation (INLA). Instead of Markov chain Monte Carlo methods for computing the joint posterior distribution of model parameters, which is computationally expensive, INLA focuses on obtaining individual posterior marginals and on models that can be expressed as Gaussian Markov random fields, reducing computational expensiveness (Gómez-Rubio, 2020; Rue et al., 2009; Rue and Held, 2005). Bayesian inference using INLA can be performed in R using the INLA package (Lindgren and Rue, 2015).

The CPM is implemented in INLA as shown in Equation 7, where η is a linear predictor on some covariates (fixed and random effects).

$$h(t) = h_0(t)exp(\eta) \quad (7)$$

The baseline hazard function is modeled as $h_0(t) = exp(b_l); t \in (s_{l-1}, s_l], l = 1, \dots, L$, therefore the baseline hazard is a piecewise constant function, where a random walk prior is given to b_l , in which $b_l - b_{l-1} \sim N(0, \delta)$, where δ is the precision for the baseline hazard.

The fitted models (one model for each trimester) included ONI as fixed effects, the growing seasons as random effects, and the vector of municipalities was included a spatially structured random effect, in which the linear predictor η model would become a reparametrized Besag-York-Mollié model (BYM-model) (Besag et al. 1991), taking into account the spatial dependence of neighboring municipalities. This type of modeling framework has been used to model the spatial distribution of Huanglongbing of citrus (Alves et al., 2021) and *X. fastidiosa* in Spain and Italy (Cendoya et al., 2020). The general form of the model is given by:

$$\eta_{ij} = \beta_0 + X_i\beta_m + Z_j + \frac{1}{\tau}(\sqrt{1-\phi}u_i + \sqrt{\phi}v_i^*) \quad (8)$$

Where β_0 is the overall intercept, β_m is the vector coefficients for the m covariates or predictors, X_i is the vector of covariates, Z_j is the vector of random effects of each j season, u_i is a zero-mean Gaussian with a precision matrix representing the unstructured random effect, v_i^* is the random effects scaled spatial component that accounts for the similarities of the neighboring municipalities (Simpson et al., 2017), and ϕ ($0 \leq \phi \leq 1$) is a mixing parameter which gives the fraction of the variance explained by the spatial structure, being directly proportional to the effect of the spatial structure. We assumed a distance of 200 km (maximum distance to consider two municipalities as neighbors) for building the spatial structure of random effects used in the models. The priors for all models used in this study were:

$$\begin{aligned} P(\beta_0) &\propto 1 \\ \beta_m &\sim N(\mu = 0, \tau = 10^{-3}), m = 1, \dots, N_\beta \\ Z_j &\sim N(0.001, \lambda) \\ b_l - b_{l-1} &\sim N(0, \delta) \\ \delta &= 0.0001 \\ \tau &\sim PCprior(0.5/0.31, 0.01), \\ \phi &\sim PCprior(0.5, 2/3) \\ \lambda &\sim Gamma(0.001, 0.001) \end{aligned}$$

Where PCprior(•) is the penalized complexity priors for the hyperparameters of the spatial component (Alves et al., 2021; Besag, 1974; Besag et al., 1991; Cendoya et al., 2020; Simpson et al., 2017).

RESULTS

Summary of data on soybean rust onset

A total of 2,441 occurrences were recorded at the municipality level from 2005 to 2021 growing seasons. The state of Paraná had the highest number of occurrences ($n = 1,239$), followed by Rio Grande do Sul ($n = 969$) and Santa Catarina ($n = 233$). These differences are expected since these states have different numbers of soybean-growing municipalities, from which 278, 269, and 87 municipalities, respectively, have recorded at least one SBR occurrence. The growing season with fewer reported occurrences was 2012 (Fig. 1), with only 27 municipalities with SBR occurrences, while 2006 had the highest, with a total of 215 entries. The earliest first SBR occurrence in the growing season was in the 2010 growing season (Fig. 1) when SBR was detected as early as September (of 2009) when soybean plants were still at the vegetative stage (data not shown). On the other hand, the latest first SBR occurrence was recorded in the 2014 growing season (Fig. 1), when SBR symptoms were found in late December (of 2013) when soybean plants were at early reproductive stages (data not shown).

Fig. 1: Distribution of date of soybean rust (SBR) occurrences in Southern Brazil from 2005 to 2021 growing seasons. Vertical lines represent a unique date in which SBR was found in a commercial field.

Data on ONI

The ONI values of each trimester (JFM, MJJ, and OND) for each soybean growing season are depicted in Fig. 2. The highest value of ONI registered among these trimesters was 2.6°C in the OND trimester of the 2016 growing season (which refers to OND accessed in the year of 2015). The lower ONI value (-1.6°C) was also obtained from OND but for the 2011 growing season. The distribution of ONI values for each semester is depicted in Fig. 3. In general, the highest variation in ONI was obtained from the OND trimester, with a standard deviation (SD) of 1.15°C, followed by JFM (SD= 0.94°C) and MJJ (SD=0.47°C). The mean ONI values for each trimester were -0.05, -0.01, and -0.04, for JFM, MJJ, and OND, respectively.

Fig. 2. Oceanic Niño Index (ONI) of the January, February, and March (JFM), May, June, and July (MJJ), and October, November, and December (OND) trimesters from 2005 to 2021 growing seasons. JFM and MJJ refer to trimesters before the beginning of the soybean growing season in Brazil.

Fig. 3. Boxplot of the distribution of Oceanic Niño Index (ONI) of the January, February, and March (JFM), May, June, and July (MJJ), and October, November, and December (OND) trimesters from 2005 to 2021 growing seasons. JFM and MJJ refer to trimesters before the beginning of the soybean growing season in Brazil.

The effect of ONI on the disease onset time

There was not enough evidence to reject the null hypothesis that ONI_{JFM} is associated with the time of SBR onset in Southern Brazilian commercial fields of soybean in the following growing season (95% highest posterior density interval of its associated coefficient contained zero; Table 4). There was, however, evidence of the association of the ONI_{MJJ} and ONI_{OND} on the timing of SBR outbreaks (Table 4). Both models presented positive posterior means, which indicates positive associations of the ONI from those two periods, i.e. the increase in ONI in these trimesters is associated with the increase in the probability of early onsets of SBR epidemics in Southern Brazil. When comparing the two models, the posterior mean of the coefficient from ONI_{MJJ} was slightly higher than that from ONI_{OND} , meaning a larger effect on disease onset. However, a larger SD was observed for the posterior distribution of the coefficient associated with ONI_{MJJ} , compared with the other trimesters, indicating a more variable effect of ONI_{MJJ} . The mixing parameters for the spatial effect (ϕ) of the three models were very similar (Table 4), which indicates that more than one-fourth of variability on the response variable is explained by the contribution of the spatial neighboring structure of municipalities, i.e. the risk of disease onset in one municipality is affected by neighboring municipalities that have already recorded SBR occurrences within the growing season.

Table 1: Mean, median, standard deviation (SD), 95% highest posterior density interval (HPDI), and posterior mode of model parameters and hyperparameters for the effect of Oceanic Niño Index (ONI) on time to onset of soybean rust in southern Brazil.

Trimester ^a	Parameters and hyperparameters ^b	Mean	Median	Mode	SD	HPDI _{lower}	HPDI _{upper}
JFM							
	β_o	-3.76	-3.76	-3.77	0.17	-4.09	-3.43
	ONI _{JFM}	0.08	0.08	0.08	0.16	-0.24	0.4
	λ	3.17	3	2.65	1.22	1.1	5.56
	τ	2.14 x 10 ⁹	1.07 x 10 ⁸	7.94 x 10 ⁶	6.53 x 10 ¹⁰	2.02 x 10 ³	2.32 x 10 ¹¹
	ϕ	0.28	0.2	0.02	0.25	0	0.8
	δ	2.97 x 10 ¹	2.79 x 10 ¹	2.43 x 10 ¹	1.19 x 10 ¹	9.78	5.30 x 10 ¹
MJJ							
	β_o	-3.79	-3.79	-3.79	0.14	-4.07	-3.5
	ONI _{MJJ}	0.7	0.7	0.7	0.26	0.18	1.21
	λ	4.91	4.63	4.06	1.92	1.68	8.67
	τ	1.73 x 10 ⁹	9.66 x 10 ⁷	6.57 x 10 ⁶	4.49 x 10 ¹⁰	7.62 x 10 ³	1.47 x 10 ¹¹
	ϕ	0.28	0.2	0.02	0.25	0	0.79
	δ	2.97 x 10 ¹	2.79 x 10 ¹	2.42 x 10 ¹	1.19 x 10 ¹	9.76	5.30 x 10 ¹
OND							
	β_o	-3.79	-3.79	-3.79	0.14	-4.06	-3.52
	ONI _{OND}	0.32	0.32	0.32	0.1	0.13	0.52
	λ	5.8	5.47	4.8	2.26	1.99	1.02 x 10 ¹
	τ	2.16 x 10 ⁹	1.11 x 10 ⁸	7.94 x 10 ⁶	6.36 x 10 ¹⁰	1.88 x 10 ³	2.30 x 10 ¹¹
	ϕ	0.28	0.2	0.01	0.25	0	0.8
	δ	2.98 x 10 ¹	2.80 x 10 ¹	2.44 x 10 ¹	1.19 x 10 ¹	9.83	5.31 x 10 ¹

^a JFM = January-February-March, MJJ = May-June-July, OND = October-November-December.

^b β_o = Model intercept; ONI_{JFM} = Oceanic Niño index for January-February-March; ONI_{MJJ} = Oceanic Niño index for May-June-July; ONI_{OND} = Oceanic Niño index for October-November-December; λ = Precision for seasons as random effects; τ = Precision for the spatial effect; ϕ = Mixing parameter for the spatial effect; δ = Precision for the baseline hazard function.

DISCUSSION

In this study, we explored the large database of 2,441 first reports of soybean rust in commercial fields at the municipality level within 17 growing seasons (2005 to 2021) in the three southernmost Brazilian states. Considerable variability in the timing of disease

onset was uncovered. Results from spatially structured Bayesian survival models indicated that the timing of disease onset was influenced by anomalies in the normal SST of the El Niño 3.4 region in the central Pacific before and during the crop season: MJJ and OND, respectively. The increase in ONI (e.g: warmer SST than normal) in these trimesters is expected to trigger the early onset of SBR epidemics in southern Brazil.

Results showed that soybean rust was detected in commercial fields as early as September, the beginning of the growing season in Brazil) or as late as mid-March (Fig. 1). The variation in detection timing may be due to several reasons, especially those linked to inoculum availability. For example, prior to the establishment of the soybean-free period in Brazil, it was common to detect the disease during the vegetative stages (Godoy et al., 2016). Crops grown during the off-season (winter) allowed the inoculum to build up and, consequently, spread and reach the crops grown in the main growing season (Godoy et al., 2016). Another reason is related to the early onset of rain and maintenance of an abnormally wet condition early in the growing season, which influences the soybean sowing schedule and also may boost inoculum production and infections early in the season.

The effect or association of ENSO with epidemic data (observation or simulation) was previously investigated for coffee leaf rust in Brazil (Hinnah et al., 2020), *Fusarium* head blight in wheat in the United States (Kriss et al., 2012), and wheat rust in China and in the United States (Scherm and Yang, 1995). All these studies, although using different methodologies, highlighted the effects of El Niño (Hinna et al 2020) or La Niña (Kriss et al. 2012) in increasing the risk of the disease under study. Furthermore, Kriss et al. (2012) and Hinnah et al. (2020) also demonstrated the differential effects of the ENSO across different regions or states. This was more evident for coffee leaf rust, which showed that the differences in predicted infection rates between warm (El Niño) and cold (La Niña) phases were only significant in states further south of Brazil, the region in which we focused our study.

Previous works on the effects of ENSO-related variables on SBR were based on simulation of disease prediction/risk models using relatively long historical observations of weather data (Del Ponte et al., 2011; Fattori et al., 2021; Radons et al., 2021). For instance, Del Ponte et al. (2011) used a rainfall-based model (Del Ponte et al., 2006b) to predict final severity levels across 30 years (1979–2008) of rainfall observation in several locations across Rio Grande do Sul (RS), the southernmost state in the Southern Brazilian region. In another effort, also targeting the same region (RS), Radons et al. (2020) used an infection-based model (that uses air temperature and leaf wetness duration) to predict a “climate risk”, from which they derived the number of fungicide applications per cycle. Contrary to Del Ponte et al. (2006), who found that SBR severity levels were generally increased during El Niño, and more strongly correlated depending on the location, the effect of the ENSO phases on the predicted number of applications per crop season across the locations studied was not clear (Radons et al., 2021). By linking a process-based soybean model and a rainfall-based SBR model adjusted to predict daily severity progress that penalized simulated yields, Fattori et al (2021) predicted increased severity levels during El Niño years. Consequently, higher yield losses were reported in Southern Brazil than in any other mega-production region of Brazil, agreeing with Del Ponte et al. (2011).

Using SBR-presence data, also reported by the consortium, Minchio et al. (2018) explored the effects of weather and ENSO-related variables on the final prevalence data reported for two states in Brazil: Mato Grosso (Mid-Western Region) and Paraná, both

spanning 11 seasons (from 2004/05 to 2014/15 seasons). The SST values from August to December were included in the model as a predictor of the prevalence in Paraná State, suggesting that warmer SST (El Niño) should influence the regional spread of SBR. Our results are in general agreement with those. However, besides the differences in the modeling approach, those authors kept multiple occurrences for unique municipalities in the database, which inflates the number of occurrences in a single location. Furthermore, the absence of spatial effects (effects between municipalities) in their models may lead to misleading inferences (Alves et al., 2021; Besag, 1974; Cendoya et al., 2020; Ojiambo and Kang, 2013).

We found that the risk of SBR outbreaks was positively affected by ONI values during the OND and MJJ trimesters. No relationship between the risk of SBR outbreaks and the ONI values in JFM was observed. The effect of the ONI_{OND} was not unexpected because of its effect on the rainfall during the growing season (late spring and early summer) (Del Ponte et al., 2011). However, our model using ONI_{MJJ} provided a higher posterior mean effect of the anomaly in that period (compared to OND) on the risk of SBR onset. Possibly, the increase in the risk may be associated with an early onset of rainfall previously to the crop season, which boosts inoculum production on alternative hosts and voluntary soybean plants. This result is encouraging to allow an early warning of soybean rust at least three months prior to the start of the season. Similarly, Kriss et al. (2020) found that higher intensities of Fusarium head blight epidemics in wheat in Ohio, United States, would be expected one year after observing low ONI values, i.e., La Niña. Our results provide novel insights into the mechanisms and factors that drive the large-scale spread of soybean rust across Southern Brazil, which may be useful for seasonal outlook and decision-making in soybean rust management such as the timing of fungicide applications.

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DATA AVAILABILITY STATEMENT

The data and codes that support the findings of this study are openly available in the Open Science Framework at <https://doi.org/10.17605/OSF.IO/2KHFV>.

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