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Early-season warning of soybean rust regional epidemics using El Niño Southern/Oscillation information

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Abstract Soybean rust (SBR) is a disease of significant impact to Brazilian soybean production. Twenty-four locations in a major growing region in southern Brazil, where long-term (30 years) weather information was available, were selected to estimate the risk of SBR epidemics and identify potential predictors derived from El Niño 3.4 region. A rainfall-based model was used to predict SBR severity in an "epidemic development window" (the months of February and March for the studied region) in the time series. Twenty-eight daily simulations for each year-location (n = 720) were performed considering each day after 31 January as a hypothetical detection date (HDD) to estimate a severity index (SBRindex). The mean SBRindex in a single year was defined as the 'growing season severity index' (GSSI) for that year. A probabilistic risk assessment related GSSI and sea surface temperatures (SST) at the El Niño 3.4. region (here categorized as warm, cold or neutral phase) in October–November–December (OND) of the same growing season. Overall, the median GSSI across location-years was 34.5%. The risk of GSSI exceeding 60% was generally low and ranged from 0 to 20 percentage points, with the higher values found in the northern regions of the state when compared to the central-western. During a warm OND-SST phase, the probability of GSSI exceeding its overall mean (locations pooled) increased significantly by around 25 percentage points compared to neutral and cold SST phases, especially over the central western region. This study demonstrates the potential to use El Niño/Southern Oscillation information to anticipate the risk of SBR epidemics up to 1 month in advance at a regional scale.

Keywords Probabilistic risk assessment · Agricultural risk · El Niño · Plant disease

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Introduction

Soybean rust (SBR) is caused by *Phakopsora pachyrhizi* Syd., a foliar fungal pathogen that has spread throughout the world's major production regions, often causing yield reductions (Sinclair and Hartman 1999). Yield loss by SBR is a function of both the reduction in healthy leaf area and defoliation (Kumudini et al. 2008; Yang et al. 1991). Soybean cultivars available so far lack resistance or tolerance to SBR, while cultural practices other than fungicide application have proven largely ineffective (Yorinori et al. 2005). Most of the fungicide spraying programs in Brazil are calendar-based. Although empirical evidence indicates that SBR inoculum is not limiting and environmental conditions are in general conducive for SBR outbreaks (Del Ponte et al. 2006a; Yorinori et al. 2005) the year-to-year variation in epidemic levels and its impact on yield is variable across Brazilian soybean production regions, especially in the southernmost regions (Costamilan and Ferreira 2009; Godoy et al. 2009).

Weather-related variables are of utmost importance for SBR epidemics, especially rainfall, which seems to influence epidemic development greatly during the growing season (Del Ponte et al. 2006a; Del Ponte and Esker 2008). Several empirical or mechanistic models have been proposed to predict SBR epidemics using weather inputs (Del Ponte et al. 2006b). However, a rigorous quantitative risk assessment for SBR epidemic potential at large scale (Yang 2006) in Brazilian growing regions is still not available. In Rio Grande do Sul, the southernmost state in Brazil, SBR has had an apparently erratic impact since it was first found (Costamilan and Ferreira 2009), which makes the use of climate-based forecasting models appealing, and growing season outlooks useful for preparedness and tactical decisions (Del Ponte and Yang 2006; Yang 2006).

Previous botanical epidemiology research showed ENSO (El Niño/Southern Oscillation) influences on spatial and/or temporal patterns of plant diseases such as wheat stem rust in the United States and China (Scherm and Yang 1995), sorghum ergot in Australia (Wang et al. 2003), and fusarium head blight in China (Zhao and Yao 1989) and southern Brazil (Del Ponte et al. 2009). Although some studies provided a basis to either understand long-term cyclic disease patterns connected to ENSO (Scherm and Yang 1995) or the influence of long-term inter-annual climate variability on the potential risk of infection events over the course of a year (Wang et al. 2003) or during critical windows for infection defined by varying planting dates (Del Ponte et al. 2009), not all focused directly on the potential use of observed or forecast ENSO information to provide early warning of crop epidemic risk for the regional scale.

The influence of ENSO on precipitation in the Southeastern portion of South America has been investigated thoroughly (Coelho et al. 2002; Ropelewski and Halpert 1987; Paegle and Mo 2002). There is clear evidence that rainfall in the Austral Spring months during El Niño (La Niña) years tends to be higher (lower) than the long-term average (Baethgen and Magrin 2001; Diaz et al. 1998; Grimm and Tedeschi 2009). Moreover, ENSO seems to influence crop yields in subtropical South America for several summer crops such as rice (Mota 2000), maize (Berlato et al. 2005; Ferreyra et al. 2001) and soybean (Fraisse et al. 2008).

Given the uncertainties involved in rainfall ENSO-based forecasting and climate-crop interactions, a probabilistic approach is suited for providing useful risk information for decision making in this context. Risk information may be summarized by empirical probability of exceedance (POE) functions conditional on ENSO phases. Therefore, the probability of a response variable of interest exceeding any threshold and its respective confidence bands can be derived. Despite being used widely for climate risk assessments (Meinke and Hammer 1997), including those related to plant disease risk (Wang et al. 2003), approaches based on empirical POEs rarely adopt a rigorous inferential framework (Ferreyra et al. 2001; Maia et al. 2007; Maia and Meinke 2009; Stone et al. 2000) that includes statistical hypothesis testing or uncertainty assessments (standard errors and confidence bands for quantiles and POE estimates).

Considering the relatively recent introduction of SBR into Brazil and the lack of quantitative studies to assess the climatic suitability and risk of epidemics in Southern Brazil, our objectives were twofold: (1) to provide a quantitative (probabilistic) risk assessment for SBR epidemics developing in the State of Rio Grande do Sul; and (2) to quantify the influence of and evaluate the potential to use ENSO information as a predictor in early warning of seasonal outbreaks.

Materials and methods

Study area, models and climate data

Rio Grande do Sul (RS) is the third largest soybean producing state in Brazil, accounting for 18% of the total national production in an average cropping area of around 4 million ha (IBGE 2010). For this study we assumed, based on current epidemiological evidence for the region, that: (1) inoculum is not limiting for epidemics to occur (Pivonia and Yang 2004); (2) there is a calendar time (late January to February) for the peak of disease establishment and further development in any given growing season across major growing regions of the state (Spolti et al. 2009); and (3) temperature is not a limiting factor for SBR epidemics to develop (Del Ponte et al. 2006a).

Therefore, we used an existing rainfall-based empirical regression model in order to estimate maximum disease severity levels corresponding to a hypothetical day when first symptoms were observed in the field (Del Ponte et al. 2006a). For instance, if disease is hypothetically detected on 10 February, the number of rainy days and the accumulated rain (mm) for the following 30 days are used as predictors in the model that estimates maximum disease severity (SBRindex) at full seed (R6) to beginning maturity (R7) soybean growth stages. Details on the linear relationships between rainfall variables and disease severity can be found in Del Ponte et al. (2006a).

Long-term daily rainfall information was available from ANA (Agência Nacional de Águas). A set of weather stations was selected from ANA's database according to the following criteria: (1) they should be distributed throughout the major soybean regions in RS state (northern and central-western); and (2) in order to assure the absence of missing data, only entire records of rainfall data for January–April available for the last 30 years (1979–2008) should be used. Twenty-four locations matched these criteria and were used in the analyses.

Modeling overall and inter-seasonal SBR risk

A "growing season severity index" (GSSI) was composed for each location-year combination (n = 24 locations x 30 years = 720) using simulated data from sequential runs of the rust model during the epidemic window of the year, here defined as 28 days after 31 January, each day being considered a hypothetical rust detection date (HDD). Hence, GSSI is the mean of 28 simulations of SBRIndex for each location-year. Our calendar-based "epidemic window" for an average regional rust onset and development was defined based on the analysis of SBR detection dates reported by the soybean rust consortium for the state of RS (Spolti et al. 2009).

The SBR risk was quantified via probability of the GSSI exceeding threshold values (y) by using the empirical probability of exceedance functions [POE(y)=P(GSSI>y], Maia et al. 2007), e.g., P(GSSI> overall median of the simulated data), or P(GSSI>60%), an arbitrarily defined minimal severity level that may lead to severe damage). Overall regional risk (using pooled data from 24 locations) was summarized by POEs for the mean GSSI with respective 95% confidence bands. Inter-annual GSSI variability between locations was characterized via a box-plot time series (1979–2008). Mean GSSI for the years was mapped to depict its spatial variability across the study area.

Soybean rust risk and ENSO influence

Approaches based on information arising from GSSI simulated time series and ENSO-based predictors can be useful for near future disease severity forecasting under a changing climate as an alternative to risk assessment approaches based on climate model projections. Therefore, we opted for an analogue year approach that accounts for ENSO impacts via observed sea surface temperature (SST) anomalies as predictors (Maia and Meinke 2009). This approach captures climate variability and change via SST anomalies, and assumes that the ENSO-rainfall relationship remains stable at least in the near future (McKeon et al. 1998).

An oceanic index derived from Tropical Pacific (El Niño 3.4 region, bounded by 120W–170W and 5S–5N limits) sea surface temperature (SST) anomalies in October–November–December (OND), previous to the SRB epidemic window (January–February) was used to define ENSO-like phases ("OND-SST phases"). Years were classified accordingly to SST anomaly quartiles (Stone et al. 1996) as follows: "Warm OND-SST phase" (upper quartile, >0, 80°C, "El Niño"-like years), "Neutral SST-phase" (central 50%, i.e., between 25 and 75% ,−0.82°C and +0.80°C) and "Cold OND-SST phase" (lower quartile, <0.82°C, "La Niña"-like years). SST anomaly data were obtained from NOAA's CPC website for all the years covered by the study (NOAA 2009).

Risk information was summarized by empirical POE functions conditional on ENSO phases using descriptive and inferential tools (Maia and Meinke 2006; Maia et al. 2007). This method provides an objective spatial assessment of ENSO influence on epidemic risks across locations by quantifying maximum changes in the risk estimates when conditioning to a certain SST phase. Hence, POEs for both GSSI and weather variables used in the SBR model (number of rainy days and accumulated rain in a 30-day period; Del Ponte et al. 2006) were estimated for each SST phase. Evidences of the phases' influence on SBR risk were quantified by using nominal significance levels (P-values) coming from Log-Rank (Mantel 1966) and Kruskal-Wallis (KW) tests (Maia et al. 2007). While the log-rank test accounts for divergences between conditional and unconditional POEs across the whole GSSI range, KW accounts only for maximum vertical distances and was used for assessing SST influence on both median GSSI for the region and each location. Vertical distances between conditional and unconditional POEs, representing maximum ENSO influence (MaxDif) on SBR risk estimates were calculated for each location. Mathematically, MaxDif=$(\max_{phase}\ [(\max_{GSSI}\ (POE^*\ (GSSI)\ -\ POE_{phase}\ (GSSI)))]$, where POE* is unconditional distribution and POE phase is POE conditional to each OND-SST phase.

Maximum vertical distances and P-values from Log-Rank were mapped to display the spatial variability of the ENSO-like phases across the region. Statistical analysis for SBR risk estimation and associated uncertainties as well as quantification of ENSO influence on SBR risks was performed via the LIFETEST and NPAR1WAY procedures of the statistical software SAS/STAT® (SAS 2004a). The graphs were constructed using the GPLOT Procedure of the SAS/GRAPH® Software (SAS 2004b).

Results

Overall growing season severity index

GSSI values for the location-year simulations ranged from 2.1 to 91.2% with an overall median of 34.5 % (CI 95% = 26.0–38.1%) (Fig. 1). The overall frequency of GSSI > 60%

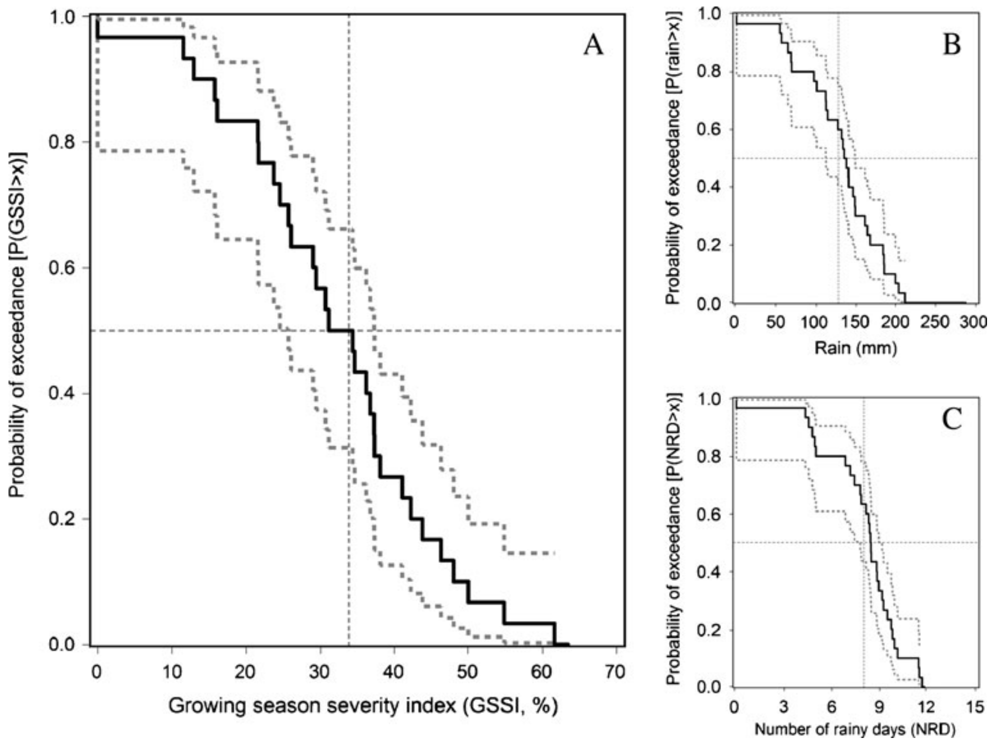

Fig. 1 Probability of exceedance (POE) functions for **a** the predicted growing seasonal severity index (GSSI) estimated by an empirical rainfall-model and for the two rainfall variables (predictors) of the model corresponding to February–March period, **b** mean accumulated rainfall per month (RAIN), and **c** mean number of rainy days per month (NRD) over 30 days after detection. *Solid lines* Empirical probability of exceeding functions, *dashed lines* upper and lower limits of the 95% confidence interval

was generally very low and ranged from 0 to 0.20 across locations; however, the frequency of GSSI > 40% varied between 0.25 and 0.45. POE for the two rainfall predictor variables shows median values of around 150 mm (Fig 1b) and less than 9 days (Fig. 1c) for the time period considered, which explains the relatively low GSSI on average. There was spatial variation of GSSI, with higher values observed in the northern part of the state, in contrast to central-western locations (Fig. 2).

Inter and intra-annual GSSI variability

Non-homogeneous inter-annual variability was observed for the 30-year median GSSI time series. Favorable weather conditions for epidemic development occurred more frequently during the 1990s than in the other two decades. Thus, in the 1990s, 8 out of 10 years presented GSSI values above the median, compared to 4 years during the 1980s and 2 years between 2000 and 2008 (Fig. 3). Relatively high intra-annual variability (box-plot size in Fig. 3) was observed in some years as a consequence of the spatial variation in rainfall over the study region.

ENSO influence on SBR risks

As expected when using SST anomaly quantiles, 15 years of the 30-year-long time series were classified as belonging to either having a warm (8 years) or cold (7 years) OND-SST, while the remaining 15 years were classified as neutral. Conditional and unconditional POEs for mean accumulated rainfall per month during January–February (RAIN), the mean number of rainy days per month (NRD) over 30 days after hypothetical soybean rust detection and the predicted GSSI are shown in Fig. 4a. The ENSO phases had a significant influence on GSSI at most individual locations, with Log-Rank *P*-values ranging from 0.001 to 0.30 (76% of *P*-values <0.10). For the pooled GSSI (all locations), the Log-Rank *P*-value was 0.04. The five highest GSSI median values were observed in “warm” years; three of which occurred during the 1990s (Fig. 3). For the “cold” OND-SST phase, only two years had SSI above the median. For the “neutral” OND phases, GSSI values were distributed approximately equally below or above the median. In general, the risk of GSSI > 34.5% (overall median) increased by 25 percentage points (average of all locations) during a warm OND-SST phase, compared to the risk estimated without accounting for ENSO influence (unconditional POE, all years, Fig. 1). However, the equivalent risk of GSSI>60% was estimated as zero for both “neutral” and “cold” OND-SST phases, while around 0.10 during a “warm” OND-SST phase. Using GSSI = 40% as threshold the risk in “cold” years was still zero and, in “warm” years, risk was five times higher than that in “neutral” years (Fig. 4a). The temporal pattern of OND-SST phase influence on the rust severity for each HDD in a year used to estimate GSSI showed a decreasing effect of OND-SST phase on the severity for HDD after the 3rd week of February (Fig. 5).

The spatial distribution of ENSO influence on SBR risk, as measured by maximum differences (MaxDif) between

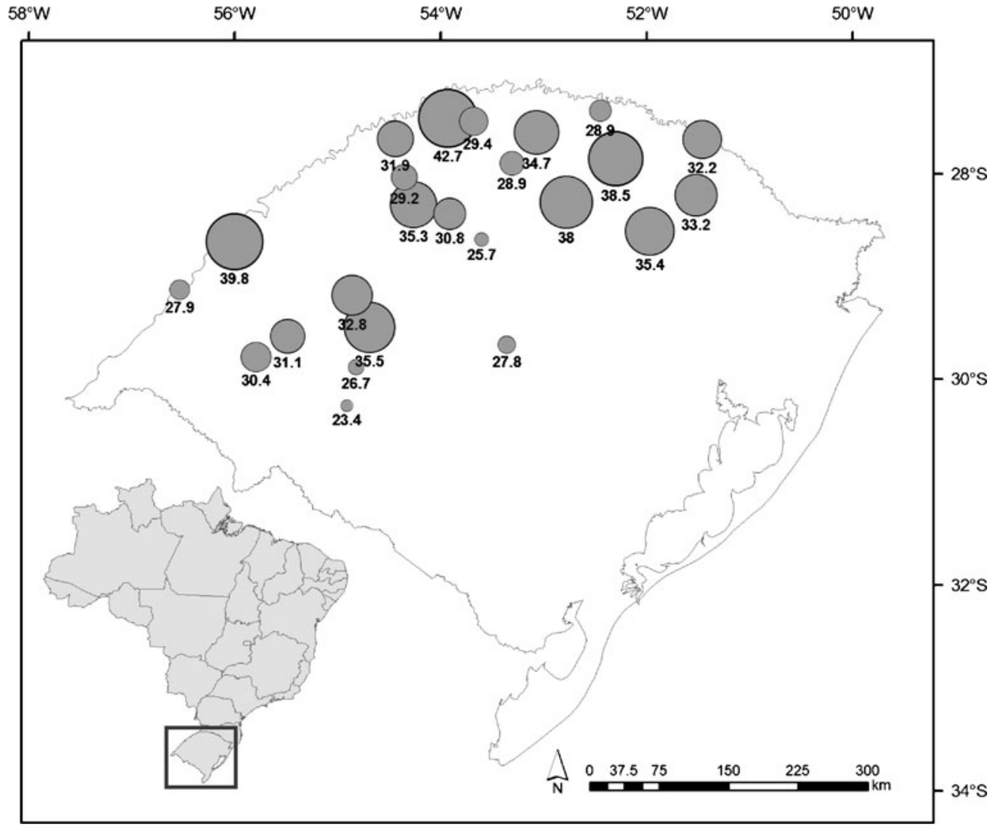

Fig. 2 Spatial variability of the median GSSI. Medians were estimated from a 30-year period of yearly simulations (1979–2008). In each year, a soybean rust (SBR) severity index was averaged based on simulations of a rainfall-based model that predicts final SBR severity for 28 sequential hypothetical disease detection (HDD) dates after 31 January

conditional (ENSO) and unconditional risk estimates, is shown in Fig. 6. MaxDif ranged from 0.15 to 0.44, with the highest influences observed in the central-western localities.

Discussion

This study provide an objective means of quantifying the conduciveness of climate for SBR epidemic development in the State of RS under the assumption of unlimited inoculum supply. Overall, we found that the region is at a relatively lower risk for severe rust epidemics compared to the other regions of the country, such as the central-western (Cerrado) region of Brazil (Del Ponte et al. 2006b). Few epidemics monitored in non fungicide-treated experimental plots across several location and years in Brazil reach final severity values below the overall median disease severity index found in this work (34.5%), which are more likely when drought conditions prevail during the growing

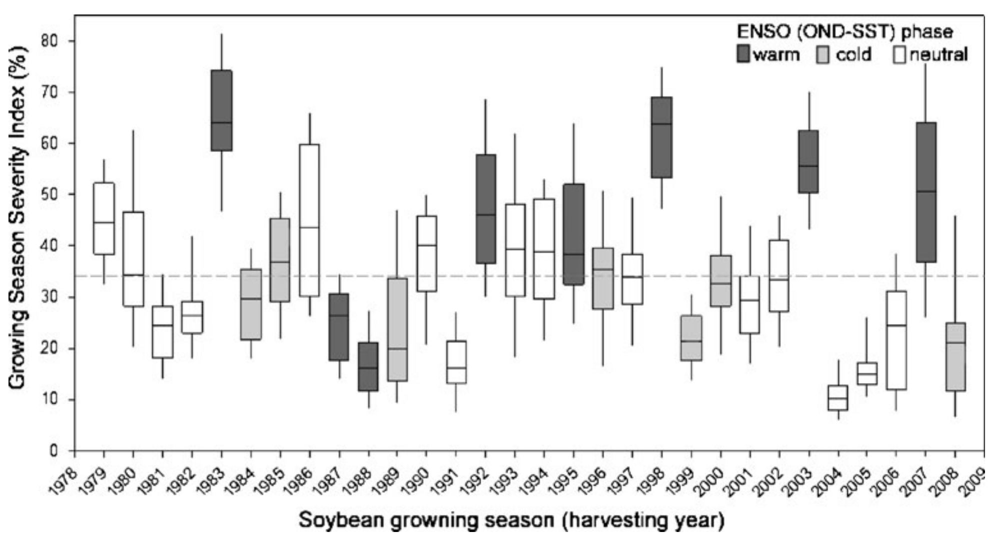

Fig. 3 Box-plots of GSSI over time (1979–2008) showing its inter-seasonal and spatial (*box*) variability. El Niño/Southern Oscillation (ENSO) phases (warm, cold and neutral) were derived from preceding tropical Pacific - El Niño 3.4 region for the Oct-Nov-Dec (OND) sea surface temperature (SST) anomaly data

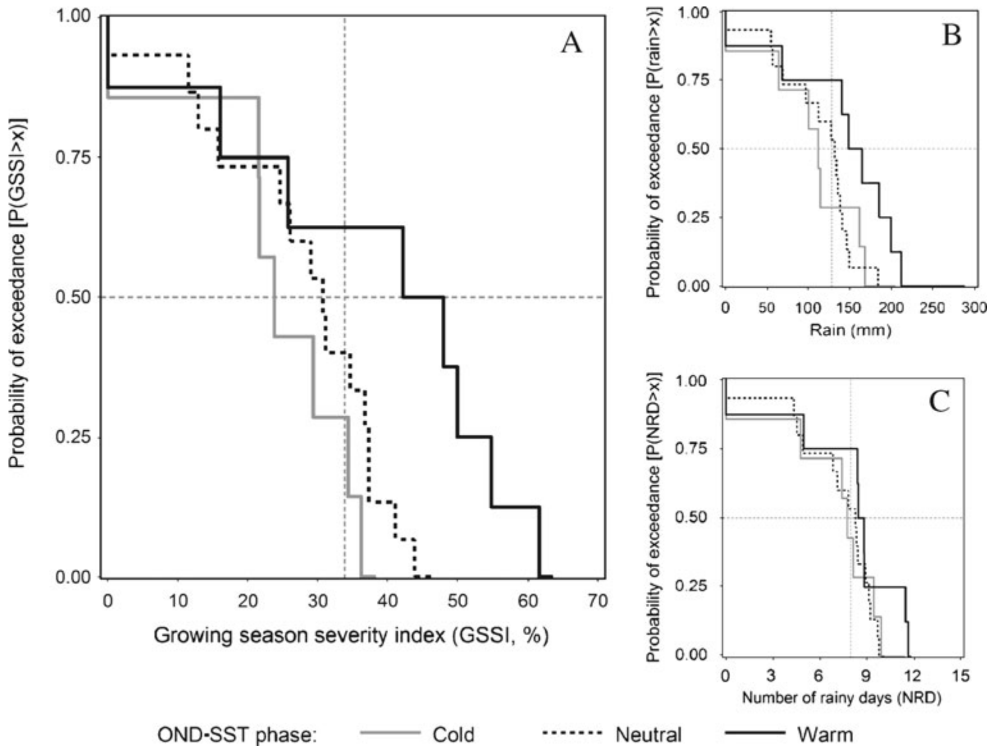

Fig. 4 Conditional POE estimates for **a** the predicted GSSI by an empirical rainfall-model and for the two rainfall variables (predictors) of the model during the February–March period, **b** mean accumulated rainfall per month (RAIN), and **c** mean NRD over 30 days after detection. ENSO phases were derived from preceding tropical Pacific—El Niño 3.4 region—for the OND-SST anomaly data

season, suppressing the development of rust epidemics (Del Ponte et al. 2006a; Godoy et al. 2009). Northern locations in RS are at higher risk than those in the central-western region—a marginal area for soybean cropping (about 10% of the sown area). The more humid climate in the northeastern production region of the state contributes to higher average soybean yield (Melo et al. 2004).

In our assessment, SBR epidemic risk was modeled for a 30-year period (1979–2008) while its actual detection in the region occurred only after the 2001/2002 growing season (Costamilan et al. 2002; Yorinori et al. 2005). In 7 years within this period (2002–2008), our results showed that, for most locations, the GSSI was higher than the overall median (34.5%) in only two years (2003 and 2007), which parallels empirical observations. Despite seasonal weather being favorable for outbreaks across a large region, and also the lack of knowledge regarding adequate disease control by growers (Yorinori et al. 2005), relatively low levels of initial inoculum may have delayed regional outbreaks during the 2002/2003 season (the first after

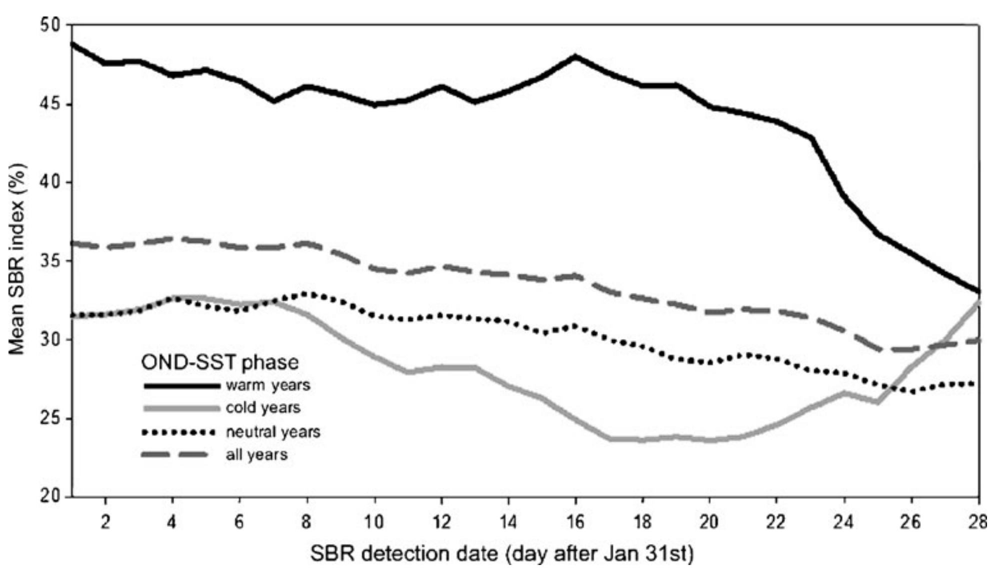

Fig. 5 Soybean rust severity index (SBRIndex) variation across HDD dates. *Lines* Mean SBRIndex across 24 locations and 30 years (1979–2008) (*dashed line*), or all locations and for years classified as "warm" (*solid black line*), "cold" (*solid gray line*) or "neutral" (*dotted line*) accordingly to SST anomaly data for the OND period in the Tropical Pacific (El Niño 3.4 region)

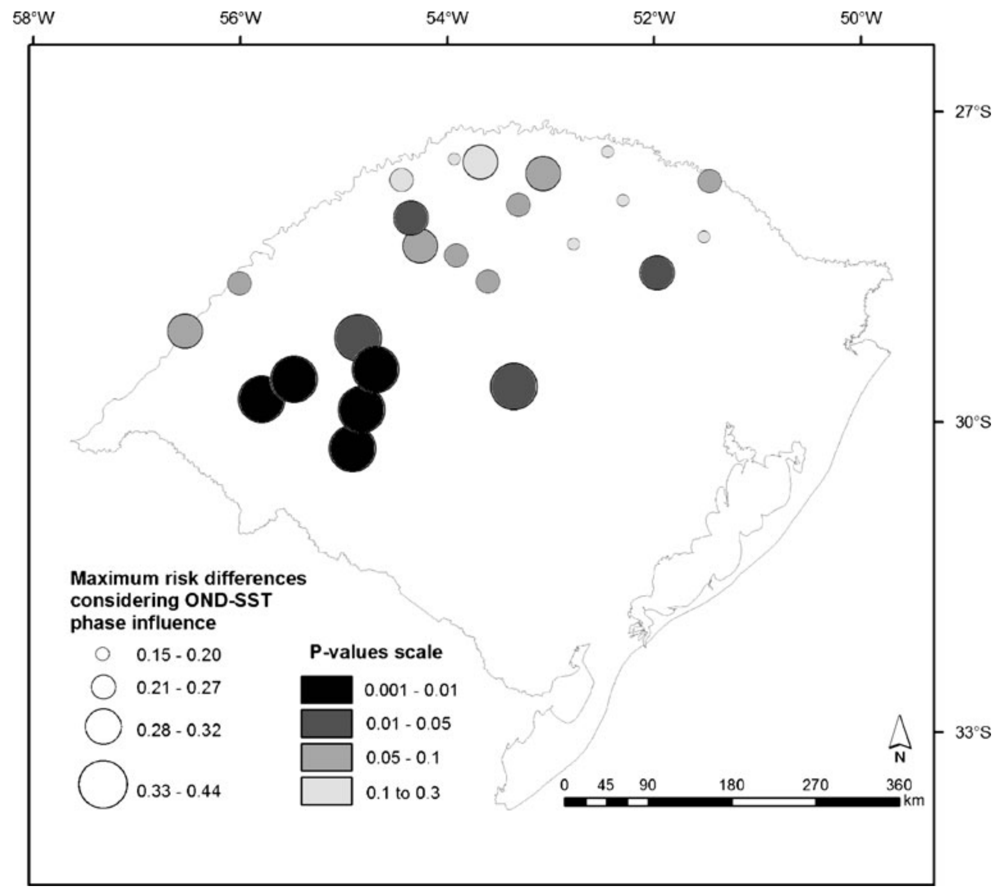

Fig. 6 Location-specific maximum differences between unconditional (all years) and conditional (ENSO phases) POE functions for GSSI. Risk differences describe maximum change in SBR risk estimates as consequence of accounting for ENSO information from the OND period previous to the epidemic SBR window (February). Evidences of the ENSO influence were quantified via Log-Rank nominal significance levels, represented in the map as *P*-values classes (*gray scale*)

detection of *P. pachyrhizi* in the state of RS in 2002). An exception was the 2006/2007 growing season, when SBR spread quickly across the state and severe losses were reported in non-treated trial plots and in commercial fields where fungicide management was sub-optimal (Costamilan and Ferreira 2009). Survey information on fungicide use and rust-induced soybean yield losses in the state revealed that the impact on yield was around 20% in the 2006/2007 season whereas rust-induced losses reported for the 2003/2004, 2004/2005 and 2007/2008 seasons were estimated as minimal, with the most severe being related to prevailing drought condition during the growing season (Costamilan and Ferreira 2009). These observations are consistent with our regional predictions, which seemed to adequately capture inter-annual variations in the SBR epidemic patterns in the recent years across the state.

We used February as the critical detection epidemic window for computing the seasonal severity index. In terms of large-scale seasonal risk prediction, it may be more critical to predict epidemic development earlier in the season when impact on yield can be highest (Kumudini et al. 2008) and earlier fungicide sprays are necessary if a high risk is warned. Moreover, conducive weather conditions during February, when the disease spreads out in the state, may impact further on regional epidemic development in subsequent months because of the dynamic nature of the large-scale temporal and spatial spread and development of this polycyclic epidemic (Christiano and Scherm 2007).

The relatively recent (post-2001) appearance of soybean rust in RS state seemed to occur in a decade characterized by lesser conducive weather conditions across the critical period than the 1990s, when a more severe impact of the disease could have occurred if the disease had arrived. In our study, Niño 3.4 SST anomalies in the OND period were used to predict epidemic risks of SBR developing in the subsequent February and March, i.e., with a 1- to 2-month lead time. However, within a growing season, the most marked influence was observed for detection in the first 3 weeks of February, declining thereafter (Fig. 5). This could be due to the weakening of the lagged relationship between OND-SSTs and rainfall during late February–March. There were a few years in our simulated GSSI time series when moderate-to-high values did not correspond to warm phases. Further studies are needed to verify the influence of other phenomena such as rainfall variability associated with the Pacific Decadal Oscillation (Kayano and Andreolli 2007), South Atlantic Convergence Zone or South Atlantic Sea Surface Temperatures (Barros et al. 2000), which are all known to influence rainfall patterns in our study region.

In terms of practical management decisions, monitoring or even forecasts of SST for the OND period could aid operational planning and decisions making by soybean growers. In the case of a high risk warning, a soybean producer can be better prepared to time two or three fungicide applications. This would be especially interesting because higher soybean yields are expected in El Niño years in the region (Berlato and Fontana 1999) and yield protection is warranted with the use of timely, preventative sequential fungicide sprayings for SBR control (Scherm et al. 2009). Likewise, agribusinesses could use such information for logistical planning (ordering / storing of chemicals). On the other hand, if a low risk is expected (for example, due to expected drier conditions), a logical decision would consist of saving unnecessary spraying and to schedule one or two timely applications depending on the region within the state and lower yield expectation due to a higher risk of drought (Fig. 5). The average number of fungicide applications in RS state is around two (Costamilan and Ferreira 2009), regardless the overall low SBR risk derived from our study.

As far as we know, this is the first study demonstrating the potential use of probabilistic ENSO-based information in forecasting seasonal outbreaks of soybean rust 2 or more months in advance. In the continental United States, SBR forecasts are generated using complex simulation models that integrate biological, geographical and weather data to simulate spatial and temporal soybean rust progress arising from known inoculum sources early during the season (Isard et al. 2007). Other efforts in disease risk outlooks include the use of rainfall forecasts from regional climate models for the following 30 or 15 days (combined with observed 15 days) to generate maps outlining areas in the country favorable for epidemic development (Del Ponte and Yang 2006). While SBR epidemics developing in the central soybean-belt in the US will depend on inoculum surviving at the southernmost regions of the country (Christiano and Scherm 2007), SBR inoculum in Brazil is likely to survive in most regions since live hosts overwinters in the region. Hence the assumption of unlimited supply of inoculum seems justified and a forecasting scheme that considers only seasonal weather conditions would be sufficient.

Since plant diseases are likely to respond to longer-term changes in climate, ENSO-disease studies are important in the context of climate change research (Yang and Scherm 1997). Statistical approaches using indices derived from oceanic/atmospheric anomalies as predictors have the advantage of intrinsically accounting for climate change since such predictors capture trends in SST or sea level pressure that might be a consequence of a changing environment (Maia and Meinke 2009). However, if empirical evidence shows that the temporal stability of the predictor-to-response variables relationship is influenced by longer term trends in climate (decadal variability or climate change), statistical seasonal forecasting systems would require revision. Until then, these forecasting systems are still likely to provide useful information for agricultural decision making (McKeon et al. 1998).

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