Análise de sensibilidade temporal do modelo AgS agrupada por macrorregiões sojícolas

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Resumo - Análise de sensibilidade é uma técnica utilizada para quantificar quais fatores mais influenciam a saída de um modelo. Uma avaliação robusta de um modelo de crescimento de culturas agrícolas requer que essas análises sejam feitas levando em consideração os fatores que podem afetar as respostas do modelo. Tipicamente, isso se dá considerando as diversas regiões e épocas de plantio em que o modelo será usado. Uma análise de sensibilidade dos parâmetros de espécie do modelo AgS, realizada paras as macrorregiões sojícolas brasileiras, seguindo o cronograma do Zoneamento Agrícola de Risco Climático, mostrou que parâmetros ligados à evapotranspiração foram mais importantes do que os ligados à temperatura para todas as regiões. Quando houve discrepância entre os índices de sensibilidade de uma região e os das demais, isso ocorreu porque a evapotranspiração fora afetada pela água disponível no solo.

Palavras-chave: *Glycine max*, Zoneamento Agrícola de Risco Climático, Modelos de crescimento.

Temporal sensitivity analysis of the AgS model grouped by soybean-producing macro-regions

Abstract - Sensitivity analysis is a technique used to quantify which factors have the greatest influence on a model's output. A robust evaluation of a crop growth model requires that such analyses account for the factors that may affect the model's responses. Typically, this involves considering the various regions and planting seasons in which the model will be applied. A sensitivity analysis of the species parameters in the AgS model, conducted for the Brazilian soybean-producing macro-regions following the schedule of the Agricultural Zoning for Climate Risk, showed that parameters related to evapotranspiration were more important than those related to temperature across all regions. When there was a discrepancy between the sensitivity indices of one region and those of the others, it was due to evapotranspiration being affected by the available soil water.

Key-words: *Glycine max*, Agricultural Climate Risk Zoning, Crop model.

Introdução

Crop models are used to simulate the responses of crops to the environmental conditions. Through them, one can evaluate the impacts on, for example, yield, of different management practices, choices of cultivars, changes of planting dates and locations, among other factors (Wallach et al., 2019). These responses are governed by the interaction of model's parameters and equations and its inputs.

Sensitivity analysis is a technique used to determine which of these factors affect the most the model outcome (Pianosi et al., 2016). In crop model studies, weather inputs and parameters are those often assessed. Evaluating inputs often come with the expectation of understanding the crop's response to the environment. Meanwhile, evaluating parameters is often associated with model understanding or parameter calibration.

The AgS model (Cuadra et al., 2025) is being developed and calibrated for crops that are relevant to the Brazilian economy. As such, its results must be evaluated and understood for all the regions in which the model is expected to be used. We performed a sensitivity analysis of the model's parameters for several municipalities and following the planting dates recommended by the Agricultural Climate Risk Zoning (ZARC) (Monteiro et al., 2021). The analysis aimed at determining which parameters are more influential to the simulations of evapotranspiration and yield considering the different soybean producing regions in Brazil.

Material e métodos

To perform a sequential global sensitivity analysis, we needed to run the model thousands of times, varying only the elements we wanted to better understand: AgS parameters at different moments in the cycle. As we also wanted to assess the regional effect, we performed the analyses for each of the soybean edaphoclimatic macroregions (Kaster and Farias, 2012). We ranked the municipalities responsible for the highest accumulated production from 2018 to 2022, as recorded by the Brazilian Institute of Geography and Statistics (IBGE), and chose the top three in each state and macroregion to characterize the relevant growing conditions (Figure 1).

To run the simulations for the chosen locations, the model requires data regarding the weather, planting dates and soil. The model had been previously calibrated and adjusted to be compatible with the yield levels from the surveys recorded by IBGE. A post-calibration assessment was applied to determine the soil class that resulted in the lowest simulations errors. Weather was retrieved from the NASA Power database. Because dew point temperature was included, the model calculated evapotranspiration through the method FAO-56 (Allen et al., 1998). Planting dates were selected to represent the crop seasons correspondent to the ZARC dates associated with lower risk (20%), for cultivars of medium-length cycle and medium soil texture in three dates: start of the planting window, 10 days and 20 days after the start.

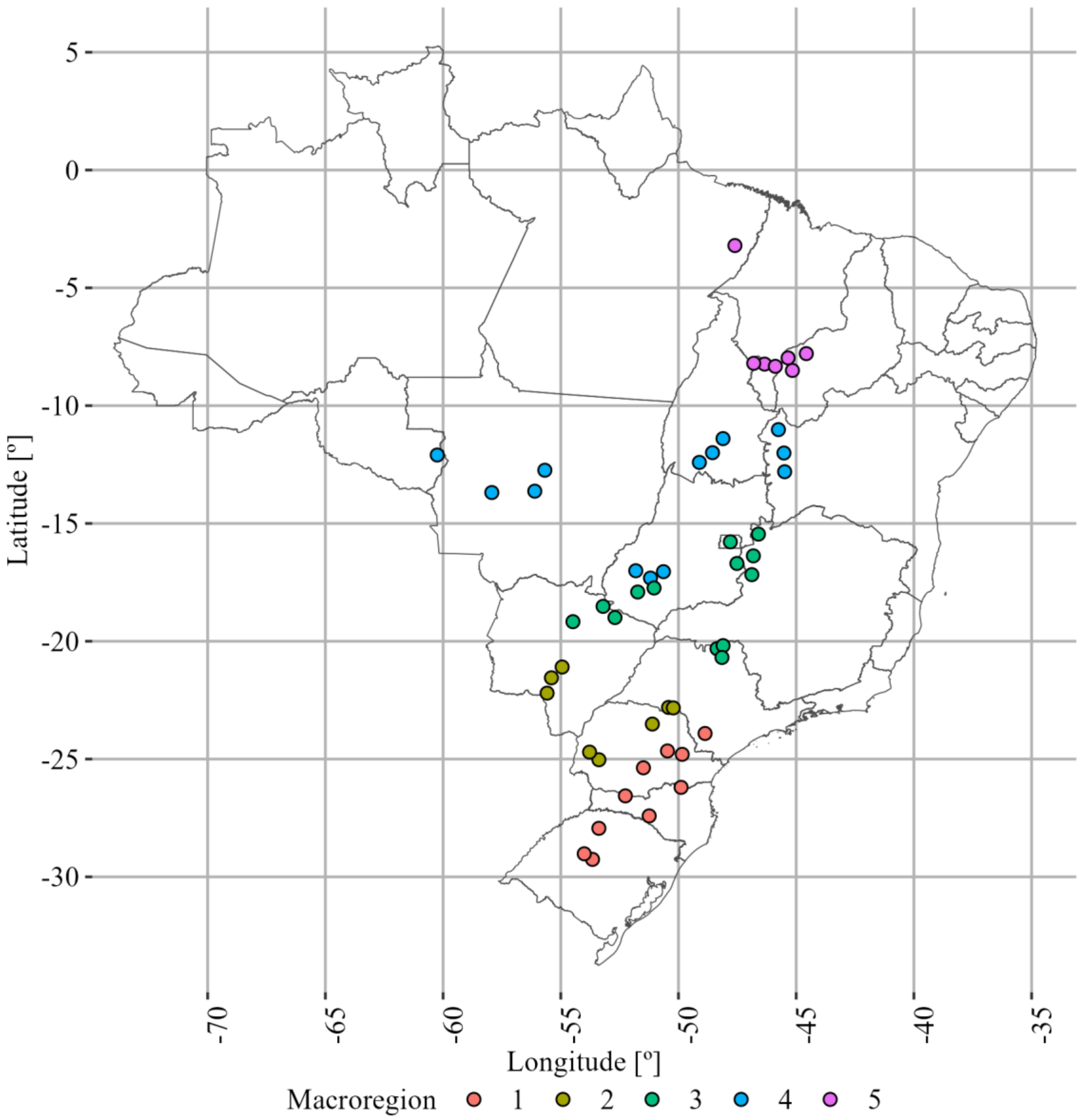

Figure 1. Locations used to retrieve the meteorological data and their associated macroregions.

The variance-based sensitivity indices, calculated using the R Package *sensobol* (Puy et al., 2022) with the default values, were determined for evapotranspiration and grain biomass, at each location and for the three planting dates, at three periods in the cycle: first third, second third and last third. The indices were calculated for the parameters from Table 1, using 10,000 initial samples drawn from a uniform distribution. The previous calibration determined the values for the many parameters that were kept fixed. Cycle length was also fixed following the thermal sum associated with the cultivar so that we could ascertain the outputs at the desired fractions of the cycle.

Tabela 1. Descrição da Tabela

Process	Parameter	Description	Lower bound	Upper bound
Biomass accumulation	Tbase	Daily temperature threshold when PGmax becomes 0 due low temperature [° C]	4	10

	Topt1	Optimal temperature for biomass production, lower threshold [° C]	16	22
	Topt2	Optimal temperature for biomass production, upper threshold [° C]	22.1	32
	ExtremeT	Daily temperature threshold when PGmax becomes 0 due high temperature [° C]	40	50
	PGmax	Maximum gross photosynthesis [g CH2O MJ^{-1}]	1.8	3
Evapotranspiration	Kcmin	Minimum crop coefficient applied to ETo [-]	0.25	1
	Kcmax	Maximum crop coefficient applied to ETo [-]	0.5	2
	KcStart	ETo from when the plant starts to reduce ET [-]	2	5
	KcSlope	Slope crop coefficient reduction when ETo goes above KcStart [-]	-0.2	-0.05
Stress effects on canopy	I50AmaxW	The maximum daily increase in I50A due to water stress [° C d]	0	15
	I50BmaxW	The maximum daily increase in I50B due to water stress [° C d]	0	7.5
Water stress effects on growth	RZDGR	Daily root growth rate [mm day^{-1}]	10	40
	DryStart	Fraction of plant available water when stress start to reduce ET [-]	0.2	0.8
Partitioning to organs	RTSP1	Root to shoot biomass before the allocation to harvestable components phase [-]	0.1017	0.2383
	RTSP2	Root to shoot biomass during the allocation to harvestable components phase [-]	0.0953	0.3247

Resultados e discussão

The first-order sensitivity index represents the individual contribution of each parameter to the total variance of the model's outputs as a result from the multiple plausible values for this parameter (Puy et al., 2022). As such, most parameters contributed with less than 5% of the overall variance of both outputs assessed, in most of the scenarios. Since even in the scenarios in which they presented higher importance, it often did not exceed 10%, we focus the discussion on those cases with higher impact either in evapotranspiration or grain biomass.

PGmax and RTSP2 impact grain biomass the most and Kcmax and Kcmin, evapotranspiration (Figure 2). Evapotranspiration is governed by the Kc coefficients and by the solar radiation interception, and therefore is only indirectly affected by PGmax, as PGmax affects leaf and LAI development and can limit radiation interception. Grain biomass, and biomass production in general, are affected by evapotranspiration coefficients and PGmax, and both outputs are affected by RZDGR; these aspects are directly connected to how the model is structured. It is interesting to note then that for all locations assessed, throughout the cycle, the parameters deemed as most important were more connected to water consumption than to temperature. Likely, for all conditions assessed, temperatures did not exceed any threshold that would trigger the model response captured by temperature parameters, either reducing biomass production or shifting the reference evapotranspiration.

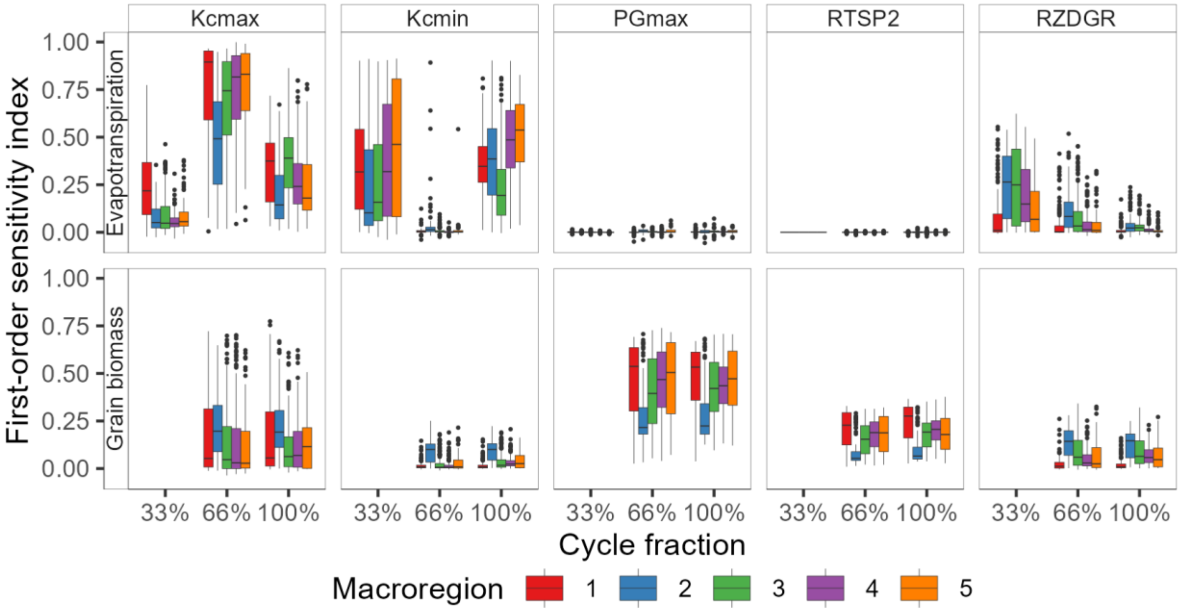

Figure 2. First-order sensitivity index associated with the grain biomass and evapotranspiration for the most important model parameters.

As for the variability in the responses associated with the different environments, it is noticeable that in Region 2 Kcmax is less impactful for evapotranspiration but more for grain biomass. There are some different aspects of this result. One is purely mathematical: because first-order indices sum to one, whichever uncertainty associated with yield caused by evapotranspiration factors is going to reduce the importance of the factors associated with biomass production. Another is that, given the predominance of lower water holding capacity of the soils selected for this region, this factor determined the outcome the most rather than potential evapotranspiration.

Similarly, through the cycle, we note the shift between Kcmax and Kcmin in the middle of the season. In this case, potential evapotranspiration could have become too high in the period and no longer dominated the process, which becomes governed by the soil water available for extraction.

Parameters could also have an additional effect as a consequence of their interactions and this is measured by the total sensitivity index. We see evapotranspiration is more susceptible to be affected by these interactions with a larger difference between the first order and the total sensitivity index (Figure 3). We also see that the regional component again appears, and that overall, Region 2 again shows higher discrepancies.

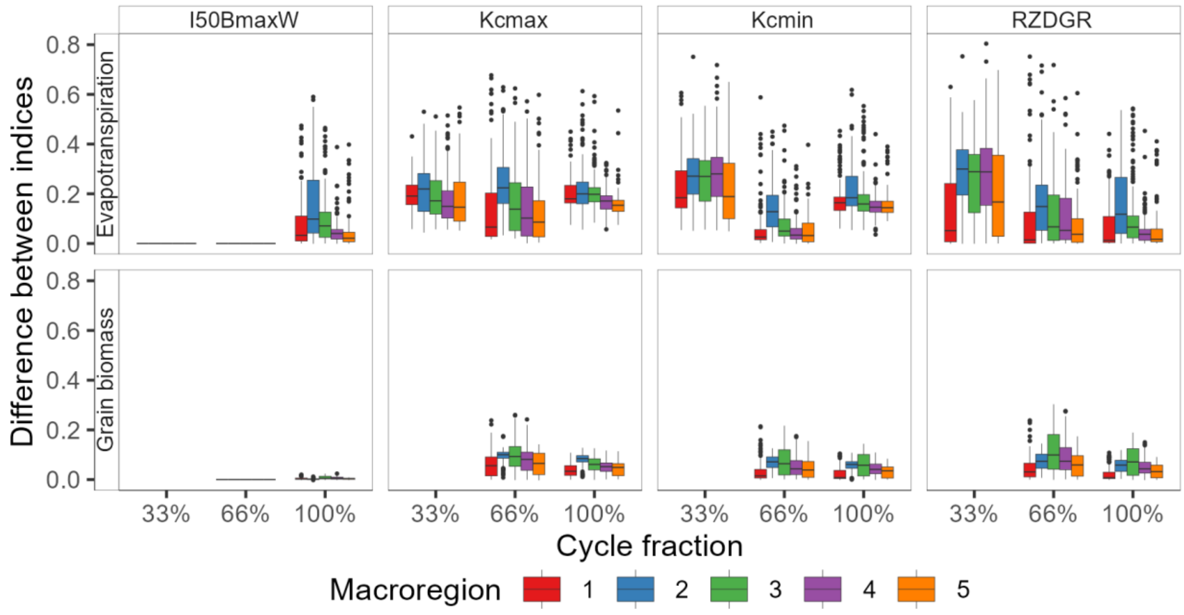

Figure 3. Difference between the total sensitivity index and the first-order sensitivity index for each scenario evaluated, associated with the grain biomass and evapotranspiration for the most important model parameters that showed interactions.

Conclusões

1. Regardless of location PGmax and RTSP2 are the overall most important parameters for grain biomass, and Kcmax and Kcmin, for evapotranspiration.

2. Responses to water consumption seem more pronounced than to temperature thresholds.

3. Evapotranspiration results are strongly connected to soil water holding capacity.

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