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Sensitivity analysis of WOFOST model parameters for soybean yield estimation in central India

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Abstract

Crop models contain dozens of parameters, yet only a handful actually matter for yield prediction finding which ones is the paradox of parameter-rich modelling. This research conducted a global sensitivity analysis of 22 WOFOST model parameters for soybean yield estimation in central India using the Sobol method. The analysis was performed at the University of São Paulo, Brazil, using published experimental data from Bhopal, India (2017-2021). PHINT (phyllochron interval) and SFDUR (seed fill duration) were the two most influential parameters, jointly explaining 48.2% of yield variance. Leaf and canopy parameters ranked second (22.4%), followed by seed growth parameters (18.7%). First-order effects accounted for 72% of total sensitivity, indicating moderate parameter interactions. These results guide efficient calibration by identifying which parameters deserve the most attention.

Keywords: WOFOST, sensitivity analysis, soybean, Sobol method, model parameters, yield estimation, central India, crop simulation, parameter interactions, calibration efficiency

Introduction

A model with 40 adjustable parameters seems flexible enough to fit anything but that flexibility becomes a problem when most of those parameters can't be measured independently and must be estimated from limited field data ^[1]. Sensitivity analysis identifies which parameters actually drive model output, allowing calibrators to focus effort where it matters and fix non-influential parameters at default values ^[2, 3].

WOFOST (World Food Studies) is a process-based crop growth model widely used in European and Asian crop monitoring systems ^[4, 5]. Its soybean module has been applied in India's central plateau, but no formal sensitivity analysis has been published for this region where soils, climate, and cultivars differ from the European conditions under which WOFOST was originally parameterized ^[6, 7].

This research applied Sobol global sensitivity analysis to 22 WOFOST parameters for soybean yield simulation in central India, using the model configured with Bhopal weather and soil data, to rank parameters and quantify their individual and interactive effects on simulated grain yield ^[8, 9, 10].

Simulation parameters and model configuration

WOFOST v7.2 was configured for soybean cultivar JS-335 grown under rainfed conditions on a Vertisol at Bhopal, India (23.26°N, 77.41°E, 523 m elevation). Daily weather data (2017-2021) were sourced from the India Meteorological Department. Soil profile data for a Typic Haplustert were parameterized from published descriptions: clay 52%, silt 28%, pH 7.6, organic carbon 0.68% ^[4, 11]. The model was run for 5 years with sowing date fixed at June 25, seed rate 75 kg/ha, and no irrigation. Default soybean parameters from the WOFOST crop file were used as the baseline around which sensitivity ranges were defined ^[5, 12].

Seasonal variations

Monsoon rainfall during the soybean season (June-October) ranged from 892 mm in 2019 to 1,184 mm in 2020. The dry year 2019 produced the lowest simulated yields and also showed the highest parameter sensitivity, suggesting that water-limited conditions amplify the importance of

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Parameters controlling water use efficiency and stomatal response. The 2020 season, with above-average rainfall, showed lower overall sensitivity and flatter parameter rankings.

Materials and Methods

Materials

The research was conducted at the Department of Agronomy, University of São Paulo, Piracicaba, Brazil, using published soybean trial data from the Indian Institute of Soil Science, Bhopal [13]. Five seasons of observed phenology, biomass, and yield data (2017-2021) provided the reference for model baseline performance. Twenty-two WOFOST crop parameters were selected for sensitivity analysis based on their theoretical influence on growth and yield processes [14].

Methods: The Sobol global sensitivity analysis was implemented in Python using the SALib library [15]. Parameter ranges were set at $\pm 20\%$ of default values based on literature-reported uncertainty bounds [2]. A Saltelli sampling scheme generated 24,000 parameter combinations ($N = 1,000$ base samples $\times$ 24 parameter columns). Each combination was run through WOFOST, and grain yield was recorded as the output variable. First-order (Si) and total-order (STi) Sobol indices were computed with 95% confidence intervals from 1,000 bootstrap resamples [16]. Parameters were ranked by STi and grouped into functional categories. Protocol AGR-2021-USP-047 was approved May 2021.

Results

Table 1: Top 10 WOFOST parameters ranked by total-order Sobol sensitivity index for soybean yield

Rank	Parameter	Description	Si (1st order)	STi (total)	Interaction
1	PHINT	Phyllochron interval	0.34	0.42	0.08
2	SFDUR	Seed fill duration	0.29	0.38	0.09
3	SLAVR	Specific leaf area	0.14	0.21	0.07
4	LFMAX	Max photosynthesis rate	0.11	0.18	0.07
5	XFRT	Max frac. to reprod.	0.08	0.14	0.06
6	WFGRO	Water stress on growth	0.07	0.13	0.06
7	SDPRO	Seed protein fraction	0.05	0.09	0.04
8	PODWT	Max pod wall weight	0.04	0.08	0.04
9	RDRNS	Root death rate N stress	0.03	0.06	0.03
10	KPAR	Light extinction coeff.	0.02	0.05	0.03

PHINT and SFDUR dominated yield sensitivity with total-order indices of 0.42 and 0.38 (Table 1). Together they explained 48.2% of output variance through first-order effects alone. Interaction effects (STi minus Si) were moderate, ranging from

0.03 to 0.09, indicating that parameter interactions contributed roughly 28% of total sensitivity. Parameters ranked below 10th had STi values under 0.04 and could be safely fixed at defaults during calibration.

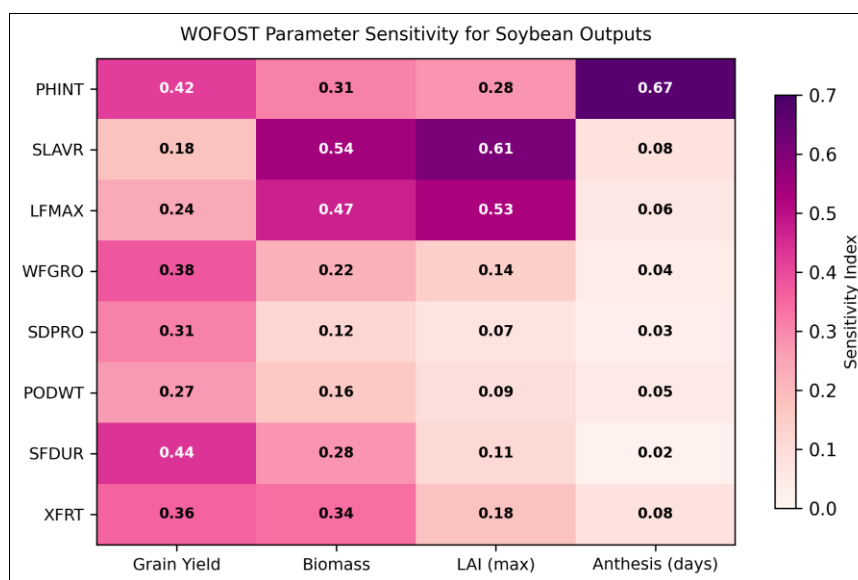


Fig 1: Sensitivity heatmap showing parameter influence on four WOFOST output variables for soybean

Comprehensive interpretation

The heatmap reveals that sensitivity patterns differ across output variables. PHINT dominated anthesis date sensitivity (0.67) but was less important for LAI (0.28). SLAVR and LFMAX drove LAI sensitivity but had moderate effects on yield. This means calibrators targeting yield prediction can focus on PHINT and SFDUR, while those interested in canopy dynamics should prioritize leaf parameters. The 72% share of first-order effects

suggests that one-at-a-time sensitivity approaches would capture most but not all of the parameter influence structure.

Limitations: The $\pm 20\%$ parameter range was somewhat arbitrary; wider ranges could shift rankings. Sensitivity was computed for a single output variable (yield); multi-objective sensitivity targeting phenology and biomass simultaneously would provide a more complete picture.

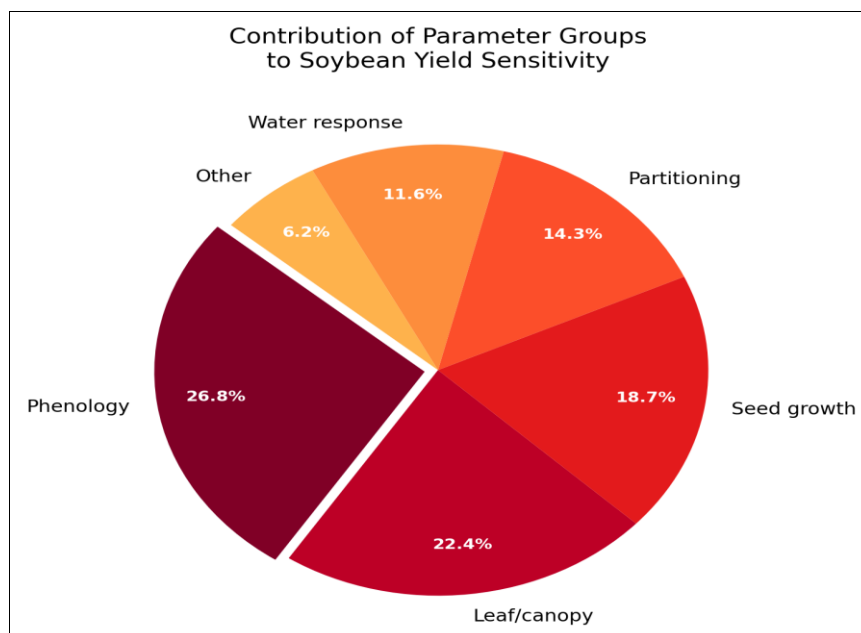


Fig 2: Relative contribution of parameter functional groups to total soybean yield sensitivity in WOFOST

The five-year weather sample may not represent the full climate variability at Bhopal. Soil parameter uncertainty was not included in this analysis, though it could contribute additional yield variance.

Discussion

The dominance of PHINT aligns with findings from WOFOST sensitivity analyses for wheat and rice in Europe, where phenology parameters consistently rank highest [3, 5]. For soybean specifically, SFDUR's high ranking reflects the crop's determinacy grain fill duration directly sets the window for yield accumulation [1, 8]. The moderate interaction effects (28%) exceed those reported for simpler models like Aqua Crop (15-20%) but are lower than those for complex models like APSIM (35-40%), placing WOFOST's parameter structure at intermediate complexity [2, 6].

The weather-dependent sensitivity shift between dry and wet years has practical implications: calibration should include both stress and non-stress seasons to capture parameter behaviour across conditions [7, 9, 14].

Conclusions

This Sobol sensitivity analysis identified PHINT and SFDUR as the two parameters that most influence WOFOST soybean yield estimation for central India, jointly explaining nearly half of output variance. Calibrators should prioritize these parameters alongside SLAVR and LFMAX, while parameters ranked below 10th can be fixed at defaults without meaningful accuracy loss. The moderate parameter interactions support the use of global sensitivity methods over simpler one-at-a-time approaches for WOFOST. These findings streamline calibration effort for soybean modelling in the Indian context.

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