Satellite Data Assimilation in Calibration of Crop Growth Model, more Emphasize on Sensitivity Analysis Techniques

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Extended Abstract

Introduction: Crop growth models are convenient tools for understanding and predicting the interactions between crop growth, environmental conditions, and land management practices such as irrigation (Servin-Palestina et al., 2022; Li et al., 2023). The crop models comprise several computational stages and parameters along with climate, soil, crop, management, temperature, salinity, fertility, and water stress conditions (Akbari et al., 2024b). These factors can significantly challenge model calibration, even potentially leading to uncertainties in the results (Guo et al., 2019).

To successfully run a crop simulation model, the selected model needs to be calibrated with accurate crop model parameters based on local soil conditions, weather, management practices, and other conservative/non-conservative parameters that may be difficult to measure locally (Shan et al., 2021). To address this challenge, it demands a spatially explicit data assimilation strategy that incorporates the observed data to calibrate the model parameters. It minimizes the difference between observed data and the state variables simulated by the crop growth model and then estimates the model parameters (Hoefsloot et al., 2012). The assimilation of the satellite-derived products and their spatial variability as pixels in each farm into such models can, to some extent, resolve the uncertainties introduced by the assumption of homogeneity in croplands (Hoefsloot et al., 2012; Jin et al., 2017).

Calibrating a crop growth model for the specific location and agricultural conditions of a region can thus be a powerful tool for developing effective water management strategies that enhance production while minimizing water consumption (Hsiao et al., 2009). Furthermore, when calibrating crop growth models on a spatial scale beyond an individual farm, it is necessary to reduce the uncertainties related to input data to account for the lack of information about land management and the structure of the model. To cope with these limitations (e.g., data scarcity, uncertainty), the pragmatic practice seeks to simplify crop growth models with fewer parameters and data requirements. It is therefore necessary to determine the minimum number of effective parameters in each of the crop growth models to achieve a more accurate and optimal model calibration, or, in other words, apply a sensitivity analysis (SA) (Silvestro et al., 2017).

Material and methods: This study examines the critical role of sensitivity analysis (SA) in model parameter calibration as a part of assimilating satellite data into crop growth models with the purpose of improving the accuracy of crop growth simulations and yield estimation. Calibration involves adjusting model parameters with the purpose of minimizing discrepancies between observed variables and model simulations. Undoubtedly, the choice of the calibration method for optimizing crop model parameters depends on the specific model and requires knowledge of its most influential and sensitive parameters, as can be defined by SA. In this light, aiming for optimizing assimilation of data streams of satellite products in crop growth modeling, it is indispensable to identify the most sensitive model parameters and those that can be fixed. Restricting input parameters reduces redundancy and uncertainty, particularly when calibrating models for specific study sites. This review explores the diversity of SA techniques applicable to crop growth models, aiding readers in choosing the best SA method for their needs.

Results and discussion: The study reveals that global SA methods are predominantly employed in crop growth model calibration practices, especially when data streams of satellite products have been assimilated into the model. As a general trend in the reviewed studies, the EFAST model tends to outperform Sobol in use and accuracy. In cases where complexity is high, it is suggested to use the Morris method for screening parameters in combination with applying the EFAST model to reduce computational complexity and crystallize the most effective parameters at relatively high accuracies. Furthermore, this review study shows the ensemble, i.e., combination, of global SA methods Morris and Extended Fourier Amplitude Sensitivity Test (EFAST) outperforms other SA methods in calculation efficiency and in precision of identifying driving parameters. Such ensemble strategies excel in finding the driving parameters, which can lead to fine-tuned calibration and, in turn, to more precise crop growth model simulations.

Conclusion: We conclude that an ensemble of global SA methods is an appropriate choice for overcoming the challenges and limitations of each technique and reducing the computational complexities when introducing satellite data assimilation into common crop growth models.

Keywords: Crop growth models; Sensitivity analysis; Satellite Data Assimilation; Calibration; Ensemble strategy.

References:

Akbari, E., Boloorani, A. D., Verrelst, J., & Pignatti, S. (2024b). Assimilating Satellite-Based Biophysical Variables Data into AquaCrop Model for Silage Maize Yield Estimation Using Water Cycle Algorithm. Remote Sensing, 16(24), 4665. https://doi.org/10.3390/rs16244665.

Guo, D.; Zhao, R.; Xing, X., & Ma, X. (2019). Global sensitivity and uncertainty analysis of the AquaCrop model for maize under different irrigation and fertilizer management conditions. Arch. Agron. Soil Sci. 1-19. https://doi.org/10.1080/03650340.2019.1657845.

Hoefsloot, P.; Ines, A. V.; van Dam, J.; Duveiller, G.; Kayitakire, F., & Hansen, J. (2012). Combining crop models and remote sensing for yield prediction: Concepts, applications and challenges for heterogeneous smallholder environments. Report of CCFAS-JRC Workshop at Joint Research Centre, Ispra, Italy, June 13-14, 2012. Joint Research Center Technical Report. Luxembourg: Publications Office of the European Union. doi:10.2788/72447.

Hsiao, T. C.; Heng, L.; Steduto, P.; Rojas-Lara, B.; Raes, D., & Fereres, E. (2009). AquaCrop—the FAO crop model to simulate yield response to water: III. Parameterization and testing for maize. Agron. J. 101(3), 448-459. Doi: 10.2134/agronj2008.0218s.

Jin, X.; Li, Z.; Yang, G.; Yang, H.; Feng, H.; Xu, X.; Wang, J.; Li, X. and Luo, J. (2017). Winter wheat yield estimation based on multi-source medium resolution optical and radar imaging data and the AquaCrop model using the particle swarm optimization algorithm. ISPRS J. Photogramm. Remote Sens. 126, 24-37. Doi: 10.1016/j.isprsjprs.2017.02.001.

Li, X.; Tan, J.; Li, H.; Wang, L.; Niu, G., & Wang, X. (2023). Sensitivity Analysis of the WOFOST Crop Model Parameters Using the EFAST Method and Verification of Its Adaptability in the Yellow River Irrigation Area, Northwest China. Agron. J. 13(9). 2294. https://doi.org/10.3390/agronomy13092294.

Servin-Palestina, M.; López-Cruz, I. L.; Zegbe-Domínguez, J. A.; Ruiz-García, A.; Salazar-Moreno, R., & Medina-García, G. (2022). Spatiotemporal Uncertainty and Sensitivity Analysis of the SIMPLE Model Applied to Common Beans for Semi-Arid Climate of Mexico. Agron. J. 12(8). 1813. https://doi.org/10.3390/agronomy12081813.

Shan, Y., Huang, M., Harris, P., & Wu, L. (2021). A sensitivity analysis of the SPACSYS model. Agriculture. 11(7), 624. https://doi.org/10.3390/agriculture11070624.

Silvestro, P. C.; Pignatti, S.; Yang, H.; Yang, G.; Pascucci, S.; Castaldi, F., & Casa, R. (2017). Sensitivity analysis of the Aquacrop and SAFYE crop models for the assessment of water limited winter wheat yield in regional scale applications. PloS one. 12(11), e0187485. Doi: 10.3390/rs9050509.

داده‌گواری سنجش از دور در کالیبراسیون مدلهای رشد محصول: با تاکید بیشتر بر روشهای تحلیل حساسیت

چکیده:

مقدمه: مدل‌های رشد محصول، ابزارهای مناسبی برای درک و پیش‌بینی تعاملات بین رشد محصول، شرایط محیطی و شیوه‌های مدیریت اراضی مانند آبیاری هستند (Servin-Palestina et al., 2022; Li et al., 2023). مدل‌های رشد محصول شامل چندین مرحله و پارامتر محاسباتی به همراه شرایط آب و هوایی، خاک، گیاه، مدیریت، دما، شوری، حاصلخیزی و تنش آبی هستند (Akbari et al., 2024b). این عوامل می‌توانند کالیبراسیون مدل را به طور قابل توجهی به چالش بکشند، حتی به طور بالقوه منجر به عدم قطعیت در نتایج شوند (Guo et al., 2019).

برای اجرای موفقیت‌آمیز یک مدل شبیه‌سازی محصول، مدل انتخاب‌شده باید با پارامترهای دقیق مدل بر اساس شرایط محلی خاک، آب و هوا، شیوه‌های مدیریتی و سایر پارامترهای conservative/non-conservative که اندازه‌گیری آنها به صورت محلی ممکن است دشوار باشد، کالیبره شود (Shan et al., 2021). برای پرداختن به این چالش، به استراتژی داده‌گواری سنجش از دور نیاز است که داده‌های مشاهده‌شده را برای کالیبره کردن پارامترهای مدل در نظر بگیرد. این استراتژی تفاوت بین داده‌های مشاهده شده و متغیرهای حالت شبیه‌سازی‌شده توسط مدل رشد محصول را به حداقل می‌رساند و سپس پارامترهای مدل را تخمین می‌زند (Hoefsloot et al., 2012). داده‌گواری محصولات مشتق‌شده از ماهواره و تغییرپذیری مکانی آنها به صورت پیکسل در هر مزرعه در چنین مدل‌هایی می‌تواند تا حدودی عدم قطعیت‌های ناشی از فرض همگنی در مزارع را برطرف کند (Hoefsloot et al., 2012; Jin et al., 2017).

بنابراین، کالیبره کردن یک مدل رشد محصول برای موقعیت مکانی خاص و شرایط کشاورزی یک منطقه می‌تواند ابزاری قدرتمند برای توسعه استراتژی‌های مؤثر مدیریت آب باشد که تولید را افزایش داده و در عین حال مصرف آب را به حداقل می‌رساند (Hsiao et al., 2009). علاوه بر این، هنگام کالیبره کردن مدل‌های رشد محصول در مقیاس مکانی فراتر از یک مزرعه منفرد، لازم است عدم قطعیت‌های مربوط به داده‌های ورودی کاهش یابد تا کمبود اطلاعات در مورد مدیریت زمین و ساختار مدل در نظر گرفته شود. برای مقابله با این محدودیت‌ها (به عنوان مثال، کمبود داده‌ها و عدم قطعیت)، روش عملی به دنبال ساده‌سازی مدل‌های رشد محصول با پارامترها و داده‌های مورد نیاز کمتر است. بنابراین، برای دستیابی به کالیبراسیون دقیق‌تر و بهینه مدل، یا به عبارت دیگر، اعمال تحلیل حساسیت (SA) ضروری است (Silvestro et al., 2017).

مواد و روشها: در این مطالعه، نقش تحلیل حساسیت (SA) را در کالیبراسیون پارامترهای مدل به عنوان بخشی از داده‌گواری داده‌های ماهواره‌ای در مدل‌های رشد محصول با هدف بهبود دقت شبیه‌سازی‌های رشد محصول و تخمین عملکرد بررسی می‌کند. کالیبراسیون شامل تنظیم پارامترهای مدل با هدف به حداقل رساندن اختلافات بین متغیرهای مشاهده شده و شبیه‌سازی‌های مدل است. بدون شک، انتخاب روش کالیبراسیون برای بهینه‌سازی پارامترهای مدل محصول به مدل خاص بستگی دارد و نیاز به آگاهی در مورد تأثیرگذارترین و حساس‌ترین پارامترهای آن دارد، که می‌توان آن را با SA تعریف کرد. در این راستا، با هدف بهینه‌سازی داده‌گواری جریان‌های داده محصولات ماهواره‌ای در مدل‌سازی رشد محصول، شناسایی حساس‌ترین پارامترهای مدل و پارامترهایی که می‌توانند ثابت در نظر گرفته شوند، ضروری است. محدود کردن پارامترهای ورودی به ویژه هنگام کالیبراسیون مدل‌ها برای مکان‌های مطالعه خاص، افزونگی و عدم قطعیت را کاهش می‌دهد. در این تحقیق، تکنیک‌های مختلف SA قابل اجرا در مدل‌های رشد محصول، بررسی می‌شود و به خوانندگان در انتخاب بهترین روش SA برای رفع نیازهایشان کمک می‌کند.

نتایج و بحث: این مطالعه نشان می‌دهد که روش‌های SA سراسری عمدتاً در کالیبراسیون مدل رشد محصول به کار می‌روند، به ویژه هنگامی که داده‌گواری محصولات ماهواره‌ای در مدل انجام شده‌اند. به عنوان یک روند کلی در مطالعات بررسی شده، مدل EFAST از نظر استفاده و دقت، عملکرد بهتری نسبت به Sobol دارد. در مواردی که پیچیدگی زیاد است، پیشنهاد می‌شود از روش موریس برای غربالگری پارامترها در ترکیب با مدل EFAST استفاده شود تا پیچیدگی محاسباتی کاهش یابد و موثرترین پارامترها با دقت نسبتاً بالا مشخص شوند. علاوه بر این، این مطالعه مروری نشان می‌دهد که ترکیب، یعنی ترکیب روش‌های SA سراسری موریس و EFAST از

سایر روش‌های SA در کارایی محاسبه و دقت شناسایی پارامترهای تاثیرگذارتر، بهتر عمل می‌کند. چنین استراتژی‌های ترکیبی در یافتن پارامترهای تاثیرگذار برتری دارند، که می‌تواند منجر به کالیبراسیون دقیق و به نوبه خود، شبیه‌سازی‌های دقیق‌تر مدل رشد محصول شود.
نتیجه‌گیری: نتیجه گرفته می‌شود که ترکیبی از روش‌های سراسری SA، انتخاب مناسبی برای غلبه بر چالش‌ها و محدودیت‌های هر تکنیک و کاهش پیچیدگی‌های محاسباتی هنگام وارد کردن و داده‌گواری داده‌های ماهواره‌ای به مدل‌های رایج رشد محصول است.

کلمات کلیدی: مدل‌های رشد محصول؛ تحلیل حساسیت؛ داده‌گواری داده‌های ماهواره‌ای؛ کالیبراسیون؛ استراتژی ترکیبی.

1 Introduction

Crop growth models are convenient tools for understanding and predicting the interactions between crop growth, environmental conditions, and land management practices such as irrigation (Servin-Palestina et al., 2022; Li et al., 2023). In essence, crop growth models aim to translate natural processes into mathematical equations, which involve certain assumptions and simplifications of realities, with the risk of introducing uncertainty and inaccuracies in a model output (Ma et al., 2023). In all generality, crop models are built upon complex relationships and parameters that vary with cultivars, field management, and environmental conditions. The crop models comprise several computational stages and parameters along with climate, soil, crop, management, temperature, salinity, fertility, and water stress conditions. The models mainly simulate crop yield by defining conservative and non-conservative parameters (Akbari et al., 2024b). Conservative parameters of the crop growth models are crop specific, but do not change with cultivar, time, management practices, geographic locations, or climate (Raes et al., 2017). These parameters are not supposed to require a local calibration for a well-studied crop such as wheat, but would need to be calibrated using data from multiple locations for a species new to crop growth models (Silvestro et al., 2017). Readers can refer to appendix1 of Akbari et al., (2024a) for more information and examples. The conservative and non-conservative parameters can significantly challenge model calibration, even potentially leading to uncertainties in the results (Guo et al., 2019).
To successfully run a crop simulation model, the selected model needs to be calibrated with accurate crop model parameters based on local soil conditions, weather, management practices, and other conservative/non-conservative parameters that may be difficult to measure locally (Shan et al., 2021). To address this challenge, it demands a spatially explicit data assimilation strategy that incorporates the observed data to calibrate the model parameters. It minimizes the difference between observed data and the state variables simulated by the crop growth model and then estimates the model parameters (Hoefsloot et al., 2012). Compared to ground survey data, data streams of the satellite-derived products can be acquired at a significantly lower cost and in less time, accounting for larger areas and virtually all stages of crop growth (Hassanpour et al., 2024). The assimilation of the satellite-derived products (such as fraction vegetation cover (FVC), and leaf area index (LAI)) and their spatial variability as pixels in each farm into such models can, to some extent, resolve the uncertainties introduced by the assumption of homogeneity in croplands (Jin et al., 2017). Vegetation biophysical variables extracted from optical satellite data, including biomass, FVC, and LAI, are predominantly used as observed variables and assimilated into crop growth models for calibration (Jin et al., 2018a), but also other used observed variables such as soil moisture (SM), and evapotranspiration (ET) can be produced by radar and thermal satellite data (Ines et al., 2013; Huang et al., 2015b; Jin et al., 2018a; Akbari, 2023).
The default values for the parameters of crop growth models are provided based on some average conditions of crop type, climate, and management practices. Anticipatingly, parameterization accounting for local environmental conditions leads to more accurate calibrations, and that can be customized to different conditions and regions (Vanuytrecht et al., 2014). For instance, crop growth models become of growing importance for optimizing irrigation management as water scarcity

intensifies due to irregular rainfall and frequent droughts (Zhang et al., 2022). Calibrating a crop growth model for the specific location and agricultural conditions of a region can thus be a powerful tool for developing effective water management strategies that enhance production while minimizing water consumption (Hsiao et al., 2009). Furthermore, when calibrating crop growth models on a spatial scale beyond an individual farm, it is necessary to reduce the uncertainties related to input data to account for the lack of information about land management and the structure of the model.

To cope with these limitations (e.g., data scarcity, and uncertainty), the pragmatic practice seeks to simplify crop growth models with fewer parameters and data requirements. Typically, the values of the less effective parameters in the crop growth model can be treated as constant. At the same time, identifying the key model input parameters and variables that drive the output is fundamental for all applications relying on crop growth models (Akbari et al., 2024a). Also, limitations in the data access affect proper estimation of the key model input parameters and cause additional uncertainty, especially in assimilating satellite data into crop growth models (Huang et al., 2019). It is therefore necessary to determine the minimum number of effective parameters in each of the crop growth models to achieve a more accurate and optimal model calibration, or, in other words, apply a sensitivity analysis (SA) (Silvestro et al., 2017). To minimize those uncertainties, a proper way of deducing the impacts from each parameter involved in crop growth models is applying a SA. A SA is essentially a process for estimating and evaluating how the model output is sensitive to "uncertain" parameters (Vanuytrecht et al., 2014; Silvestro et al., 2017; Lu et al., 2021). The primary objective of an SA is to estimate and identify the degree of impact coming from parameters in process-based models (Ma et al., 2023; Guo et al., 2019; de Souza et al., 2022). Alternatively put, SA identifies the impacts of uncertain parameters on the model outputs as a key process for understanding how the model behaves (Specka et al., 2019). SA also serves in determining: (1) less influential parameters that could be considered as constants to further simplify the model for optimal calibration; and, (2) parameters with the highest impact that can be used to calibrate the crop growth model, thus providing guidelines for managerial strategies and policies in agriculture (Krishnan et al., 2021).

Yet, the SA results are likewise influenced by the environmental conditions in which the model is implemented, such as different climatic and geographical regions, soil types, etc. Therefore, it is important to investigate the general sensitivity of the model in various environmental conditions (Vanuytrecht et al., 2014). Further, in traditional model calibration, conducted studies typically assumed average parameter values from similar conditions (e.g., (Andarzian et al, 2011; Jin et al., 2014; Ahmadi et al., 2015; Tavakoli et al., 2015; Hassanli et al., 2016; Sarangi et al., 2016; Wang et al., 2022). This implies that the assumption of the model or the experience of the experts determines the effective parameters and their values. Alternatively, after identifying more effective parameters in the model through SA, for an increasing number of crop growth models, it is possible to optimize their values with satellite data assimilation methods (Silvestro et al., 2017). To fine-tune and streamline the ingestion of relevant satellite products requires evaluating what types of SA methods are applicable for analyzing and identifying the most effective parameters of crop growth models.

In light of the above-discussed importance of SA strategy in satellite data assimilation into crop growth models, this review dives into evaluating popular SA techniques, highlighting their advantages and limitations for crop growth modeling applications. This literature survey was conducted to broaden academic spheres and attract researchers toward identifying the most effective parameters for optimizing and adjusting crop growth model parameters using satellite data assimilation. The rationale pursued here is that crop growth models can be better fine-tuned through parameter adjustments, ultimately leading to more integrated models with the output estimates (such as yield, crop response to environmental stress, optimizing resource use, and informing management decisions) closer to actual land survey measurements. Altogether, the objectives of our study are threefold: (1) a literature review of studies conducted in the scope of SA methods applied to crop growth models; (2) an assessment of the advantages and challenges of SA methods used in crop growth models; and (3) a discussion of satellite data assimilation into crop growth models for their calibration and the following steps, the crop model challenges and solutions.

2 Crop Growth Models

Spanning nearly 40 years of developments, crop growth models have shifted from initial qualitative simulations of growth dependent on single growth processes (i.e., physiological and ecological) to quantitative simulations that cover all crop growth processes (Jin et al., 2018a). During these years, a diversity of models was introduced and subsequently progressively optimized and updated, including WOrld FOod STudies (WOFOST) (Van Diepen et al., 1989), Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 1998), Agricultural Production Systems sIMulator (APSIM) (McCown et al., 1996), Simulateur mulTIdisciplinaire pour les. Cultures Standard (STICS) (Brisson et al., 1998), MOdel of Nitrogen and Carbon dynamics in Agro-ecosystems (MONICA) (Nendel et al., 2011), DAta Information SYstem (DAISY) (Abrahamsen and Hansen, 2000), and Aquacrop (Hsiao et al., 2009; Steduto et al., 2009) to simulate the various states of crop growth and improve the estimation of crop yield (Jin et al., 2018a; Akbari, 2023). Over time, crop growth model developers have strived to enhance our ability to analyze how crops respond to changes in management practices and environmental conditions worldwide. This ongoing effort involves continuous model refinement to better reflect real-world processes (Wang et al., 2024). Concurrently, model users actively seek to optimize model performance by comprehensively calibrating crop growth models across diverse crops and environmental conditions globally.

On the application side, factors influencing model selection in crop growth simulation studies include study objectives, accuracy, complexity, and flexibility. Another determining factor is the number of input parameters, which the number of parameters depending on the model complexity, with more parameters requiring more data to insert and tune. Challenges related to accessibility and data collection can impede the application of these models. In these situations, the common practice is to parameterize the model with values coming from previous studies, which in turn may introduce a degree of uncertainty (Akbari, 2023). To address this challenge and reduce uncertainty, users often attempt to constrain non-influential parameters based on specific environmental conditions and crop types. For achieving this purpose, several SA methods can be applied for evaluating driver and non-influential parameters, as will be outlined in the next sections.

3 Types of Sensitivity Analysis

SA refers to methods that measure changes in the output y of a model given the input variables X1, X2, …, Xm. Essentially, SA attempts to answer the questions: (1) which input variables cause the greatest change in the model output?; (2) which factors have no significant impact on the output?; and (3) whether hidden correlations can be identified among multiple factors that amplify or attenuate the effects of individual parameters? Selecting a specific SA method critically affects the identified driving parameters and the perceived model behavior. We can distinguish different types of sensitivity analysis depending on how these questions are formulated and addressed. In the following, we introduce the main categories of SA methods based on Pianosi et al., (2016).

3.1 Local and Global Sensitivity Analysis

Generally, SA can be categorized into two strategies: (1) local and (2) global. Local sensitivity analysis (LSA) seeks to measure the effects of changes in an individual factor x on the model output. In contrast, global sensitivity analysis (GSA) measures the impact of changes in the entire input variance scale on the output. Consequently, LSA depends strongly on a single value x as the input variable, while GSA expands further towards incorporating the entire range of variance for a given input variable x (Saltelli et al., 2008).

Local methods only evaluate the impacts of each input parameter on the model output, while the effects of other parameters are considered constant, arbitrary values. LSA is not well-suited for analyzing crop growth models due to the complexity of the models and the extensive prior knowledge required to define and tune parameters and their interactions (Cariboni et al., 2007). Also, Saltelli & Annoni (2010) argued that local methods are inefficient for identifying the most impactful parameters in nonlinear models. For these reasons, the GSA is a more suitable choice. GSA methods can evaluate the effects of simultaneous changes in some or all input parameters on the model output (Saltelli et al., 2008).

3.2 One-at-a-Time and All-at-a-time sensitivity analysis

Regarding sampling methods used in SA for estimating SA indices, SA is categorized to one-at-a-time (OAT) and all-at-a-time (AAT). In general, SA indices are impossible to measure analytically given the complex network of relations between inputs and outputs and thus can only be calculated based on certain sample inputs for evaluating model outputs. The difference between OAT and AAT lies in their approach to input sample selection. In the OAT format, changes in output are measured against changes in one input factor at a time, while other parameters are kept constant. AAT approaches measure the output variance based on changes in all input factors at once, thereby accounting for the direct impacts of a specific factor and indirect implications from other correlating factors.

LSA uses OAT sampling, whereas GSA can use both OAT and AAT strategies. Overall, AAT methods produce finer descriptions of the inherent relations between input variables, some of which (including variance-based methods) allow the user to analyze correlations between factors. The disadvantage of AAT is found in its need for wider ranges of sampling and therefore further evaluation of models (Pianosi et al., 2016). For these reasons, the combination of OAT and AAT is a more suitable choice to reduce temporal complexities and increase GSA accuracy in complex crop growth models especially in satellite data assimilation into calibration of the models.

3.3 Quantitative and qualitative sensitivity analysis

Another way to categorize SA methods is into: (1) quantitative or (2) qualitative analysis. Quantitative SA is the term often used to present methods in which the input factors are represented as repeatable quantities and the correlative impacts between factors are identified based on a set of SA principal indices (Pianosi et al., 2016). So, quantitative SA serves as a powerful tool for understanding how much various input factors influence a model's output. It goes beyond simply identifying which factors are important; it quantifies their influence using mathematical techniques and specialized indices.

Qualitative SA takes a distinct approach as opposed to its quantitative counterpart. Here, the focus is not on precise numbers but rather on gaining a visual understanding of how the model behaves under different conditions (DeJonge et al., 2012). This qualitative exploration facilitates researchers to identify key factors influencing the model and potential areas of concern. So, for satellite data assimilation into calibration of the crop growth models, the qualitative exploration is a more suitable choice to find important parameters of these models with SA.

3.4 Objectives (adjustment) of sensitivity analysis

Selecting the appropriate SA method depends on the research objectives, as each method has unique strengths. Three objectives/purposes can be identified for SA; (1) Ranking (prioritizing factors) input variables X1, X2, …, Xm, with respect to their relative contribution to changes in the model output; (2) Screening (factor fixing) for purposes of identifying input factors with insignificant impacts on the model output (or negligible influence on the output variability); (3) Mapping or Visualizing the variance space for input parameters with significant impacts on the model output (Saltelli et al., 2008). Mapping aims at determining the region of the input variability space that produces significant, e.g., extreme, output values (Pianosi et al., 2016). The Morris and Extended Fourier Amplitude Sensitivity Test (EFAST) methods are used as screening and visualizing the variance space for input parameters as more explain in the next section.

4 **Screening and Variance-based Methods** Frequently Used in SA on crop growth models

According to reviewed SA literature on crop growth models, the Morris and EFAST methods are frequently used as screening and variance-based methods in GSA, so, to prevent increasing the size of the article, we only explain these methods.

The Morris method, the most common method for screening purposes, is based on OAT sampling, where one input factor varies while other factors are considered constant (Iooss & Lemaître, 2015). Screening methods such as Morris (Morris, 1991), are often used before implementing global methods such as EFAST (Saltelli et al., 1999) to identify the least and most effective parameters. The former is then considered constant and excluded from complex variance-based processes (Vanuytrecht et al., 2014). Such combinative approaches have also proven to be successful, as shown in several studies (Vanuytrecht et al., 2014; Akbari et al., 2024a; Silvestro et al., 2017; Lu et al., 2021; Specka et al., 2019; Sun et al., 2012; Upreti et al., 2020; Akbari, 2020; Colombi et al., 2022).

When used for identifying the sensitivity of parameters, the Morris method starts with an initial evaluation of the impacts coming from all parameters (d_i) on the model output (equation 1).

$$d_i\,(x_1, x_2, \ldots, x_k, \Delta) = \frac{[y(x_1, \ldots, x_{i-1}, x_{i+\Delta}.x_{i+1}, \ldots, x_k)]}{\Delta}, \tag{1}$$

where y(x) is the model output, X= (x_1, x_2, …, x_k) is the k-dimensional parameters vector, and Δ is the pre-assumed value equivalent to 1/(p-1), in which p is the number of levels corresponding to parameter distribution values. The absolute mean for initial impacts (μ*) represents the most influential parameters in the model (equation 2).

$$EE_{ij} = \frac{Y\,(X_1,\ X_2,\ \ldots, X_i + \Delta_i\ ,\ \ldots, X_k) - Y\,(X_1,\ X_2,\ \ldots, X_i.\ \ldots, X_k)}{\Delta_i} \tag{2}$$

$$\mu_j^* = \frac{1}{r}\sum_{i=1}^{r} |EE_{i,j}|$$

$$\sigma_j = \sqrt{\frac{1}{r}\sum_{i=1}^{r} (EE_{i,j} - \frac{1}{r}\sum_{i=1}^{r} (EE_{i,j}))^2}\,,$$

where EE is the initial effects, r shows the number of trajectories, and μ^* and σj are the absolute mean and standard deviation for initial effects used for measuring the Morris sensitivity value and uncertainty, respectively (Franczyk, 2019). Higher values of μ^* represent more effective parameters. The primary advantage of the Morris model is its relatively low complexity.

Variance-based GSA methods are distinguished based on different sampling methods in the parameter search space. These methods look for more effective parameters iteratively, the EFAST method considers the search space of each continuous parameter in a non-linear mode. In this method, the search space is defined based on the search curve of the sin function, and in multiple iterations, combinations of different parameters are considered, and the output variance is calculated (Vanuytrecht et al., 2014), and applying the Fourier transform to the Y function obtains the variance based on this function (XING et al., 2017).

Higher-order relations between input parameters are also included in this model in the form of output variance V(Y), as formulated in equation (3).

$$V(Y) = \sum_{i=1}^{m} V_i + \sum_{1\leq i\leq j\leq m} V_{ij} + \cdots + V_{1\ldots m}, \tag{3}$$

where $V_i = V[E(Y/x_i)]$ is the primary effect from parameter x_i with $E(Y/x_i)$ and $V_{1 \ldots m}$, in which V_{ij} refers to relations among m parameters.

GSA methods measure two sensitivity indices for each parameter, i.e., the Main Sensitivity Index (S_i) (first-order) and Total Sensitivity Index (ST_i) (including higher-order effects) (equation 4). S_i is the contribution of a single parameter to the output variance, whereas ST_i refers to the relations between parameters. S_i and ST_i range from 0 to 1, where higher values represent the more significant and effective parameters:

$$S_i = \frac{V_i}{V(Y)} \qquad ST_i = \frac{V(Y) - V_{-i}}{V(Y)} \tag{4}$$

where V_{-i}, is the sum of all variances excluding i (Pianosi et al., 2016). It should be mentioned that the temporal complexity of the EFAST model is much higher than the Morris method (Vanuytrecht et al., 2014).

5 Sensitivity Analysis Studies on Crop Growth Models

Table 1 lists some of the studies conducted in the scope of SA for crop growth models. This table illustrates the types of SA (i.e., local/global) methods and the SA purposes and methods in each crop growth model. The studies have been mostly employed using GSA methods, and specifically ranking (variance-based) methods. This table reveals the dominance of the EFAST method to achieve SA in crop growth models. The table also highlights the growing emphasis on SA within crop growth modeling research, with a significant proportion of studies conducted in recent years, particularly during the current decade. SA ensemble strategies in our paper refer to combining multiple SA methods to improve the accuracy and robustness of the results. This can be particularly useful when dealing with complex models with many uncertain parameters. So, ensemble strategies can achieve a deeper understanding of the driving factors that influence the behavior of complex models (Silvestro et al., 2017).

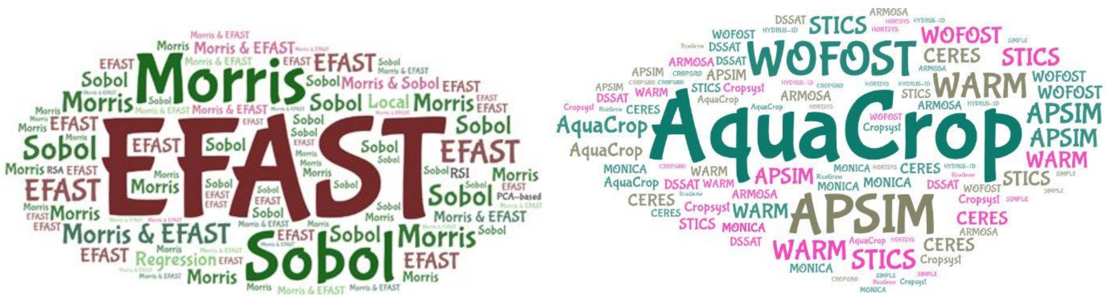
Table 1. Research in the field of SA of crop growth models. The search has been conducted by 31 December 2024.

Crop growth model	Types of SA (Local/Global)	SA Purpose	SA Method	References
CROPGRO	local and Global	unclear/absent	unclear/absent	Pathak et al., (2007)
	Global	Ranking (Variance-based	EFAST	Xu et al., (2021)
CropSyst, WARM and WOFOST	Global	Screening	Morris	Confalonieri et al., (2006)
CERES	Global	Ranking	PCA-based, sequential	Lamboni et al., (2009)
		Screening and Ranking (Variance-based)	Morris and Sobol	Dejonge et al. (2012)
		Ranking (Variance-based)	Sobol	Ge et al., (2021)
			EFAST	Ma et al., (2023)
WARM	Global	Screening and Ranking (Variance-based)	Variance (Sobol, EFAST), Screening (Morris), Regression method (Latin hypercube, Quasi-Random LpTau)	Confalonieri et al., (2010a)
	Global	Screening and Ranking (Variance-based)	Morris and Sobol	Confalonieri et al. (2010b)
STICS	Global	Ranking (Variance-based)	EFAST	Varella et al., (2010; 2012)
			Sobol	Chen & Cournède, (2014)
SWAP-EPIC	Global	Ranking (Variance-based	Regression method (Latin Hypercube and OAT sampling)	Xu et al., (2016)
HYDRUS-1D	Global	Ranking (Variance-based)	EFAST	Zeng et al., (2018)
MONICA	Global	Screening and Ranking (Variance-based)	Morris and EFAST	Specka et al., (2019)
		Ranking (Variance-based)	Sobol	Gasanov et al., (2020)
SSM_iCrop2	Local		Local SA	Nehbandani et al., (2020)
RiceGrow	Global	Ranking (Variance-based)	EFAST	Meng et al., (2021)
HORTSYST	Global	Ranking (Variance-based)	Sobol	Martinez-Ruiz et al., (2021)
ARMOSA	Global	Screening and Ranking (Variance-based)	Morris and Sobol	Colombi et al., (2022) Colombi et al., (2024)
WOFOST	Global	Ranking (Variance-based)	EFAST	Wang et al. (2013b); QIN et al., (2022); Li et al., (2023); Ruan et al., (2024)
			Sobol	Li et al., (2024a)
		Ranking and Mapping	RSA	Shafiei et al., (2018)
WheatSM	Global	Ranking (Variance-based)	Sobol	Li et al., (2024a)
STICS, CropSyst and WOFOST	Global	Screening and Ranking (Variance-based	Morris and EFAST	Paleari et al., (2021)
APSIM	Global	Ranking (Variance-based)	EFAST	Zhao et al. (2014); WEI and NIE (2024)
		Screening	Morris	Chenu et al., (2016); Casadebaig et al., (2016)
		Ranking (Variance-based)	EFAST	Liu et al., (2019)
			Sobol	Hao et al., (2021); Hao et al., (2024)
			EFAST	Zhang et al., (2023)
DSSAT	Global	Screening and Ranking (Variance-based)	Morris and EFAST	Song et al., (2014)
		unclear/absent	Regression method (Co-inertia analysis based on Latin Hypercube Sampling method)	Corbeels et al., (2016)
		Ranking (Variance-based	Sobol	Attia et al., (2021)

Crop growth model	Types of SA (Local/Global)	SA Purpose	SA Method	References
CROPGRO	local and Global	unclear/absent	unclear/absent	Pathak et al., (2007)
	Global	Ranking (Variance-based	EFAST	Xu et al., (2021)
SIMPLE	Global	Ranking (Variance-based	Sobol	Servin-Palestina et al., (2022)
InfoCrop	Global	unclear/absent	Regression method (Co-inertia analysis based on Latin Hypercube Sampling method)	Krishnan et al., (2021)
SAMUCA	Global	Ranking (Variance-based)	EFAST	Pereira et al., (2023)
Functional-Structural Plant Model	Global		Relative sensitivity index	Rutjens et al., (2024)
ORYZA-N	Global	Ranking (Variance-based)	EFAST	Gao et al., (2024)
AquaCrop	Global	Ranking (Variance-based)	EFAST	Xing et al. (2016); XING et al., (2017); Jin et al., (2018b); Guo et al., (2019); Li et al., (2024b)
		Screening and Ranking (Variance-based)	Morris and EFAST	Silvestro et al., (2017)
		Screening and Ranking (Variance-based)	Morris, EFAST, density-based PAWN method	Upreti et al., (2020)
			Morris and EFAST	Vanuytrecht et al., (2014); Akbari (2020); Lu et al., (2021); Akbari et al., (2024a)
			Morris and FAST	Oulaid et al., (2024)
		Ranking (Variance-based)	Sobol	Rahimikhoob et al., (2023)
		unclear/absent	Relative sensitivity index	de Souza et al., (2022); Rosa et al., (2023)
	Local	unclear/absent	Local SA	Adabi et al., (2020); Haruna et al., (2023)

Extended Fourier Amplitude Sensitivity Test (EFAST), Water Accounting Rice Model (WARM), One-factor-At-a-Time (OAT), Agricultural Production Systems sIMulator (APSIM), WOrld FOod STudies (WOFOST), decision support system for agrotechnology transfer (DSSAT), Simulateur mulTIdisciplinaire pour les Cultures Standard (STICS), Crop Environment Resource Synthesis (CERES), Soil Water Atmosphere Plant (SWAP), regional sensitivity analysis (RSA).

A tag cloud visually highlights key themes, with word size reflecting frequency. Figure 1 illustrates the frequency of methodologies used concerning: (a) SA methods applied in crop growth models, and (b) the crop growth models were assessed by SA over the years (2006 - 2024). This figure proves that the EFAST method has been predominantly used to achieve SA in crop growth models, and the Sobol, Morris, and ensemble of Morris and EFAST methods are the next logical models, too. Also, this figure illustrates more SA studies applied in crop growth models, especially AquaCrop, but also APSIM, WOFOST, and WARM models, respectively. Among the most common crop growth models, the DSSAT model is underrepresented in SA evaluations, appearing only three times across all methods.



(A) **(B)**

Figure 1. (**A**) A tag cloud of the literature methods related to SA methods used in crop growth models and (**B**) the assessed crop growth models with SA, where a larger font denotes a higher frequency in consulted studies. The number of assessed studies about SA in crop growth models between 2006-2024 were 65.

To illustrate what types of GSA methods are most commonly used in crop models (i.e., Morris, Sobol, EFAST, ensemble of Morris and EFAST, and ensemble of Morris and Sobol), we attempt to show in separate subfigures (A) Morris, (B) Sobol, and EFAST, (C) ensemble of Morris and EFAST, and ensemble of Morris and Sobol (Figure 2). Based on this figure, we can conclude which GSA methods were used in what crop model yearly and also the research gap of enhancing driver parameters for satellite data assimilation calibration. The Morris method alone as a screening strategy can recognize the less important parameters, so this method is hardly used in complex crop growth models (e.g., DSSAT) where there is more relationship between parameters (subfigure A). Among variance-based GSA methods, which are capable of evaluating parameter interactions, the EFAST method has been more frequently employed than the Sobol method for identifying key drivers in crop growth models, as evidenced in subfigure B. The figure further reveals a strong preference for the EFAST method, either used independently or within ensemble strategies. Based on subfigure C of the figure, the ensemble of the Morris and EFAST SA method was used in DSSAT, STICS, CropSyst, WOFOST, and MONICA models in one study and seven times in the AquaCrop model. That figure also revealed little attention to the use of the Morris and EFAST GSA in crop growth models, especially in complex models. Noteworthy, the ensemble GSA strategy (especially Morris and EFAST methods) was not considered in the APSIM crop model studies. So, further developments are encouraged in applying GSA ensemble methods to other crop models.

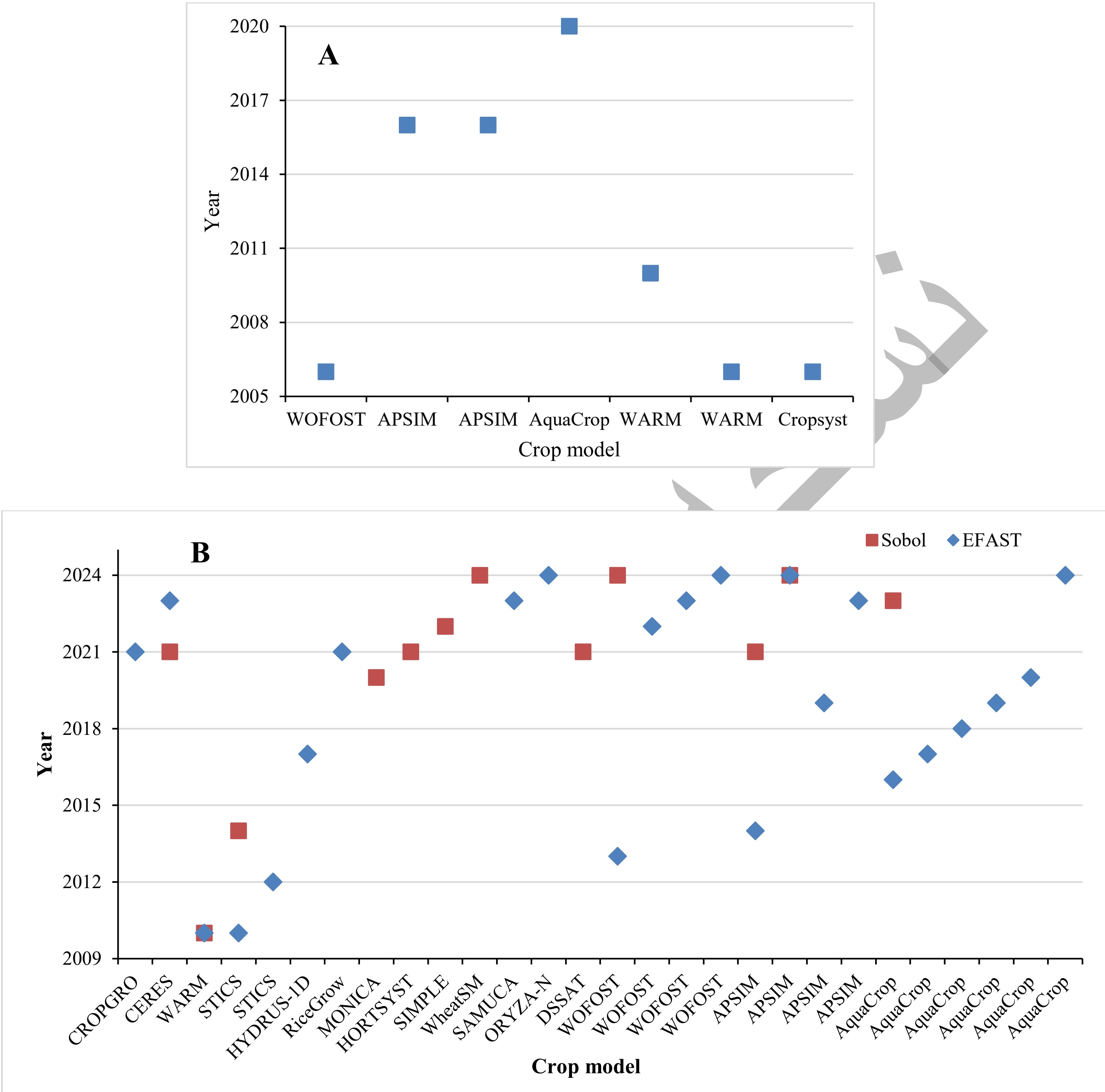


Figure 2. SA methods used in crop models in each year. (**A**) Morris, (**B**) Sobol, and EFAST, (**C**) ensemble of Morris and EFAST, and ensemble of Morris and Sobol.

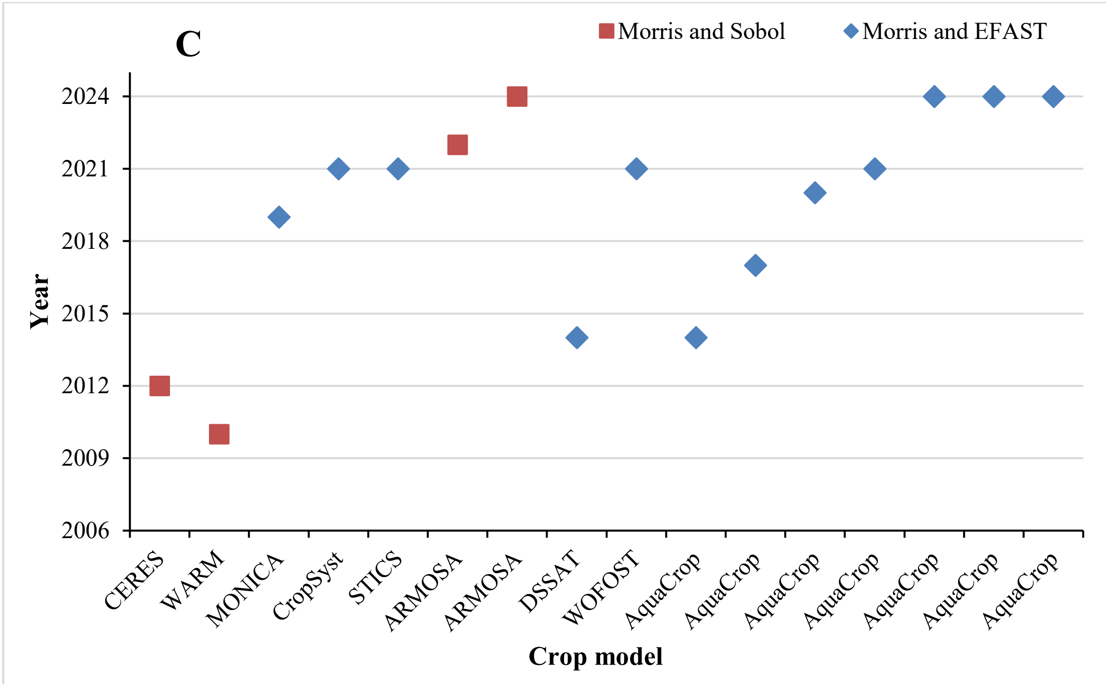


Figure 2. Continued. SA methods used in crop models in each year. (**A**) Morris, (**B**) Sobol, and EFAST, (**C**) ensemble of Morris and EFAST, and ensemble of Morris and Sobol.

We cannot conclude which parameters were found to be most sensitive to particular simulated outputs due to the following reasons. GSA assessment of model parameters is highly dependent on environmental conditions and the crop type under study, such that no single GSA scenario can be interchangeably used for a range of climatic and environmental circumstances (Zhao et al., 2014; Vanuytrecht et al., 2014; Xing et al., 2016; Silvestro et al., 2017; Xing et al., 2017). GSA results thus vary for different environmental conditions, not only in terms of the magnitude of impact, but also in terms of the order and ranking of parameters. EFAST is more coherent compared to the Morris method, and it prioritizes and sequences parameters more stably across a range of environmental circumstances (Vanuytrecht et al., 2014; Silvestro et al., 2017). Hence, the Morris method can only be used to screen fewer sensitive parameters, and can only rank parameters qualitatively and not quantitatively (Dejonge et al., 2012; Vanuytrecht et al., 2014). It is essential to determine the correct range of variation in parameter values. The GSA results are related to corresponding environmental conditions, so inhibits the generalizability of results to other regions (Wang et al., 2013b). So, readers can select the best strategy of SA for their own studies by comparing this article reviewed findings, and advantages/ challenges of SA methods.

6 Advantages and Challenges of SA Methods in Crop Growth Models

This section addresses the advantages and challenges of SA methods used in crop growth models by undertaking a systematic literature review. A combination (i.e., ensemble) of the Morris and Sobol methods was also proposed by Confalonieri et al. (2010a) as a technique to incorporate the simplicity of the Morris model for identifying fewer effective parameters to reduce the number of parameters in the Sobol method. Various GSA methods were applied to the WARM crop growth model by Confalonieri et al. (2010a) (table 1). As per their results, for a crop model of average complexity such as WARM, the Morris method is the simplest approach to GSA with comparable performance to more computationally expensive methods such as regression-based methods. Variance-based GSA methods are more suitable for conditions where the number of model parameters is limited or some parameters can be considered constant. This result was also confirmed by (Confalonieri et al., 2010b), who analyzed the combination of these two methods for evaluating the WARM crop growth model, indicating reductions in the complexity of the Sobol method after using the Morris approach to identify the least effective parameters.

Sobol and EFAST are the most prominent variance-based GSA methods employed in the assessment of crop growth models. Both methods are relatively similar in performance and temporal complexity, albeit the EFAST model produces superior evaluations of how correlations between parameters affect the model variance compared to Sobol (Saltelli et al., 1999). Vanuytrecht et al. (2014) confirmed the proposed strategy of (Confalonieri et al., 2010a) for combining Morris with Sobol, with a slight adjustment of using EFAST instead of Sobol, given the mentioned advantages. They initially used Morris for screening out the least effective parameters and then used variance-based EFAST to measure the output sensitivity of the AquaCrop model to varying environmental conditions and model parameters. Silvestro et al. (2017) likewise highlighted EFAST's superiority over Morris as a more integrated sensitivity analysis method, a finding corroborated by studies (Cariboni et al., 2007; DeJonge et al., 2012). EFAST effectively accounts for varying environmental scenarios, enabling robust and consistent parameter ranking. The Morris method serves thus better for initial screening of the least effective parameters, as reported by (Vanuytrecht et al., 2014; DeJonge et al., 2012). This method can only produce a qualitative ranking of parameters as opposed to a quantitative one. Altogether, using the Morris for screening purposes prior to implementing EFAST to reduce temporal complexities and increase GSA accuracy for obtaining the most effective parameters in complex crop growth models suggested by (Vanuytrecht et al., 2014; Silvestro et al., 2017; Lu et al., 2021; Specka et al., 2019; Sun et al., 2012; Upreti et al., 2020; Akbari, 2020; Colombi et al., 2022). Summarizing, the key advantages of SA methods in crop growth models are: (1) Variance-based GSA methods as opposed to the screening methods are more suitable for finding the most effective parameters; (2) reductions in the complexity of the variance-based GSA complex methods after using the Morris screening approach by identifying the least effective parameters; (3) a combination (i.e., ensemble) of the Morris and variance-based GSA methods to identify fewer effective parameters for tuning complex crop growth models; (4) Sobol and EFAST are the most prominent variance-based GSA methods, albeit the EFAST model produces superior evaluations and enables robust and consistent parameter ranking for varying environmental scenarios; and, (5) a combination of the Morris and EFAST to reduce temporal complexities and increase GSA accuracy in complex crop growth models.

Regarding challenges, Vanuytrecht et al. (2014) indicated a strong bond between GSA and environmental conditions, such that a GSA scenario working in one climate condition may not be transferable to other circumstances. This suggests that GSA should be customized to the specific climatic and environmental conditions of the study region, the results of which are not necessarily generalizable to other regions. Multiple authors further underline the need for SA procedures specific to different geographical, climatic, and cultivation conditions to produce more stable SA results (e.g., Guo et al., 2019; Vanuytrecht et al., 2014; Silvestro et al., 2017; Upreti et al., 2020; Akbari, 2020; XING et al., 2017; Xing et al., 2016; Haruna et al., 2023). Related to this, several authors addressed the necessity of comprehensive investigating parameters to further validate GSA instead of analyzing model sensitivity with a limited number of parameters (XING et al., 2017; Wang et al., 2013b; Zhao et al., 2014; Xing et al., 2016). These authors encountered challenges in defining appropriate parameter ranges and identifying significant parameters due to the variability in model parameters. So, one of the most important challenges in GSA of crop models is related to finding the optimum range of variations for each parameter of the model; it is necessary to assess the extent of GSA uncertainty. As observed in the literature, a key issue in GSA is identifying the range of involved parameter values, or alternatively, the minimum and maximum acceptable values (bounds) for each parameter (Vanuytrecht et al., 2014; Akbari et al., 2024a; Paleari and Confalonieri, 2016). More stable GSA results can be achieved by following the advantages and overcoming the challenges. Summarizing, the key challenges of SA methods in crop growth models are: (1) strong relations between GSA and environmental conditions and may not be transferable to other circumstances; (2) the necessity of comprehensive investigating parameters to further validate GSA; and (3) defining appropriate parameter ranges and identifying significant parameters due to the variability in model parameters.

7 Satellite Data Assimilation into Crop Growth Model for its Calibration

7.1 Crop Growth Model Challenge and One Promising Solution

Crop growth models confront the challenge of neglecting spatial variability of cropland conditions with potential negative consequences to guide effective farm management strategies (Clevers et al., 2002; Claverie et al., 2012; Akbari et al., 2024b). To compensate for the complexity, costliness, and time-consuming nature of determining spatiotemporal inputs, most models consider spatial homogeneity across croplands and often assume uniform growing conditions across a field. This assumption, however, could propagate error and an increased uncertainty in the estimated outputs (Hansen and Jones, 2000; Launay and Guerif, 2005). These uncertainties inherent in crop growth simulations, input data, and model assumptions propagate throughout the process, leading to imprecise yield predictions and compounding the overall uncertainty (Fang et al., 2008; Lizumi et al., 2009; Niu et al., 2009; Ceglar et al., 2011; Challinor et al., 2012). While crop growth models often simplify field conditions (Gao et al., 2011), in turn this simplification creates a cascade of inherent uncertainties. These uncertainties propagate through the model structure and parameters, including those governing FVC/LAI, biomass, and evapotranspiration. Consequently, simulations of crop growth and yield become increasingly inaccurate. However, the primary culprit behind these uncertainties remains the unreliability of input crop parameters (Wang et al., 2013a; Huang et al., 2015a).

One promising solution lies in integrating spatially explicit data assimilation strategies. This approach integrates observed data, often acquired from satellites, with the crop growth model. The observed data act as a real-time update for the model's internal state variables, leading to more accurate simulations. Additionally, this approach can be used to refine the model's parameters itself (Hoefsloot et al., 2012). As opposed to traditional ground surveys, satellite-derived products offer significant advantages. Satellite data integration offers lower costs, faster acquisition, and broad coverage, providing a comprehensive view of seasonal crop growth (Quaife et al., 2008). Assimilating satellite-derived products and spatial variability into models can mitigate uncertainties arising from the assumption of homogeneous croplands (Hoefsloot et al., 2012; Jin et al., 2017).

Data streams of satellite products assimilated into crop growth models offer significant potential for enhancing crop monitoring, improving yield estimation accuracy, and advancing precision farming practices (Jin et al., 2017; Jin et al., 2018a). By assimilating satellite products, crop models become more precisely calibrated, enabling us to track crop health better and predict potential problems like pest outbreaks or water stress (Wang et al., 2024). Also, by incorporating real-world field and satellite data, crop models can provide more reliable yield forecasts, aiding in agricultural planning and decision-making. This information can be used to optimize resource use (e.g., water or fertilizer) for individual fields, leading to more sustainable agricultural practices (Akbari et al., 2024b). Thus, careful attention to the steps of satellite data assimilation within crop growth models is indispensable for optimal results.

7.2 Steps of Satellite Data Assimilation into Crop Growth Model for its Calibration

Satellite data assimilation into a crop growth model essentially involves 3 main steps: (1) products extracted from satellite data, including SM, aboveground nitrogen, ET, biomass, FVC, LAI, and etc., are used as observed variables; (2) SA and find driver parameters of crop growth model; (3) satellite data extracted assimilation into the crop growth model to calibrate its driver parameters and optimize the crop model. In satellite data assimilation into crop growth models, it is aimed to reduce the difference between observed and simulated variables. Close agreement between observed and simulated variables suggests that the driving parameters have been effectively optimized, resulting in values that are more compatible with the specific environmental conditions and crop types.

The first step of satellite data assimilation into a crop growth model can be realized based on the nature of observed variables; mostly optical vegetation products are used, such as LAI, and FVC. Satellite vegetation products can be retrieved through: (1) parametric methods like vegetation indices (VIs), (2) non-parametric methods like machine learning regression algorithms (MLRAs), (3) physically-based methods like radiative transfer models (RTMs), and (4) hybrid methods to retrieve the biophysical variables from satellite data (Verrelst et al., 2015; Akbari et al., 2023). Biophysical variable retrieval remains a challenging task, with no single technique consistently outperforming others in terms of accuracy, robustness, and computational efficiency. However, despite widespread use of empirical methods like VIs, they often exhibit unstable performance across diverse case studies and are typically limited to 2–5 bands, raising questions about the optimal band combinations and the impact of confounding factors like vegetation structure and background conditions (Verrelst et al., 2010; 2012a, b). Physically-based methods, i.e., RTM inversion, offer the potential for improved accuracy, but they are computationally intensive and require detailed site-specific information, which may not always be readily available or accurate (Akbari et al., 2023). Conversely, MLRAs can generate adaptive and robust relationships in a given study area and are easily applicable with less site-specific information (Hastie et al., 2009). Kernel-based MLRAs can typically cope with strong nonlinearity involving few and intuitive hyper-parameters for model tuning and can achieve flexible input-output nonlinear mapping (Müller et al., 2018). Furthermore, the hybrid methods combine the potential of improved accuracy of physically-based models with the flexibility and computational efficiency of MLRAs in retrieving of satellite vegetation products. Some researchers concluded that hybrid methods can achieve more accuracy (e.g., Verrelst et al., 2016; Fernández-Guisuraga et al., 2021; Ranghetti et al., 2023; Sahoo et al., 2024). So, to cope with the limitation of biophysical variable retrieval methods, researchers can use the hybrid strategy and new sources of satellite data, such as drones, hyperspectral satellites, and satellite data fusion.

The second step can be implemented to extract driver parameters by GSA methods like Morris and EFAST methods (Akbari et al., 2024a, for more information). Crop models often rely on parameters difficult to measure directly. Some researchers use averaged values from previous studies (e.g., (Andarzian et al., 2011; Jin et al., 2014; Ahmadi et al., 2015; Tavakoli et al., 2015; Hassanli et al., 2016; Sarangi et al., 2016; Wang et al., 2022) for optimization, but this approach can introduce uncertainty. Alternatively, we argued that GSA methods can find the driving and non-influential parameters based on environment and crop type. Given the complexity of assimilation methods and crop growth models, we should prioritize GSA methods that specifically target and extract driver parameters for subsequent optimization. This review article focused on the second step and assessed the SA methods, advantages, and challenges.

Regarding the third step, principally, satellite data assimilation into the crop growth model can be achieved through three main methods, i.e., (1) forcing, (2) updating, and (3) recalibration (Dorigo et al., 2007; Jin et al., 2018a; Akbari, 2023; Dlamini et al., 2023). Exploiting only through forcing methods, i.e., replacing the state variables (e.g., LAI, FVC, biomass in the crop simulation models) with the observation data (especially satellite data products), leads to errors entering the model without any optimization (Wang et al., 2013a). Updating methods refer to continuously updating crop model simulation data based on the latest available satellite data input into the crop models. This approach assumes that a simulation process based on satellite data input at a given day “t” will improve the accuracy of the simulation data on succeeding days (Jin et al., 2018a). In the recalibration method, the state variables are re-estimated to an optimal level using optimization algorithms that minimize the difference between the entered and model-simulated state variables (Dlamini et al., 2023; Akbari et al., 2024b).

The obvious weakness of the forcing method is the loss of model information, and the output of the model is mainly determined by the observational data that are affected by the observed uncertainty (Wang et al., 2013a). When satellite data are entered into the assimilation process of the crop growth model, then recalibration and updating methods prove to be more flexible than the forcing method and can minimize simulation errors. The recalibration method can be used to compensate for the structural and model input errors and better match the results with ground reality during the crop growth period (Gao et al., 2011). As opposed to the forcing and updating methods, the recalibration method is supposedly better in some circumstances, but the main problem with this method is that it requires a large number of optimization iterations, and as a result, the calculation time will increase (Jin et al., 2018a). The date of selected satellite images is also an important and effective factor in the accuracy of crop yield estimation using the update method (Xiong, 2022). The effect of phenology shift (i.e., temporal and phenological differences between the in-situ data used in crop growth simulation and the satellite data) reduces the efficiency of data assimilation in the updating method. Then, in this situation, the recalibration method can be estimated with better results (Curnel et al., 2011).

7.3 Review of Satellite Data Assimilation into Crop Growth Models

This comprehensive review of methods on satellite data assimilation into crop growth models serves to enhance researchers' understanding of the field's advancements, ultimately facilitating more informed and impactful research within this domain. We searched the keywords “crop model”, “data assimilation”, and “remote sensing” in google search for 36 years of research data (1988−2024). The satellite data assimilation methods into the crop growth models used in 106 papers were surveyed and summarized as the recalibration methods (n=45), the forcing methods (n=17), and the updating methods (n=44). “n” in the previous and following sentences means the number of papers which were surveyed in the mentioned methods. We concluded:

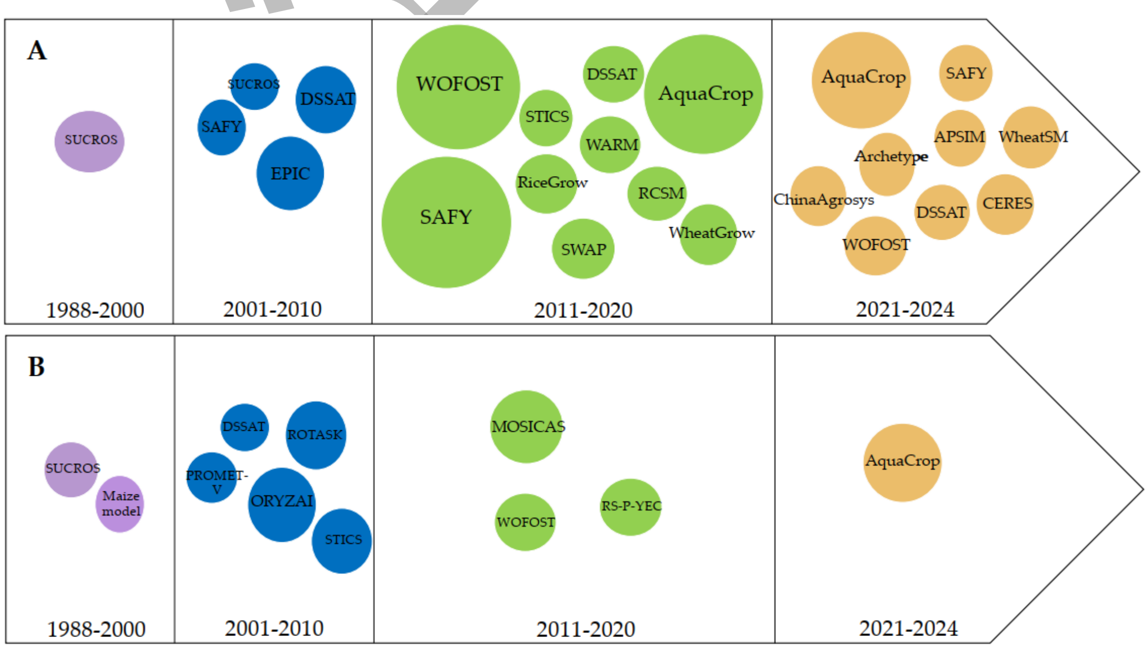
A) the recalibration and updating assimilation methods are the most widely used algorithms in the field of data assimilation, especially the ensemble Kalman filter (EnKF) algorithm in the updating assimilation method. EnKF (n=33) (as the updating method), particle swarm optimization (PSO) (n=15) (as the recalibration method), shuffled complex evolution-university of Arizona (SCE-UA) (n=10) (as the recalibration method), simplex algorithm (n=7) (as the recalibration method), and four-dimensional variational data assimilation (4DVar) (n=6) (as the updating method) were the popular algorithms in the data assimilation system that were used as optimization/decreasing algorithms to minimize discrepancies between observed variables and model simulations.

B) The WOFOST (n=23), AquaCrop (n=17), DSSAT (n=13), and simple algorithm for yield (SAFY) (n=10) are the most common crop models in the research of data assimilation for yield estimation (Figure 3). We can conclude that while the acceptance of the forcing method has been decreasing in the years under review, the updating and recalibration methods have been more accepted, especially updating methods. WOFOST, AquaCrop, and SAFY crop models were more interested in studies of recalibration assimilation methods between 2011-2024, while WOFOST, AquaCrop, and DSSAT crop models were more interested in studies of updating assimilation methods between 2011-2024. State variables were used to minimize discrimination of satellite products and simulation ones extracted by crop growth models (Figure 4). For example, for optimizing the AquaCrop model by recalibration method, the difference between the FVC which simulated by the crop model and the satellite data product (FVC) decreased repeatedly and at last, the parameters optimized.

The size of circles in figure 4 shows the magnitude or how many used the state variables in altogether three data assimilation methods, i.e., recalibration, forcing, and updating methods. In this figure, aboveground nitrogen (AGN) refers to the nitrogen content found in the living biomass of plants, excluding their roots. It encompasses the nitrogen stored in leaves, stems, flowers, fruits, and other aboveground plant parts (Salmerón-Miranda et al., 2007). fraction of absorbed photosynthetically active radiation (FAPAR) is defined by the ratio APAR/PAR, where PAR is the incident PAR on the top of the canopy and APAR is the PAR absorbed by the photosynthesizing tissue of the canopy (Senna et al., 2005). water use efficiency (WUE) is defined as the amount of carbon assimilated as biomass or grain produced per unit of water used by the crop (Hatfield and Dold, 2019). leaf nitrogen accumulation (LNA) refers to the total amount of nitrogen (N) contained within a plant's leaves, measured per unit of leaf area (Sun et al., 2022). Gross primary production (GPP) is the total amount of solar energy that plants convert into chemical energy through photosynthesis, forming organic matter, or biomass (Ashton et al., 2012).

C) In terms of assimilation state variables, LAI, FVC, SM, and biomass are relatively common assimilation variables.

Both FVC and biomass state variables simultaneously used in the AquaCrop model, as opposed to only the FVC, found that using both variables led to significantly higher calibration accuracy in our preview article (Akbari et al., 2024b). Since, we recommend that researchers focus on the mostly used state variables (i.e., LAI, and FVC) and use them simultaneously with the next logical state variables (i.e., SM, and Biomass) in future studies of satellite data assimilation into crop models. Therefore, by assimilating data streams of more diverse satellite products into the crop models, we can significantly advance our understanding of crop growth and improve agricultural practices for a more sustainable and productive future.



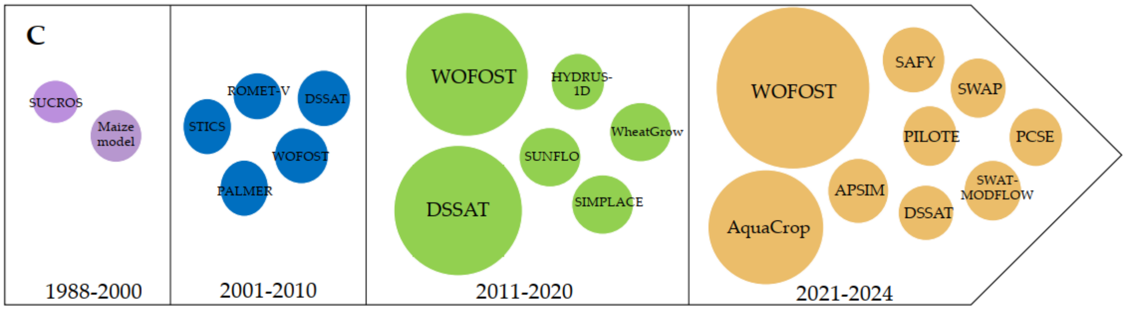


Figure 3. Crop models used in RS data assimilation of (**A**) recalibration, (**B**) forcing, (**C**) updating methods over years. The size of the circles indicated the amount of use of crop models; therefore, larger and smaller circles mean more and less crop models used in the articles, respectively.

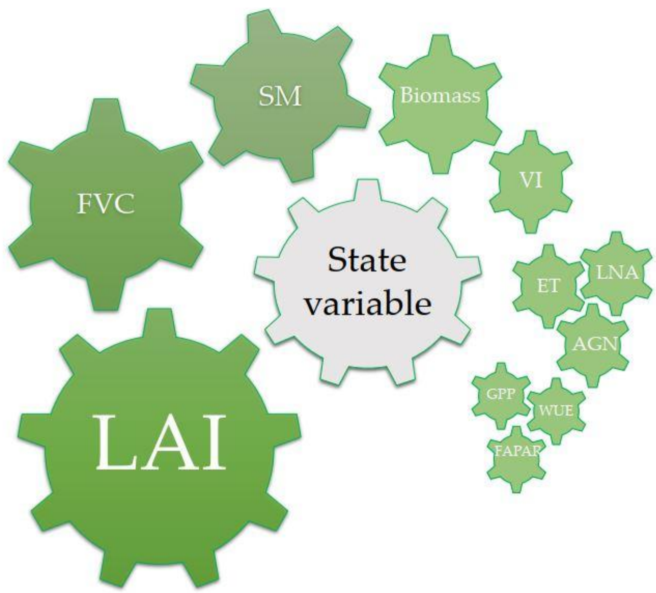


Figure 4. Assimilation state variables used to minimize discrimination of satellite products and simulation ones extracted by crop growth models. The size of circles showed the magnitude of using the state variables in altogether three data assimilation methods (i.e., recalibration, forcing, and updating). (The abbreviations are: aboveground nitrogen (AGN), fraction of absorbed photosynthetically active radiation (FAPAR), water use efficiency (WUE), leaf nitrogen accumulation (LNA), Gross primary production (GPP)).

As a final remark, we advocate integrating satellite data assimilation within a broader environmental extent to enhance the robustness of crop growth models. This necessitates generalizing the proposed assimilated model to accommodate diverse geographical, climatic, and crop conditions. Progressing along this line would require collaboration among the scientific community. In parallel, new sources of satellite data, such as drones, hyperspectral satellites, etc., and satellite data fusion integrated with state-of-the-art variable retrieval methods maybe improve robustness and accuracy of satellite products. To achieve the full potential of precision agriculture, substantial research is needed to further refine crop growth models with GSA techniques and spatially explicit data and enhance their ability to accurately simulate complex biological processes.

8 Conclusion

The crop growth models need to be successfully calibrated with accurate crop model parameters based on local soil/weather/management conditions, and other conservative/non-conservative parameters that may be difficult to measure locally. To address this challenge, a spatially explicit satellite data assimilation strategy incorporates the observed data to calibrate the model parameters. Limitations in the data access affect proper estimation of the key model input parameters and cause additional uncertainty, especially in assimilating satellite data into crop growth models. It is therefore necessary to determine the minimum number of effective parameters or SA in each of the crop growth models to achieve a more accurate and optimal model calibration. This review sought to discuss the various methods of SA to identify the most effective parameters with an assessment of the pros and cons of these methods. These parameters were used for calibrating crop growth models with satellite data assimilation, leading to more spatially precise simulations of crop growth at the regional scale.

SA studies for crop growth models generally point to the strong dependence between model parameters and environmental conditions, such that one SA scenario cannot be generalized for different climate conditions. This highlights the importance of applying SA tailored to the environmental conditions of a target region, the results of which are also specific to that region and cannot be analytically transformed to other regions. Some studies also underline the need for including more parameters in SA analysis to validate SA results. These studies were mainly challenged in terms of defining the variance range for parameters and accurately identifying the range of parameters, which are considered key drivers. SA should be employed in distinct geographical regions with varying climates and cultivation conditions to further stabilize and validate SA results.

We can conclude that global SA methods are predominantly employed in crop growth model calibration practices, especially when data streams of satellite products have been assimilated into the model. As a general trend in the reviewed studies, the EFAST model tends to outperform Sobol in use and accuracy. In cases where complexity is high, it is suggested to use the Morris method for screening parameters in combination with applying the EFAST model to reduce computational complexity and crystallize the most effective parameters at relatively high accuracies. Such ensemble strategies excel in finding the driving parameters, which can lead to fine-tuned calibration and, in turn, to more precise crop growth model simulations. More generally, applying ensemble strategies would be an appropriate option for overcoming the challenges and limitations of each GSA method and reducing the computational complexities of some crop growth models.

The comprehensive review of methods on satellite data assimilation into crop growth models serves the recalibration and updating assimilation methods are the most widely used. The WOFOST, AquaCrop, DSSAT, and SAFY are the most common crop models in the research of data assimilation for yield estimation. In terms of assimilation state variables, LAI, FVC, SM, and biomass are relatively common assimilation variables. Also, one state variable is relatively used in most studies of satellite data assimilation into crop growth models. However, we recommend that researchers focus on assimilating simultaneously two or more state variables of more diverse satellite products into the crop models, which it led to significantly higher calibration accuracy and improve agricultural practices for a more sustainable and productive future.

9 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

10 Author Contributions

EA: Writing—original draft, Writing—review & editing, Conceptualization, Formal analysis, Investigation, Supervision, Validation, Visualization. JV: Writing—original draft, Writing—review & editing, Conceptualization, Investigation.

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Reference

Abrahamsen, P., & Hansen, S. (2000). Daisy: an open soil-crop-atmosphere system model. Environmental modelling & software, 15(3), 313-330. https://doi.org/10.1016/S1364-8152(00)00003-7.

Adabi, V.; Azizian, A.; Ramezani Etedali, H.; Kaviani, A., & Ababaei, B. (2020). Local sensitivity analysis of AquaCrop model for wheat and maize in Qazvin Plain and Moghan Pars-Abad in Iran. Iranian J. Irrigation Drainage. 13(6), 1565-1579. Doi: 20.1001.1.20087942.1398.13.6.3.9.

Ahmadi, S. H.; Mosallaeepour, E.; Kamgar-Haghighi, A. A., & Sepaskhah, A. R. (2015). Modeling maize yield and soil water content with AquaCrop under full and deficit irrigation managements. Water Resour. Manage. 29, 2837-2853. doi: 10.1007/s11269-015-0973-3.

Akbari E.; Darvishi Boloorani A.; Verrelst J.; Pignatti S.; Neysani Samany N.; Soufizadeh S. and Hamzeh S. (2024a). How global sensitive is the AquaCrop model to input parameters? A case study of silage maize yield on a regional scale. Front. Agron. 6: 1304611. doi: 10.3389/fagro.2024.1304611.

Akbari, E. (2020). Assimilation of remote sensing data in crop growth model for yield estimation. Thesis of PhD. Degree of remote sensing and GIS, remote sensing. University of Tehran. Geography faculty. Remote sensing and GIS group. Supervisr professor: Ali darvishi bolourani and Najme neisani samani. (in Persian with English Summary).

Akbari, E. (2023). A review of Remotely Sensed Data Assimilation into Crop Simulation Models. Iranian J. Soil Water Res. 54(5), 753-770, doi: 10.22059/ijswr.2023.357472.669478. (in Persian with English Summary).

Akbari, E., Boloorani, A. D., Verrelst, J., & Pignatti, S. (2024b). Assimilating Satellite-Based Biophysical Variables Data into AquaCrop Model for Silage Maize Yield Estimation Using Water Cycle Algorithm. Remote Sensing, 16(24), 4665. https://doi.org/10.3390/rs16244665.

Akbari, E.; Boloorani, A. D.; Verrelst, J.; Pignatti, S.; Neysani Samany, N.; Soufizadeh, S., & Hamzeh, S. (2023). Biophysical Variable Retrieval of Silage Maize with Gaussian Process Regression and Hyperparameter Optimization Algorithms. Remote Sensing. 15(14), 3690. https://doi.org/10.3390/rs15143690.

Andarzian, B.; Bannayan, M.; Steduto, P.; Mazraeh, H.; Barati, M. E.; Barati, M. A., & Rahnama, A. (2011). Validation and testing of the AquaCrop model under full and deficit irrigated wheat production in Iran. Agric. Water Manage. 100(1), 1-8. Doi: 10.1016/j.agwat.2011.08.023.

Ashton, M. S., Tyrrell, M. L., Spalding, D., & Gentry, B. (Eds.). (2012). Managing forest carbon in a changing climate. Springer Science & Business Media.

Attia, A.; El-Hendawy, S.; Al-Suhaibani, N.; Tahir, M.U.; Mubushar, M.; dos Santos Vianna, M.; Ullah, H.; Mansour, E. and Datta, A. (2021). Sensitivity of the DSSAT model in simulating maize yield and soil carbon dynamics in arid Mediterranean climate: Effect of soil, genotype and crop management. Field Crops Res. 260, 107981. Doi: 10.1016/j.fcr.2020.107981.

Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M.H., Ruget, F., Nicoullaud, B., Gate, P., DevienneBarret, F., Antonioletti, R., Durr, C., Richard, G., Beaudoin, N., Recous, S., Tayot, X., Plenet, D., Cellier, P., Machet, J.M., Meynard, J.M., Delecolle, R., (1998). STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory and parameterization applied to wheat and corn. Agronomie, 18, 311-346. https://doi.org/10.1051/agro:19980501.

Cariboni, J.; Gatelli, D.; Liska, R., & Saltelli, A. (2007). The role of sensitivity analysis in ecological modelling. Ecol. Modell. 203(1-2), 167-182. Doi: 10.1016/j.ecolmodel.2005.10.045.

Casadebaig, P.; Zheng, B.; Chapman, S.; Huth, N.; Faivre, R., & Chenu, K. (2016). Assessment of the potential impacts of wheat plant traits across environments by combining crop modeling and global sensitivity analysis. PloS one 11(1), e0146385. https://doi.org/10.1371/journal.pone.0146385.

Ceglar, A.; Crepinsek, Z.; Kajfez-Bogataj, L.; Pogacar, T. (2011). The simulation of phenological development in dynamic crop model. The Bayesian comparison of different methods. Agric. For. Meteorol. 151, 101–115. https://doi.org/10.1016/j.agrformet.2010.09.007.

Challinor, A.J.; Smith, M.S.; Thornton, P. (2012). Use of agro-climate ensembles for quantifying uncertainty and informing adaptation. Agric. For. Meteorol. 170, 2–7. https://doi.org/10.1016/j.agrformet.2012.09.007.

Chen, Y., & Cournède, P. H. (2014). Data assimilation to reduce uncertainty of crop model prediction with convolution particle filtering. Ecol. Modell. 290, 165-177. https://doi.org/10.1016/j.ecolmodel.2014.01.030.

Chenu, K.; Casadebaig, P., & Christopher, J. (2016). From a global sensitivity analysis of a crop model to wheat improvement in the field. In iCROPM2016 International Crop Modelling Symposium" Crop Modelling for Agriculture and Food Security under Global Change". International Crop Modelling Symposium iCROPM2016, Berlin, Germany, 15-17 March 2016. Germany: AgMIP.

Claverie, M.; Demarez, V.; Duchemin, B.; Hagolle, O.; Ducrot, D.; Marais-Sicre, C.; Dejoux, J.F.; Huc, M.; Keravec, P.; Béziat, P. and Fieuzal, R. (2012). Maize and sunflower biomass estimation in southwest France using high spatial and temporal resolution remote sensing data. Remote Sens. Environ. 124, 844-857. https://doi.org/10.1016/j.rse.2012.04.005.

Clevers, J.; Vonder, O. W.; Jongschaap, R. E. E.; Desprats, J. F.; King, C.; Prevot, L., and Bruguier, N. (2002). Using SPOT data for calibrating a wheat growth model under Mediterranean conditions. Agronomie. 22(6), 687-694. doi: 10.1051/agro:2002038.

Colombi, A., Bancheri, M., Acutis, M., Basile, A., Botta, M., & Perego, A. (2024). A sound understanding of a cropping system model with the global sensitivity analysis. Environmental Modelling & Software, 173, 105932. https://doi.org/10.1016/j.envsoft.2023.105932.

Colombi, A.; Acutis, M.; Bancheri, M.; Basile, A.; Botta, M., & Perego, A. (2022). A Two-Step Global Sensitivity Analysis of the Crop-Growth Armosa Model. Available at SSRN 4234834. Available at SSRN: https://ssrn.com/abstract=4234834 or http://dx.doi.org/10.2139/ssrn.4234834.

Confalonieri, R.; Acutis, M.; Bellocchi, G.; Cerrani, I.; Tarantola, S.; Donatelli, M., & Genovese, G. (2006). Exploratory sensitivity analysis of CropSyst, WARM and WOFOST: a case-study with rice biomass simulations. RIVISTA ITALIANA DI AGROMETEOROLOGIA. 11(3), 17-25. JRC35589.

Confalonieri, R.; Bellocchi, G.; Bregaglio, S.; Donatelli, M., & Acutis, M. (2010a). Comparison of sensitivity analysis techniques: a case study with the rice model WARM. Ecol. Modell. 221(16), 1897-1906. https://doi.org/10.1016/j.ecolmodel.2010.04.021.

Confalonieri, R.; Bellocchi, G.; Tarantola, S.; Acutis, M.; Donatelli, M., & Genovese, G. (2010b). Sensitivity analysis of the rice model WARM in Europe: exploring the effects of different locations, climates and methods of analysis on model sensitivity to crop parameters. Environ. Modell. Soft. 25(4), 479-488. https://doi.org/10.1016/j.envsoft.2009.10.005.

Corbeels, M.; Chirat, G.; Messad, S., & Thierfelder, C. (2016). Performance and sensitivity of the DSSAT crop growth model in simulating maize yield under conservation agriculture. Eur. J. Agron. 76, 41-53. https://doi.org/10.1016/j.eja.2016.02.001.

Curnel, Y.; de Wit, A.J.; Duveiller, G.; Defourny, P. (2011). Potential performances of remotely sensed LAI assimilation in WOFOST model based on an OSS Experiment. Agric. For. Meteorol. 151, 1843–1855. https://doi.org/10.1016/j.agrformet.2011.08.002.

de Souza, J. L. M.; de Oliveira, C. T.; Rosa, S. L. K., & Tsukahara, R. Y. (2022). Sensitivity analysis of the AquaCrop model for maize crop in Southern Brazil. Agric. Eng. Inter.: CIGR Journal. 24(3).

DeJonge, K. C.; Ascough II, J. C.; Ahmadi, M.; Andales, A. A., & Arabi, M. (2012). Global sensitivity and uncertainty analysis of a dynamic agroecosystem model under different irrigation treatments. Ecol. Modell. 231, 113-125. https://doi.org/10.1016/j.ecolmodel.2012.01.024.

Dlamini, L.; Crespo, O.; van Dam, J., & Kooistra, L. (2023). A Global Systematic Review of Improving Crop Model Estimations by Assimilating Remote Sensing Data: Implications for Small-Scale Agricultural Systems. Remote Sensing. 15(16), 4066. https://doi.org/10.3390/rs15164066.

Dorigo, W. A.; Zurita-Milla, R.; de Wit, A. J.; Brazile, J.; Singh, R., & Schaepman, M. E. (2007). A review on reflective remote sensing and data assimilation techniques for enhanced agroecosystem modeling. Int. J. Appl. Earth Obs. Geoinf. 9(2), 165-193. DOI:10.1016/j.jag.2006.05.003.

Fang, H.; Liang, S.; Hoogenboom, G.; Teasdale, J., & Cavigelli, M. (2008). Corn-yield estimation through assimilation of remotely sensed data into the CSM-CERES-Maize model. Int. J. Remote Sens. 29(10), 3011-3032. https://doi.org/10.1080/01431160701408386.

Fernández-Guisuraga, J. M., Verrelst, J., Calvo, L., & Suárez-Seoane, S. (2021). Hybrid inversion of radiative transfer models based on high spatial resolution satellite reflectance data improves fractional vegetation cover retrieval in heterogeneous ecological systems after fire. Remote sensing of environment, 255, 112304. https://doi.org/10.1016/j.rse.2021.112304.

Franczyk, A. (2019). Using the Morris sensitivity analysis method to assess the importance of input variables on time-reversal imaging of seismic sources. Acta Geophys. 67(6), 1525-1533. https://doi.org/10.1007/s11600-019-00356-5.

Gao, C.; Wang, H.; Weng, E.S.; Lakshmivarahan, S.; Zhang, Y.F.; Luo, Y.Q., (2011). Assimilation of multiple data sets with the ensemble Kalman filter to improve forecasts of forest carbon dynamics. Ecol. Appl. 21 (5), 1461–1473. https://doi.org/10.1890/09-1234.1.

Gao, Y., Sun, C., Ramos, T.B., Tan, J., Oliveira, A.R., Huang, Q., Huang, G. and Xu, X. (2024). Global Sensitivity Analysis of the Advanced ORYZA-N Model with Different Rice Types and Irrigation Regimes. Plants, 13(02). https://doi.org/10.3390/plants13020262.

Gasanov, M.; Petrovskaia, A.; Nikitin, A.; Matveev, S.; Tregubova, P.; Pukalchik, M., & Oseledets, I. (2020). Sensitivity analysis of soil parameters in crop model supported with high-throughput computing. In Computational Science–ICCS 2020: 20th International Conference, Amsterdam, The Netherlands, June 3–5, 2020, Proceedings, Part VII 20 (pp. 731-741). Springer International Publishing. DOI: 10.1007/978-3-030-50436-6_54.

Ge, H.; Ma, F.; Li, Z.; Du, C. (2021). Global Sensitivity Analysis for CERES-Rice Model under Different Cultivars and Specific-Stage Variations of Climate Parameters. Agron. J. 11, 2446. https://doi.org/10.3390/agronomy11122446.

Guo, D.; Zhao, R.; Xing, X., & Ma, X. (2019). Global sensitivity and uncertainty analysis of the AquaCrop model for maize under different irrigation and fertilizer management conditions. Arch. Agron. Soil Sci. 1-19. https://doi.org/10.1080/03650340.2019.1657845.

Hansen, J. W. and Jones, J. W. (2000). Scaling-up crop models for climate variability applications. Agric. Syst. 65(1), 43-72. doi: 10.1016/s0308-521x (00)00025-1.

Hao, S., Ryu, D., Western, A. W., Perry, E., Bogena, H., & Franssen, H. J. H. (2024). Global sensitivity analysis of APSIM-wheat yield predictions to model parameters and inputs. Ecological Modelling, 487, 110551. https://doi.org/10.1016/j.ecolmodel.2023.110551.

Hao, S.; Ryu, D.; Western, A.; Perry, E.; Bogena, H., & Hendricks Franssen, H. J. (2021). Sensitivity Analysis of APSIM Wheat Yield Predictions. In AGU Fall Meeting Abstracts (Vol. 2021, pp. H53C-01).

Haruna, M. M.; Ismail, H.; Bashir, A. U., & Dibal, J. M. (2023). Local sensitivity analysis of the AquaCrop model outputs for wheat under Semi-Arid water stress condition. Algerian J. Eng. Tech. 8(1), 22-30.

Hassanli, M.; Ebrahimian, H.; Mohammadi, E.; Rahimi, A., & Shokouhi, A. (2016). Simulating maize yields when irrigating with saline water, using the AquaCrop, SALTMED, and SWAP models. Agric. Water Manage. 176, 91-99. Doi: 10.1016/j.agwat.2016.05.003.

Hassanpour, R.; Majnooni-Heris, A.; Fakheri Fard, A.; Verrelst, J. (2024). Monitoring Biophysical Variables (FVC, LAI, LCab, and CWC) and Cropland Dynamics at Field Scale Using Sentinel-2 Time Series. Remote Sens. 16, 2284. https://doi.org/10.3390/rs16132284.

Hastie, T., Tibshirani, R., Friedman, J.H. (2009). The elements of statistical learning: data mining, inference, and prediction (2nd ed.). New York: Springer-Verlag.

Hatfield, J. L., & Dold, C. (2019). Water-use efficiency: advances and challenges in a changing climate. Frontiers in plant science, 10, 103. https://doi.org/10.3389/fpls.2019.00103.

Hoefsloot, P.; Ines, A. V.; van Dam, J.; Duveiller, G.; Kayitakire, F., & Hansen, J. (2012). Combining crop models and remote sensing for yield prediction: Concepts, applications and challenges for heterogeneous smallholder environments. Report of CCFAS-JRC Workshop at Joint Research Centre, Ispra, Italy, June 13-14, 2012. Joint Research Center Technical Report. Luxembourg: Publications Office of the European Union. doi:10.2788/72447.

Hsiao, T. C.; Heng, L.; Steduto, P.; Rojas-Lara, B.; Raes, D., & Fereres, E. (2009). AquaCrop—the FAO crop model to simulate yield response to water: III. Parameterization and testing for maize. Agron. J. 101(3), 448-459. Doi: 10.2134/agronj2008.0218s.

Huang, J., Ma, H., Su, W., Zhang, X., Huang, Y., Fan, J., & Wu, W., (2015b). Jointly assimilating MODIS LAI and ET products into the SWAP model for winter wheat yield estimation. IEEE JSTAR. 8, 4060–4071. DOI: 10.1109/JSTARS.2015.2403135.

Huang, J.; Gómez-Dans, J.L.; Huang, H.; Ma, H.; Wu, Q.; Lewis, P.E.; Liang, S.; Chen, Z.; Xue, J.H.; Wu, Y. and Zhao, F. (2019). Assimilation of remote sensing into crop growth models: Current status and perspectives. Agric. For. Meteorol. 276, 107609. https://doi.org/10.1016/j.agrformet.2019.06.008.

Huang, J.; Tian, L.; Liang, S.; Ma, H.; Becker-Reshef, I.; Huang, Y.; Su, W.; Zhang, X.; Zhu, D. and Wu, W. (2015a). Improving winter wheat yield estimation by assimilation of the leaf area index from Landsat TM and MODIS data into the WOFOST model. Agric. For. Meteorol. 204, 106-121. https://doi.org/10.1016/j.agrformet.2015.02.001.

Ines, A.V., Das, N.N., Hansen, J.W. & Njoku, E.G., (2013). Assimilation of remotely sensed soil moisture and vegetation with a crop simulation model for maize yield prediction. Remote Sensing of Environment. 138, 149-164. https://doi.org/10.1016/j.rse.2013.07.018.

Iooss, B., & Lemaître, P. (2015). A review on global sensitivity analysis methods. Uncertainty management in simulation-optimization of complex systems: algorithms and applications, Part of the Operations Research/Computer Science Interfaces Series book series (ORCS, volume 59). 101-122.

Jin, X.; Kumar, L.; Li, Z.; Feng, H.; Xu, X.; Yang, G., & Wang, J. (2018a). A review of data assimilation of remote sensing and crop models. Eur. J. Agron. 92, 141-152. Doi: 10.1016/j.eja.2017.11.002.

Jin, X.; Li, Z.; Nie, C.; Xu, X.; Feng, H.; Guo, W., & Wang, J. (2018b). Parameter sensitivity analysis of the AquaCrop model based on extended fourier amplitude sensitivity under different agro-meteorological conditions and application. Field Crops Res. 226, 1-15. https://doi.org/10.1016/j.fcr.2018.07.002.

Jin, X.; Li, Z.; Yang, G.; Yang, H.; Feng, H.; Xu, X.; Wang, J.; Li, X. and Luo, J. (2017). Winter wheat yield estimation based on multi-source medium resolution optical and radar imaging data and the AquaCrop model using the particle swarm optimization algorithm. ISPRS J. Photogramm. Remote Sens. 126, 24-37. Doi: 10.1016/j.isprsjprs.2017.02.001.

Jin, X.L.; Feng, H.K.; Zhu, X.K.; Li, Z.H.; Song, S.N.; Song, X.Y.; Yang, G.J.; Xu, X.G. and Guo, W.S. (2014). Assessment of the AquaCrop model for use in simulation of irrigated winter wheat canopy cover, biomass, and grain yield in the North China Plain. PloS one. 9(1), e86938. https://doi.org/10.1371/journal.pone.0086938.

Jones, J.W., Tsuji, G.Y., Hoogenboom, G., Hunt, L.A., Thornton, P.K., Wilkens, P.W., Imamura, D.T., Bowen, W.T. and Singh, U. (1998). Decision support system for agrotechnology transfer: DSSAT v3. In Understanding options for agricultural production (pp. 157-177). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-017-3624-4_8.

Krishnan, P.; Maity, P. P., & Kundu, M. (2021). Sensitivity analysis of cultivar parameters to simulate wheat crop growth and yield under moisture and temperature stress conditions. Heliyon. 7(7). https://doi.org/10.1016/j.heliyon.2021.e07602.

Lamboni, M.; Makowski, D.; Lehuger, S.; Gabrielle, B., & Monod, H. (2009). Multivariate global sensitivity analysis for dynamic crop models. Field Crops Res. 113(3), 312-320. https://doi.org/10.1016/j.fcr.2009.06.007.

Launay, M., and Guerif, M. (2005). Assimilating remote sensing data into a crop model to improve predictive performance for spatial applications. Agric. Ecosyst. Environ. 111(1-4), 321-339. doi: http://dx.doi.org/10.1016/j.agee.2005.06.005.

Li, W., Song, R., Awais, M., Ji, L., Li, S., Liu, M., Lang, T. and Qi, H. (2024b). Global Sensitivity Analysis of Crop Parameters Based on AquaCrop Model. Water Resources Management. 38(6), 2039-2058. https://doi.org/10.1007/s11269-024-03740-z.

Li, X.; Tan, J.; Li, H.; Wang, L.; Niu, G., & Wang, X. (2023). Sensitivity Analysis of the WOFOST Crop Model Parameters Using the EFAST Method and Verification of Its Adaptability in the Yellow River Irrigation Area, Northwest China. Agron. J. 13(9). 2294. https://doi.org/10.3390/agronomy13092294.

Li, Y., Zou, C., Feng, L., Yao, X., Li, T., Chen, X., & Zhao, J. (2024a). Estimation of winter wheat yield in Hebi city based on crop models and remote sensing data assimilation. In Journal of Physics: Conference Series (Vol. 2791, No. 1, p. 012079). IOP Publishing. DOI=10.1088/1742-6596/2791/1/012079.

Liu, J.; Liu, Z.; Zhu, A. X.; Shen, F.; Lei, Q., & Duan, Z. (2019). Global sensitivity analysis of the APSIM-Oryza rice growth model under different environmental conditions. Sci. Total Environ. 651, 953-968. https://doi.org/10.1016/j.scitotenv.2018.09.254.

Lizumi, T.; Yokozawa, M.; Nishimori, M. (2009). Parameter estimation and uncertainty analysis of a large-scale crop model for paddy rice: Application of a Bayesian approach. Agric. For. Meteorol. 149 (2), 333–348. https://doi.org/10.1016/j.agrformet.2008.08.015.

Lu, Y.; Chibarabada, T. P.; McCabe, M. F.; De Lannoy, G. J., & Sheffield, J. (2021). Global sensitivity analysis of crop yield and transpiration from the FAO-AquaCrop model for dryland environments. Field Crops Res. 269, 108182. https://doi.org/10.1016/j.fcr.2021.108182.

Ma, H.; Wang, J.; Liu, T.; Guo, Y.; Zhou, Y.; Yang, T.; Zhang, W. & Sun, C. (2023). Time series global sensitivity analysis of genetic parameters of CERES-maize model under water stresses at different growth stages. Agric. Water Manage. 275, 108027. https://doi.org/10.1016/j.agwat.2022.108027.

Martínez-Ruiz, A.; Ruiz-García, A.; Prado-Hernández, J. V.; López-Cruz, I. L.; Valencia-Islas, J. O., & Pineda-Pineda, J. (2021). Global sensitivity analysis and calibration by differential evolution algorithm of HORTSYST crop model for fertigation management. Water J. 13(5), 610. https://doi.org/10.3390/w13050610.

McCown, R. L., Hammer, G. L., Hargreaves, J. N. G., Holzworth, D. P., & Freebairn, D. M. (1996). APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. Agricultural systems, 50(3), 255-271. https://doi.org/10.1016/0308-521X(94)00055-V.

Meng, Y.; Qiu, X.; Liu, L.; Liu, B.; Zhu, Y.; Cao, W.; Tang, L. (2021). Sensitivity Analysis of Genetic Parameters of RiceGrow Model. Journal of Agricultural Big Data. 3(3): 23-32. doi: 10.19788/j.issn.2096-6369.210303.

Morris, M.D. (1991). Factorial sampling plans for preliminary computational experiments. Technometrics. 33, 161-174. https://doi.org/10.2307/1269043.

Müller, K. R., Mika, S., Tsuda, K., & Schölkopf, K. (2018). An introduction to kernel-based learning algorithms. In Handbook of neural network signal processing (pp. 4-1). CRC Press.

Nehbandani, A.; Soltani, A.; Nourbakhsh, F., & Dadrasi, A. (2020). Estimating crop model parameters for simulating soybean production in Iran conditions. OCL. 27, 58. https://doi.org/10.1051/ocl/2020057.

Nendel, C., Berg, M., Kersebaum, K.C., Mirschel, W., Specka, X., Wegehenkel, M., Wenkel, K.O. and Wieland, R., (2011). The MONICA model: Testing predictability for crop growth, soil moisture and nitrogen dynamics. Ecological Modelling, 222(9), 1614-1625. https://doi.org/10.1016/j.ecolmodel.2011.02.018.

Niu, X.Z.; Easterling, W.; Hays, C.J.; Jacobs, A.; Mearns, L., (2009). Reliability and input data induced uncertainty of the EPIC model to estimate climate change impact on sorghum yields in the U.S. Great Plains. Agric. Ecosyst. Environ. 129 (1–3), 268–276. https://doi.org/10.1016/j.agee.2008.09.012.

Oulaid, B., Milne, A. E., Waine, T., El Alami, R., Rafiqi, M., & Corstanje, R. (2024). Stepwise model parameterization using satellite imagery and hemispherical photography: Tuning AquaCrop sensitive parameters for improved winter wheat yield predictions in semi-arid regions. Field Crops Research. 309, 109327. https://doi.org/10.1016/j.fcr.2024.109327.

Paleari, L. and Confalonieri, R. (2016). Sensitivity analysis of a sensitivity analysis: We are likely overlooking the impact of distributional assumptions. Ecol. Modell. 340, 57-63. https://doi.org/10.1016/j.ecolmodel.2016.09.008.

Paleari, L.; Movedi, E.; Zoli, M.; Burato, A.; Cecconi, I.; Errahouly, J.; Pecollo, E.; Sorvillo, C. and Confalonieri, R. (2021). Sensitivity analysis using Morris: Just screening or an effective ranking method? Ecol. Modell. 455, 109648. https://doi.org/10.1016/j.ecolmodel.2021.109648.

Pathak, T. B.; Fraisse, C. W.; Jones, J. W.; Messina, C. D., & Hoogenboom, G. (2007). Use of global sensitivity analysis for CROPGRO cotton model development. Trans. ASABE. 50(6), 2295-2302. doi: 10.13031/2013.24082.

Pereira, R. A. D. A., Vianna, M. S., & Marin, F. R. (2023). Sample size, range of parameters and time-dependent effects on global sensitivity analysis in sugarcane modelling. The Journal of Agricultural Science. 161(6), 817-834. DOI: https://doi.org/10.1017/S0021859624000030.

Pianosi, F.; Beven, K.; Freer, J.; Hall, J. W.; Rougier, J.; Stephenson, D. B., & Wagener, T. (2016). Sensitivity analysis of environmental models: A systematic review with practical workflow. Environ. Model. Softw. 79, 214-232. https://doi.org/10.1016/j.envsoft.2016.02.008.

QIN, G.X.; WU, J.; LI, C.B.; SHEN, S.J.; LI, H.H.; YANG, D.H.; JIAO, M.R. & QI, Q. (2022). Sensitivity analysis of WOFOST model crop parameters in different grassland types. Acta Prataculturae Sinica. 31(5), 13. (in Chinese with English Summary). DOI: https://doi.org/10.11686/cyxb2021391.

Quaife, T.; Lewis, P.; De Kauwe, M.; Williams, M.; Law, B.E.; Disney, M.; Bowyer, P. (2008). Assimilating canopy reflectance into an ecosystem model with an ensemble Kalman filter. Rem. Sens. Environ. 112, 1347–1364. Doi: 10.1016/j.rse.2007.05.020.

Raes, D., Steduto, P., Hsiao, T., Fereres, E. (2017). AquaCrop Version 6.0 Reference Manual. Annex I. Food Agric. Organ. United Nations, Rome, Italy. http//www.fao.org/land-water/ databases-and-software/aquacrop/en/.

Rahimikhoob, H.; Sohrabi, T., and Delshad, M. (2023). Variance-based global sensitivity analysis and uncertainty quantification of the AquaCrop model parameters for basil (Ocimum basilicum L.) under different nitrogen fertilizer rates. J. Plant Nutr. 1-18. https://doi.org/10.1080/01904167.2023.2280142.

Ranghetti, M., Boschetti, M., Ranghetti, L., Tagliabue, G., Panigada, C., Gianinetto, M., Verrelst, J. and Candiani, G., (2023). Assessment of maize nitrogen uptake from PRISMA hyperspectral data through hybrid modelling. European journal of remote sensing, 56(1), 2117650. https://doi.org/10.1080/22797254.2022.2117650.

Rosa, S. L. K.; Souza, J. L. M. D.; Tsukahara, R. Y., & Kochinski, E. G. (2023). Sensitivity analysis of the AquaCrop model for wheat crop in Campos Gerais region, Paraná. Revista Ceres. 70, 32-41. https://doi.org/10.1590/0034-737X202370010004.

Ruan, S., Cao, H., Wu, S., Ma, Y., Li, W., Jin, Y., Deng, H., Chen, G., Wu, W. and Yang, P. (2024). Rape Yield Estimation Considering Non-Foliar Green Organs Based on the General Crop Growth Model. Plant Phenomics. 6, 0253. https://doi.org/10.34133/plantphenomics.0253.

Rutjens, R. J., Evers, J. B., Band, L. R., Jones, M. D., & Owen, M. R. (2024). Are we focusing on the right parameters? Insights from Global Sensitivity Analysis of a Functional-Structural Plant Model. in silico Plants. 6(2), diae011. https://doi.org/10.1093/insilicoplants/diae014.

Sahoo, R.N., Rejith, R.G., Gakhar, S., Verrelst, J., Ranjan, R., Kondraju, T., Meena, M.C., Mukherjee, J., Dass, A., Kumar, S. and Kumar, M., (2024). Estimation of wheat biophysical variables through UAV hyperspectral remote sensing using machine learning and radiative transfer models. Computers and Electronics in Agriculture, 221, 108942. https://doi.org/10.1016/j.compag.2024.108942.

Salmerón-Miranda, F., Båth, B., Eckersten, H., Forkman, J., & Wivstad, M. (2007). Aboveground nitrogen in relation to estimated total plant uptake in maize and bean. Nutrient Cycling in Agroecosystems, 79(2), 125-139. https://doi.org/10.1007/s10705-007-9102-x.

Saltelli, A.; Annoni, P. (2010). How to avoid a perfunctory sensitivity analysis. Environ. Model. Softw. 25, 1508-1517. https://doi.org/10.1016/j.envsoft.2010.04.012.

Saltelli, A.; Ratto, M.; Andres, T.; Campolongo, F.; Cariboni, J.; Gatelli, D.; Saisana, M. & Tarantola, S. (2008). Global Sensitivity Analysis: The Primer. New York: Wiley.

Saltelli, A.; Tarantola, S.; Chan, K.P.S. (1999). A quantitative model-independent method for global sensitivity analysis of model output. Technometrics. 41, 39-56. https://doi.org/10.1080/00401706.1999.10485594.

Sarangi, A.; Bandyopadhyay, K. K.; Samal, A., & Pathan, A. (2016). Evaluation of FAO AquaCrop model for wheat under different irrigation regimes. J. App. Nat. Sci. 8(1), 473-480. DOI:10.31018/jans.v8i1.820.

Senna, M. C., Costa, M. H., & Shimabukuro, Y. E. (2005). Fraction of photosynthetically active radiation absorbed by Amazon tropical forest: A comparison of field measurements, modeling, and remote sensing. Journal of Geophysical Research: Biogeosciences, 110(G1). https://doi.org/10.1029/2004JG000005.

Servin-Palestina, M.; López-Cruz, I. L.; Zegbe-Domínguez, J. A.; Ruiz-García, A.; Salazar-Moreno, R., & Medina-García, G. (2022). Spatiotemporal Uncertainty and Sensitivity Analysis of the SIMPLE Model Applied to Common Beans for Semi-Arid Climate of Mexico. Agron. J. 12(8). 1813. https://doi.org/10.3390/agronomy12081813.

Shafiei, M.; Ghahreman, B.; Saghafian, B.; Davari, K., & Vazifeh Doost, M. (2018). Global sensitivity analysis of WOFOST model parameters for maize and wheat yield simulation. Iranian J. Soil. Water. Res. 49(4), 831-839. (in Persian with English Summary). doi: 10.22059/ijswr.2018.133882.667317.

Shan, Y., Huang, M., Harris, P., & Wu, L. (2021). A sensitivity analysis of the SPACSYS model. Agriculture. 11(7), 624. https://doi.org/10.3390/agriculture11070624.

Silvestro, P. C.; Pignatti, S.; Yang, H.; Yang, G.; Pascucci, S.; Castaldi, F., & Casa, R. (2017). Sensitivity analysis of the Aquacrop and SAFYE crop models for the assessment of water limited winter wheat yield in regional scale applications. PloS one. 12(11), e0187485. Doi: 10.3390/rs9050509.

Song, M. D.; Feng, H.; Li, Z. P., & Gao, J. E. (2014). Global Sensitivity Analyses of DSSAT–CERES–Wheat Model Using Morris and EFAST Methods. Transactions of the Chinese Society for Agricultural Machinery. 45(10), 124-131. DOI:10.6041/j.issn.1000-1298.2014.10.020.

Specka, X.; Nendel, C., & Wieland, R. (2019). Temporal sensitivity analysis of the MONICA model: Application of two global approaches to analyze the dynamics of parameter sensitivity. Agric. 9(2), 37. https://doi.org/10.3390/agriculture9020037.

Steduto, P.; Hsiao, T.C.; Raes, D.; Fereres, E. (2009). AquaCrop—The FAO crop model to simulate yield response to water: I. Concepts and underlying principles. Agron. J. 101, 426–437. https://doi.org/10.2134/agronj2008.0139s.
Sun, H., Feng, M., Yang, W., Bi, R., Sun, J., Zhao, C., Xiao, L., Wang, C. and Kubar, M.S. (2022). Monitoring leaf nitrogen accumulation with optimized spectral index in winter wheat under different irrigation regimes. Frontiers in Plant Science, 13, 913240. https://doi.org/10.3389/fpls.2022.913240.
Sun, X.Y.; Newham, L.T.H.; Croke, B.F.W.; Norton, J.P. (2012). Three complementary methods for sensitivity analysis of a water quality model. Environ. Model. Softw. 37, 19-29. https://doi.org/10.1016/j.envsoft.2012.04.010.
Tavakoli, A. R.; Moghadam, M. M., & Sepaskhah, A. R. (2015). Evaluation of the AquaCrop model for barley production under deficit irrigation and rainfed condition in Iran. Agric. Water Manage. 161, 136-146. https://doi.org/10.1016/j.agwat.2015.07.020.
Upreti, D.; Pignatti, S.; Pascucci, S.; Tolomio, M.; Li, Z.; Huang, W., & Casa, R. (2020). A Comparison of Moment-Independent and Variance-Based Global Sensitivity Analysis Approaches for Wheat Yield Estimation with the Aquacrop-OS Model. Agron. J. 10(4), 607. https://doi.org/10.3390/agronomy10040607.
Van Diepen, C. V., Wolf, J. V., Van Keulen, H., & Rappoldt, C. (1989). WOFOST: a simulation model of crop production. Soil use and management, 5(1), 16-24. https://doi.org/10.1111/j.1475-2743.1989.tb00755.x.
Vanuytrecht, E.; Raes, D., & Willems, P. (2014). Global sensitivity analysis of yield output from the water productivity model. Environ. Modell. Software. 51, 323-332. Doi: 10.1016/j.envsoft.2013.10.017.
Varella, H.; Buis, S.; Launay, M., & Guérif, M. (2012). Global sensitivity analysis for choosing the main soil parameters of a crop model to be determined. Agric. Sci. 3(7). DOI: 10.4236/as.2012.37116.
Varella, H.; Guérif, M., & Buis, S. (2010). Global sensitivity analysis measures the quality of parameter estimation: The case of soil parameters and a crop model. Environ. Modell. Soft. 25(3), 310-319. https://doi.org/10.1016/j.envsoft.2009.09.012.
Verrelst, J., Alonso, L., Camps-valls, G., Delegido, J., Moreno, J. (2012a). Retrieval of Vegetation Biophysical Parameters Using Gaussian Process Techniques. IEEE Trans. Geosci. Remote Sens, 50(5), 1832–1843. doi: 10.1109/TGRS.2011.2168962.
Verrelst, J., Dethier, S., Rivera, J. P., Munoz-Mari, J., Camps-Valls, G., & Moreno, J. (2016). Active learning methods for efficient hybrid biophysical variable retrieval. IEEE Geoscience and Remote Sensing Letters, 13(7), 1012-1016. Doi: 10.1109/LGRS.2016.2560799.
Verrelst, J., Muñoz, J., Alonso, L., Delegido, J., Pablo Rivera, J., Camps-valls, G., Moreno, J. (2012b). Machine learning regression algorithms for biophysical parameter retrieval: Opportunities for Sentinel-2 and -3. Remote Sens. Environ. 118, 127–139. doi: 10.1016/j.rse.2011.11.002.
Verrelst, J., Schaepman, M.E., Malenovský, Z., Clevers, J.G.P.W. (2010). Effects of woody elements on simulated canopy reflectance: Implications for forest chlorophyll content retrieval. Remote Sens. Environ 2010, 114(3), 647–656. https://doi.org/10.1016/j.rse.2009.11.004.
Verrelst, J.; Rivera, J. P.; Veroustraete, F.; Muñoz-Marí, J.; Clevers, J. G.; Camps-Valls, G., & Moreno, J. (2015). Experimental Sentinel-2 LAI estimation using parametric, non-parametric and physical retrieval methods–A comparison. ISPRS J. Photogramm. Remote Sens. 108, 260-272. https://doi.org/10.1016/j.isprsjprs.2015.04.013.
Wang, G.; Mehmood, F.; Zain, M.; Hamani, A. K. M.; Xue, J.; Gao, Y., & Duan, A. (2022). AquaCrop Model Evaluation for Winter Wheat under Different Irrigation Management Strategies: A Case Study on the North China Plain. Agron. J. 12(12), 3184. https://doi.org/10.3390/agronomy12123184.
Wang, J., Wang, Y., & Qi, Z. (2024). Remote Sensing Data Assimilation in Crop Growth Modeling from an Agricultural Perspective: New Insights on Challenges and Prospects. Agron. J. 14(9), 1920. https://doi.org/10.3390/agronomy14091920.
Wang, J.; Li, X.; Lu, L. and Fang, F. (2013a). Estimating near future regional corn yields by integrating multi-source observations into a crop growth model. Eur. J. Agron. 49, 126-140. https://doi.org/10.1016/j.eja.2013.03.005.
Wang, J.; Li, X.; Lu, L., & Fang, F. (2013b). Parameter sensitivity analysis of crop growth models based on the extended Fourier Amplitude Sensitivity Test method. Environ. Modell. Soft. 48, 171-182. https://doi.org/10.1016/j.envsoft.2013.06.007.
WEI, X., & NIE, Z. (2024). Sensitivity analysis and optimization of leaf area index related parameters of dryland wheat based on APSIM model. Chinese Journal of Eco-Agriculture. 32(1), 119-129. DOI: 10.12357/cjea.20230345.
XING, H. M.; XU, X. G.; LI, Z. H.; CHEN, Y. J.; FENG, H. K.; YANG, G. J., & CHEN, Z. X. (2017). Global sensitivity analysis of the AquaCrop model for winter wheat under different water treatments based on the extended Fourier amplitude sensitivity test. J. Integr. Agric. 16(11), 2444-2458. https://doi.org/10.1016/S2095-3119(16)61626-X.
Xing, H.; Xu, X.; Yang, F.; Feng, H., & Yang, G. (2016). Global sensitivity analysis of winter wheat yield and process-based variable with AquaCrop model. In Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International (pp. 5929-5932). IEEE. DOI: 10.1109/IGARSS.2016.7730549.
Xiong, W. (2022). In-Season Crop Yield Forecasting in Africa by Coupling Remote Sensing and Crop Modeling: A Systematic Literature Review. Available online: https://cgspace.cgiar.org/server/api/core/bitstreams/30d1f3cc-065d-40cd-8730-de6d87004c51/content (accessed on 10 July 2022).
Xu, M.; Wang, C.; Ling, L.; Batchelor, W. D.; Zhang, J., & Kuai, J. (2021). Sensitivity analysis of the CROPGRO-Canola model in China: A case study for rapeseed. Plos one. 16(11), e0259929. https://doi.org/10.1371/journal.pone.0259929.

Xu, X.; Sun, C.; Huang, G., & Mohanty, B. P. (2016). Global sensitivity analysis and calibration of parameters for a physically-based agro-hydrological model. Environ. Modell. Soft. 83, 88-102. https://doi.org/10.1016/j.envsoft.2016.05.013.

Zeng, W.; Lei, G.; Zha, Y.; Fang, Y.; Wu, J., & Huang, J. (2018). Sensitivity and uncertainty analysis of the HYDRUS-1D model for root water uptake in saline soils. Crop Pasture Sci. 69(2), 163-173. https://doi.org/10.1071/CP17020.

Zhang, M.; Gao, Y.M.; Zhang, Y.Q. (2023). Sensitivity analysis and calibration of the APSIM next-generation model under different irrigation and sowing density in wheat. Chinese Journal of Eco-Agriculture. 31(1): 102−112 doi: 10.12357/cjea.20220384. (in Chinese with English Summary).

Zhang, X.; Guo, P.; Guo, S.; Zhang, F., & Zhang, C. (2022). An integrated model to optimize irrigation amount and time in shallow groundwater area under drought conditions. J. Contam. Hydrol. 246, 103956. https://doi.org/10.1016/j.jconhyd.2022.103956.

Zhao, G.; Bryan, B. A., & Song, X. (2014). Sensitivity and uncertainty analysis of the APSIM-wheat model: Interactions between cultivar, environmental, and management parameters. Ecol. Modell. 279, 1-11. https://doi.org/10.1016/j.ecolmodel.2014.02.003.