Agricultural and Forest Meteorology 263 (2018) 25–40

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Sensitivity of simulated crop yield and nitrate leaching of the wheat-maize cropping system in the North China Plain to model parameters

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ARTICLE INFO

Keywords:
Morris sensitivity analysis
Crop modelling
RDAISY toolbox
Crop yield
Nitrogen leaching
Wheat - maize cropping system

ABSTRACT

Process-based crop simulation models are often over-parameterised and are therefore difficult to calibrate properly. Following this rationale, the Morris screening sensitivity method was carried out on the DAISY model to identify the most influential input parameters operating on selected model outputs, i.e. crop yield, grain nitrogen (N), evapotranspiration and N leaching. The results obtained refer to the winter wheat-summer maize cropping system in the North China Plain. In this study, four different N fertiliser treatments over six years were considered based on a randomised field experiment at Luancheng Experimental Station to elucidate the impact of weather and nitrogen inputs on model sensitivity. A total of 128 parameters were considered for the sensitivity analysis. The ratios [output changes/parameter increments] demonstrated high standard deviations for the most relevant parameters, indicating high parameter non-linearity/interactions. In general, about 34 parameters influenced the outputs of the DAISY model for both crops. The most influential parameters depended on the output considered with sensitivity patterns consistent with the expected dominant processes. Interestingly, some parameters related to the previous crop were found to affect output variables of the following crop, illustrating the importance of considering crop sequences for model calibration. The developed RDAISY toolbox used in this study can serve as a basis for following sensitivity analysis of the DAISY model, thus enabling the selection of the most influential parameters to be considered with model calibration.

1. Introduction

Process-based models have been extensively used to assess how the interaction ofgenotype × environment × management may affect crop productivity and dynamics of hydrology and nitrogen (N) in cropping systems (Chapman, 2008). Simulation models are also considered essential tools for scenario analyses and decision support for policy making (Ewert et al., 2015). Process-based models, traditionally contingent on a mathematical formulation of physical processes, typically contain a broad set of parameters and are therefore often considered over-parameterised (Reichert and Omlin, 1997). Many model parameters are often uncertain because, among other things, of insufficient data for their estimation. Generally, finding an accurate estimate for all the parameters for which a model best fits the experimental data is a complicated and computationally expensive process for complex simulation models (Whittaker et al., 2010). Therefore, rigorous analysis of parameter sensitivity and reduction of the parameter space are essential to facilitate the calibration process.

Sensitivity analysis (SA) examines how model parameters and/or model inputs affect model outputs (Song et al., 2015; Pianosi et al., 2016). Through SA, the various parameters can be ranked based on their relative importance. The parameters having a substantial impact on the model outputs are considered for model calibration and those that are less-essential in influencing the model response can be fixed to their nominal values (Sarrazin et al., 2016) reducing hence the model dimensionality. Identifying those parameters and processes which are

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https://doi.org/10.1016/j.agrformet.2018.08.002
Received 15 March 2018; Received in revised form 29 July 2018; Accepted 8 August 2018

most influential on model outputs can guide the efforts towards improving the accuracies of the most influential parameters and help to better understand the model structure and behaviour (Saltelli et al., 2004; Sarrazin et al., 2016), and reduce model complexity (Crout et al., 2009). This is especially important for complex process-based models which are often considered as over-parameterised leading to problems of non-uniqueness in parameter sets (also called equifinality).

There is a wide variety of available approaches to sensitivity analysis (Hamby, 1994; Campolongo et al., 2007; Saltelli et al., 2010). These techniques vary from the most straightforward approach of One parameter At a Time (OAT) perturbation to more commonly used global approaches. While OAT quantifies model output variation in relation to changes of one parameter at a time, global sensitivity analyses evaluate model output sensitivity to simultaneous changes in several parameters and can thus provide more robust sensitivity measures accounting for non-linearity and interactions among model parameters. Despite OAT methods being straightforward to apply, they are usually considered unreliable for high-dimensional and non-linear models. On the other hand, global methods which are suitable for models of various complexity are often considered computationally intensive (Borgonovo and Plischke, 2016). The Morris screening method is considered as a compromise between OAT and global methods, and it is well-designed to identify influential parameters of large models since it is computationally inexpensive (Campolongo et al., 2007). Moreover, it has been shown to identify the same influential parameters as when using global SA methods (Confalonieri et al., 2010a; Qin et al., 2016). The Morris method has been widely used in analysing sensitivities in a wide range of applications, including chemical (Sin and Gernaey, 2009), hydrological (Francos et al., 2003; Gan et al., 2014), biological (Zi, 2011) and environmental (Cartailler et al., 2014) models.

Parameter sensitivities might be influenced by the crop type, the agricultural management (e.g. N fertilisation) and biophysical environments (e.g. soil and weather) (Confalonieri et al., 2010b; Richter et al., 2010; Zhao et al., 2014). Also, the influence of agricultural practices and weather may vary among crops. For example, the importance of the parameters used in the modelling of processes relevant to water stress could be altered by the timing of the crop growing season, irrigation practices, soil properties and weather conditions. Further, the sensitivity of parameters used in the modelling of N losses might be irrelevant when evaluated in conditions of limited N supply. Thus, ignoring the influence of the specific conditions on parameter sensitivity may produce misleading results.

Despite increasing awareness of the importance of SA in model implementation and particularly in identifying influential parameters to consider during model calibration (Moriasi et al., 2016; Sarrazin et al., 2016; Xu et al., 2016; Hjelkrem et al., 2017), screening SA methods have not yet, to the best of our knowledge, been applied to the DAISY model; a widely used model for simulating water, carbon and N transport and transformation processes in soils and plants (Hansen et al., 2012). Although sensitivities of parts of the model have been studied using simpler local SA techniques with a limited number of parameters (e.g., Salazar et al., (2013); Kröbel et al., (2010) and Manevski et al., (2016)). Therefore, this study aims to analyse the sensitivity of key outputs of a widely used process-based simulation model (DAISY), applied to the winter wheat-summer maize cropping system in North China Plain (NCP), to crop and soil relating parameters and the extent to which parameter sensitivities are affected by crop sequence, field management and weather conditions.

2. Materials and methods

The sensitivity of the four essential model outputs grain yield (Mg ha^{-1}), grain N content at harvest (kg N ha^{-1}), cumulated evapotranspiration (mm) and N leaching (kg N ha^{-1}) to crop and soil relating parameters of the DAISY model were considered. The analysis was performed using long-term experimental data of a winter wheat-summer maize double cropping system from the Luancheng Experimental Station in the North China Plain. The Morris method (Morris, 1991) was selected in this study as it shares many of the positive qualities of the variance-based techniques whilst having the advantage of being able to screen out less influential parameters with a relatively few runs of the multi-parameter model like DAISY (Campolongo et al., 2007). Because output sensitivity to crop and soil input parameters may vary across seasons and crop management, the sensitivity was computed for different cropping seasons with diverse weather conditions (e.g., wet, average, dry seasons) and under different N fertiliser treatments (e.g. below average, average, high, and very high N rates).

2.1. Experimental data

The data used for model sensitivity analysis were collected from an ongoing experiment using the conventional double cropping system, with winter wheat (*Triticum aestivum* L., early October to mid-June) and summer maize (*Zea mays* L., late June to late September) in the NCP. The field experiment was conducted at Luancheng Agro-Ecosystem Experimental Station (37°50′N, 114°40′E, elevation of 50 m) of the Chinese Academy of Sciences, located in the piedmont plain of the Taihang Mountains in Hebei Province in the NCP. A completely randomized block design with four N fertiliser rates (200, 400, 600, and 800 kg urea-N ha^{-1} year^{-1}) was used. These rates reflect possible fertiliser inputs (below average, average, high, and very high) currently used in the NCP. The summary of the crop management details such as tillage, wheat and maize varieties, time for crop sowing and harvest, and fertilisation and irrigation amounts and application dates used to set up the DAISY model are given by Hu et al., (2006) and Li et al., (2007). Data from nine consecutive years (1997 to 2006) were included in our study. The first 3 years (1997–2000) were used as a warm-up period to obtain model states that are independent of the chosen initial values and were excluded in the following analysis. The warm-up period was judged to be sufficient for the current analysis.

Daily weather inputs required by the model were measured at a nearby weather station placed at a distance of 300 m from the field experiment. During the maize growing season, the mean seasonal

Table 1
Weather and irrigation data for winter wheat and summer maize growing seasons at the NCP during the study period.

Winter wheat						Summer maize				
Season	Tmean*	ETo	P	I	ETo-P	Tmean	ETo	P	I	ETo-P
2000-01	6.2	395	86	200	309	24.3	311.1	215.6	150	95.5
2001-02	7.2	363	107	373	256	23.9	312.3	263.4	325	48.9
2002-03	5.0	297	156	233	141	23.5	340.2	292.6	187	47.6
2003-04	6.0	396	121	140	275	22.2	350.4	434.4	0	−84.0
2004-05	5.1	448	99	70	349	24.9	426.8	312.5	140	114.3
2005-06	6.4	490	34	280	456	24.2	372.9	347.2	140	25.7

* Tmean: Mean temperature (°C); ETo: Reference evapotranspiration (mm); P: Precipitation (mm); I: Irrigation (mm).