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A global sensitivity analysis of cultivar trait parameters in a sugarcane growth model for contrasting production environments in Queensland, Australia

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ABSTRACT

New sugarcane cultivars are continuously developed to improve sugar industry productivity. Despite this sugarcane crop models such as the 'Sugar' module in the **A**gricultural **P**roductions **S**ystem s**IM**ulator (APSIM-Sugar) have not been updated to reflect the most recent cultivars. The implications of misrepresenting cultivar parameters in APSIM-Sugar is difficult to judge as little research has been published on the likely values of these parameters and how uncertainty in parameter values may affect model outputs. A global sensitivity analysis can be used to better understand how cultivar parameters influence simulated yields. A Gaussian emulator was used to perform a global sensitivity analysis on simulated biomass and sucrose yield at harvest for two contrasting sugarcane-growing regions in Queensland, Australia. Biomass and sucrose yields were simulated for 42 years to identify inter-annual variability in output sensitivities to 10 parameters that represent physiological traits and can be used to simulated differences between sugarcane cultivars. Parameter main effect (S_i) and total effect (ST_i) sensitivity indices and emulator accuracy were calculated for all year-region-output combinations. When both regions were considered together parameters representing radiation use efficiency (*rue*), number of green leaves (*green_leaf_no*) and a conductance surrogate parameter (k_L) were the most influential parameters for simulated biomass in APSIM-Sugar. Simulated sucrose yield was most sensitive to *rue*, *sucrose_fraction* (representing the fraction of biomass partitioned as sucrose in the stem) and *green_leaf_no*. However, climate and soil differences between regions changed the level of influence cultivar parameters had on simulation outputs. Specifically, model outputs were more sensitive to changes in the *transp_eff_cf* and k_L parameters in the Burdekin region due to lower rainfall and poor simulated soil conditions. Collecting data on influential traits that are relatively simple to measure (e.g. number of green leaves) during cultivar development would greatly contribute to the simulation of new cultivars in crop models. Influential parameters that are difficult to measure directly such as *transp_eff_cf* and *sucrose_fraction* are ideal candidates for statistical calibration. Calibrating crop models either through direct observation or statistical calibration would allow crop modellers to better test how new cultivars will perform in a range of production environments.

1. Introduction

The Australian sugarcane industry is continuously developing, testing and releasing new sugarcane cultivars for commercial production. Many complex interactions contribute to how well these cultivars perform. Process-based crop models capable of simulating cultivar differences give researchers the opportunity to simulate cultivar performance in different production environments and identify traits that provide advantages in given environments (Jeuffroy et al., 2006). Inman-Bamber et al. (2012) used the **A**gricultural **P**roductions **S**ystems s**IM**ulator (APSIM; Holzworth et al., 2014) to identify sugarcane traits that could confer a yield advantage in water stressed environments. The study found that, among other traits, increased rooting depth and reduced stomatal or root conductance could give a yield advantage depending on the specific environment and soil type. Few other simulation

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studies have closely considered how such process-based models can be used to investigate cultivar-environment interactions for sugarcane.

The limited literature on sugarcane cultivar by environment studies may in part be due to the relatively low number of sugarcane cultivars currently defined in leading sugarcane models. Of the Australian sugarcane cultivars defined in the APSIM 'Sugar' module (APSIM-Sugar; Keating et al., 1999), none are generally grown as commercial crops (Sexton, 2015; Sexton et al., 2014). The Australian sugarcane cultivars Q117 is one of the few cultivars available in the APSIM-Sugar model and was one of the most widely used cultivars across a range of environments when the model was developed. This included high rainfall growing regions such as Tully, Queensland (approx. 22.5% total area harvest in 1999) and low rainfall growing regions such as the Burdekin (approx. 30.4% total area harvest in 1999) (SRA, 2015). Comparatively, in the recent 2014 season the leading cultivars grown in these contrasting environments were Q208 (Tully; approx. 43.8% by area harvested) and Q183 (Burdekin; approx. 39.9% by area harvested) (SRA, 2015). Neither of these two cultivars are described in the current version of APSIM-Sugar (V7.7 r3615). Identifying any differences in these cultivars and their response to different environments would help improve crop simulation studies.

In the APSIM-Sugar model, cultivars differ primarily for parameters that represent cane and sucrose partitioning and the leaf area profile (Keating et al., 1999). Using current cultivar definitions, Sexton et al. (2014) found that APSIM-Sugar can struggle to simulate differences between cultivars and cultivar specific responses to water stress. This agreed with previous studies that have found sugarcane crop models are limited in their ability to simulate stress response (Keating et al., 1999; O'Leary, 2000). Including extra parameters that represent traits not classically considered to differ between cultivars may help improve simulations under different environmental conditions. For example transpiration efficiency is not considered cultivar specific in APSIM-Sugar (Keating et al., 1999) but has been identified as potentially conferring a yield advantage under stressed conditions (Inman-Bamber et al., 2012) and has shown evidence of significant genetic variance (Jackson et al., 2014).

Directly measuring the wide range of parameter values used to represent cultivar specific traits can be difficult and resource intensive. In calibrating APSIM-Sugar for Mauritian cultivar R570, Cheeroo-Nayamuth et al. (2000) derived values for leaf area as a function of leaf number; fraction of biomass partitioned into cane; fraction of cane partitioned into sucrose; amount of cane dry matter accumulated before start of sucrose storage and thermal time from emergence to start of stalk formation. This required measurements taken throughout the growing season which are not regularly recorded in breeding trials. Collecting data on extra parameters such as transpiration efficiency as cultivars are released would require even more resources.

An alternative is to calibrate difficult to measure parameter values statistically against data that is readily available such as harvest yields. Marin et al. (2011) calibrated two Brazilian cultivars in the Canegro sugarcane model (Singels et al., 2008). Of the 20 cultivar parameters calibrated in Marin et al. (2011), 7 were derived from experimental data and 10 were statistically calibrated using the Generalized Likelihood Uncertainty Estimation (GLUE) procedure available in the Decision Support System for Agrotechnology Transfere environment (DSSAT; Jones et al., 2011). To reduce resource requirements for measured calibrations and avoid over-parameterization during statistical calibration it can be advantageous to reduce the number of parameters to calibrate. Parameters that are influential but are not easily measurable are ideal candidates for statistical calibration, while parameters that do not influence model outputs or do not vary greatly between cultivars could remain fixed to default values. Sensitivity analysis is a statistical tool that can be used to identify such parameters (Makowski et al., 2006).

Sensitivity analyses can be broadly defined as either local or global (Saltelli et al., 2008). Local sensitivity analysis consider small changes in a single parameter holding all other parameters constant, while global sensitivity analysis considers changes in all parameters over their likely range as well as interactions between parameters (Saltelli et al., 1999). A wide range of analysis techniques for sensitivity have been applied to process-based crop models. The most popular of these are variance based methods such as the Sobol' method (Sobol, 1993), Fourier amplitude sensitivity test (FAST) (Cukier et al., 1973; Cukier et al., 1975; Schaibly and Shuler, 1973) and Extended-FAST (Saltelli et al., 1999).

The FAST method uses a suitably defined search curve to calculate the contribution of each parameter to the output variance—the "main effect" index of each parameter. The Extended-FAST method built on the FAST method allowing for the computation of the total contribution of a parameter to output variance including contributions from all interactions—the "total effect" index (Saltelli et al., 1999). The extended-FAST method has been used to perform variance based sensitivity analysis on crop models for wheat (Zhao et al., 2014), rice (Confalonieri et al., 2010) and maize (Vanuytrecht et al., 2014). Zhao et al. (2014) considered the sensitivity of wheat yields to 10 cultivar parameters and were able to identify *grains.per.gram.stem*, *max.grain.size* and *potential.grain.filling.rate* as the most influential parameters. Zhao et al. (2014) also identified that fertilization rate influenced the rank order of parameter sensitivities. Using the extended-FAST analysis Zhao et al. (2014) required 10,000 simulator runs per study site/fertilizer treatment combination. This large number of simulator runs can be inefficient for computationally expensive models such as process-based crop models.

The Morris method (Morris, 1991) estimates a global main effect (called the elementary effect) of a parameter by averaging a number of local based measures for different points in the parameter space (Saltelli et al., 2008) for each parameter individually. The advantage of the Morris method is the relatively small number of simulations required (Vanuytrecht et al., 2014). To improve the efficiency of variance based analysis such as the Extended-FAST, one-at-a-time analysis such as the Morris method can be used as a screening measure (Confalonieri, 2010; Vanuytrecht et al., 2014). However, removing parameters can result in losing information about parameter interactions. An alternative approach can be to perform the sensitivity analysis on a less resource intensive emulator of the crop simulator.

An emulator is a statistical approximation of a more complex model (O'Hagan, 2006). Because the emulator is a simplified model it is computationally less expensive than running the actual simulator. An emulator of sufficient accuracy can then be used in place of the actual simulator in order to perform the sensitivity analysis (Uusitalo et al., 2015). The simulator itself then only needs to be run a limited number of times in order to build the emulator. Sexton and Everingham (2014) performed a sensitivity analysis of the APSIM-Sugar model using a Gaussian Process emulator (Kennedy, 2005). Sexton and Everingham (2014) analysed the sensitivity of simulated biomass and sucrose yields to 14 trait parameters. By simulating a first ratoon crop grown under well irrigated and water stressed conditions, Sexton and Everingham (2014) were able to identify parameters that were not invoked in the simulations (such as the thermal time parameter controlling flowering) as well as parameters that were most influential in the given production environment. The Gaussian emulator was built using only 400 runs of the APSIM-Sugar simulator.

The objectives of this paper were to use a Gaussian Process based emulator to (1) identify how inter-annual variability effects the