Data requirements for automated model-based control of irrigation and fertiliser application

Alison McCarthy[1] and Steven Raine[2]

[1]National Centre for Engineering in Agriculture, Institute for Agriculture and the Environment, University of Southern Queensland, Toowoomba, QLD 4350, mccarthy@usq.edu.au
[2]Institute for Agriculture and the Environment, University of Southern Queensland, Toowoomba, QLD 4350

Abstract
Model-based adaptive control strategies can be used to determine site-specific irrigation and fertiliser volumes with the aim of maximising crop water use efficiencies and/or yield. These strategies use a crop model to predict the crop's response to climate and management throughout the crop season, and identify which irrigation and fertiliser application volume and timing produces the desired crop response or condition (e.g. maximum yield). The model can be calibrated with infield weather, soil and crop measurements to ensure the model predictions accurately reflect infield measurements. However, data collection of soil and plant parameters spatially over a field and throughout the crop season will potentially lead to a large sensed data requirement which may be impractical in a field implementation. In addition, not all the data may be required to calibrate the crop model with sufficient accuracy. A smaller dataset consisting of only the most influential sensor variables may be sufficient for adaptive control purposes.

This paper reports on a simulation study which evaluated the relative significance of weather, soil and plant variables (either individually or in combination) for calibration of the APSIM french bean crop production model. This involved comparing the outputs of a crop with variations in evaporative demand, soil moisture, leaf area, canopy size and/or thermal time for growth stages. The most significant parameters for the simulated pod size, height, soil moisture and total nitrogen were the thermal times for each growth stage.

Key Words
APSIM simulation, beans, adaptive control, optimisation

Introduction
Crop production models can be used to simulate the soil and plant response to irrigation and fertiliser inputs for manual what-if scenario analysis, and, potentially, automated irrigation and fertiliser control systems. The automated control system would iteratively execute the model with different irrigation and fertiliser treatments and select the treatment that maximised water use efficiency or yield (McCarthy et al. 2011).

An automated model-based control system will be evaluated for a french bean crop in Kalbar, QLD in 2016. However, the crop model must accurately reflect the infield conditions to be used for on-farm management. The crop models can be calibrated by adjusting input parameters that define how the plant produces vegetation and fruit and consumes nutrients and water in response to the weather and soil properties. To automate the calibration procedure of crop models (e.g. in APSIM), all possible combinations of soil and crop parameter values may be evaluated. However, simulating all of the possible combinations of parameters to calibrate crop models would be time-consuming and computationally intensive. For example, there are 21 crop growth-related parameters in the french bean crop properties file and there would be $3^{21} = 10.5 \times 10^9$ possible combinations of parameters to evaluate for three possible states of each parameter. Hence, only the parameters with the greatest effect on the crop model outputs are adjusted in the calibration procedure.

Materials and method
A sensitivity analysis was conducted to identify the most influential input parameters in the french bean crop model. The sensitivity analysis involved the following procedure:
1. Identifying the model input parameters and output variables
2. Executing the model with a range of input parameter values that define how the plant grows and recording the output variables
3. Calculating a sensitivity index to quantify the difference in each output with the adjustment of each input parameter
4. Ranking the influence of each parameter on the model output

Identification of model input and output parameters
For the sensitivity analysis, the simulated response was analysed after each input parameter was adjusted between an appropriate minimum and maximum value. The lower and upper ranges of the input parameters utilised in the sensitivity analysis 50% of the value and the upper range utilised was 150% of the default value of the corresponding parameter in the input files. The parameter input values that were evaluated were equally distributed at sampling points between the lower and upper limits of input parameter (Table 1).

Table 1. Crop parameters in french bean APSIM input variety file

Parameter	Original value	Range of values	Interval
thermal time for emergent	100	50-150	10
thermal time for vegetation	529	264-794	53
thermal time for flowering	185	90-280	19
thermal time for pod filling	265	130-400	27
main stem final node number	40	20-60	4
height during cooler temperatures	50	25-75	5
height during higher temperatures	750	375-1125	75
branching rate at each growth stage	0	0-1	0.1
maximum size of pod	0.68	0.34-1.02	0.068
mortality of each growth stage	0	0-1	0.1
filling rate of early growth stage	0.002	0.001-0.003	0.0002
filling rate late pod growth	7E-.05	3.5E-.05-10.5E-.05	0.7E-.05
water content at each growth stage (start pod growth, end grain fill, maturity, harvest)	0.93	0.465-1.395	0.093
proportion of leaf area killed by frost	0	0-1	0.1

The output variables considered in this sensitivity analysis were soil moisture content, total nitrogen, pod size and plant height. These were selected because they are the most likely to be measured in a field experiment and used to calibrate the growth model.

Model execution
A one at-a-time analysis was conducted which involved repeatedly varying one parameter at a time while fixing the other parameters (Hamby 1994) and evaluating the effect of changing each input parameter on the modelled outputs. The one-at-a-time analysis was conducted for a range of field conditions. This is because if the analysis was only conducted for one particular combination of weather, plant and soil properties and irrigation treatment, the variation in the output may be dependent on the set of field conditions used. A total of 54 possible sets of field conditions were evaluated as follows:

- Two soil types: grey sandy loam and brown clay loam with starting soil moisture content of 100%
- Three irrigation treatments: 10, 20 and 30 mm applied at 20, 30 mm and 40 mm soil moisture deficit, respectively
- Three fertiliser treatments: 15, 25 and 35 kg N/ha applied at 40, 50 and 60 kg N/ha deficit, respectively
- Three weather profiles: Kalbar, QLD for GPS location -27.898960°N and 152.631759°E for three seasons over 2012-2014 obtained from Australian Bureau of Meteorology SILO data set.

A total of 12474 simulations were conducted for the sensitivity analysis (with the 10 adjustments made to each of the 21 input parameters with 54 sets of field conditions). Daily simulated output was recorded for soil moisture content, total nitrogen, pod size and plant height for each simulation.

Calculating the sensitivity indices
Separate sensitivity indices were calculated for each set of field conditions and day of the crop season. This ensured that any variation in the simulated response was caused by the adjustment of an input parameter rather than the temporal variation of the crop response and/or a change in the weather, soil or plant properties. The sensitivity index ($Si_{p,r,i(t)}$) was calculated (Hamby 1994) as follows:

$$SI_{p,r,i}(t) = \frac{D_{p.r.i.max}(t) - D_{p.r.i.min}(t)}{D_{p.r.i.max}(t)}$$

where $D_{p,r,i,max(t)}$ and $D_{p,r,i,min(t)}$ are the respective maximum and minimum simulated values of output r (i.e. soil moisture content, plant height, pod size) when the pth parameter is adjusted over its range and for the ith combination of field conditions and day t.

The sensitivity indices were combined to quantify the overall sensitivity of each simulated output to each input parameter. The first-order indices are commonly averaged to measure the overall sensitivity of the output to each input parameter (Braddock & Schreider 2006). Hence, the sensitivity indices for each field condition and day were averaged as follows:

$$\mu_{p,r} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{d}\sum_{t=1}^{d} SI_{p,r,i}(t)\right)$$

where $\mu_{p,r}$ is the mean sensitivity index, N is the total number of field conditions (81 in this case) and d is the number of days in the simulated crop season. Averaging the daily sensitivity indices throughout the crop season masks the temporal changes in the most significant parameters; however, it also identifies the most significant parameters over the entire crop season.

Discussion

The averaged sensitivity indices for each parameter in the french bean model are shown in Figure 1 for the simulated soil moisture, total nitrogen, plant height and pod size. These indices were assigned ranks from one (highest) to 21 (lowest) where the lowest summed rank was the most significant parameter (Table 2). For each simulated output the sensitivity indices were summed to determine the overall ranking of each parameter (last column of Table 2). From these rankings the following observations were made:

- The thermal time and branching rates for the vegetation, flowering and pod filling stages were the highest overall rank for the pod size, height, soil moisture and total nitrogen. This suggests that the day degrees for growth stages and, hence, weather station data, are required for crop model calibration.
- The most influential parameters for the simulated pod size were thermal time for pod flowering and vegetation, branching rate during vegetation and late pod filling rate. It was expected that pod filling rate would be the most influential parameter for simulating pod size, however the filling rate of late pod growth was only the fourth most influential parameter. This is likely because the sensitivity index was averaged over the season with each day weighted equally although the pod filling occurs over a short period of time (i.e. days). This suggests that the influence of each parameter differs depending on the time the season. Another sensitivity analysis is required that calculates a sensitivity index for each crop growth stage.
- For the simulated bean plant height, the highest ranking crop parameters were height growth after flowering, thermal time for vegetation, and branching rate during vegetation. These parameters are all related to vegetation.
- For the simulated soil moisture content, the thermal time for vegetation and flowering, and branching rate during vegetation were the most influential parameters. This is consistent with the properties of crop water use and soil moisture content which are affected by both vegetative growth and fruit production.
- For the nitrogen simulations, the thermal time for the vegetation, flowering and pod filling stages had the highest ranking.
- The plant water content and proportion of leaf area killed by frost had the smallest influence on the simulated outputs. This is because there was no frost during the simulated bean season.

Conclusions

A sensitivity analysis has been conducted to identify the most significant parameters in the calibration of the french bean module in APSIM. In this analysis, the most significant parameters for the simulated pod size, height, soil moisture and total nitrogen were the thermal times and branching rates for each growth stage and filling rate of pods. These parameters influence both the vegetative and fruiting growth throughout the crop season. This suggests that calibrations of the french bean module for model-based control systems should focus on measurement of weather, plant height and pod size to ensure accurate calibration of the french bean model. Further simulations and analysis will be conducted for different growth stages of the bean crop.

Acknowledgements

The authors are grateful to the Queensland Government for funding the Early Career Accelerate Fellowship.

References

Braddock, R. & Schreider, S. (2006) 'Application of the Morris algorithm for sensitivity analysis of the REALM model for the Goulburn irrigation system', Environmental Modelling and Assessment 11, 297-313.

Hamby, D. (1994) 'A review of techniques for parameter sensitivity analysis of environmental models', Environmental Modelling and Assessment 32, 135-154.

McCarthy, A. C., Hancock, N. H. and Raine, S. R. (2011) Real-time data requirements for model-based adaptive control of irrigation scheduling in cotton. Australian Journal of Multi-Disciplinary Engineering, 8 (2). pp. 189-206. ISSN 1448-8388

Figure 1. Sensitivity analysis results

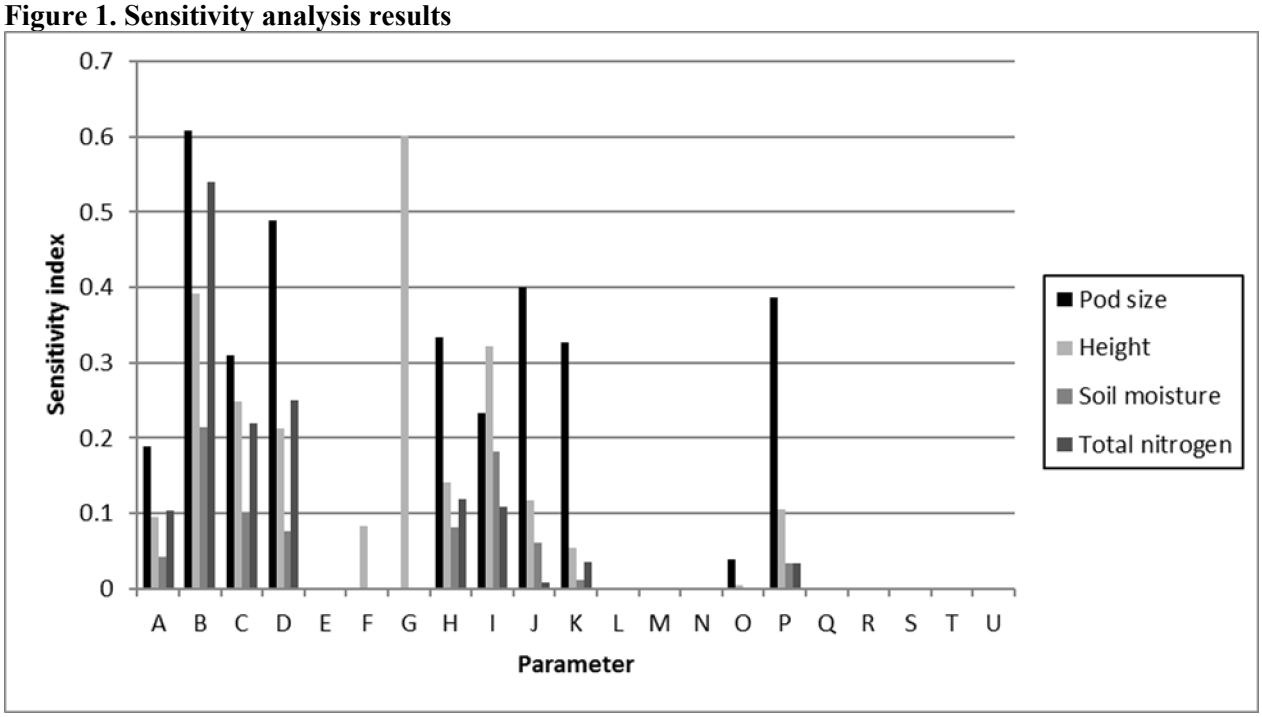

Table 2. Ranks of the first-order sensitivity indices for each parameter

ID	Parameter	Pod size	Height	Soil moisture	Total nitrogen	Overall rank
A	thermal time for emergent	9	9	7	6	8
B	thermal time for vegetation	1	2	1	1	1
C	thermal time for flowering	7	4	3	3	3
D	thermal time for pod filling	2	5	5	2	2
E	main stem final node number	11	13	11	11	12
F	height growth before flowering	12	10	12	12	13
G	height growth after flowering	13	1	13	13	10
H	branching rate during emergence	5	6	4	4	5
I	branching rate during vegetation	8	3	2	5	4
J	branching rate during flowering	3	7	6	9	6
K	maximum size of pod	6	11	9	7	9
L	mortality of early pod growth	14	14	14	14	14
M	mortality of mid pod growth	15	15	15	15	15
N	mortality of late pod growth	16	16	16	16	16
O	filling rate of early pod growth	10	12	10	10	11
P	filling rate of late pod growth	4	8	8	8	7
Q	water content at start pod growth	17	17	17	17	17
R	water content at end grain fill	18	18	18	18	18
S	water content at maturity	19	19	19	19	19
T	water content at harvest	20	20	20	20	20
U	proportion of leaf area killed by frost	21	21	21	21	21