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ARTICLE

Simulating maize yield at county scale in southern Ontario using the decision support system for agrotechnology transfer model

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Abstract: The objectives of this study were to evaluate the ability of the decision support system for agrotechnology transfer (DSSAT) CERES-Maize model to simulate the response to applied nitrogen and soil water storage for maize (*Zea mays* L.) yields in Woodslee, Ontario. A second objective was to evaluate the CERES-Maize module for maize yield in five southern Ontario counties. The calibrated CERES-Maize module was used in 117 maize yield simulations involving combinations of 45 regional soil datasets and 35 weather datasets covering the five counties. The model evaluation showed a good agreement between the simulated and measured grain yields (i.e., index of agreement, $d \geq 0.96$; modeling efficiency, $EF \geq 0.83$; normalized root-mean-square error, $nRMSE \leq 15\%$). The model showed a large deviation using the default soil parameters from 0 to 0.4 m. A sensitivity analysis was made for three soil water parameters, and the calibrated soil parameters showed moderate to good agreements for total soil water storage in the 0–1.1 m soil profile. The model resulted in moderate to good agreement between the simulated and the measured above-ground biomass across growing seasons. There were significant yield differences across the soil types. Drought periods in August 2010 resulted in lower yields in 2010 compared with 2011 and 2012. The simulated average maize yields at each county matched well with the measured data for 2010–2012 except for lower estimated yields in Lambton county in 2010. We concluded that DSSAT CERES-Maize can adequately simulate regional maize yields using the CERES-Maize module calibrated to regional soil and daily weather databases.

Key words: CERES-Maize module, yield, soil water storage, soil landscapes of Canada, regional simulation.

Résumé : L'étude devait établir la capacité du module CERES-Maize du DSSAT à simuler la réaction du maïs (*Zea mays* L.) à l'application d'azote et au stockage de l'eau dans le sol à Woodslee (Ontario). Un deuxième objectif consistait à évaluer le module CERES-Maize d'après le rendement du maïs dans cinq comtés du sud de l'Ontario. Après étalonnage, les auteurs ont appliqué le module CERES-Maize à 117 simulations du rendement du maïs en combinant 45 jeux régionaux de données sur le sol et 35 jeux de données météorologiques sur les cinq comtés. L'évaluation du modèle révèle une bonne concordance entre le rendement grainier théorique et le rendement réel (indice de concordance $d \geq 0,96$; efficacité de la modélisation $EF \geq 0,83$; erreur quadratique moyenne normalisée $nRMSE \leq 15$ %). Le modèle affiche toutefois un écart important quand on utilise les paramètres par défaut du sol de 0 à 0,4 m. Les auteurs ont déterminé la sensibilité du modèle avec trois paramètres de l'eau du sol; les paramètres du sol étalonnés concordent de façon moyenne à bonne avec la quantité d'eau totale stockée dans le profil de sol de 0 à 1,1 m. La biomasse aérienne obtenue par simulation correspond modérément à bien avec la quantité mesurée. Le rendement varie sensiblement avec le type de sol. La sécheresse d'août 2010 a diminué le rendement de 2010, comparativement à celui relevé en 2011 et en 2012. Le rendement du maïs obtenu par simulation dans chaque comté concorde bien avec celui mesuré de 2010 à 2012, sauf pour le rendement estimatif plus

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faible dans le comté de Lambton, en 2010. Les auteurs en concluent que le module CERES-Maize du DSSAT simule adéquatement le rendement régional du maïs pourvu qu'on l'étalonne avec les données régionales sur le sol et les données météorologiques quotidiennes. [Traduit par la Rédaction]

Mots-clés : module CERES-Maize, rendement, stockage de l'eau dans le sol, profils pédologiques du Canada, simulation régionale.

Introduction

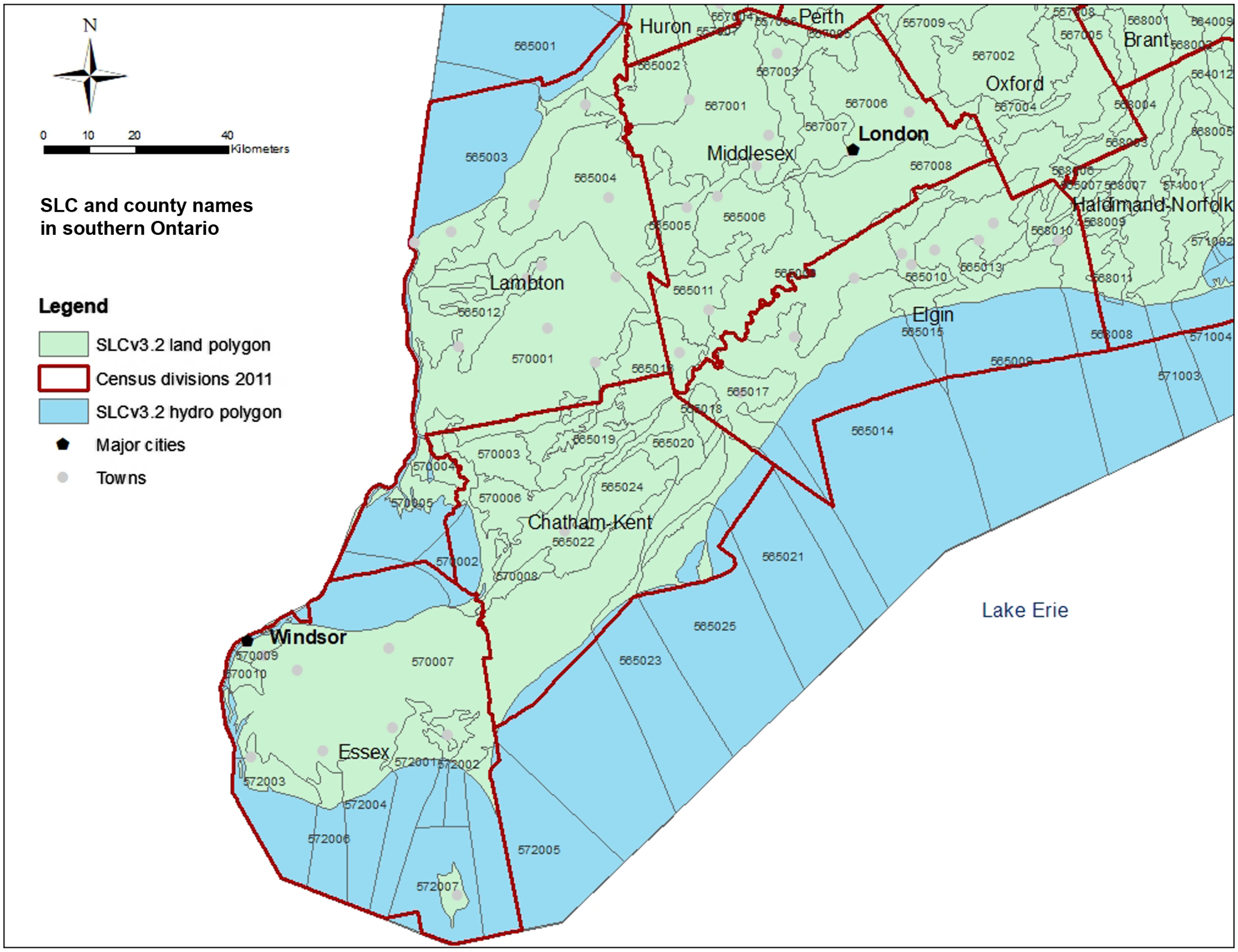
Maize (*Zea mays* L.) is one of the most important cereal crops in Ontario. Maize grain yield has increased by about 5 t·ha^{-1} during the last 30 yr due to continuous improvements in crop breeding and agronomic management practices (Ontario Ministry of Agriculture, Food and Rural Affairs 2018). Agricultural practices, such as fertilization, have a direct impact on the sustainability of agroecosystem crop performance and on physical, chemical, and biological properties of soil (Pernes-Debuyser and Tessier 2004; Drury et al. 2011; Jung et al. 2011; Li et al. 2012).

Nitrogen (N) is the most limiting nutrient for maize production, and an adequate supply is important to maximize yields (Ogola et al. 2002; Celik et al. 2010; Liu et al. 2012; Zou et al. 2012). Soil organic carbon (C) and N concentration can be improved when crop biomass production, and the amount of residue returned to the soil, is increased (Mitchell et al. 1991; Li et al. 2012). Excessive N fertilization, however, can lead to soil N loss by leaching and runoff, and it can also lead to gaseous N emissions by denitrification and ammonia volatilization (Divito et al. 2011; Pelster et al. 2011; Wang et al. 2013). Field experiments have been conducted over the last 60 yr at Woodslee, Ontario, to improve crop yields and reduce nitrate leaching, surface runoff, and gaseous N emissions. For example, studies have been conducted to evaluate (*i*) the impacts of N source, application rates, and time and tillage methods on soil nitrous oxide emission and maize yield (Drury et al. 2011; Liu e al. 2011); (*ii*) the impact of N placement depth and crop rotations on crop yield (Drury and Tan 1995; Drury et al. 2006); (*iii*) the impact of cover crops and water table management on nitrate leaching losses (Drury et al. 2009; Drury et al. 2014); and (*iv*) the impact of enhanced efficiency fertilizers and N placement on ammonia volatilization losses (Drury et al. 2017; Woodley et al. 2018; Woodley et al. 2020). Similarly, fertilization experiments have been conducted on wheat, canola, and various crop rotations in the Black and Brown soil zones of the Saskatchewan (Campbell et al. 1991; Campbell and Zentner 1993) and Alberta (Johnston 1997; Izaurralde et al. 2001) prairies. These experiments have been conducted over several decades to examine the impacts of management practices on soil and environmental quality. Recent experiments examined management practices that could improve N efficiency including N source (regular urea vs. polymer-coated urea), application time (at planting vs. side-dress), and tillage methods (conventional vs. conservation) (Drury et al. 2011; Soon et al. 2011). The fertilizer industry has also adopted the 4R nutrient stewardship (right source, right rate, right time, and right place). Optimizing the N application rate will help to balance maize N requirements and environmental quality, and it is regarded as one of the best management practices for all field crops (Kelley and Sweeney 2005; Chen and Zhang 2010; Cela et al. 2011).

Field experiments are, however, both labour intensive and expensive to conduct (Khaledian et al. 2009; Liu et al. 2013). The effect of fertilization on crop growth and soil nutrient dynamics depends on soil and climatic conditions, crop types, field management, and the interactions of these factors (Mulvaney et al. 2009; Liu et al. 2012). Thus, process-based crop and soil simulation models are being increasingly used as a means for simulating the effects of agricultural management practices, which could save time, resources, and reduce uncertainties (Liu et al. 2011). Many soil–crop models have been developed and applied to nutrient management practices, including AquaCrop (Raes et al. 2009; Adedinpour et al. 2012), MOPECO (de Juan et al. 1996; Domínguez et al. 2012), STICS (Brisson et al. 1998; Constantin et al. 2012), RZWQM (Hanson et al. 1998; Ma et al. 2012), and the decision support system for agrotechnology transfer (DSSAT) (Jones and Kiniry 1986; Jones et al. 2003; Hoogenboom et al. 2017). In recent years, DSSAT, CERES-Maize, CROPGRO-Soybean, and CENTURY-based soil C N models have been evaluated for simulating crop yield, N uptake, soil N leaching, and soil water dynamics in short- and long-term field experiments at Woodslee, Ontario (Liu e al. 2011, 2012, 2013). In this study, DSSAT performance will be evaluated under a large range of soil inorganic N levels (very low to very high), so that the model can simulate grain yield, above-ground biomass, and soil water storage under a range of soil N levels. For these reasons, a field experiment using multiple N rates was used to calibrate the model, so that an optimum N rate to obtain a high maize yield could be determined.

Maize was grown on 180 700–248 000 ha during 2010–2012 in the five counties of southern Ontario, accounting for 25%–28% of total maize production area in Ontario (Fig. 1). Average maize grain dry yield ranged from 7.6 Mg·ha^{-1} in 2004 to 10 Mg·ha^{-1} in 2015 (Ontario Ministry of Agriculture, Food and Rural Affairs 2018). For each of the five counties, soil profile data were compiled from the soil layer files of the Soil Landscapes

Fig. 1. Soil Landscapes of Canada (SLC) numbers and county maps in southern Ontario. Woodslee is located 11 km northeast of Essex township. The base map is the SLC v3.2, projected in Canada Lambert Conformal Conic system using the NAD83 datum. [Colour online.]



of Canada (SLC, v3.2) 1:1M database (Soil Landscapes of Canada Working Group 2010). Weather station datasets are compiled in the weather database which is used in the model simulations. Accordingly, the first objective of this study was to verify the ability of the DSSAT CERES-Maize module to simulate maize grain yield, above-ground biomass, and soil water storage dynamics with five N fertilization rates at Woodslee (Essex county) over 3 yr in southern Ontario, Canada. The second objective was to apply the calibrated maize cultivar and optimum N rate to simulate maize yield for 117 locations that correspond to five counties in southern Ontario and to compare these predictions to reported county-level yields. This was accomplished using 40 soil profile datasets from the Soil Landscapes of Canada database, and 35 daily weather datasets that cover these five counties.

Materials and Methods

Field experiment

Field experimental data were collected from Woodslee, Ontario from 2010 to 2012 for model calibration and evaluation. Woodslee is located in Essex county, which is one of the five counties that were modelled in this study. The measured datasets included maize grain dry yields, above-ground biomass, and soil water content, which were collected from N treatment experiments. Maize seeds 'Pioneer 35F40' were sown in mid-May at a planting density of 76 000 seeds·ha^{-1}. Starter fertilizer (0–45–0) was applied at 142 kg·ha^{-1} with the planter 5 cm beside and 5 cm below the seed. The five fertilizer N treatments included (*i*) N0 (0 kg N·ha^{-1}), (*ii*) N50 (50 kg N·ha^{-1}), (*iii*) N100 (100 kg N·ha^{-1}), (*iv*) N150 (150 kg N·ha^{-1}), and (*v*) N200 (200 kg N·ha^{-1}). All N fertilizers were applied by injecting a 28% liquid urea amonium nitrate at side-dress in late May to mid-June at the designated N rates. Plots (30 m long by 10 m wide) were laid out using a randomized complete block design each with four replicates. Dual II Magnum was applied at 1.75 kg·ha^{-1} to control weeds.

Above-ground biomass and in situ soil water content were measured 4–5 times during the maize growing seasons from 2010 to 2012. The final maize grain yield and moisture contents were measured in late October each year, and dry grain biomass was calculated and used in the model evaluation. Total soil water storage in the 0–1.1 m soil profile was calculated by summing the total of the corresponding volumetric water content θ_i (cm^3·cm^{-3}) in all soil layers. Detailed descriptions of the field management, sampling, and laboratory analysis are included in the Supplementary Materials[1] section.

DSSAT model and evaluation

The CERES-Maize module in the DSSAT version 4.7 (Hoogenboom et al. 2017) was used to simulate maize growth (biomass, plant N, and final dry grain yield). The CENTURY-based soil module, together with a soil water balance module, was selected and used for simulating the soil C, N, and water dynamics and interactions with the soil and atmosphere at the field scale (Tsuji et al. 1994; Gijsman et al. 2002; Porter et al. 2009). After calibrating and evaluating the field data from Woodslee, Ontario, the CERES-Maize module was then used to simulate maize grain yield in five counties in southern Ontario over the same 3 yr period.

Field management, weather, and soil data

Field management data were used to construct a DSSAT management input file (XFILE), including treatment, cultivar, initial soil N, water contents, the dates of maize seeding, tillage operation and timing, harvest, seeding depth and density, row spacing, and the fertilizer N application rates from 2010 to 2012 (Supplementary Materials[1]). Daily weather data at Woodslee were obtained and formatted to the DSSAT weather input file (WTH), including daily solar radiation, precipitation, and the maximum and minimum air temperatures, which are the minimum weather input requirements for the DSSAT model (Pickering et al. 1994; Jones et al. 2003; Wilkens 2004). The monthly, seasonal, and annual weather data from 2010 to 2012 are shown in Supplementary Fig. S1[1]. The 0–0.4 m soil physical data measured in the spring of 2010 were used to construct a default DSSAT soil input profile (SOL). The parameter values for the 0.4–0.6 m and 0.6–1.1 m layers were based upon the 0.3–0.4 m layer as there were no measured values. Key soil parameters required by the DSSAT soil module include texture, i.e., percentage of clay (<0.002 mm), silt (0.05–0.002 mm), and sand (>0.05 mm); bulk density (g·cm^{-3}); organic C content (wt. %); pH (measured in water); root growth factor (0–1); and soil hydraulic properties including saturated water content (vol. %), field capacity water content (drained upper limit, −0.33 MPa), and wilting point water content (lower limit, −1.5 MPa) (Table 1).

Maize cultivar calibration

For the CERES-Maize module, three maize cultivar coefficients (P1, P2, and P5) determine important phenology stages, including the anthesis and maturity dates (Table 2). Two cultivar coefficients determine the grain yield (i.e., G2: maximum number of kernels per plant, G3: kernel growth rate), and the PHINT coefficient estimates the phenological successive leaf tip appearance times (Table 2) (Liu et al. 2013, 2014). Because these cultivar coefficients can vary on a regional scale (Table 2), they should be calibrated for each climatic condition and soil type to ensure that they are compatible with maize growth, development, yield, and growing period objectives.

The three simulated growing seasons included two dry years (2010 and 2012) and one wet year (2011). For this reason, separate cultivar calibrations were carried out in 2010 and 2011 using measured grain yields. The above-ground biomass and soil water data in 2010 and 2011, together with all data in 2012, were used for model evaluation (Table 2). The maize cultivar 'Pioneer 35F40' was calibrated using minimum root-mean-square error (RMSE) between measured and simulated yields. To evaluate model performance, calibrated cultivar coefficients for 2010 were used for all treatments in both 2010 and 2012 (the dry growing seasons), whereas calibrated cultivar coefficients for 2011 were used for all treatments in 2011 (wet growing season). In 2010 and 2012, calibrated cultivar parameter P5 was 899.8 °C, and G3 was 9.71 mg·d^{-1} (Table 2). In 2011, P5 was 852.8 °C, and G3 was 5.45 mg·d^{-1} (Table 2).

Statistical evaluation method

Several statistics were employed in this study to test model performance, including the normalized root-mean-square error (nRMSE), mean error (E), index of agreement (d), and modeling efficiency (EF). The paired t test was also used to detect whether the mean error (E) was significantly different from zero at $p < 0.05$ (Nash and Sutcliffe 1970; Willmott 1982; Akinremi et al. 2005; Krause et al. 2005; Liu et al. 2013; Yang et al. 2014). Graphical display and statistical evaluations were conducted using EasyGrapher version 4.7 software (Yang and Huffman 2004; Yang et al. 2010).

Based upon previous published studies, $d \geq 0.75$, EF ≥ 0, and nRMSE $\leq 15\%$ were considered as having good

[1]Supplementary data are available with the article at https://doi.org/10.1139/cjss-2020-0116.

Table 1. Soil physical and chemical data for the profile collected from the field site in spring 2010 as input for the DSSAT CERES-Maize model.

Soil depth (m)	Bulk density ($g \cdot cm^{-3}$)	Soil water content at −0.33 Mpa ($m^3 \cdot m^{-3}$)[a]	Soil water content at −1.50 Mpa ($m^3 \cdot m^{-3}$)[b]	Saturated water content ($m^3 \cdot m^{-3}$)	Silt content (%)	Clay content (%)	Organic carbon content (%)	Root grow factor	pH
0–0.1	1.45	0.390	0.208	0.4540	33.7	40.1	1.84	1.000	6.0
0.1–0.2	1.56	0.380	0.202	0.4420	32.6	43.3	1.26	1.000	6.3
0.2–0.3	1.56	0.388	0.213	0.4200	32.6	43.3	1.00	0.607	6.3
0.3–0.4	1.56	0.384	0.221	0.4040	32.6	43.3	1.00	0.497	6.3
0.4–0.6	1.56	0.384	0.227	0.4040	32.6	43.3	0.40	0.368	6.3
0.6–1.1	1.56	0.384	0.227	0.4040	32.6	43.3	0.40	0.172	6.3

[a]Soil water contents at −0.33 Mpa is the field capacity.
[b]Soil water contents at −1.50 Mpa is the wilting point.

model-data agreement for crop growth variables; $d \geq 0.60$, $EF \geq 0$, and $15\% \leq nRMSE \leq 30\%$ as moderate model-data agreement; and $d < 0.60$, $EF < 0$, and $nRMSE \leq 30\%$ as poor agreement (Liu et al. 2013, 2014). The above statistics were calculated as follows:

$$(1) \qquad \mathrm{nRMSE} = \sqrt{\sum_{i=1}^{n} (S_i - M_i)^2 / n} \Big/ \overline{M} \times 100$$

$$(2) \qquad E = \sum_{i=1}^{n} (S_i - M_i)/n$$

$$(3) \qquad \mathrm{EF} = 1 - \sum_{i=1}^{n} (S_i - M_i)^2 \Big/ \sum_{i=1}^{n} (M_i - \overline{M})^2$$

$$(4) \qquad d = 1 - \sum_{i=1}^{n} (S_i - M_i)^2 \Big/ \sum_{i=1}^{n} (|S_i - \overline{M}| + |M_i - \overline{M}|)^2$$

where S_i and M_i are the ith model-simulated and measured values, respectively, n is the number of data pairs of simulated and measured values, and $\overline{M}$ is the average of the measured values.

Regional simulation data

Regional maize management data

The validated CERES-Maize parameters derived over the 3 yr using the field study data were then used for simulation of regional maize yields in five Ontario counties because all modelled locations were within 150 km of the Woodslee field site (Fig. 1). Model input included (*i*) crop sowing dates ranging from 10 to 25 May in 2010 to 2012, based on the average planting dates in five counties with a planting density of 76 000 $seeds \cdot ha^{-1}$; (*ii*) fertilizer N application of 150 kg $N \cdot ha^{-1}$ as side-dress in mid-June each year, which corresponds to the corn 5–6 leaf stage; and (*iii*) conventional moldboard plow tillage (includes Disc tandem and sprocket packed). Soil profile and daily weather input for each simulation location varied among the five counties based on the Soil Landscapes of Canada (SLC) soil maps and the Environment Canada weather database.

Regional soil profile data

The DSSAT soil input data requires soil name, location, profile depth, and detailed soil physical and chemical properties in each layer. MS Access was used to extract this information from the SLC version 3.2 database located in Canadian Soil Information System (http://sis.agr.gc.ca/cansis/nsdb/slc/v3.2/index.html).

Data from 40 soil profiles were accessed corresponding to the soils found in the five target counties in the SLC version 3.2 (Table 3). The soil layer table provides soil physical and chemical data, including soil water contents at permanent wilting point, at field capacity and saturation, bulk density, soil C, N, pH and cation-exchange capacity, and the soil texture (sand, silt, and

Table 2. Default cultivar coefficient ranges in DSSAT and calibrated maize cultivar coefficients for 2010, 2011, and 2012.

Maize cultivar parameter		Cultivar	Calibrated cultivar		
		Range	FN2010	FN2011	FN2012
ECO No.	Maize ecotype coefficient (MZCER047.ECO)	—	IB0002	IB0002	IB0002
P1	Time from seedling emergence to the end of juvenile phase during which the plant is not responsive to photoperiod (degree day >8 °C)	100–400	210	210	210
P2	Extent to which development (expressed as days) is delayed for each hour increase in photoperiod > the longest photoperiod 12.5 h)	0–4.0	0.52	0.52	0.52
P5	Thermal time from silking to physiological maturity (degree day >8 °C)	600–900	899.8	852.8	899.8
G2	Maximum possible number of kernels per plant	380–1000	680	680	680
G3	Kernel growth rate during the linear grain filling stage under optimum conditions ($mg{\cdot}d^{-1}$)	5–12	9.71	5.45	9.71
PHINT	Phyllochron interval between successive leaf tip appearances (degree day per tip)	38.9–55.0	38.9	38.9	38.9
RUE[a]	Radiation use efficiency (g plant dry matter·MJ PAR^{-1})	4.2–4.5	4.5	4.5	4.5

Note: The maize cultivar used in this research is 'Pioneer 35F40' and the cropping cycle is 300 d.
[a]IB0002 ecotype coefficient was selected in each year of 2010–2012; therefore, the value of the RUE = 4.5.

clay composition). Soil names and polygon attributes were extracted from the name table and the attributes table. Dominant soils in each polygon were extracted from the component table, and soil suitability for agriculture was obtained from the landscape segmentation table.

Regional weather data

A total of 35 weather datasets were collected from the SLC polygons in the five counties over the 3 yr period (2010, 2011, and 2012). The datasets included maximum and minimum daily air temperature ($T_{\max}$ and $T_{\min}$), and daily precipitation. Daily solar radiation, R_s, was estimated from daily $T_{\max}$ and $T_{\min}$ using (Allen et al. 1998).

$$(5) \qquad R_s = k_{R_s}\sqrt{(T_{\max} - T_{\min})}R_a$$

where k_{R_s} is an adjustment coefficient (0.19 for locations near a large body of water and 0.16 for locations not near a body of water), and R_a represents extraterrestrial radiation:

$$(6) \qquad R_a = \frac{24(60)}{\pi} G_{sc} d_r[\omega_s \sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\sin(\omega_s)]$$

where G_{sc} is the solar constant of 0.0820 $MJ{\cdot}m^{-2}{\cdot}min^{-1}$, d_r is the inverse relative distance between the earth and the sun, and the angles φ, δ, and ω_s (measured in radians) represent latitude, solar declination angle, and sunset hour angle, respectively.

Regional simulation design

DSSAT simulation files (XFILE) (Jones et al. 2003) were developed for each county to simulate regional maize yield at different locations using the same management practice. This resulted in 18 simulations for Essex county, 31 for Chatham-Kent, 30 for Elgin, nine for Lambton, and 29 for Middlesex in each of the 3 yr (2010, 2011, and 2012) (Table 3). Soil names, profile depths, clay, and silt contents, and "A" horizon depths are listed in Table 3, along with the number of weather stations for each soil type in each county.

Regional reported maize yield

Maize yields from the five counties in each of the 3 yr were obtained from Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA 2018). Grain corn harvested area (acre) and total production (1000 t grain) were reported by county by year. Grain dry weight ($Mg{\cdot}ha^{-1}$) was calculated by adjusting for the 14.5% water content (i.e., dry weight = 0.855 × yield) and then converting the dry grain yield per acre to dry grain yield per hectare. The grain dry weights in the five counties from 2010 to 2012 were used to evaluate the ability of the CERES-Maize module to accurately simulate dry grain yields.

Results and Discussion

Weather conditions

The annual and growing season (planting to harvest) precipitation amounts for Woodslee, Ontario were 778 and 428 mm in 2010, 1335 and 610 mm in 2011, 732 and 419 mm in 2012, respectively (Supplementary Fig. S1[1]). Compared with long-term (1961–2005) average annual and growing season precipitation of 831 and 459 mm, 2011 was above normal by 151 mm in the growing season, whereas 2010 and 2012 were 31 and 40 mm below average. The distribution of monthly precipitation varied across the 3 yr. For example, the monthly precipitation during the growing season was found to be higher

Table 3. List of soil types, particle size in top and deep layers, and weather station numbers in each of five counties in southern Ontario.

County	Soil name	Profile number	Weather number	Simulation number	Simulation number at county	Top layer clay (%)	Top layer silt (%)	Top layer depth (cm)	Profile depth (cm)
Essex	Berrien	4	3	12	18	4–13	10–20	25	100
	Brookston[a]	3	1	3	—	15–37	33–48	22	100
	Perth[a]	3	1	3	—	22–23	40–55	27	103
Chatham-Kent	Brookston	3	1	3	31	Same as above			
	Clyde	2	1	2	—	29–45	25–58	27	100
	Kintyre[a]	1	1	1	—	9	24	32	100
	Normandale[a]	2	2	4	—	6	10–15	28	125
	Tavistock	5	1	5	—	13–27	27–63	20	100
	Toledo	5	3	15	—	18–42	26–63	24	91
	Walsingham[a]	1	1	1	—	2	9	25	150
Elgin	Beverly	3	1	3	30	13–38	21–53	20	102
	Globes[a]	4	4	16	—	10–29	19–52	24	100
	Kintyre	1	1	1	—	Same as above			
	Normandale	2	1	2	—	Same as above			
	Plainfield	2	4	8	—	1–5	2–4	15	183
Lambton	Brookston	3	1	3	9	Same as above			
	Caistor	2	1	2	—	20–29	30–52	20	100
	Perth	3	1	3	—	Same as above			
	Walsingham	1	1	1	—	Same as above			
Middlesex	Beverly	3	2	6	29	Same as above			
	Brookston	3	1	3	—	Same as above			
	Embro	1	2	2	—	15	49	20	100
	Globes	4	2	8	—	Same as above			
	Huron	2	1	2	—	27	55	18	100
	Perth	3	2	6	—	Same as above			
	Walsingham	1	2	2	—	Same as above			
Total		40	35	117	117	—	—	—	—
Repeated soil and weather		27	7	—	—	—	—	—	—

Note: Soil profile number multiplied by weather number equals simulation number.
[a]The profile values of Brookston, Perth, Kintrye, Nomandale, Walsingham, and Globes soils are only listed in the first appearance.

in May to July and September in 2010, in April to November (except June) in 2011, and in July and August in 2012 compared with the long-term average.

Regional weather precipitation distribution in the growing season and on an annual basis was listed using the data from 35 weather stations. For example, in 2010, the growing season precipitation ranged from 457 to 499 mm in Chatham-Kent, from 495 to 548 mm in Elgin, from 490 to 543 mm in Essex, from 445 to 470 mm in Lambton, and from 447 to 534 mm in Middlesex. The distribution of monthly precipitation varied across the five counties, especially in August which had a range from 8 to 58 mm. The average precipitation in Elgin was 43 mm in August, significantly higher than in the four other counties, which ranged from 12 mm in Lambton to 20 mm in Middlesex (Supplementary Table S1[1]).

Maize grain yield

Measured grain yield

The measured maize grain yield increased with N fertilization rates for all three years (Fig. 2). Similar results were reported by other researchers (Ding et al. 2010; Yang et al. 2011; Sindelar et al. 2012). In 2010, the measured maize grain yield for the N150 and N200 treatments was significantly higher than for the N0, N50, and N100 treatments (Fig. 2*a*), whereas no statistical difference was found between the N150 and N200 treatments. The measured maize grain yield across all N treatments was lower in 2011 than in 2010 and 2012, except at N200 (Fig. 2). The lower grain yield in 2011 may reflect late planting due to wet spring conditions. The lower yields may also reflect generally high rainfall throughout this growing season (Supplementary Fig. S1[1]), which probably caused larger

Fig. 2. Comparison of the measured and simulated dry maize grain yields for N0, N50, N100, N150, and N200 treatments (where N0, N50, N100, N150, and N200 represent 0, 50, 100, 150, and 200 kg N·ha^{-1} applied in the treatments) during 2010–2012 at Woodslee, Ontario. The vertical bars represent ± standard error of the measured dataset. [Colour online.]

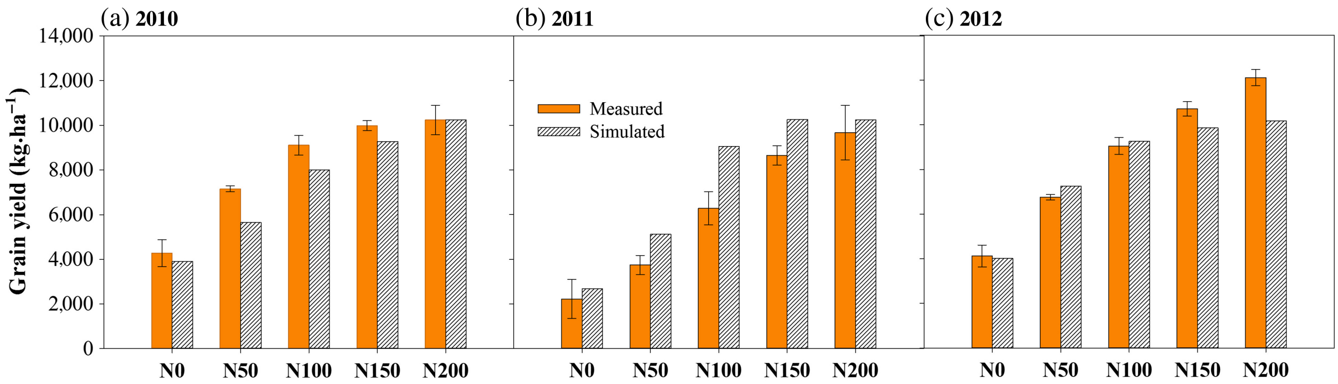


Table 4. Statistical evaluation of the measured and simulated maize grain yield, above-ground biomass, and soil water storage.

Variables	Treatment	Year	Data number	Measured mean (kg·ha^{-1})	Simulated mean (kg·ha^{-1})	*d*	EF	*E*[a]	*t* value	nRMSE (%)
Calibration										
Grain yield (kg·ha^{-1})	N0 to N200	2010	5	8152	7414	0.96	0.83	−738	−2.78	11.2
	N0 to N200	2011	5	7113	7468	0.96	0.84	**355**	0.72	14.7
Evaluation										
Grain yield (kg·ha^{-1})	N0 to N200	2012	5	8552	8117	0.96	0.88	**−435**	−1.00	11.4
Above-ground biomass (kg·ha^{-1})	N0 to N200	2010	15	7160	8190	0.93	0.77	**1031**	1.07	52.2
	N0 to N200	2011	20	9126	11 899	0.94	0.72	2773	8.06	34.6
	N0 to N200	2012	20	10 333	8932	0.98	0.92	−1401	−3.91	20.3
Soil water storage (mm)	N150	2010	127	263	284	0.84	0.37	22	4.70	21.3
	N150	2011	146	423	410	0.66	0.16	−13	−3.16	12.5
	N150	2012	146	236	258	0.92	0.73	23	8.07	17.2

Note: *d*, index of agreement; EF, modeling efficiency; *E*, mean error; nRMSE, normalized root mean square error. N0, N50, N100, N150, and N200 represent 0, 50, 100, 150, and 200 kg N·ha^{-1} applied in the treatments.
[a]Bold value indicates a significant difference ($p < 0.05$) between the simulated and measured data.

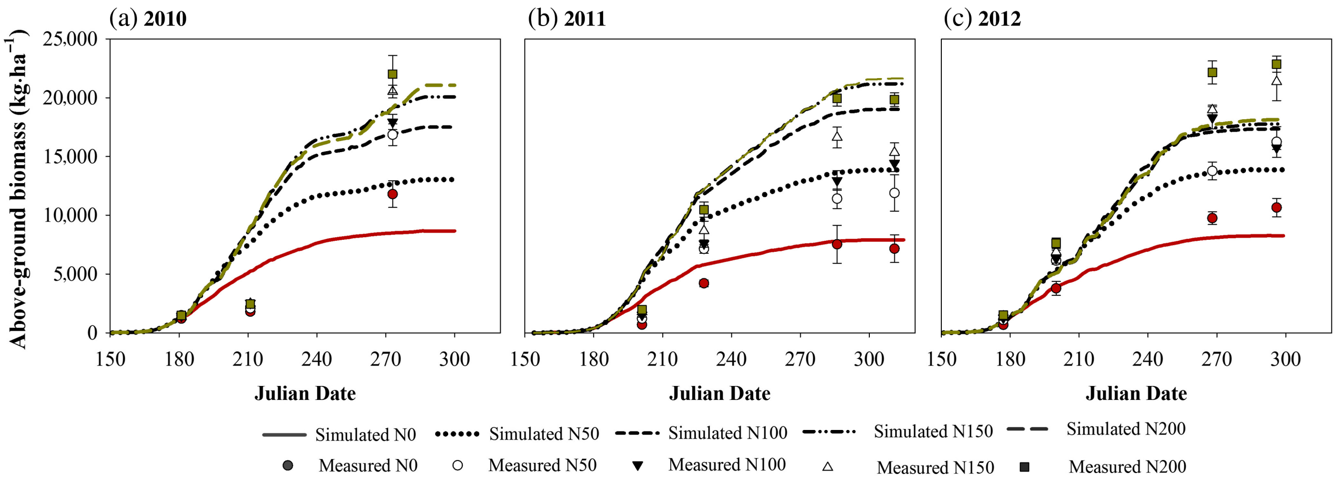
than normal N losses through enhanced gaseous N_2O and N_2 emissions and (or) increased nitrate N leaching.

Simulated grain yield

Using the 2010 grain yield to calibrate the maize cultivar (Table 2), a good agreement was achieved between the simulated and measured grain yields using the calibrated coefficients with $d = 0.96$, EF = 0.83, and nRMSE = 11.2% (Fig. 2*a*, Table 4). Using the 2011 grain yield to calibrate the maize cultivar in a normal precipitation year, a good agreement was also achieved with $d = 0.96$, EF = 0.84, and nRMSE = 14.7% (Fig. 2*b*, Table 4). The corresponding *E* value of −738 kg·ha^{-1} in 2010 and 355 kg·ha^{-1} in 2011 indicated that the maize grain yield was underestimated by the model for 2010 and overestimated for 2011, although there were no statistically significant differences based on the paired *t* test (Table 4). These results suggest that the maize cultivar coefficients were successfully calibrated for the CERES-Maize module.

The maize grain yield under all treatments in 2012 was used to evaluate the CERES-Maize module. The calculated *d*, EF, and nRMSE values were 0.96%, 0.88%, and 11.4%, respectively, in 2012, indicating good agreement between the simulated and measured maize grain yields (Fig. 2*c*, Table 4). The corresponding *E* value in 2012 was −435 kg·ha^{-1}, indicating that the model under-estimated the grain yield, but this value was not statistically different from zero based on the paired *t* test (Table 4). The performance of the CERES-Maize module in simulating maize grain yield in this study is generally comparable with those of other simulation studies (Liu et al. 2011, 2012; Monzon et al. 2012). The calibrated CERES-Maize module successfully simulated maize grain yield for different levels of N fertilization in 2010, 2011, and 2012.

Fig. 3. Comparison of the measured and simulated above-ground biomass during 2010–2012 maize growing seasons for N0, N50, N100, N150, and N200 treatments (where N0, N50, N100, N150, and N200 represent 0, 50, 100, 150, and 200 kg N·ha^{-1} applied in the treatments). The vertical bars represent ± standard error of the measured dataset. [Colour online.]



Above-ground biomass

The measured above-ground biomass for all five N rates increased with plant growth from May to September for all years as expected (Fig. 3). Yields increased with increasing N rates except at the two highest N rates. No significant differences were found between N150 and N200 at Julian day 273 in 2010 (Fig. 3*a*), at days 285 and 305 in 2011 (Fig. 3*b*), and at days 265 and 285 in 2012 (Fig. 3*c*). These results coincided with other studies that reported increased yields with N addition that reached a plateau (Ogola et al. 2002; Varvel et al. 2008; Wang et al. 2010; Sindelar et al. 2012). For example, Ogola et al. (2002) reported that application of 100 kg N·ha^{-1} increased total above-ground biomass from 28% to 42% under three irrigation experiments compared with zero N rate. Also, Sindelar et al. (2012) evaluated the maize above-ground biomass over 2 yr under different N fertilization rates at two irrigated locations and two rain-fed locations across Minnesota; they found that the maize above-ground biomass increased as the N fertilization rate increased up to the optimum N fertilizer rate for all locations and experiment conditions compared with zero N rate.

The simulated above-ground biomass followed a trend similar to the measured data. Above-ground biomass increased with N rate and then reached a plateau. For example, there were no obvious differences between the simulated growth curves for N150 and N200 (Fig. 3), whereas distinct differences occurred among the other fertilizer N levels, especially in the middle to final crop growth stages.

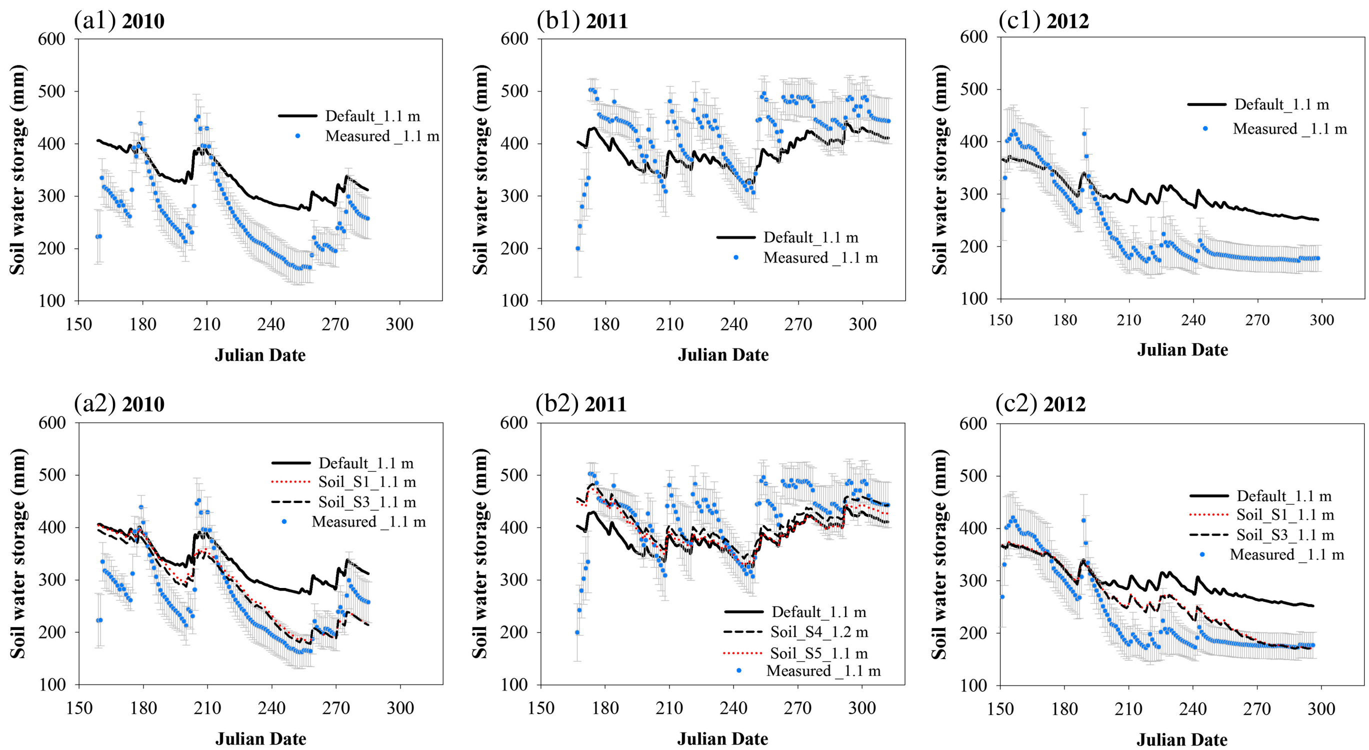
The above-ground biomass was significantly overestimated by the model as shown by positive E values of 1031 and 2773 kg·ha^{-1} in 2010 and 2011 but underestimated by the model in 2012 ($E = -1401$ kg·ha^{-1}) (Table 4). Moderate agreements were achieved between the simulated and measured above-ground biomass in 2011 and 2012 as indicated by $d = 0.94$–0.98 and EF = 0.72–0.92 (Table 4). The lowest nRMSE was 20.3% in 2012, whereas the largest nRMSE was 52.2% in 2010. The high nRMSE in 2010 (indicating poor model-data agreement) may be due to a single large deviation between measured biomass and simulated biomass on Julian day 211 (Fig. 3*a*, Table 4).

Sensitivity analysis of soil water storage

Daily soil water storage in the 0–1.1 m soil depth range during the growing season was evaluated for the N150 treatment using the default soil (Table 1). This N rate was selected because it was close to optimal and also typical amount of N used by the corn growers in southern Ontario. The measured soil water storage ranged from 162 ± 32 to 452 ± 32 mm in 2010, from 200 ± 55 to 503 ± 20 mm in 2011, and from 172 ± 26 to 421 ± 50 mm in 2012, respectively (Fig. 4). Although simulated soil water storage generally mimicked measured storage, the simulations were significantly overestimated in dry conditions (2010) and underestimated in wet conditions (2012) (Figs. 4*a*1, 4*c*1). In addition, the simulations consistently predicted more gradual decreases in soil water storage than were measured (Fig. 4). These discrepancies may indicate that the default soil profile was not a good representation of the actual soil in the 0–1.1 m depth, perhaps because measured soil parameters were available only for the top 0.4 m (Table 1). The higher soil water storage in 2011 (Fig. 4*b*1) was likely due to greater precipitation in 2011 compared with 2010 and 2012 (Supplementary Fig. S1[1]), and the simulated soil water storage was systemically lower than the measured data (Fig. 4*b*1).

Sensitivity analyses were conducted in an attempt to determine why the simulated decreases in soil water

Fig. 4. Measured and simulated total soil water in the 1.1 m profile for N150 (the 150 kg N·ha^{-1} treatment) during 2010–2012 at Woodslee, Ontario. The vertical bars represent ± standard deviation from four measured fields in each year. (*a*1–*c*1) Simulated soil water storage using the default soil profile (Table 1). (*a*2–*c*2) Sensitivity analysis using soil_ S1 to S5 profile. Soil_S1, changing the soil LL = 15% and the SAT = 45%; Soil_S2_1.2 m, equal soil_S1 but set up 1.2 m soil profile; Soil_S3, changing the soil LL = 15%, DUL = 40%, and SAT = 45%; Soil_S4_1.2 m, equal soil S3 but set up 1.2 m soil profile; Soil_S5, changing the soil LL = 11%, DUL = 43%, and SAT = 47%, which was based on the measured maximum soil water contents ranged 47%–55% in the 0.4–1.1 m soil from 2010 to 2012. [Colour online.]



storage were consistently more gradual than the measured decreases (Figs. 4*a*2–4*c*2). Previous DSSAT studies at Woodslee found that soil water storage was sensitive to profile upper and lower drainage limits (He et al. 2016); and for this study, maximum measured soil water contents ranged from 47% to 55% in the 0.4–1.1 m during the 2010–2012 growing seasons. Based on this information, the sensitivity of six soil water parameters was determined, including (*i*) soil water drainage upper limit (DUL), (*ii*) soil water drainage lower limit (DLL), (*iii*) saturated soil water content (SAT), (*iv*) soil bulk density (BD), (*v*) saturated hydraulic conductivity (K_{sat}), and (*vi*) soil silt and clay contents. The preliminary sensitivity was conducted by a ±5% to ±30% change of each parameter. The results showed that the soil water storage was sensitive to DUL, DLL, and SAT but not sensitive to the BD, K_{sat}, or clay/silt contents (data not shown).

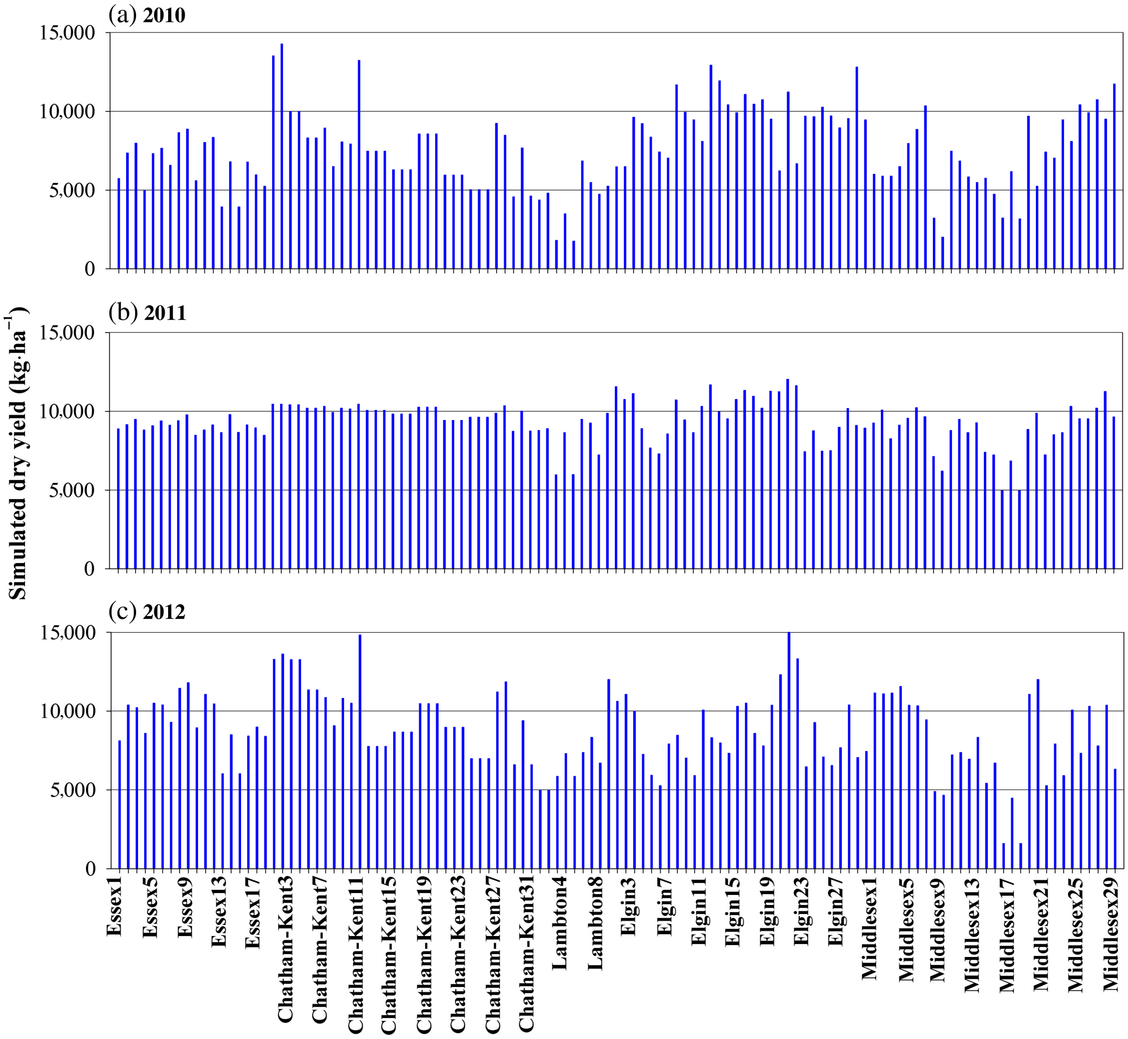
Based on the above results, the following five soil profiles were developed for further sensitivity analysis of soil water storage:

- Soil_S1: changing the soil DLL = 15% and the SAT = 45%
- Soil_S2_1.2 m: equal soil_S1 but set up 1.2 m soil profile
- Soil_S3: changing the soil DLL = 15%, DUL = 40%, and SAT = 45%
- Soil_S4_1.2 m: equal soil_S3 but set up 1.2 m soil profile
- Soil_S5: changing the soil DLL = 11%, DUL = 43%, and SAT = 47%, which was based on the measured maximum soil water contents ranging from 47% to 55% in the 0.4–1.1 m soil during 2010–2012.

The results of re-running the model using the above five soil profiles are shown in Figs. 4*a*2–4*c*2, with the corresponding evaluation metrics given in Table 4. In 2010 and 2012, the Soil_S1 and S3 obtained the better match to the measured soil water storage at 1.1 m soil profile (Figs. 4*a*2 and 4*c*2). In 2011, however, the Soil_S4 and Soil_S5 showed better matches to the measured soil water at 1.2 and 1.1 m, respectively (Fig. 4*b*2).

Higher growing season precipitation occurred in 2011 than in 2010 and 2012, which was the main reason for greater soil water storage in 2011, as evapotranspiration was similar for all three years (Supplementary Table S2[1]). For instance, simulated soil water storage ranged from

Fig. 5. Simulated maize dry grain yield in five counties of southern Ontario in 2010, 2011, and 2012. [Colour online.]



338 to 483 mm in 2011 but was only 173–395 mm in 2010 and 2012 (Fig. 4). The high precipitation in 2011 resulted in the high measured soil water content throughout the growing season, which ranged between 47% and 55% in the soil profile, whereas the simulated soil water storage at the Soil_S1 was controlled by the soil water DUL 0.384–0.390 (Table 1), which cannot hold more soil water in the same soil depth. It appears that the measured soil water storage in 2011 in the 0–1.1 m depth could be adequately simulated either by Soil_S4 in the 1.2 m soil profile or the Soil_S5 in the 1.1 m soil profile.

Using the re-calibrated soil profiles, moderate to good agreements were achieved between simulated and measured soil water storage as indicated by $d = 0.84$, EF = 0.37, and nRMSE = 21.3% in 2010, and by $d = 0.92$, EF = 0.73, and nRMSE = 17.2% in 2012. The E values of 22 mm in 2010 and 23 mm in 2012 indicated that the model overestimated the measured soil water storage in the drier years. In 2011, a moderate agreement was achieved as indicated by $d = 0.66$ and nRMSE = 12.5%. An E value of −13 mm indicated the model generally underestimated soil water storage in 2011 (Fig. 4*b*2, Table 4). The small value of EF = 0.16 was mainly caused by the larger differences at early soil water storage from Julian days 170 to 175.

Regional maize grain yield simulation

Maize grain yield variation by years

The simulated maize dry grain yields varied with location, soil, and year for 117 simulations in each of 3 yr (Fig. 5). Average maize grain yields at the SLC level were mapped by five classes in each of the 3 yr (Supplementary Figs. S2-a–S2-c[1]). The simulated maize grain yields averaged 7048, 9088, and 8772 kg·ha^{-1} with standard deviations of 2648, 1414, and 2685 kg·ha^{-1} in 2010, 2011, and 2012, respectively (Table 5). Among the 117 simulations, 76 (64%), 16 (13%), and 48 (41%) showed maize grain yields below 8000 kg·ha^{-1} in 2010, 2011, and 2012, respectively (Table 5). It can be concluded that the yield variation in 2011 was mainly caused by soil type because of minimal water stress in 2011, whereas the low yields with large variation (large standard deviation)

Table 5. Simulated grain dry yield in five yield classes, 117 simulations in five counties of southern Ontario from 2010 to 2012.

Yield classes (kg·ha^{-1})	2010 (SN)	2011 (SN)	2012 (SN)	2010 (%)	2011 (%)	2012 (%)
Class 1 (<6000)	45	4	15	38	3	13
Class 2 (6000–8000)	31	12	33	26	10	28
Class 3 (8000–10 000)	24	63	24	21	54	21
Class 4 (10 000–12 000)	15	37	35	13	32	30
Class 5 (≥12 000)	2	1	10	2	1	9
Total	117	117	117	100	100	100
Average yield	7048	9088	8772	—	—	—
Standard deviation	2648	1414	2685	—	—	—

Note: SN, simulation numbers.

in 2010 were affected by both soil type and water stress during the growing season.

To analyze yield variation, the simulated maize grain yields were grouped by soil types, counties, and years (Supplementary Table S3[1]). The minimum yields across all soil types ranged from 1758 to 6213 kg·ha^{-1} in 2010 which had drought conditions during the growing season; and they ranged from 5910 to 8485 kg·ha^{-1} in 2011 which had above-average growing season rainfall. The maize yield variations in 2010 (dry year) were caused by both weather and soil type, whereas yield variations in 2011 (wet year) were caused mainly by soil type. The minimum yields ranged from 3033 to 6589 kg·ha^{-1} in 2012, and the minimum yield of 3303 kg·ha^{-1} might reflect brief drought periods.

Maize grain yield variation by soil

High predicted maize grain yields were found in Elgin, followed by Chatham-Kent and Essex, whereas low yields were in Lambton and Middlesex county. Large yield variations were found due to the soil types in each county. Across 2010–2012, the average simulated maize yields were on the order of 9358 kg·ha^{-1} (6213–15 126 kg·ha^{-1}) in Elgin, 8342 kg·ha^{-1} (3929–10 845 kg·ha^{-1}) in Essex, 8188 kg·ha^{-1} (3638–14 820 kg·ha^{-1}) in Chatham-Kent, 7861 kg·ha^{-1} (2617–12 008 kg·ha^{-1}) in Middlesex, and 6521 kg·ha^{-1} (1758–12 008 kg·ha^{-1}) in Lambton (Supplementary Table S3[1]). We concluded that Elgin had the highest maize grain yield potentials in all 3 yr, whereas Lambton achieved the lowest yields, especially in 2010.

Maize grain yield variation by weather

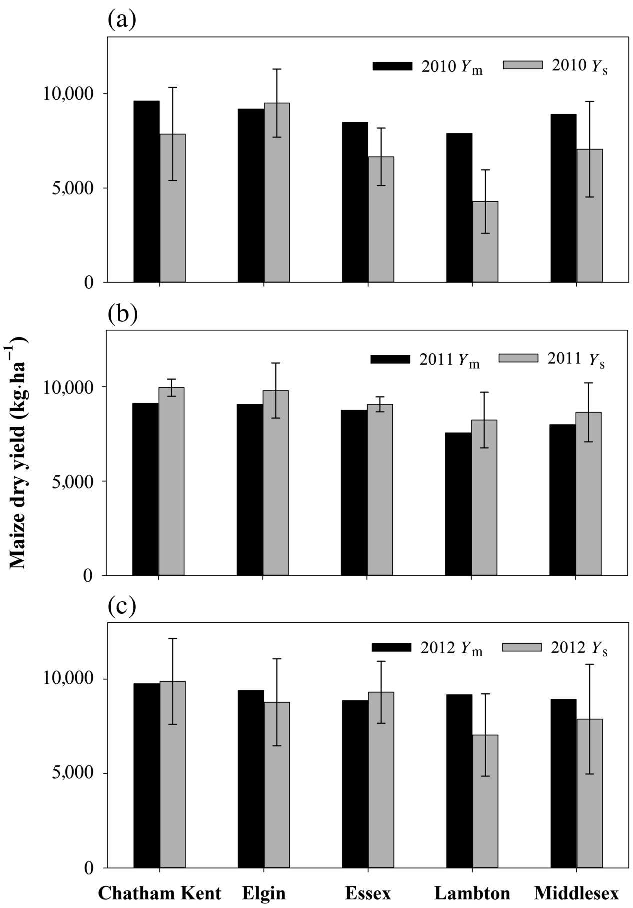
In 2010, a dry growing season, the variation in maize yields among 117 simulations that correspond to distinct soil profile and weather combinations in the five counties were affected by both soil and growing season rainfall as evidenced lower yields (1758–11297 kg·ha^{-1}) compared with 2011 (Supplementary Table S3[1]). For example, a significant positive correlation ($r = 0.6427$) was found between maize yields in 2010 and growing season rainfall (simulations starting on 10 April and ending on 7 November at harvest). When checking yield by county (Supplementary Table S3[1]), we found that maize yield in 2010 in Elgin county still had a fairly wide range even with having the highest yields among the five counties (i.e., yields ranged between 6213 and 11 297 kg·ha^{-1}). We found that low rainfall in August was the main reason, as it caused water stress for maize growth. For example, rainfall in August 2010 averaged 43 mm (21–58 mm) in Elgin compared with <20 mm in the other four counties (Supplementary Table S1[1]).

Comparison between average maize grain yield at county level

The measured maize grain yields from each county were compared with the average simulated yields along with standard deviation (Fig. 6). In general, the average simulated grain yields matched the measured yields very well (i.e., within two standard deviations) in 2011 and 2012 (Figs. 6*b* and 6*c*), whereas the model significantly underestimated the maize grain yields in one of five counties (Lampton) in 2010 (i.e., the differences were ≥2 standard deviations in Fig. 6*a*). The simulated yields in Essex county were within ~2 standard deviations of the actual yield (Fig. 6). The underestimation was mainly caused by water stress during the grain filling season. For example, the monthly rainfall in August 2010 was 15, 10, and 26 mm in three weather stations in Lambton and 9, 12, 14, and 15 mm in four weather stations in Essex, as compared with 30 yr (1985–2015) normal rainfall of 80 mm in southern Ontario in August (Supplementary Table S1[1]).

From the regional simulation, we concluded that in the normal precipitation year of 2011, the model simulated the maize grain yield very well using the Soil Landscapes of Canada soil layer database (Fig. 6*b*). However, in a dry year, such as 2010, the model simulation performed well in three counties, but underestimated dry grain yields in two other counties (Fig. 6*a*). The model showed a severe water stress when monthly rainfall for July and August is less than 20 mm, especially in the maize grain filling stage (July to August)

Fig. 6. Comparison between the measured (Y_m) and simulated (Y_s) maize dry grain yield in five counties of southern Ontario in 2010, 2011, and 2012. The vertical bars represent ± standard deviation of simulated grain yield from different soils in each county.



(Supplementary Table S1[1]). When available soil water is less than 20% (field capacity water content minus wilting point water content), the soil cannot provide enough water for plant growth which reduces grain yield. For this reason, using updated soil profile data could be key to improving the simulation of maize grain yields especially in dry years. We concluded that the DSSAT model calibrated maize cultivar in the region was able to simulate regional maize production well in the same climate zone in 2011 and 2012 in the southern Ontario region (i.e., up to 300 km from the Woodslee of Essex site), although the model tended to underestimate the maize yields in a dry year of 2010.

Summary and Conclusions

The maize cultivar coefficients were successfully calibrated using the measured maize grain yields in 2010 and 2011, as evidenced by d, EF, nRMSE, and E values of 0.96, 0.83–0.84, 11.2%–14.7%, and −738 to 355 kg·ha^{-1}, respectively. Good agreement was also achieved for the 2012 maize yield as indicated by d, EF, nRMSE, and E values of 0.96%, 0.88%, 11.4%, and −435 kg·ha^{-1}, respectively. Moderate agreement between the measured and simulated maize above-ground biomass for all treatments in 2011 and 2012 was indicated by $d = 0.94–0.98$ and EF = 0.72–0.92. Using default soil profiles, the model tended to underestimate soil water storage in wet years and overestimate water storage in dry years. A sensitivity analysis concluded that soil water storage was sensitive to the DUL, DLL, and SAT soil water contents. Simulated soil water storage using re-calibrated soil profiles better matched the measured soil water dataset for 2010–2012. Moderate to good model-data agreement was indicated by $0.66 \le d \le 0.92$, $0.16 \le \text{EF} \le 0.73$, and $12.5\% \le \text{nRMSE} \le 21.3\%$. Regional simulations should be based on local soil profiles, rather than the generalized profiles in the SLC database.

Maize yield was successfully simulated in five counties of southern Ontario using 117 simulations based on data from 45 SLC version 3.2 soil profiles and 35 corresponding weather data files. The average maize grain yield simulated for five counties of southern Ontario matched the measured maize grain yield well for 2010–2012, except for one county in 2010 where it overestimated dry grain yields. The simulated maize yields reflected large soil and weather variation as expected. The simulated maize yields were lower than 6000 kg·ha^{-1} for 76 simulations in 2010 and for 16 simulations in 2011. Lower simulated yields in 2010 were due to low (<20 mm) rainfall in August of that year. We concluded that using the DSSAT CERES-Maize module to simulate regional maize yields in southern Ontario requires realistic soil profile and daily weather datasets.

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