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Modelling stover and grain yields, and subsurface artificial drainage from long-term corn rotations using APSIM

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ABSTRACT

The Agricultural Production Systems Simulator (APSIM) is a key tool to identify agricultural management practices seeking to simultaneously optimize agronomic productivity and input use efficiencies. The aims of this study were to validate APSIM for prediction of stover and grain yield of corn in four contrasting soils with varied N fertilizer applications (156–269 kg N ha^{-1}) and to predict timing and volume from artificial subsurface drains in continuous corn and corn-soybean rotations in a silty clay loam soil at West Lafayette, IN. The APSIM validation was carried-out using a long-term dataset of corn stover and grain yields from the North Central Region of IN. The CCC (Concordance Correlation Coefficient) and SB (Simulation Bias) were used to statistically evaluate the model performance. The CCC integrates precision through Pearson's correlation coefficient and accuracy by bias, and SB indicates the bias of the simulation from the measurement. The model demonstrated very good (CCC = 0.96; SB = 0%) and satisfactory (CCC = 0.85; SB = 2%) ability to simulate stover and grain yield, respectively. Grain yield was better predicted in continuous corn (CCC = 0.73–0.91; SB = 19–21%) than in corn-soybean rotations (CCC = 0.56–0.63; SB = 17–18%), while stover yield was well predicted in both crop rotations (CCC = 0.85–0.98; SB = 1–17%). The model demonstrated acceptable ability to simulate annual subsurface drainage in both rotations (CCC = 0.63–0.75; SB = 2–37%) with accuracy being lower in the continuous corn system than in corn-soybean rotation system (CCC = 0.61-0.63; SB = 9–12%). Daily subsurface drainage events were well predicted by APSIM during late spring and summer when crop water use was high, but under-predicted during fall, winter and early spring when evapotranspiration was low. Occasional flow events occurring in summer when soils were not saturated were not predicted by APSIM and may represent preferential flow paths currently not represented in the model. APSIM is a promising tool for simulating yield and water losses for corn-based cropping systems in north central Indiana US.

1. Introduction

The US Corn Belt is not only an important contributor for global corn (*Zea mays* L.) grain supply but also is an increasing provider of cellulosic feedstock for biofuels (Perlack et al., 2005; Wilhelm et al., 2007; Wallander et al., 2011). In fact, bioenergy products are essential elements for a global policy to increase energy supplies and reduce dependence on petroleum (Perlack et al., 2005). Currently, corn grain accounts for the feedstock of more than 90% of the feedstock used for US ethanol production (Morris and Hill, 2006), however, corn stover is expected to provide the majority of the estimated biofuel from crop residues in the future (Graham et al., 2007; Cibin et al., 2012). Stover residues on soil surface protect it from erosion and contributes to soil organic carbon pools (Shaver et al., 2003; Wilhelm et al., 2007), a key factor of soil quality (Wilhelm et al., 2004). Surface residues also reduce water losses by runoff and evaporation (Hatfield, 2015).

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As a consequence, there is increasing concern of the potential negative impacts of removing stover for biomass on soil and water resources and the environment (Jaynes and Miller, 1999; Zhang et al., 2001; Caviglia et al., 2004; Hatfield, 2015; Stephens et al., 2001; Simpson et al., 2008; Graham et al., 2007).

The most extensively used crop rotations in the US Corn Belt are continuous corn and corn-soybean (*Glycine max* L. Merr.). Rainfall often exceeds evapotranspiration (ET) in spring (King et al., 2014) delaying crop establishment and in fall slowing harvest (Smith et al., 2015) generating excess water. This excess soil water is commonly drained through a network of subsurface tile or perforated plastic drains (Randall et al., 1997; Smith and Pappas, 2007; Smith et al., 2015). It has been estimated that 25% of the land currently in crop production in US and Canada could not be farmed without a subsurface drainage system (Skaggs et al., 1994), and 37% of US Corn Belt has benefited from these systems (Zucker and Brown, 1998).

Biophysical models are a key tool to predict impacts of crop management scenarios on both watershed hydrology (Cibin et al., 2016) and stover production (Persson et al., 2009). Although considerable effort has been devoted in the development of simulation models for hydrological processes at watershed-scale (*e.g.* Hanson et al., 1998; Arnold et al., 1998; Cibin et al., 2016), the validation of certain processes like subsurface water loss from artificial drains and corn stover/biomass production have not been thoroughly evaluated for the US Corn Belt (Dietzel et al., 2016).

The Agricultural Production Systems Simulator (APSIM) model (Keating et al., 2003; Holzworth et al., 2014) has been shown to predict biomass production of perennial rhizomatous grasses across several US environments (Ojeda et al., 2017) and grain yields of corn (Lyon et al., 2003; Hammer et al., 2009; Lobell et al., 2013; Archontoulis et al., 2014a) and soybean (Malone et al., 2007; Archontoulis et al., 2014b; Dietzel et al., 2016). The ability of APSIM to accurately predict stover and grain yields of corn while simultaneously estimating the timing and volume of subsurface drainage from these fields is not known. Corn growth using the *Maize* module of APSIM has been tested in several environments (Carberry et al., 1989, 1996; Shamudzarira and Robertson 2002; Chen et al., 2010; Liu et al., 2012; Pembleton et al., 2013). Several sub-module routines representing key processes like growth, soil water, soil N, climate, etc., form APSIM programmatic elements. Plant growth (*Maize* module) responds to climate (temperature, rainfall and solar radiation from the *Met* module), soil water supply (from the *SoilWat* module) and soil nitrogen (N) (from the *SoilN* module). Likewise, the model can differentiate between different water-loss mechanisms (*e.g.* drainage versus runoff) and includes the ability to predict the flow of water and nutrients through artificial subsurface drainage systems (*e.g.* Snow et al., 2007). Therefore, APSIM could be used to predict field-scale water balances if appropriately calibrated and validated. If successful this would improve our understanding of the relationship between corn production, water use efficiency, and environmental impacts of production system choices.

In this study, we used several field datasets to evaluate the ability of APSIM to simulate the corn stover and grain yield of continuous corn and corn-soybean rotations in three Indiana (IN) locations and the subsurface water loss to artificial drains in one IN location. The aims of this study were to validate APSIM: (i) to predict corn stover and grain yield in four contrasting soils from IN and (ii) to predict subsurface drainage in continuous corn and corn-soybean rotations in a silty clay loam soil at West Lafayette, IN.

2. Materials and methods

The APSIM validation was carried-out as follows using data from three Indiana US locations: (i) data on climate (Table 1), soil (Table 2), and management (Table 3) were provided to the model, (ii) soil parametrization was generated for each experiment, (iii) the validation was performed through graphical comparison and statistical analyses of observed and modelled corn stover and grain yields with the objective to increase the Concordance Correlation Coefficient (CCC) and decrease the Simulation Bias (SB). Finally, an additional model validation was carried-out in order to predict corn stover and grain yields and timing and drainflow volume from artificial subsurface drains as influenced by crop rotation and N fertilizer rate using data from Purdue University's Water Quality Field Station (WQFS, 2017). A complete description of datasets used for model validation is provided in Table 3.

2.1. Data used for model simulations

The datasets used in this study covered the most important crop processes during the crop growth season (Table 3). Briefly, the detailed data used for model validation were obtained from three Purdue University Research Stations. Two datasets were from the Agronomy Center for Research and Education (ACRE, 2017) near West Lafayette IN (40° 28′ 12″ N, 87° 0′ 36″ W) with additional datasets from Pinney-Purdue Agricultural Center (PPAC, 2017) near Wanatah IN (41° 26′ 24″ N, 86° 56′ 24″ W) and Throckmorton Purdue Agricultural Center (TPAC, 2017) south of Lafayette IN (40° 17′ 60″ N, 86° 54′ 0″ W).

The West Lafayette location included field experiments in two soil series, Chalmers and Drummer (Table 2). The APSIM's validation dataset from the experiment conducted on the Chalmers soil was derived from Robles et al. (2012). These dataset included data on stover and grain yields during the 2009 and 2010 growing seasons and, in all cases, field experiments followed soybean. Nitrogen fertilizer was pre-plant applied as NH_3 at a rate of 225 kg N ha^{-1}. Conventional tillage practices involved full-width spring cultivation after NH_3 application and before planting. The WQFS, a highly-instrumented in-field laboratory dedicated to the study of agricultural impacts on water and air quality, is located on the Drummer soil series at ACRE and was the source for linked datasets on corn productivity and subsurface drainage losses. A long-term dataset (1995–2012, excluding 1996) on corn yield was derived from four cropping systems: corn-soybean rotations fertilized with 156 or 201 kg N ha^{-1} and continuous corn rotations fertilized with 224 kg N ha^{-1} or 72500 L ha^{-1} of manure effluent (Hofmann, 2002; Ruark et al., 2009; Hernandez-Ramirez et al., 2011; Issa, 2012). However, corn yield data from the cropping systems mentioned before were not available during the whole period of years (Table 3). The N rate applied as manure in continuous corn was 247 kg N ha^{-1} (determined as Kjeldahl-N; Bremner, 1996). All plots received starter fertilizer that contained an additional 22 kg N ha^{-1} at sowing. The starter N and the primary N application are reported in Table 3 as the first and second N application, respectively, and the total N application used to describe these treatments (*e.g.* 22 + 247 = 269 kg N ha^{-1}). During this long-term experiment, 13 corn hybrids were used (Table 4). These data sets included detailed measurements of grain and stover yields at the final harvest, but also in-season corn stover dry matter accumulation.

An accompanying WQFS drainage water dataset for the treatments described above was used to validate APSIM's ability to accurately predict the timing and volume of subsurface drainage. Available drainage data spanned 1998–2011 but excluded 2007 due to missing data associated with facility rehabilitations. At the WQFS, subsurface water loss to artificial drains is monitored on a daily basis throughout the year. To permit the collection of subsurface drainage from a hydrologically isolated volume of soil, each WQFS treatment plot (10.8 m × 48 m; 518 m^2), contains a large, in-ground lysimeter (10.8 m × 24.4 m; 264 m^2) constructed as a bottomless clay box. The lysimeters are centrally located in the

Table 1
Climate characterization of Indiana locations used for the validation of the Agricultural Production Systems Simulator (APSIM).

Location	(latitude, longitude)	Rainfall (mm)	Tmax/Tmin[a] (°C) Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
West Lafayette	40.47, −87.01	978	0.3/ −7.4	2.6/−5.1	9.0/0.3	16.7/6.5	22.9/12.7	27.8/17.2	29.6/19.0	28.9/18.0	24.7/13.8	17.9/8.2	9.9/2.0	2.5/−4.5
Lafayette	40.30, −86.90	969	0.4/ −7.2	2.4/−5.1	8.7/0.1	16.3/6.3	22.5/12.4	27.2/16.9	29/ 18.6	28.4/17.8	24.4/13.5	17.5/7.8	9.8/1.9	2.6/−4.4
Wanatah	41.44, −86.94	965	0.0/ −9.8	2.0/−8.1	8.4/−3.0	15.6/2.7	21.8/8.7	27.1/14.2	28.7/15.8	27.7/14.4	24.4/9.9	17.6/4.3	9.4/−0.9	2.6/−6.7

[a] Temperature maximum/Temperature minimum.

plots and the bentonite clay walls extend down to the glacial till (1.5 m depth). Running lengthwise down each plot are a pair (collection and companion) of plastic agricultural drains (0.1 m diameter) buried at 0.9 m. The collection drain is perforated only for the length of the lysimeter and is unperforated as it passes through the plot area outside the lysimeter. The companion drain is immediately adjacent to the collection drain; it is not perforated within the lysimeter but is perforated outside the lysimeter. Collectively the paired tiles maintain similar soil moisture status throughout a treatment plot and simulate 10 m drain spacing. Companion drains discharge to a surface ditch while the collection drains discharge into instrument huts where calibrated tipping buckets quantify hourly drainflow volume. In this study, the hourly volumes were aggregated into daily volumes to validate APSIM. A complete description of the subsurface drainflow measurements are presented in Ruark et al. (2009) and Ale et al. (2009). At the time of WQFS construction (1992), the simulated 10 m drain spacing at the WQFS was closer than typically recommended (12–24 m) for IN soils (Franzmeier et al., 2001), but drainage management has intensified dramatically in the last 20 years and subsurface drain spacings <10 m are now commonly studied (Christianson and Harmel, 2015).

The Wanatah location included field experiments in a Sebewa soil series (Table 2). The APSIM's validation dataset from the experiment conducted on this location was derived from Ciampitti and Vyn (2011). This dataset included data on aboveground biomass partitioned into leaf, stem, ear and grain components of two corn genotypes (Table 4) measured at four developmental stages (V14, R1, R3 and R6; Ritchie and Hanway, 1982) grown at three plant densities (5.4, 7.9 and 10.4 pl m^{-2}) and fertilized with three N side-dress rates (0, 165 and 330 kg N ha^{-1}) during 2009. At planting time, all treatments received 25 kg N ha^{-1} (10–34-0) as starter fertilizer. The N fertilizer source for side-dress application was urea ammonium nitrate (UAN) (28-0-0). Corn field experiments were established following soybean, and conventional tillage practices involved full-width spring field cultivation before planting (Ciampitti and Vyn, 2011).

Model validation also used additional corn data from TPAC's field experiments in a Lauramie soil series located at Lafayette (unpublished data). These experiments included data on stover and grain yields at three plant densities (6.1, 6.7 and 7.3 pl m^{-2}) fertilized with three N rates (0, 50, 100, 150 and 200 kg N ha^{-1}) during 2011, 2012 and 2013. A complete description of crop management is provided in Table 3.

2.2. APSIM platform

The Agricultural Production Systems Simulator (APSIM) is a crop simulation platform used around the world to assess complex interactions between climate, soils, crops and management practices (Keating et al., 2003; Holzworth et al., 2014). The APSIM framework integrates sub-models describing soil, crop and farm management processes with weather data in a mechanistic approach to simulate crop growth and development as well as soil water and N dynamics (Keating et al., 2003; Pembleton et al., 2016). Details on APSIM performance in a diverse range of studies carried-out in different environments can be found at APSIM website (APSIM, 2017).

2.3. Model configuration

2.3.1. Plant module and manager rules

Crop simulations were undertaken using a daily time step of the APSIM Version 7.5 (Keating et al., 2003; Holzworth et al., 2014). Corn was simulated by the *Maize* module (Carberry et al., 1989). This module is based on enhancements to CERES-Maize (Ritchie, 1972; Jones and Kiniry, 1986; Carberry and Abrecht, 1991) combined with modifications to simulate biomass accumulation based on resource capture concepts (Monteith, 1986). Different management rules (*i.e.* tillage, sowing, harvesting, fertilization, plant density, row spacing, etc.) were created according to practices used in the field and are reported in detail in Table 3.

The corn in the corn-soybean rotation was sown in paired plots every year in order to obtain data on both crop components of this system each year. Every year crop residues were incorporated into the soil using the tillage manager rule on fixed date provided by the model. The corn hybrids used in these studies were not pre-identified in APSIM. Therefore, new hybrids were created within the model based on thermal time requirements at each phenological stage (Table 4). The crop was harvested at 0.1 m above the ground (Issa, 2012) using the model harvesting rule. If the exact dates of management interventions were not available, local average dates for the application of these practices were used. The model outputs called *LeafGreenWt*, *StemGreenWt*, *stover* and *yield* were used for validation.

2.3.2. Manure module

In West Lafayette, the manure manager rule on fixed date provided by the model was used to simulate manure effluent. The *Manure* module allows specification of the manure C:N ratio. This enables APSIM to model the effect of manure composition on N-mineralisation patterns following manure application (Delve and Probert, 2004). The following information was needed to specify the rule in the model: application amount (72500 L ha^{-1}), manure C:N ratio (12; Archontoulis et al., 2014a) and manure C:P ratio (30; default APSIM value).

2.3.3. Climate data sources

Daily climate data for each location were derived from two data sources. The daily solar radiation was obtained from the NASA Prediction of Worldwide Energy Resource – Climatology Resource for Agroclimatology (NASA-POWER, 2017). Maximum and minimum air temperatures and rainfall were obtained from the National Oceanic and Atmospheric Administration (NOAA). This US agency through their National Centers for Environmental Information is responsible for providing public access to the US's climate and historical weather data and information (NOAA, 2017). Following the methodology used by Ojeda et al. (2017), this long-term database was used as a secondary source of maximum and minimum air tem-

Table 2
Soil parameters for soil series used in the model validation in three experimental stations at Purdue University, Indiana. Estimated data were obtained from actual data using pedotransfer functions (see Materials and methods section).

Location	Soil series, Taxonomic classification	Depth	*Actual data*					*Estimated data*									
		Depth	Texture			OC	pH 1:1	OM	pH 1:5	Texture class	AD	LL	DUL	SAT	BD	PO	SWCON
			sand	silt	clay												
		cm	%	%	%			%			mm water mm soil^{-1}				g cm^{-3}	(0–1)	day^{-1}
West Lafayette	Drummer, Typic Haplaquolls	0–23	15	56	30	2.5		4.3	5.8	silty clay loam	0.095	0.189	0.361	0.483	1.24	0.52	0.277
		23–43	12	56	32	1.0		1.7	6.2	silty clay loam	0.180	0.200	0.371	0.490	1.22	0.53	0.270
		43–71	9	60	31	0.7		1.2	6.5	silty clay loam	0.194	0.194	0.373	0.493	1.21	0.53	0.268
		71–94	14	62	23	0.3		0.6	7.1	silty loam	0.152	0.152	0.342	0.478	1.25	0.52	0.292
		94–109	65	26	9	–		–	8.0	sandy loam	0.075	0.075	0.174	0.441	1.35	0.48	0.575
		109–190	64	29	6	–		–	8.0	sandy loam	0.075	0.075	0.177	0.441	1.35	0.48	0.565
		190–244	41	41	18	–		–	8.1	loam	0.126	0.126	0.269	0.447	1.33	0.49	0.372
		244–330	42	42	16	–		–	8.1	loam	0.126	0.126	0.267	0.446	1.33	0.49	0.375
	Chalmers, Typic Haplaquolls	0–15	16	63	21	2.7	6.2	4.6	6.1	silty loam	0.076	0.151	0.352	0.535	1.10	0.58	0.284
		15–36	13	60	27	1.2	6.0	2.1	5.8	silty loam	0.086	0.172	0.353	0.473	1.26	0.51	0.283
		36–58	6	54	40	0.8	6.2	1.3	6.1	silty clay	0.120	0.239	0.398	0.489	1.22	0.53	0.251
		58–86	6	59	35	0.0	6.8	0.0	6.7	silty clay loam	0.106	0.212	0.383	0.478	1.25	0.52	0.261
		86–107	33	43	24	0.0	7.3	0.0	7.2	loam	0.076	0.152	0.298	0.428	1.38	0.47	0.336
		107–122	43	36	21	0.0	7.8	0.0	7.7	loam	0.068	0.135	0.265	0.417	1.41	0.46	0.377
Lafayette	Lauramie, Mollic Hapludalfs	0–20	10	73	17	2.0	6.0	3.5	5.8	silty loam	0.059	0.118	0.329	0.461	1.30	0.50	0.304
		20–30	10	71	20	1.5	6.3	2.6	6.2	silty loam	0.119	0.132	0.333	0.449	1.33	0.49	0.300
		30–48	10	61	29	1.2	5.6	2.1	5.4	silty clay loam	0.180	0.180	0.358	0.458	1.30	0.50	0.279
		48–64	27	44	30	0.9	5.7	1.5	5.5	clay loam	0.184	0.184	0.332	0.434	1.37	0.47	0.301
		64–89	38	35	27	0.9	5.9	1.5	5.7	loam	0.167	0.167	0.300	0.418	1.41	0.46	0.333
		89–112	47	31	23	0.5	6.4	0.9	6.3	loam	0.144	0.144	0.263	0.407	1.44	0.45	0.380
		112–130	50	29	21	–	6.3	–	6.2	sandy clay loam	0.144	0.144	0.257	0.404	1.45	0.44	0.389
		130–147	54	23	24	–	7.0	–	6.9	sandy clay loam	0.150	0.150	0.255	0.402	1.45	0.44	0.392
		147–160	56	30	14	–	7.7	–	7.6	sandy loam	0.091	0.091	0.198	0.399	1.46	0.44	0.505
		160–178	56	35	9	–	7.9	–	7.9	sandy loam	0.062	0.062	0.172	0.399	1.46	0.44	0.581
Wanatah	Sebewa, Aquollic Hapludalfs	0–20	63	22	14	2.1	5.7	2.7	5.5	sandy loam	0.053	0.105	0.206	0.438	1.36	0.48	0.485
		20–30	65	22	14	1.7	7.6	2.9	7.5	sandy loam	0.054	0.107	0.205	0.442	1.35	0.48	0.488
		30–41	46	33	22	0.6	7.3	1.0	7.2	loam	0.070	0.139	0.261	0.409	1.43	0.45	0.383
		41–89	34	40	26	0.0	6.9	0.0	6.8	loam	0.086	0.171	0.318	0.459	1.30	0.50	0.314
		89–94	63	23	14	0.0	7.7	0.0	7.6	sandy loam	0.053	0.105	0.206	0.438	1.36	0.48	0.485
		94–152	89	8	4	0.0	8	0.0	8.0	sand	0.024	0.047	0.098	0.458	1.30	0.50	1.000
		152–203	87	9	4	0.0	7.6	0.0	7.5	sand	0.024	0.047	0.103	0.458	1.31	0.50	0.971
		203–225	87	9	4	0.0	7.6	0.0	7.5	sand	0.024	0.047	0.103	0.458	1.31	0.50	0.971
		225–250	87	9	4	0.0	7.6	0.0	7.5	sand	0.024	0.047	0.103	0.458	1.31	0.50	0.971

Abbreviations: OC, organic carbon; pH 1:1, pH in a 1:1 suspension of soil in water; pH 1:5; pH in a 1:5 suspension of soil in water OM, organic matter; AD, Air Dry, soil moisture limit to which soil can dry by evaporation; LL, lower limit; DUL, drained upper limit or field capacity; SAT, saturated volumetric water content; ks, hydraulic conductivity; BD, bulk density; PO, total porosity; SWCON, drainage coefficient.

Table 3
Summary of corn datasets used for the validation of the Agricultural Production Systems Simulator (APSIM).

Location	Year	NO[a]	Sowing date		Harvesting date/s			Plant component/s	Agricultural Practices												Source /reference
									Population	N fertilizer[b]						P/K fertilizer rate	Previous crop	IRS	SP	HS	
										rate (kg N ha^{-1})		timing		source							
									(plants m^{-2})	1	2	1	2	1	2	(kg ha^{-1})		(cm)	(m^2)	(m^2)	
West Lafayette	1995	4	15-May	20-Oct	21-Oct	22-Oct	23-Oct	grain	7.5	22	–	planting	–	UAN[c]	–	8/-	–	76.2	518	76	Ruark et al. (2009) Hofmann (2002) (grain yield 1995–2000) Issa (2012) (grain yield 1997–2010) Hernandez-Ramirez et al. (2011) (grain 1999–2002 and DM yield 2005–2006)
	1997	2	30-Apr	26-Sep	15-Oct			stover/grain	7.3	22	134	planting	15-Jun	UAN	UAN	8/-	–	76.2	518	1.4/76	
		2								22	179	planting	24-Apr	UAN	UAN	8/-	–				
		2								22	202	planting	24-Apr	UAN	UAN	8/-	–				
		2								22	247	planting	26-Apr	UAN	Effluent	8/-	–				
	1998	2	21-May	21-Sep	10-Oct			stover/grain	6.7	22	134	planting	14-Jul	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		2								22	179	planting	18-May	UAN	UAN	8/-	soybean				
		2								22	202	planting	18-May	UAN	UAN	8/-	corn				
		2								22	247	planting	15-Apr	UAN	Effluent	8/-	corn				
	1999	2	29-May	14-Oct				stover/grain	6.6	22	134	planting	8-Jul	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		2								22	179	planting	1-May	UAN	UAN	8/-	soybean				
		2								22	202	planting	20-May	UAN	UAN	8/-	corn				
	2000	2	24-May	19-Sep	19-Oct			stover/grain	6.7	22	134	planting	30-Jun	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		2								22	179	planting	5-May	UAN	UAN	8/-	soybean				
		2								22	202	planting	5-May	UAN	UAN	8/-	corn				
		2								22	247	planting	16-Apr	UAN	Effluent	8/-	corn				
	2001	2	2-May	19-Jun	28-Sep	29-Oct		stover/grain	7.0	22	179	planting	20-Apr	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		3								22	202	planting	20-Apr	UAN	UAN	8/-	corn				
		3								22	247	planting	3-Apr	UAN	UAN	8/-	corn				
	2002	2	4-Jun	16-Jul	9-Oct	15-Oct		stover/grain	7.3	22	134	planting	1-Jul	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		2								22	179	planting	1-Jun	UAN	UAN	8/-	soybean				
		3								22	202	planting	1-Jun	UAN	UAN	8/-	corn				
		3								22	247	planting	1-Jul	UAN	Effluent	8/-	corn				
	2003	2	28-Apr	25-Jun	3-Oct	21-Oct		stover/grain	7.0	22	134	planting	5-Jun	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		1								22	179	planting	14-Apr	UAN	UAN	8/-	soybean				
		3								22	202	planting	14-Apr	UAN	UAN	8/-	corn				
		3								22	247	planting	14-Apr	UAN	Effluent	8/-	corn				
	2004	2	5-May	27-Sep	5-Oct			stover/grain	7.3	22	134	planting	5-Jun	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		2								22	179	planting	19-Apr	UAN	UAN	8/-	soybean				
		2								22	202	planting	19-Apr	UAN	UAN	8/-	corn				
		2								22	247	planting	7-Apr	UAN	Effluent	8/-	corn				
	2005	2	5-May	17-Jun	17-Jul	13-Oct		stover/grain	7.3	22	134	planting	7-Jun	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		2								22	179	planting	5-Apr	UAN	UAN	8/-	soybean				
		3								22	202	planting	5-Apr	UAN	UAN	8/-	corn				
		3								22	247	planting	11-Apr	UAN	Effluent	8/-	corn				
	2006	2	9-May	12-Jun	26-Sep	2-Nov		stover/grain	7.0	22	134	planting	14-Jun	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		2								22	179	planting	21-Apr	UAN	UAN	8/-	soybean				
		3								22	202	planting	21-Apr	UAN	UAN	8/-	corn				
		3								22	247	planting	28-Apr	UAN	Effluent	8/-	corn				
	2007	1	27-May	5-Nov	6-Nov			grain	7.0	22	–	planting	–	UAN	–	8/-	–	76.2	518	76	
		1								22	134	planting	6-Jun	UAN	UAN	8/-	soybean				
		1								22	247	planting	9-May	UAN	Effluent	8/-	corn				

Table 3 (*Continued*)

Location	Year	NO[a]	Sowing date		Harvesting date/s			Plant component/s	Agricultural Practices												Source /reference
									Population	N fertilizer[b]						P/K fertilizer rate	Previous crop	IRS	SP	HS	
										rate (kg N ha^{-1})		timing		source							
									(plants m^{-2})	1	2	1	2	1	2	(kg ha^{-1})		(cm)	(m^2)	(m^2)	
	2008	2	28-May	6-Oct	3-Nov			stover/grain	7.3	22	134	planting	19-Jun	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		2								22	247	planting	1-May	UAN	Effluent	8/-	corn				
	2009	2	24-May	2-Jul	1-Oct	13-Nov		stover/grain	7.3	22	134	planting	12-Jun	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		3								22	247	planting	21-May	UAN	Effluent	8/-	corn				
	2010	2	26-May	28-Jun	23-Sep	11-Oct		stover/grain	6.8	22	134	planting	8-Jun	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		3								22	247	planting	14-Apr	UAN	Effluent	8/-	corn				
	2011	3	3-Jun	15-Jul	6-Oct	28-Oct		stover/grain	7.3	22	–	planting	–	UAN	–	8/-	–	76.2	518	1.4/76	
		2								22	134	planting	29-Jun	UAN	UAN	8/-	soybean				
		3								22	247	planting	14-Apr	UAN	Effluent	8/-	corn				
	2012	2	25-Apr	13-Jun	11-Sep	4-Oct		stover/grain	7.3	22	134	planting	31-May	UAN	UAN	8/-	soybean	76.2	518	1.4/76	
		1								22	247	planting	21-Mar	UAN	Effluent	8/-	corn				
	2009	2	22-May	9-Nov				stover/grain	6.9	–	225	preplant	–	NH3	–	–	soybean	76.0	91.5	0.9–45	Robles et al. (2012)
	2009	1	22-May	9-Nov				grain	8.1	–	225	preplant	–	NH3	–	–	soybean	76.0	91.5	45	
	2009	1	22-May	9-Nov				grain	9.3	–	225	preplant	–	NH3	–	–	soybean	76.0	91.5	45	
	2009	2	22-May	9-Nov				stover/grain	10.5	–	225	preplant	–	NH3	–	–	soybean	76.0	91.5	0.9–45	
	2010	2	7-May	20-Sep				stover/grain	6.9	–	225	preplant	–	NH3	–	–	soybean	76.0	91.5	0.9–45	
	2010	1	7-May	20-Sep				grain	8.1	–	225	preplant	–	NH3	–	–	soybean	76.0	91.5	45	
	2010	1	7-May	20-Sep				grain	9.3	–	225	preplant	–	NH3	–	–	soybean	76.0	91.5	45	
	2010	2	7-May	20-Sep				stover/grain	10.5	–	225	preplant	–	NH3	–	–	soybean	76.0	91.5	0.9–45	
	2009	90	14-May	20-Jul	31-Jul	14-Aug	1-Oct	leaf/stem/ear/grain	5.4/7.9/10.4	25	0	planting	–	starter fertilizer	–	85/-	soybean	76.0	82	0.6–1.1	Ciampitti and Vyn (2011)
			15-Nov							25	165	planting	3-Jun	starter fertilizer	UAN	85/-	soybean	76.0			
										25	(165 + 165)	planting	3-Jun/13-Jun	starter fertilizer	UAN	85/-	soybean	76.0			
Lafayette	2011	10	17-Jun	2-Nov				stover/grain	7.3	0	–	–	–	–	–	–		76.2	–	–	unpublished data
										50	–	14-Jun	–	UAN	–						
										100	–	14-Jun	–	UAN	–						
										150	–	14-Jun	–	UAN	–						
										200	–	14-Jun	–	UAN	–						
	2012	10	30-May	16-Oct				stover/grain	6.7	–	0	–	–	–	–	8/23		76.2	–	–	
										–	50	–	25-Jun	–	UAN						
										–	100	–	25-Jun	–	UAN						
										–	150	–	25-Jun	–	UAN						
										–	200	–	25-Jun	–	UAN						
	2013	9	7-Jun	28-Oct				stover/grain	6.1	–	0	–	–	–	–	–		76.2	–	–	
										–	50	–	27-Jun	–	UAN						
										–	100	–	27-Jun	–	UAN						
										–	150	–	27-Jun	–	UAN						
										–	200	–	27-Jun	–	UAN						
Wanatah	2009	81	7-May	18-Jul	2-Aug	13-Aug	4-Oct	leaf/stem /ear/grain	5.4/7.9/10.4	25	0	planting	–	starter fertilizer	–	85/-	soybean	76.0	82	0.6–1.1	Ciampitti and Vyn (2011)
			19-Nov							25	165	planting	27-May	starter fertilizer	UAN	85/-	soybean				
										25	(165 + 165)	planting	27-May/13-Jun	starter fertilizer	UAN	85/-	soybean				

[a] Number of observations.

[b] N fertilizer: 1, first application; 2, second application.

[c] UAN: 28% urea-ammonium-nitrate.

Table 4
Characteristics of corn hybrids used for the validation of the Agricultural Production Systems Simulator (APSIM).

Location	Genotype	*emer_endj*	*flow_mat*	*flower_startgr*	*max ker numb*	*ker filling rate*
		(°C day)				(mg day^{-1})
West Lafayette	P34G91	200	800	350	700	8.5
	P39B45	160	730	350	750	8.5
	P34G81	160	780	215	750	8.5
	P34G9102	240	680	290	750	8.5
	B5737CL	160	620	170	750	8.5
	B5737	200	790	260	750	8.5
	AS715RR	170	800	100	700	8.5
	P34A20RRLLWCB	200	800	170	700	8.5
	P34P87PR	300	800	250	700	8.5
	B6746	140	780	400	750	8.5
	B5435HXR	140	680	215	750	8.5
	Becks5731	180	500	200	700	8.5
	Becks5564	150	600	160	700	8.5
	Mycogen 2T780[a]	200	800	350	700	8.5
	Mycogen 2T787 [a]	200	800	350	700	8.5
	Monsanto[b]	150	750	300	700	8.5
Lafayette	locally adapted hybrid	200	800	350	700	8.5
Wanatah	Mycogen 2M749 [a]	200	800	350	700	8.5
	Mycogen 2M750 [a]	200	800	350	700	8.5

Abbreviations: emer_endj, thermal time accumulation between emergence and end of juvenile; *flow_mat,* thermal time accumulation between flowering and maturity; *flower_startgr,* thermal time accumulation between flowering and start of grain; *max ker numb,* maximum kernel number; *ker filling rate*, kernel filling rate.

[a] *Mycogen:* two near-isogenic hybrids with and without transgenic CRW resistance were evaluated at ACRE Mycogen 2T780 (without CRW resistance) and its near-isoline Mycogen 2T787 (with CRW resistance) while at the PPAC location the hybrid treatment comparison involved Mycogen 2M749 (non-CRW resistant) and its near-isoline 2M750 (with CRW resistance). All four hybrids were similar in Comparative Relative Maturity (CRM) at 114 days (Dow AgroSciences, Inc., Indianapolis, IN).

[b] *Monsanto:* Monsanto Company, St. Louis, MO hybrids (DKC62-54, CRM = 112; DKC61-19, CRM = 111 and DKC57-66, CRM = 107).

peratures due to the NOAA database's large number of consecutive absent values for daily maximum and minimum temperatures.

Long-term monthly mean minimum air temperature ranged from −9.8 to 19.0 °C and the monthly mean maximum air temperature between 0.0–29.6 °C. The mean annual rainfall was similar between field experiments (971 ± 7 mm). A summary of climate information by location is reported in Table 1.

2.3.4. Soil parametrization

As the soil database of APSIM did not include the soil types of the locations used in this study, new soil profiles were created (Table 2). The dominant soil series were identified for each field experiment based on data provided in previous studies (Ale et al., 2009; Ruark et al., 2009; Ciampitti and Vyn, 2011; Issa, 2012) and in consultation with local scientists. The specific soil properties (texture, organic carbon [OC] and pH) for each soil series were obtained from the National Cooperative Soil Survey Soil Characterization Database (NCSS, 2017) (Table 2). This application allows us to obtain a complete characterization of several soil profiles from the National Soil Survey Center, Kellogg Soil Survey Laboratory and cooperating laboratories.

As soil hydraulic parameters required to run the simulations were not available, drained lower limit (LL), drained upper limit (DUL), bulk density (BD) and hydraulic conductivity (ks) were estimated by the Hydraulic Properties Calculator Software (Saxton and Rawls, 2006) following the methodology described by Ojeda et al. (2017) (Table 2). In addition, for each soil, air dry water content (AD), saturated volumetric water (SAT), total porosity (PO) and the drainage coefficient (SWCON) were estimated. This parameter indicates the rate at which water drains when soil water content is above DUL (saturated flow). The soil moisture limit to which soil can dry by evaporation (AD) was estimated as 0.5*LL for 0–0.15 m soil depth, 0.9*LL for 0.15–0.30 m soil depth and equivalent to LL at deeper depths than 0.30 m (Cresswell et al., 2009). Saturated volumetric water content was calculated from BD as described by Dalgliesh and Foale (2005). The PO was estimated as 1-(BD/2.6) according to the reported by Burk and Dalgliesh (2008). The SWCON, the rate at which water drains from the "drainable porosity", *i.e.* water held between SAT and DUL, was estimated from DUL and BD (Jones and Kiniry, 1986). In addition, for each soil layer, the water extraction coefficient (KL) was set at 0.08 mm d^{-1} (Robertson et al., 1993a, 1993b; Dardanelli et al., 1997, 2004). The KL integrates soil-root interactions and it limits the rate of water uptake by the roots, *i.e.* a low KL value results in low water uptake. On the other hand, the root exploration factor (XF) was set to 1 for up to 1 m depth and then decreased exponentially to 0.6 at the maximum soil depth (Monti and Zatta 2009).

Actual OC values were used for initialization of the simulations (Table 2). To initialize the soil nitrogen pool, a 10-year simulation of previous management at the experimental locations (corn-soybean rotations), the location-specific meteorology, and soil data were used. Also for each soil, organic matter (OM, OM = OC*1.72; Dalgliesh and Foale, 2005), soil pH 1:5 (pH measured for a ratio of 1-part soil and 5-parts water solutions according to GlobalSoilMap (2012) and estimated by Libohova et al. (2014)) were estimated (Table 2).

2.3.5. SoilWat module

The *SoilWat* module, one of the two soil water models available in APSIM, was used in this study. This module runs a water balance on a daily step in which soil evaporation, plant transpiration, drainage, and runoff are included. Water limitations on yield depend on soil water supply in the root exploration area and on the conversion efficiency of water into yield, *i.e.* transpiration efficiency (Dolling et al., 2005). For the simulations, we used APSIM's default transpiration efficiency values for corn (9 Pa), which is a constant parameter during the whole period of crop growth. The hydrological processes represented in *SoilWat* were adapted from a long history of "cascading bucket" style water balances such as WATBAL (Keig and McAlpine, 1976) and CERES (Ritchie, 1972; Jones and Kiniry, 1986). The main processes that determine the water drainage in the model are (i) the saturated flow which occurs when any soil layer fills above DUL where a specified proportion (defined by the user through SWCON) of the water in excess of DUL drains to the next soil layer and (ii) the unsaturated flow at water contents below DUL where gradients in soil water content occur between layers (*e.g.* in response to rainfall events or evaporation) (Keating et al., 2003). For extractable soil water (*esw*) below DUL, water

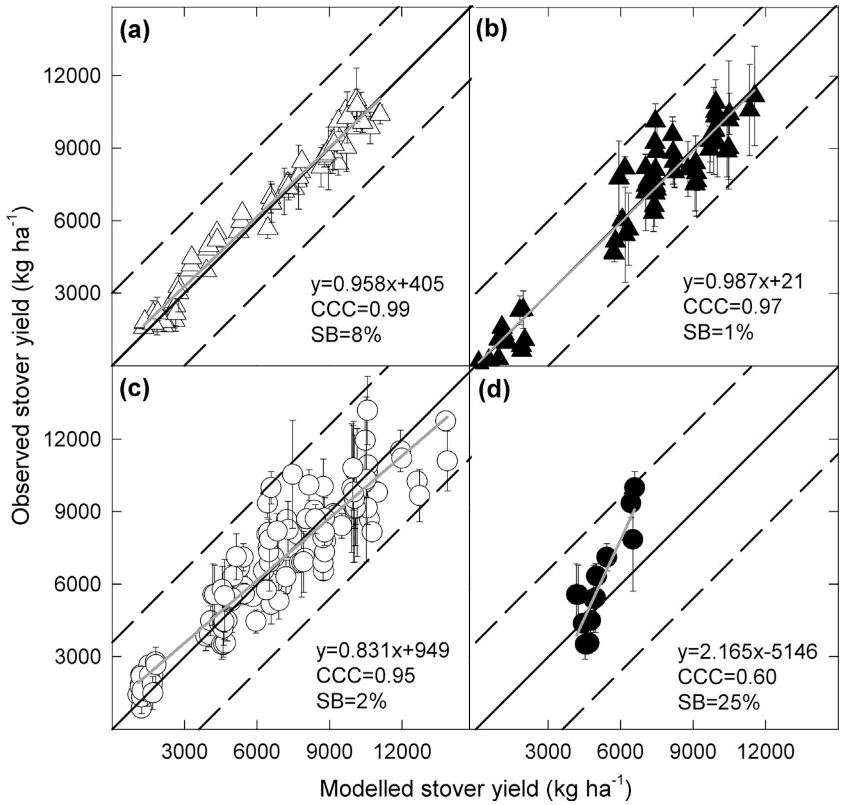

Fig. 1. Observed *v.* modelled corn stover yield resulting of the validation of APSIM for (a) Sebewa (Wanatah), (b) Drummer (West Lafayette), (c) Chalmers (West Lafayette), and (d) Lauramie soil series (Lafayette). Solid black line, grey line and dashed black lines represent 1:1 fit (*i.e.* y = x), regression line and ± 20% of curve 1:1 value, respectively. Vertical bars represent the standard deviation in observed values where such data were available. CCC and SB are the concordance correlation coefficient and the simulation bias from the measurement, respectively.

movement depends on the water content gradient between adjacent layers and the soil diffusivity, which is a function of the average water content of the two soil layers.

In this study, the diffusivity constant and slope were estimated from soil texture class according to Dalgliesh et al. (2012) (40 and 16, respectively). The associated parameter value for runoff (Cn2bare) was derived from soil hydrological group and field slope information (78; Dalgliesh et al., 2012). The soil evaporation coefficients, U (represents the amount of accumulated evaporation before soil supply become limiting) and CONA (is the ratio between the cumulative second stage evaporation and the square root of time), were estimated from soil texture according to Littleboy et al. (1989) (10 and 3.9, respectively).

Initial soil water was not available at most locations. Hence, these conditions were estimated using the approach described by Ojeda et al. (2017). Based on this analysis, initial soil water was set to 100% for all simulations, *i.e.* as a fraction of maximum available water in the soil profile. The initial soil water in spring was always close to DUL. For model validation to predict water loss by drainage, the model output called *drain* was evaluated.

2.4. Evaluation of APSIM performance

Model performance was assessed by comparing scatter plots of observed values in the y-axis *v.* modelled values in the x-axis (Piñeiro et al., 2008) for corn stover, grain yield in all locations. In West Lafayette, the over- and under-predictions of daily subsurface drainage were plotted against modelled *esw*, in order to determine the role of soil water profile variations on the model performance.

The evaluation of model performance described in Tedeschi (2006) and Kobayashi and Us Salam (2000) was used to statistically evaluate model performance to predict corn stover, grain yield and annual subsurface drainage. This included: observed and modelled mean and standard deviation, the CCC, Mean Square Error (MSE) and Root Mean Square Error (RMSE). The CCC integrates precision through Pearson's correlation coefficient, which represents the proportion of the total variance in the observed data that can be explained by APSIM, and accuracy by bias which indicates how far the regression line deviates from the line (1:1). Similarly, the MSE was partitioned into SB, the simulation bias from the observation and Mean Square Variation (MSV), the difference between the simulation and the observation with respect to the deviation from the means, using IRENE software (Fila et al., 2003). Simulation Bias and MSV are orthogonal and as a consequence, can be analysed independently (Kobayashi and Us Salam, 2000).

The crop model performance was categorically evaluated based on the values of several statistical parameters and upper and lower limits were used as the model judgment according to the suggested by Bellocchi et al. (2010). We have considered that a step of parameter optimization was not necessary because the preliminary model performance was in the range proposed by Ojeda et al. (2017), *i.e.* calibration was deemed complete when CCC > 0.60 and SB<40% for annual predictions. For model validation, upper and lower statistical limits were set as: "very good" when CCC > 0.90 and SB < 20%, "satisfactory" when 0.75 < CCC < 0.90 and 20% < SB < 30%, "acceptable" when 0.60 < CCC < 0.75 and 30% < SB < 40% and "poor" with other values.

3. Results

3.1. Stover and grain yield

Overall, the model with the default settings demonstrated very good and satisfactory ability to simulate corn stover and grain

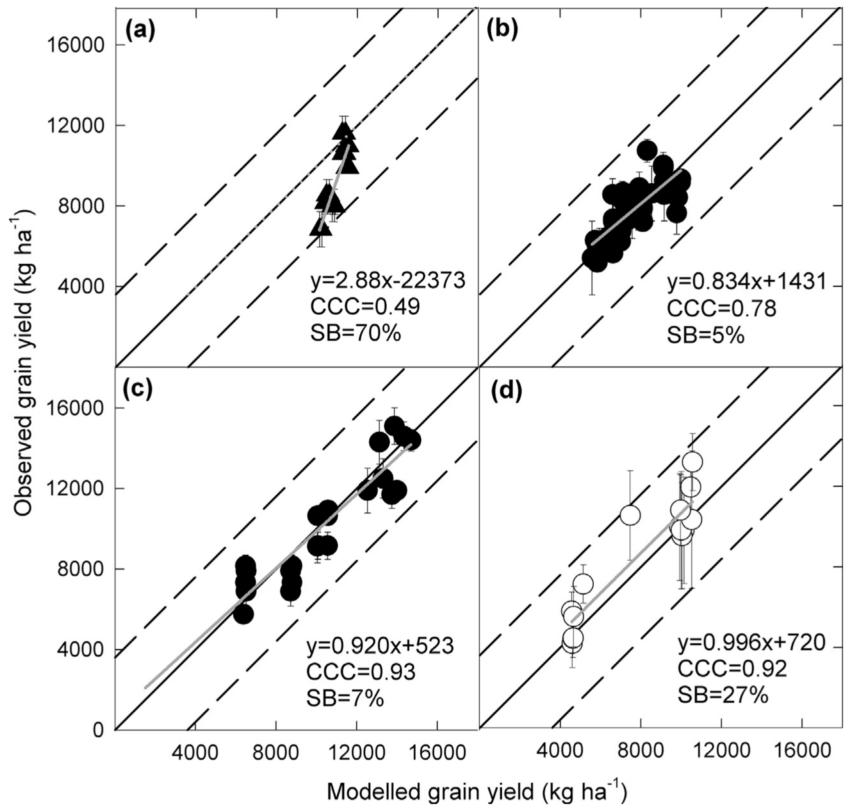

Fig. 2. Observed *v.* modelled corn grain yield resulting of the validation of APSIM for (a) Sebewa (Wanatah), (b) Drummer (West Lafayette), (c) Chalmers (West Lafayette), and (d) Lauramie soil series (Lafayette). Solid black line, grey line and dashed black lines represent 1:1 fit (*i.e.* y = x), regression line and ± 20% of curve 1:1 value, respectively. Vertical bars represent the standard deviation in observed values where such data were available. CCC and SB are the concordance correlation coefficient and the simulation bias from the measurement, respectively.

Table 5
Summary statistics indicating the performance of the Agricultural Production Systems Simulator (APSIM) in predicting the corn stover (S), grain (G) and total (T) yield by location and soil series.

	Stover					Grain					T[a]
	Wanatah	West Lafayette		Lafayette	S[a]	Wanatah	West Lafayette		Lafayette	G[a]	
	Sebewa	Drummer	Chalmers	Lauramie		Sebewa	Drummer	Chalmers	Lauramie		
Observations	63	63	76	14	216	18	54	26	15	113	329
Mean (Observed; kg ha^{-1})	6169	6518	6297	5866	6213	9185	7672	9931	8502	8823	7518
Mean (Modelled; kg ha^{-1})	6017	6583	6439	5086	6031	10941	7482	10226	7815	9116	7574
SD (Observed; kg ha^{-1})	3141	3427	3095	2073	3141	1587	1277	2769	2964	2201	3043
SD (Modelled; kg ha^{-1})	3235	3353	3572	830	3302	484	1197	2789	2734	2356	3223
Model Testing Parameters											
CCC	0.99	0.97	0.95	0.60	0.96	0.49	0.78	0.93	0.92	0.85	0.94
SB (%)	8	1	2	25	0	70	5	7	27	2	0
MSV (%)	92	99	98	75	100	30	95	93	73	98	100
RMSE (kg ha^{-1})	545	888	1073	1571	939	2099	835	1085	1324	1241	1052

Abbreviations: SD, Standard deviation; CCC, Concordance Correlation Coefficient; SB, Simulation Bias; MSV, Mean Square Variation; RMSE, Root Mean Square Error.
[a] Summary statistics for S, G and T were calculated using the stover, grain and the complete dataset, *i.e.* S + G yield data, respectively.

yields, respectively. This was indicated by the summary statistics comparing observed and modelled stover (0.96 for CCC and 0% for SB) and grain yields (0.85 and 2% for CCC and SB, respectively) (Figs. 1 and 2; Table 5). The mean observed stover and grain yields were 6213 ± 3141 kg ha^{-1} and 8823 ± 2201 kg ha^{-1}, respectively. The RMSE for stover and grain yield varied between 545–1571 and 835–2099 kg ha^{-1}.

The APSIM accuracy for predicting stover yield was better at Wanatah and West Lafayette (Fig. 1a, b and c) (CCC = 0.95–0.99 and SB = 2–8%) than at Lafayette (Fig. 1d; Table 5). A satisfactory model prediction of grain yield was found at West Lafayette and Lafayette (Fig. 2b, c and d; Table 5) as indicated by the CCC (0.78-0.93) and the SB (5–27%; Table 5). Nevertheless, the model accuracy to predict grain yield at Wanatah was poor (Fig. 2a; CCC = 0.49).

The model was also evaluated against end-of-season stover and grain yield data showing a very good performance for the long-term dataset from West Lafayette (Fig. 3). The modelled data were +/−20% of observed data most years despite of N rate and crop rotation (Fig. 3). Simulations of stover and corn grain yield matched observations more closely when data were clustered by rotation (0.76–0.98 for CCC and 0–1% for SB) and N rate (0.73–0.98 for CCC and 0–2% for SB) (Fig. 3; Table 6). Corn grain yield was predicted more accurately in continuous corn (CCC = 0.73–0.91 and SB = 19–21%) than in corn-soybean rotations (CCC = 0.56–0.63 and SB = 17–18%). However, corn stover yield was well predicted in both

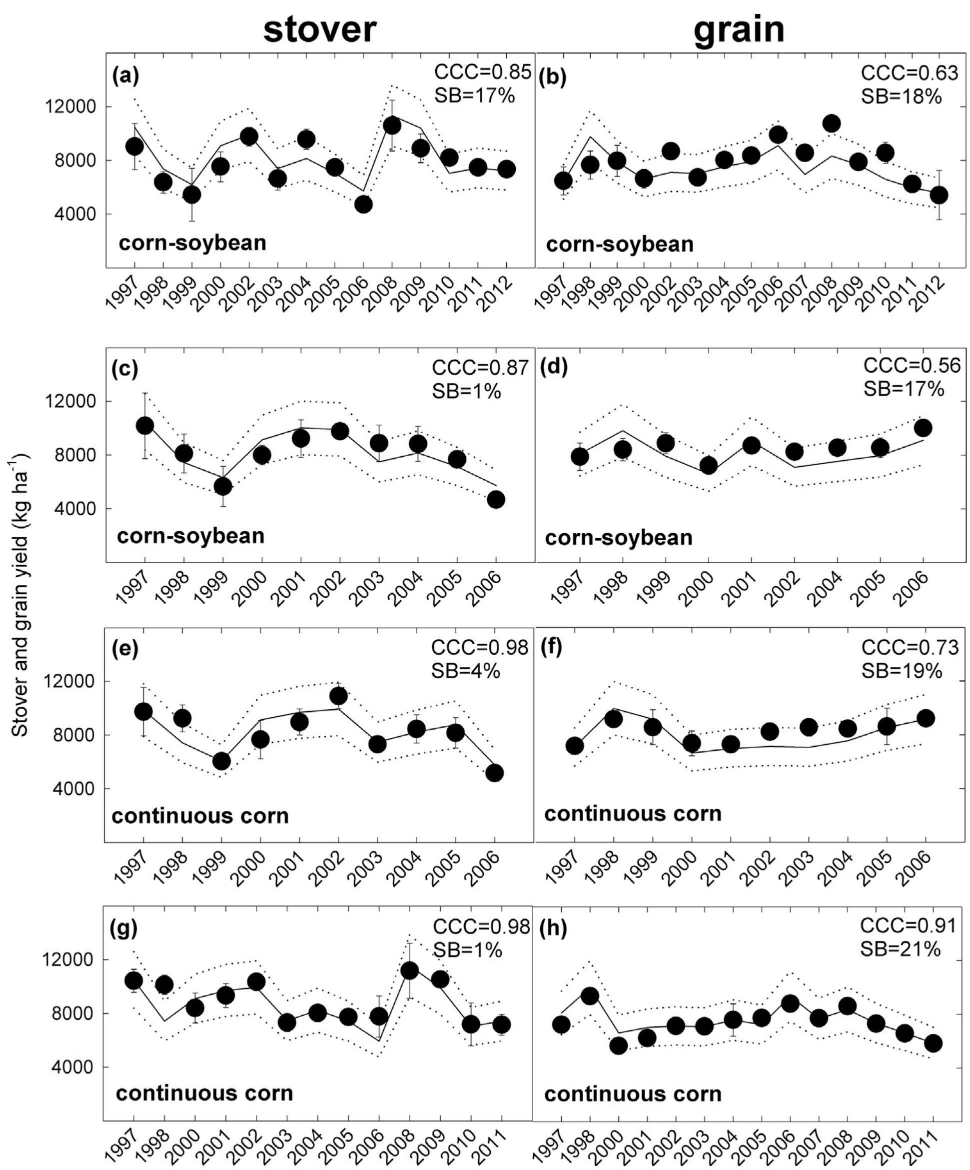

Fig. 3. Observed (black points) and modelled (solid lines) corn yields in the corn-soybean rotation fertilized with (a, b) 156 kg N ha^{-1}, (c, d) 201 kg N ha^{-1} and in the continuous corn rotation fertilized with (e, f) 224 kg N ha^{-1} and (g, h) 269 kg N ha^{-1} grown in West Lafayette. Dotted black lines represent ± 20% of modelled values. Vertical bars represent the standard deviation in observed values where such data were available. CCC and SB are the concordance correlation coefficient and the simulation bias from the measurement, respectively.

rotations (0.85–0.98 and 1–17% for CCC and SB, respectively) (Fig. 3; Table 6).

The stover and grain yield model prediction was improved as the N rate was increased, except for grain yield in the corn-soybean rotation (Fig. 3; Table 6). The CCC and SB for stover yield ranged from 0.85 and 17% for the corn-soybean rotation (fertilized with 156 kg N ha^{-1}) to 0.98 and 1% for the continuous corn rotation (fertilized with 269 kg N ha^{-1}), respectively. However, the CCC and SB for stover yield ranged from 0.56 and 17% for the corn-soybean rotation (fertilized by 201 kg N ha^{-1}) to 0.91 and 21% for the continuous corn rotation fertilized with the highest N rate, respectively.

3.2. Annual subsurface drainage

In general, the model with the default settings demonstrated acceptable ability to simulate annual subsurface drainflow from artificial drains under corn rotations (0.63–0.75 for CCC and 2–37% for SB) (Fig. 4; Table 7; Fig. A1). The RMSE for subsurface drainage varied between 60 and 96 mm. The APSIM accuracy was better for predicting subsurface drainage in the corn-soybean rotation fertilized with a low N rate (156 kg N ha^{-1}) as evidenced by the CCC (0.75) and SB (2%) (Fig. 4a; Table 7) than for the N rate 201 kg N ha^{-1} (CCC = 0.66 and SB = 37%; Fig. 4b). The model ability to predict the subsurface drainage in the continuous corn rotations was lower than in the corn-soybean rotations (CCC = 0.61–0.63 and SB = 9–12%; Fig. 4). The observed subsurface drainage ranged from 151 mm in the corn soybean rotation with 156 kg N ha^{-1} to 236 mm in the continuous corn with 201 kg N ha^{-1}. The modelled subsurface drainage was a 12–24% less than observed in all the treatments except for the corn-soybean rotation fertilized with 156 kg N ha^{-1}, where was higher in the order of 5%.

3.3. Seasonal and daily subsurface drainage

Drain flow of these corn rotations occurred primarily in winter and early spring regardless of cropping system (Fig. 5). However, monthly subsurface drainage and rainfall were not clearly associated (Fig. 5). For instance, the subsurface drainage during winter

Table 6
Summary statistics indicating the performance of the Agricultural Production Systems Simulator (APSIM) in predicting the corn stover and grain yield in a corn-soybean (CS) rotation fertilized with 156 kg N ha^{-1} (156) and 201 kg N ha^{-1} (201), in a continuous corn rotation (CC) fertilized with 224 kg N ha^{-1} (224) and 269 kg N ha^{-1} (269), and using the complete dataset (T) at West Lafayette, Indiana.

	Corn-soybean							Continuous corn							T[c]
	156			201			CS[b]	224			269			CC[b]	
	stover	grain	*t*[a]	stover	grain	*t*[a]		stover	grain	*t*[a]	stover	grain	*t*[a]		
Observations	14	15	29	10	9	19	48	15	10	25	22	14	36	61	109
Mean (Observed; kg ha^{-1})	7786	7851	7819	8101	8501	8301	8060	5656	8262	6959	5695	7335	6515	6737	7399
Mean (Modelled; kg ha^{-1})	8194	7359	7777	8182	8138	8160	7969	5809	7927	6868	5595	7557	6576	6722	7346
SD (Observed; kg ha^{-1})	1680	1409	1518	1743	757	1347	1457	3929	748	3303	4105	1079	3346	3306	2752
SD (Modelled; kg ha^{-1})	1736	1136	1492	1632	1024	1341	1433	3769	1170	3150	3903	1095	3244	3183	2653
Model Testing Parameters															
CCC	0.85	0.63	0.73	0.87	0.56	0.80	0.76	0.98	0.73	0.97	0.98	0.91	0.98	0.97	0.95
SB (%)	17	18	0	1	17	2	1	4	19	0	1	21	0	0	0
MSV (%)	83	82	100	99	83	98	99	96	81	100	99	79	100	100	100
RMSE (kg ha^{-1})	1000	1172	1092	816	878	846	1002	798	766	785	831	488	718	746	868

Abbreviations: SDStandard deviation; CCCConcordance Correlation Coefficient; SBSimulation Bias; MSVMean Square Variation; RMSERoot Mean Square Error.
[a] Summary statistics for *t* were calculated using the stover and grain yield data corresponding to each rotation and N rate, *e.g.* corn-soybean rotation fertilized with 156 kg N ha^{-1}.
[b] Summary statistics for CS and CC were calculated using data from each individual rotation.
[c] Summary statistics for T was calculated using the complete dataset, *i.e.* CS + CC yield data.

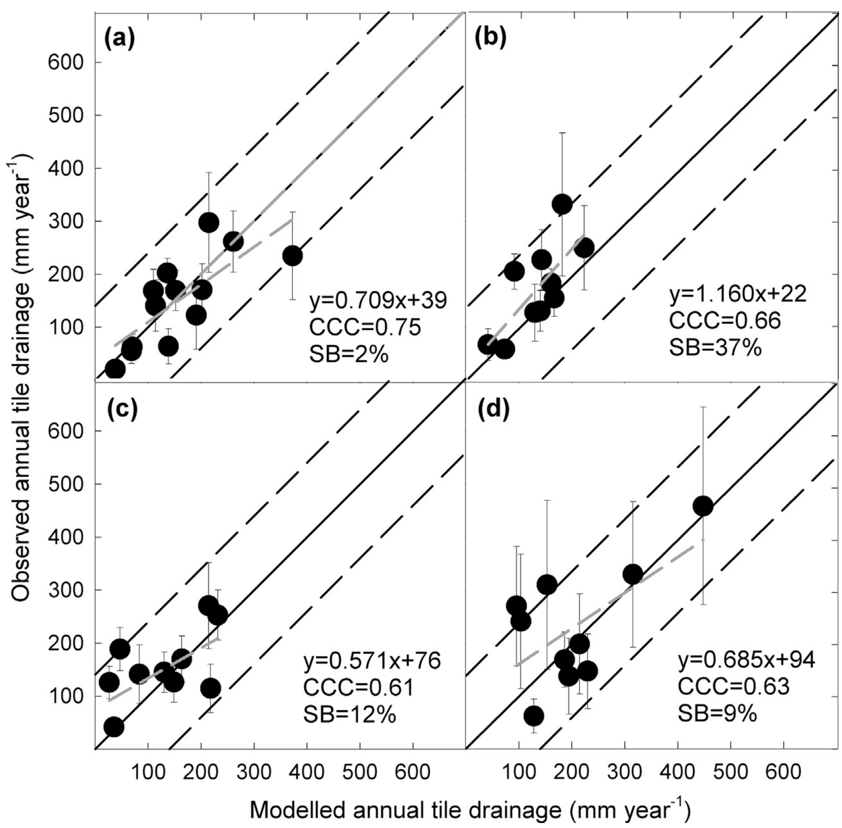

Fig. 4. Observed *v.* modelled annual subsurface drainage during 14 years resulting of the validation of APSIM in different cropping systems (a) corn-soybean with 156 kg N ha^{-1}, (b) corn-soybean with 201 kg N ha^{-1}, (c) continuous corn with 224 kg N ha^{-1} and (d) continuous corn with 269 kg N ha^{-1} (manure) grown in West Lafayette. Solid black line, dashed black and grey line represent 1:1 fit (*i.e.* y = x), ± 20% of curve 1:1 value and linear equation fit to the data, respectively. Vertical bars represent the standard deviation in observed values where such data were available. CCC and SB are the concordance correlation coefficient and the simulation bias from the measurement, respectively.

months was *circa* 2-fold that in fall with similar monthly rainfalls in both seasons (Fig. 5).

When the ratio drainage:rainfall (D:R) was plotted against rainfall (Fig. 6), a decrease of D:R was shown as the monthly (Fig. 6c and d) and daily (Fig. 6e and f) rainfalls increase. However, no evident relationship between D:R and rainfall was found plotting observed (Fig. 6a) and modelled (Fig. 6b) data by year.

The model predictions of subsurface drainage were acceptable at a monthly-base (CCC = 0.59–0.70; SB = 0-2%) and poor at a daily-base (CCC = 0.42-0.49; SB = 0%) (Table 8). Although the APSIM performance to simulate daily subsurface drainage timing and volumes was poor, the under-predicted events were higher during winter and in early spring when corn growth was slow (Figs. 7 and 8; Table 8) than during late spring and summer, *i.e.* the time with corn growth was rapid (Figs. 7 and 8; Table 8). Likewise, there were several drainage events during fall as corn growth slowed where the model under-predicted the daily subsurface drainage (Figs. 7 a, c and 8).

Table 7
Summary statistics indicating the performance of the Agricultural Production Systems Simulator (APSIM) in predicting the annual subsurface drainage in a corn-soybean rotation (CS) fertilized with 156 kg N ha^{-1} (156) and 201 kg N ha^{-1} (201), in a continuous corn rotation (CC) fertilized with 224 kg N ha^{-1} (224) and 269 kg N ha^{-1} (269), and using the complete dataset (T) at West Lafayette, Indiana.

	Corn-soybean			Continuous corn			T[1]
	156	201	CS[a]	224	269	CC[a]	
Observations	13	10	23	11	10	21	44
Mean (Observed; mm)	151	173	161	148	236	190	175
Mean (Modelled; mm)	159	131	147	125	207	164	155
SD (Observed; mm)	85	85	84	72	117	103	94
SD (Modelled; mm)	90	54	77	76	107	99	87
Model Testing Parameters							
CCC	0.75	0.66	0.68	0.61	0.63	0.69	0.69
SB (%)	2	37	5	12	9	10	7
MSV (%)	98	63	95	88	91	90	93
RMSE (mm)	60	70	65	67	96	82	73

Abbreviations: SD, Standard deviation; CCC, Concordance Correlation Coefficient; SB, Simulation Bias; MSV, Mean Square Variation; RMSE, Root Mean Square Error.
[a] Summary statistics for CS and CC, and T were calculated using data from each individual rotation (*i.e.* including both N rates by rotation) and the complete dataset (*i.e.* including all rotations and N rates), respectively.

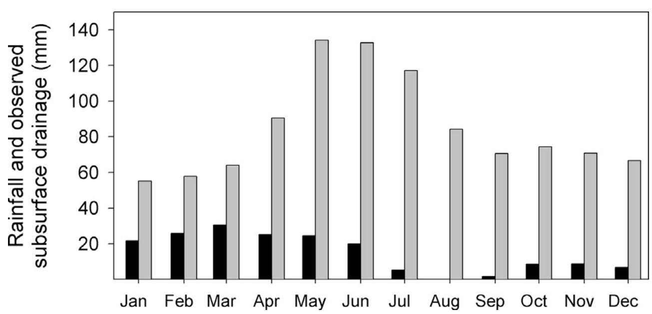

Fig. 5. Monthly average for rainfall (grey bars) and observed subsurface drainage (black bars) during 14 years (1998–2011) in West Lafayette. Each monthly average for subsurface drainage was calculated using data from continuous corn rotations fertilized with 224 and 269 kg N ha^{-1} and corn-soybean rotations fertilized with 156 and 201 kg N ha^{-1} between 1998 and 2011 in West Lafayette.

Table 8
Summary statistics indicating the performance of the Agricultural Production Systems Simulator (APSIM) in predicting the monthly and daily subsurface drainage during periods of the year with (May-Oct) and without crops (Nov-Apr) using the complete dataset at West Lafayette, Indiana.

	Monthly [a]		Daily [a]	
	Nov-Apr	May-Oct	Nov-Apr	May-Oct
Observations	288	288	7356	7624
Mean (Observed; mm)	20.0	10.1	0.80	0.41
Mean (Modelled; mm)	19.1	12.6	0.79	0.52
SD (Observed; mm)	28.9	20.4	3.06	2.17
SD (Modelled; mm)	26.5	22.9	2.96	2.61
Model Testing Parameters				
CCC	0.70	0.59	0.49	0.42
SB (%)	0	2	0	0
MSV (%)	100	98	100	100
RMSE (mm)	21.6	19.7	3.03	2.58

Abbreviations: Nov-Apr, indicates events of subsurface drainage occurred from November to April; May-Oct, indicates subsurface drainage events occurred from May to October; SD, Standard deviation; CCC, Concordance Correlation Coefficient; SB, Simulation Bias; MSV, Mean Square Variation; RMSE, Root Mean Square Error.
[a] Summary statistics for subsurface drainage on a monthly- and daily-base was calculated using data from the complete dataset (*i.e.* including all rotations and N rates, *i.e.* corn-soybean rotations fertilized with 156 kg N ha^{-1} and 201 kg N ha^{-1}, and continuous corn rotations fertilized with 224 kg N ha^{-1} and 269 kg N ha^{-1}).

The daily subsurface drainage was modelled by APSIM only when the *esw* was greater than 455 mm (Fig. 9). For *esw* values greater than DUL the model predicted a constant daily subsurface drainage of ~20 mm (Fig. 9). Likewise, the model over-predicted the daily subsurface drainage only for *esw* values greater than 455 mm (Fig. 10). However, the model under-predicted the daily subsurface drainage for a large range of *esw* values (380–470 mm). The number of under-predicted daily observations of subsurface drainage was more than 3 times than the over-predicted daily observations (Fig. 10). The model performance to predict daily subsurface drainage for continuous corn and corn-soybean rotations during 2001 and 2002 is shown, as an illustrative example, in Figs. 7 and 8, respectively. Both years were selected from the complete long-term dataset (Figs. A2–A9). The dynamics of daily subsurface drainage had similar pattern among different rotations and N rates for all years (Figs. 7, 8 and A2–A9). Observed peak daily subsurface drainage usually occurred within the same day that a major rainfall event occurred (Figs. 7 and 8). Likewise, the highest D:R values were near 15 (Fig. 6e and f). However, only 3.5 and 9.3% of the total modelled (n = 928) and observed (n = 905) D:R values were higher than 3.

4. Discussion

This study had two main objectives. Firstly, to evaluate the APSIM ability to simulate corn stover and grain yields in four contrasting soil series across three IN locations. Secondly, to evaluate the model performance to predict artificial subsurface drainage by cropping system (rotation and N rate) in a silty clay loam soil at West Lafayette, IN.

4.1. Stover and grain yield

The APSIM model through the *Maize* module of APSIM provided a very good prediction for corn stover yield and a satisfactorily prediction of grain yield at these IN locations (Fig. 1). Model performance in predicting corn grain yield was similar to that reported for other APSIM-validation studies including northern (Carberry et al., 1996) and south-eastern Australia (Pembleton et al., 2013), Zimbabwe (Shamudzarira and Robertson, 2002), and the north plain (Chen et al., 2010) and northeast China (Liu et al., 2012).

Several studies have evaluated the accuracy and precision of APSIM to simulate corn grain yield in continuous corn and corn-soybean rotations in the US Corn Belt (Lyon et al., 2003; Malone et al., 2007; Dietzel et al., 2016). Lyon et al. (2003) reported similar metrics of APSIM performance (CCC = 0.96) for grain yield prediction in IA US using a limited number of observations (n = 10). However, Malone et al. (2007) using single or split N applications in IA found that APSIM did not simulate grain yield well (CCC = 0.28) and suggested that the poor accuracy was associated with the relatively simple N-uptake routine which overemphasized N stress at floral initiation. In contrast, Archontoulis et al. (2014a) reported

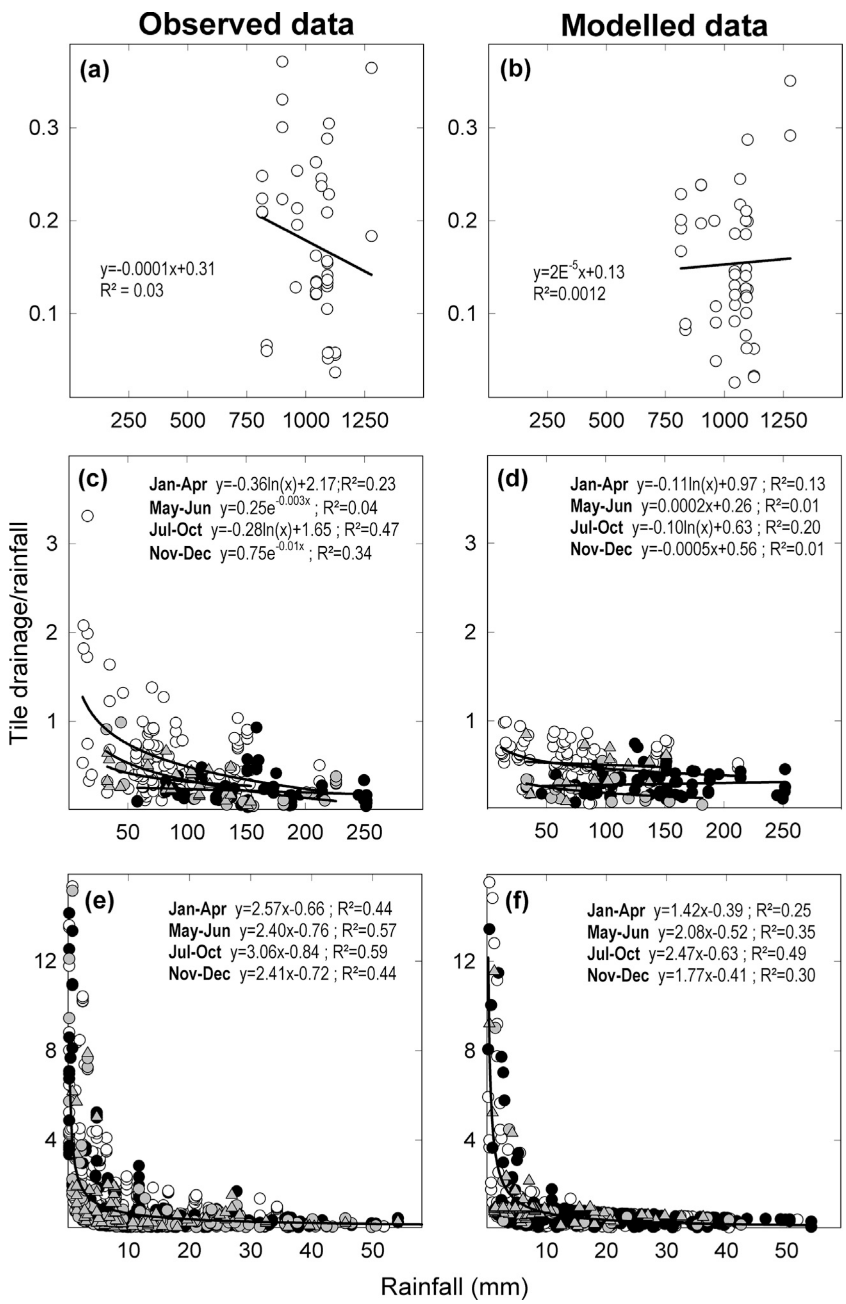

Fig. 6. Ratio subsurface drainage:rainfall *v.* daily rainfall on a (a, b) yearly-, (c, d) monthly- and (e, f) daily-base during 14 years (1998–2011) in different cropping systems included corn rotations and N rates grown in West Lafayette. The ratio subsurface drainage:rainfall in panels a, c and e was calculated using observed data. The ratio subsurface drainage:rainfall in panels b, d and f was calculated using modelled data. Solid black line represents regression lines to the data. In panels c, d, e and f dataset were partitioned in data from January to April (white circles), May to June (black circles), July to October (grey circles) and November to December (grey triangles). The regression line shown in panels e and f was calculated with basis on all dataset.

very good corn yield predictions by APSIM on three soil types (Typic, Aquic Hapludoll and Typic Endoaquoll) over multiple years in IA following best management practices for this region. In agreement with our results these authors reported excellent agreement between predicted and observed corn grain yield ($R^2 = 0.88$) and in biomass yield predictions ($R^2 = 0.97–0.99$); although they not evaluated the APSIM performance to predict corn stover yield.

Several biophysical models have been used to predicted corn yields including: The Root Zone Water Quality Model (RZWQM) (Ahmed et al., 2007), Decision Support System for Agrotechnology Transfer (DSSAT) (Liu et al., 2011; Issa, 2012) and Hybrid-Maize (Grassini et al., 2009, 2011; Issa, 2012) using data from around North America. However, with the exception of the unpublished modelling study reported by Issa (2012) using Hybrid-Maize and DSSAT, there are few published modelling reports evaluating crop model performance in predicting both corn stover and grain yield in the Eastern Corn Belt of the US.

The APSIM model showed very good accuracy for predicting stover yield at West Lafayette and Wanatah, but the model accuracy to predict stover yield at Lafayette was poor (8 out of 14 observations were under-predicted; Fig. 1d). In contrast, the APSIM ability to predict grain yield at that location was satisfactory (Table 5). Interestingly, the difference between the observed and modelled standard deviation of stover yield (60%) was much greater than for the grain yield (8%) in Lafayette. This could be attributable to differences in the experimental handling among locations added to the

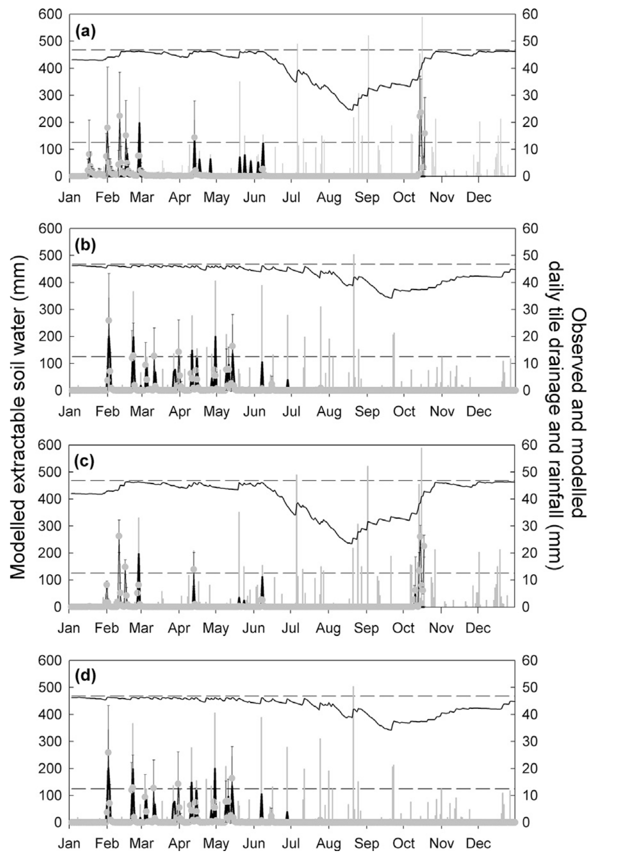

Fig. 7. Modelled extractable soil water (thin solid black line), observed (grey points) and modelled daily subsurface drainage (thick solid black line) and daily rainfall (grey columns) for the continuous corn rotation fertilized with 269 kg N ha^{-1} during (a) 2001 and (b) 2002 and fertilized with 224 kg N ha^{-1} during (c) 2001 and (d) 2002 in West Lafayette. Upper and lower solid dashed black lines represent the LL and DUL for the Drummer soil series, respectively. Vertical bars represent the standard deviation in observed values where such data were available. The years 2001 and 2002 were selected from the long term data, see all data in the appendix (Figs. A2-A9).

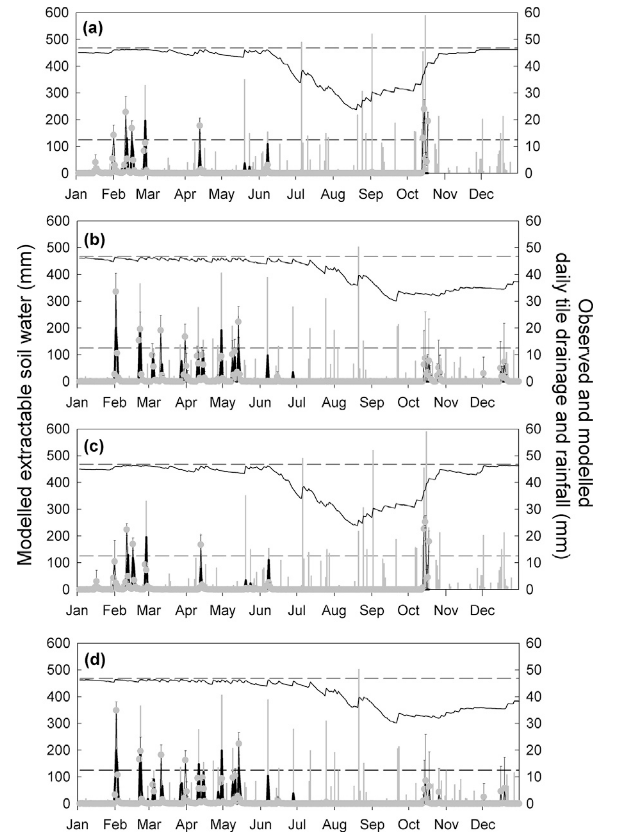

Fig. 8. Modelled extractable soil water (thin solid black line), observed (grey points) and modelled daily subsurface drainage (thick solid black line) and daily rainfall (grey columns) for the corn-soybean rotation fertilized with 201 kg N ha^{-1} during (a) 2001 and (b) 2002 and fertilized with 156 kg N ha^{-1} during (c) 2001 and (d) 2002 in West Lafayette. Upper and lower solid dashed black lines represent the LL and DUL for the Drummer soil series, respectively. Vertical bars represent the standard deviation in observed values where such data were available. The years 2001 and 2002 were selected from the long term data; see all data in the appendix.

few available data for this location (n = 14) as compared with the others (n = 63–76).

Surprisingly, APSIM performed much better for corn grain yield prediction in the continuous corn than in the corn-soybean rotations, whereas the model provided very good predictions of stover yield in both rotations (Fig. 3; Table 6). The model also predicted satisfactorily the year-to-year variability of grain and stover yield within a given cropping system (Fig. 3). However, there were notable exceptions including 1998 when the model under-predicted stover yield in the continuous corn (Fig. 3e and g) and, 2008 and 2010 where it under-predicted grain yield in the corn-soybean rotation fertilized with 156 kg N ha^{-1} (Fig. 3b). Agricultural Production Systems Simulator was able to satisfactorily predict biomass accumulation during corn growth, including early growth stages (Fig. 1). However, neither biomass nor stover accumulations were directly related with grain yield predictions (Table 6).

4.2. Annual subsurface drainage

The APSIM model through *SoilWat* module simulated the annual subsurface drainage in the corn rotations with acceptable accuracy for a silty clay loam soil at West Lafayette (Table 7). The RMSE in our study was between the values reported in the literature (<103 mm; Shen et al., 1998; Garrison et al., 1999; Ma et al., 2007; Dietzel et al., 2016). This module is interfaced with the *Residue*, *SoilN* modules and the plant module (*i.e. Maize*), which indicates that simulation

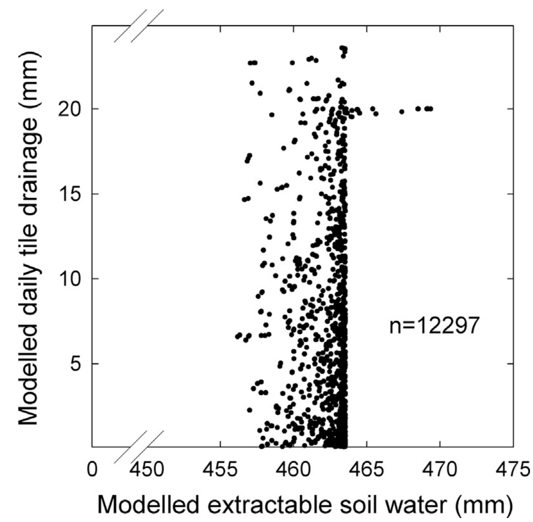

Fig. 9. Modelled daily subsurface drainage *v.* modelled extractable soil water during 14 years (1998–2011) in different cropping systems including data from continuous corn rotations fertilized with 224 and 269 kg N ha^{-1} and corn-soybean rotations fertilized with 156 and 201 kg N ha^{-1} in West Lafayette.

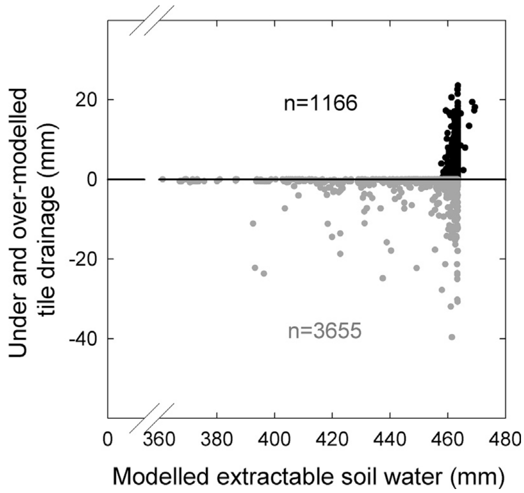

Fig. 10. Under (grey points) and over-modelled (black points) daily subsurface drainage *v.* modelled extractable soil water during 14 years (1998–2011) in different cropping systems including data from continuous corn rotations fertilized with 224 and 269 kg N ha^{-1} and corn-soybean rotations fertilized with 156 and 201 kg N ha^{-1} in West Lafayette. Solid black line represents perfect fit between observed and modelled daily water drainage.

of the soil water balance is determined by variations in the status of surface residues (*e.g.* tillage and decay rate) and canopy cover. This suggests that the model was able to capture the cropping system effect into the simulation (Fig. 4).

Early attempts to calibrate crop models to predict subsurface drainage in the US Corn Belt were conducted by Garrison et al. (1999) at IA using continuous corn and corn-soybean rotations in the CERES-Maize model. The method used by these authors was based on the estimation of two parameters (conductivity and effective drain spacing) to describe subsurface flow, and subsequently soil-water dynamics. They found RMSE values of annual subsurface drainage between 14–54 and 32–91 mm for a Typic Hapludoll and an Aquic Hapludoll, respectively. More recently, Malone et al. (2007) reported that inaccurate yield estimations by APSIM resulted in inaccurate subsurface drainage predictions. However, we did not find any correlation between grain yield and subsurface drainage at West Lafayette (not shown), either for observed and modelled data. For instance, the lowest fit between observed and modelled corn grain yield in the corn-soybean rotation fertilized with 156 kg N ha^{-1} (CCC = 0.63 and SB = 18%; Table 6) corresponded to the best fit between observed and modelled subsurface drainage at the same rotation and N rate level (CCC = 0.75 and SB = 2%; Table 7).

Several biophysical models such as RZWQM (Hanson et al., 1998), DRAINMOD (Youssef et al., 2005; Ale et al., 2009; Luo et al., 2010), SWAT (Arnold et al., 1998; Cibin et al., 2016) and APSIM (Malone et al., 2007; Dietzel et al., 2016) have been reported to simulate subsurface drainage with varying degrees of success. Recent studies have used SWAT to simulate the effects of management practices on hydrologic and water quality response at various spatial and temporal scales (Gassman et al., 2007; Baskaran et al., 2010; Chiang et al., 2010). For example, Srinivasan et al. (2010) reported a better prediction for streamflow (CCC = 1 and SB = 5%) than for corn grain yield (CCC = 0.34 and SB = 47%) in the upper Mississippi River watershed. Although most of these studies were carried-out at the watershed level, some studies have been used SWAT to simulate perennial bioenergy feedstock production at the field-scale (Trybula et al., 2014). At the same field experiment, Ale et al. (2009) showed that DRAINMOD tended to under- and over-predicted the subsurface drainage during the growing season and the whole year in continuous corn rotations, respectively.

The APSIM accuracy to predict annual subsurface drainage was better in the corn-soybean (Fig. 4a and b) than in the continuous corn rotations (Fig. 4c and d). In contrast, Malone et al. (2007) found that the subsurface drainage under no-till continuous corn was accurately predicted compared to the subsurface drainage in a no-till corn-soybean rotation because of higher residue (*i.e.* less soil evaporation) and lower transpiration on continuous corn rotation. However, APSIM predicted annual subsurface drainage at these IN locations better in the corn-soybean (Fig. 4a and b) than in the continuous corn rotations (Fig. 4c and d). This could be attributed to the fact that the high cover residues of continuous corn *v.* corn-soybean rotations were incorporated to the soil every year using spring tillage. Therefore, some effects such as increased infiltration due to additional surface residue (Weed and Kanwar, 1996) were not well simulated by APSIM. Other studies have reported greater subsurface drainage from no-till continuous corn compared to no-till corn-soybean rotations (Weed and Kanwar, 1996; Kanwar et al., 1997). While we found that subsurface drainage varied with crop rotations (Fig. 4), our results have not been consistent with the body of literature for these environments. Therefore, additional modelling studies evaluating subsurface drainage as affected by the interaction of crop rotations and tillage systems are required in this region.

4.3. Seasonal and daily subsurface drainage

The greater subsurface drainage in winter and early spring than in summer and fall was evident in this study, especially from January to June (Fig. 5). Also, the modelled *esw* values during summer and fall months, corresponding with the late crop growth, were less than DUL in the soil profile (Figs. 7, 8 and A2-A9). This indicated that evaporation and transpiration were dominant processes during summer and early fall.

Soils in this region of IN and the Eastern Corn Belt are generally frozen and snow-covered during winter months. The first drainage water flow usually occurs during the snowmelt period in late winter/early spring. Gray et al. (2001) reported up to 120 mm of snowmelt contribution to water infiltration in Canada and northern latitudes of North America. Likewise, previous modelling efforts have described snowmelt infiltration in south central MN US (Luo et al., 2010) using DRAINMOD. The *SoilWat* module of APSIM is unable to simulate soil water input originating from snow and, therefore, the estimated soil water content and drainage in our study would not reflect this additional water source. This could be the primary reason for the under-prediction of subsurface flow in winter and early spring (Fig. 6d) by APSIM, where the soil profile could have received additional water from snowmelt instead only rainfall, which may have increase the subsurface drainage (Figs. 7 and 8). However, the infiltration of meltwater into frozen soils is a complex process as it involves coupled heat and mass flow with phase changes. Likewise, this process is defined by the soil thermal and hydro-physical properties, the soil temperature and moisture regimes, and the quantity and the rate of release of meltwater from the snow-cover (Gray et al., 2001). An alternative to simulate this additional water from snowmelt could be add the equivalent rainfall amount to the rainfall input of APSIM (Dietzel et al., 2016).

The D:R increased as the rainfall events decreased either in a monthly- (Fig. 6c and d) and daily-base (Fig. 6e and f), which has been suggested as very important for the fine-textured soils in low rainfall environments (Asseng et al., 2000). However, under IN conditions soils are usually well-supplied with water most months of the year due abundant snowmelt and rainfall that collectively keeps the soil near DUL except when ET is high during the growing season (Figs. 7, 8 and A2–A9). Therefore, the subsurface drainage under IN conditions would be greater with smaller rainfall events during winter and early spring when the soils are close to DUL (Figs. 7, 8 and A2–A9). Likewise, the analysis in a monthly patterns of D:R *v.* rainfall showed a better fit for observed data from July to December than January to June, as evidenced by the R^2 (0.34-0.47 and 0.04-0.23, respectively) (Fig. 6c). This seasonal difference is associated with completely canopy cover and high ET in July to December that reduced *esw* values below the DUL (Figs. 7 and 8) and collectively leading to the very low subsurface drainage (<10 mm) (Fig. 5). By comparison, low ET and minimal canopy cover from January to June resulted in high subsurface flow rates (Fig. 5), and *esw* values near to DUL (Figs. 7 and 8).

Certain daily peaks of subsurface drainage occurred the same day when a significant daily rainfall event (higher than 30–40 mm) occurred during the corn growing season that were not simulated by the model especially when *esw* less than 463 mm (Figs. 7 a, c 8 a, c). This flow that occurs under unsaturated soil conditions suggests possible preferential flow of water through soil macropores. Similar results were found during fallow periods in Western Australia (George et al., 1997) in response to large rainfall events (Dolling et al., 2006). Moreover, preferential water flows were reported by several studies for different soil types and cropping systems (Singh and Kanwar, 1991; Edwards et al., 1993; Kanwar et al., 1997; Jiang et al., 2017). For example, Stone and Wilson (2006) reported that preferential water flow through soil macropores during storms in a subsurface-drained field in IN, contributed between 11 and 51% of total subsurface drainage, with peak contributions between 40 and 81% coinciding with times of peak subsurface flow. Similar results were found for till and no-till continuous corn and corn-soybean rotations in silty soils at IA, US (Kanwar et al., 1997). The timing of peak flow was between 0.5 h to about 6 h after the beginning of a major rainfall event (Bjorneberg and Melvin, 1996). Our study showed that APSIM poorly predicted the daily subsurface drainage within a narrow range of *esw* (Fig. 10). Additionally, there were a large number of flow under-predictions for *esw* values less than the DUL (Fig. 10). This further suggests that preferential flow occurred and APSIM, through *SoilWat,* was not able to accurately predict this pathway of water loss, which relies on the module mechanism to simulate daily subsurface drainage. While drainage from each soil layer in APSIM can be changed via the SWCON parameter (Dolling et al., 2006), as currently programmed SWCON cannot simulate preferential flow. Further research is required to determine a more accurate and independent method of determining daily subsurface drainage from one layer to the next due to preferential flow. Although the inclusion of preferential flow processes into *SoilWat* module could lead to greater APSIM accuracy to predict subsurface drainage, it is not clear at this time how best to parametrize this process. In this sense, as pointed out by others the more accurately the processes are described the greater the error introduced through incorrect parametrization (van der Laan et al., 2014). As many of the input parameters required to simulate soil water balance in the model cannot be measured directly, calibration with observed data is key, particularly for models such as APSIM where important processes are represented empirically. Likewise, a model sensitivity analysis may also help to identify key parameters or variables that should be measured to generate useful calibration data (van der Laan et al., 2014; Ojeda et al., 2016, 2017).

5. Conclusions

We used a long-term dataset of continuously cropped corn and corn-soybean rotations to demonstrate the potential of APSIM to predict corn stover and grain, and simultaneous subsurface drainage in north central Indiana US.

During winter and early spring, the model under-predicted the daily subsurface drainage.

Additionally, there were a large number of flow under-predictions for modelled extractable soil water values less than drained upper limit during the late growing corn season.

Soil water dynamic driven by the cascading bucket approach was identified as a critical aspect of the model for accurate simulation of subsurface drainage. When monthly and daily rainfalls were smaller but modelled extractable soil water values were higher than drained upper limit, more drainage per unit of rainfall was found. Our results confirm using APSIM to predict subsurface drainage in corn-based cropping systems in north central Indiana US. Additional studies will improve the model accuracy and inference space. The ability to accurately estimate subsurface drainage under US Corn Belt environments using APSIM advances efforts to characterize regional agricultural productivity and its linkages with water use efficiency, water quality, and other environmental impacts.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.agwat.2017.10.010.

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