Agricultural Systems 103 (2010) 569–584

Contents lists available at ScienceDirect

Agricultural Systems

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

Simulating landscape catena effects in no-till dryland agroecosystems using GPFARM

J.C. Ascough II [a,*], A.A. Andales [b], L.A. Sherrod [a], G.S. McMaster [a], N.C. Hansen [b], K.C. DeJonge [c], E.M. Fathelrahman [d], L.R. Ahuja [a], G.A. Peterson [b], D.L. Hoag [d]

[a] USDA-ARS, Agricultural Systems Research Unit, 2150 Centre Ave., Bldg. D, Suite 200, Fort Collins, CO 80526, USA
[b] Department of Soil and Crop Sciences, C127 Plant Sciences, Colorado State University, Fort Collins, CO 80523, USA
[c] Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, CO 80523, USA
[d] Department of Agricultural and Resource Economics, Colorado State University, Fort Collins, CO 80523, USA

ARTICLE INFO

Article history:
Received 3 September 2009
Received in revised form 26 May 2010
Accepted 22 June 2010
Available online 31 July 2010

Keywords:
Landscape catena
GPFARM
Agroecosystem modeling
Crop yield
Soil water
Soil nitrogen

ABSTRACT

This study evaluated the site-specific applicability and efficacy of the GPFARM decision support system (DSS) based on underlying simulation model performance for dry mass grain yield, crop residue, total soil profile water content, and total soil profile residual NO_3–N across a landscape catena for dryland no-till experimental locations in eastern Colorado. Relative error of simulated mean, normalized objective function (root mean square error divided by the observed mean), and index of agreement evaluation statistics were calculated to compare modeled results to observed data. A one-way, fixed-effect ANOVA was also performed to determine differences among experimental locations and summit, sideslope, and toeslope landscape positions. GPFARM simulations matched observed data trends, with the model correctly distinguishing variations between the summit and toeslope landscape positions. In addition, experimental observations and GPFARM simulations both indicated that the toeslope landscape position was the most productive for grain yield and also exhibited higher amounts of crop residue, total soil profile water content, and total soil residual NO_3–N. The GPFARM crop model performed adequately but was inconsistent in simulating winter wheat, corn, and sorghum dry mass grain yield. GPFARM performance in simulating crop residue was poorer than for crop grain yield. GPFARM predicted mean total soil profile water content was generally within ±20% of the observed mean across locations and landscape positions, with the model somewhat biased towards overpredicting total soil profile water content at the summit and sideslope landscape positions. Total soil profile residual NO_3–N was underpredicted by GPFARM across all locations and landscape positions by an average of 30%. Although GPFARM appears to have reasonably simulated long-term output responses across a landscape catena for the eastern Colorado experimental locations (especially given the simplifying assumptions in many of the GPFARM simulation components and the inherent variability present at the experimental plot level), different interpretations of GPFARM performance can be made depending on the evaluation statistic of interest. Furthermore, the model cannot fully account for water and chemical movement across the landscape catena; simulation results suggest that addition of a spatially-distributed routing component should offer improvements in GPFARM prediction accuracy across a catena where surface runoff or lateral subsurface flow is occurring.

Published by Elsevier Ltd.

1. Introduction

The ability to quickly modify farm and ranch management practices to cope with highly variable local weather fluctuations; regional and global economies; new cropping, pest management, and tillage systems; and new legislation while protecting soil, air, and water resources may determine whether or not an agricultural enterprise system survives. In agricultural regions such as the Great Plains of the United States, many farms are characterized by considerable differences (e.g., topography, soils) among and within fields that make it difficult to select alternative and sometimes unproven management techniques that enhance economic crop yields, yet protect the environment from negative impacts such as soil erosion and nitrate leaching. Peterson et al. (1993) proposed that a systems approach to the study of soil and crop management problems is useful for answering practical agricultural problems and simultaneously identifying gaps in basic research knowledge. Likewise, there has been a recognized need for system level decision support tools for agricultural advisors and producers (Hoag et al., 1999; Ascough et al., 2002). A 1995 survey of nearly 1000 Great Plains producers supported the hypothesis that many

* Corresponding author. Tel.: +1 970 492 7371; fax: +1 970 492 7310.
E-mail address: jim.ascough@ars.usda.gov (J.C. Ascough II).

0308-521X/$ - see front matter Published by Elsevier Ltd.
doi:10.1016/j.agsy.2010.06.005

farmers and ranchers could improve the management of their production systems if these obstacles were lessened or removed through an integrated systems approach, such as a decision support system (DSS) (Ascough et al., 1999). To meet the above challenges, the USDA-ARS Agricultural Systems Research Unit (ASRU), in collaboration with university and other Federal scientists, developed the Great Plains Framework for Agricultural Resource Management (GPFARM) DSS (Ascough et al., 2002; McMaster et al., 2002). The general purpose of GPFARM Version 2.6 is to provide a field-based DSS that can be scaled to a whole farm/ranch level to assist in strategic planning for comparing alternative management systems in terms of production, economic and environmental impact analysis and site-specific database generation. GPFARM specifically targets computer-oriented producers, agricultural consultants, and extension service personnel as primary users. System user requirements were determined through a series of ASRU customer focus group meetings with Great Plains farmers and ranchers; major requirements elicited were that: (1) GPFARM be simple to understand and easy to use; and (2) have minimum input data and parameter requirements.

Before applying GPFARM to actual on-farm management situations, producers and consultants must understand how well the simulation model simulates key processes such as crop growth and environmental impacts. In order to help provide this critical information, different GPFARM simulation modules have undergone testing and evaluation. Deer-Ascough et al. (1998) evaluated the grain yield simulations of the generic crop growth module in GPFARM for dryland wheat–fallow, wheat–corn–fallow, and wheat–corn–millet–fallow crop rotations in eastern Colorado. The average relative grain yield prediction error across the cropping systems was approximately 30%. Shaffer et al. (2004) evaluated GPFARM simulation of continuous corn yields and soil residual nitrates under irrigated and partially irrigated conditions, fertilized and non-fertilized applications, and high and low planting densities. Validation results for a 3-year Colorado field plot study indicated the model could simulate corn yields and soil residual NO_3–N without bias at the $P < 0.05$ level; R^2 values for predicted versus observed corn yields and soil residual NO_3–N were 0.830 and 0.833, respectively. McMaster et al. (2003) used three winter wheat plant parameter sets with different calibration levels to evaluate the GPFARM 2.01 crop growth module against observed yield data for multiple locations in eastern Colorado. The percentage of simulated yields meeting producer expectations (within 20% of the observed yield) ranged from 36% to 40% for the three plant parameter sets. Andales et al. (2003) evaluated GPFARM 2.01 using rotation-specific summit landscape position data collected from eastern Colorado dryland experimental locations. The ranges of relative error (RE) of simulated average mean at the summit landscape positions for the different locations were −27% to 84% and 0% to 23% for dry mass grain yield and total soil profile water content, respectively. Andales et al. (2003) concluded that GPFARM simulations agreed with observed trends, and verified that productivity and water-use efficiency increased with cropping intensification. Ascough et al. (2007) evaluated the regional applicability and efficacy of GPFARM based on simulation model performance for three dryland no-till experimental locations in eastern Colorado. GPFARM simulated versus observed REs ranged from −3% to 35% for dry mass grain yield, 6% to 8% for total soil profile water content, −4% to 32% for crop residue, and −25% to −7% for total soil profile residual NO_3–N. GPFARM simulations generally agreed with observed trends and showed that the model was able to correctly simulate location differences.

The results of the above evaluations have led to further corrections and enhancements in GPFARM 2.6. However, there is a continued need to evaluate GPFARM at a landscape process scale to see how well the modules work together to realistically simulate: (i) a variety of alternative cropping systems, and (ii) differences within fields and landscape catenas typically found on farms – especially for conditions in the immediate application area of eastern Colorado, USA. Therefore, the primary objective of this study is to evaluate the long-term (i.e., multiple years) performance of GPFARM 2.6 in simulating grain yield dry mass, total soil profile water content, crop residue dry mass, and total soil profile residual NO_3–N output response variables across a landscape catena (i.e., summit, sideslope and toeslope positions) for eastern Colorado, USA dryland experimental locations across a north to south potential evapotranspiration (PET) gradient. This objective expands upon the work of Ascough et al. (2007) who evaluated GPFARM across locations but not for landscape positions. A secondary objective was to verify (based on a set of statistical evaluation criteria) whether the predictive performance of GPFARM is affected by slope position within the landscape catena.

2. Materials and methods

2.1. GPFARM DSS overview

The GPFARM DSS is unique in that it brings together a group of decision support tools integrated with a complex whole farm/ranch simulation model and relational databases. The GPFARM DSS is primarily composed of five major components designed to serve as an inclusive decision support tool for farmers and ranchers: (1) a Microsoft® Windows-based graphical user interface (GUI) designed in close collaboration with producers and consultants in the Great Plains; (2) Microsoft® Access databases containing soil, crop, weed, climate, chemical, and economic parameters needed in the simulations and analysis of results; (3) an object-oriented (O-O) modeling framework (Shaffer et al., 2000) that integrates modules for simulating soil water dynamics, N dynamics, crop growth, weed growth, beef cattle production, pesticide transport, and water/wind erosion; (4) a set of analysis tools including a multicriteria decision making (MCDM) module, an output visualization module, and summary report tables and graphs for temporal and spatial comparison of different agricultural management scenarios; and (5) a stand-alone economic analysis tool utilizing production data either from the simulation model or from user input for detailed economic analyses on a management unit or farm/ranch enterprise basis.

The GPFARM science model is a land unit-by-land unit simulation framework (Shaffer et al., 2000) using C++ O-O programming. The O-O framework executes appropriate simulation modules, written in the FORTRAN 77/90 and Visual Basic procedural languages. The remainder of this section presents a brief overview of the science simulation modules directly related to the model output responses presented in this paper. For a more comprehensive description of these modules and the GPFARM DSS see Ascough et al. (2002), McMaster et al. (2002, 2003), and Shaffer et al. (2004).

- The GPFARM Water Balance and Chemical Transport (WBCT) module calculates a daily soil water budget and chemical balance for a layered soil profile using the equation:

$$SWC = SWC_{init} + P - Q - ET - D \pm S \quad (1)$$

where SWC is the soil water content in the root zone in any given day (mm), SWC_{init} is the initial soil water content in the root zone (mm), P is the precipitation (mm), Q is the surface runoff (mm), ET is the evapotranspiration (mm), D is the percolation loss below the root zone (mm), and S is the snow water content (mm) (+ for snowmelt and − for snow accumulation). Major processes considered for water movement are precipitation, snow melt, infiltration, runoff, soil water redistribution, soil water evaporation, and plant transpi-

ration. This module is a simplification of the Root Zone Water Quality Model (RZWQM) water balance routines (Ahuja et al., 2000) and uses a coarser time step (RZWQM time step ranges from 10^{-5} h to 1 h; GPFARM time step ranges from 1 h to 6 h) between precipitation events to determine soil water fluxes. A simple disaggregation scheme is used to convert the daily rainfall inputs to intensities of an average daily rainstorm to simulate infiltration and runoff. The Green–Ampt method (Green and Ampt, 1911) is used to simulate infiltration during a rainstorm at small time intervals, while redistribution of soil water is by Darcian flux calculated at 3-h to daily intervals between adjacent layers. Surface water supply exceeding the infiltration capacity in any time interval of precipitation becomes surface runoff. Drainage from the soil profile is estimated by assuming a unit gradient at the bottom layer. The WBCT module allows for adjustment of soil hydraulic properties due to tillage, residue cover, soil crust, and soil macropore presence. The module is also capable of simulating upward flux from a water table and includes the effect of restrictive soil layers on water and chemical leaching. Chemical transport is coupled with water movement based on a uniform mixing model and partitioned between aqueous and adsorbed fractions. Nitrate and pesticides are co-transported with water with possible retardation from soil adsorption; pesticide degradation is simulated as a first-order process with a known half-life.

- The GPFARM potential evapotranspiration (PET) module is also adapted from the RZWQM and calculates daily potential crop transpiration and soil evaporation using the extended Shuttleworth–Wallace model (Farahani and Ahuja, 1996). The PET module calculates net radiation and partitions the available energy for potential transpiration, bare soil evaporation, and/or residue-covered soil evaporation. Soil evaporation is a function of soil water content of the first 5 cm of the top soil layer and is limited by the Darcy flux towards the surface and the potential soil evaporation. Actual transpiration is the sum of root water uptake from each soil layer (based on root mass distribution in the profile), available water, and the potential transpiration. The potential transpiration, potential soil evaporation, and potential residue evaporation values then serve as the upper limits of actual ET calculated in the water balance module.
- The GPFARM soil properties module estimates the soil water retention curve (WRC) based on the Brooks and Corey (1964) parameters from soil texture, bulk density, and organic matter content (Rawls and Brakensiek, 1985). The saturated hydraulic conductivity (K_{sat}) is obtained from effective porosity (Ahuja et al., 1989), and unsaturated hydraulic conductivity is estimated from the WRC and K_{sat} using the Campbell (1974) approach. Hydraulic properties are updated using the regression equations of Rawls and Brakensiek (1985).
- The GPFARM carbon/nitrogen (C/N) model contains integrated modules for C/N cycling processes on the soil surface and within the soil profile. These modules were adapted from the Nitrate Leaching and Economics Analysis Package (NLEAP) model (Shaffer et al., 1991, 2001) and simulate mineralization/sequestration of soil organic matter (SOM); decomposition (mineralization/immobilization) of crop residues, manure, other organics; and transformations of inorganic nitrogen fertilizers applied to the soil surface or incorporated into the soil profile. The modules account for nitrification, denitrification, and gaseous losses of NH_3, and also estimate NH_4–N and NO_3–N available for surface runoff, residual NO_3–N available for leaching from the crop root zone, and soil NO_3–N and NH_4–N available for crop uptake. The C/N cycle modules interact with GPFARM modules for water and chemical transport, crop growth and N uptake, surface runoff and erosion. The GPFARM C/N cycle model has been widely used and validated within the NLEAP model context in the United States, Europe, and Canada (Delgado, 1998; Delgado et al., 2000).
- The GPFARM crop growth module is based on the Water Erosion Prediction Project (WEPP) model crop growth component (Arnold et al., 1995; Deer-Ascough et al., 1998), which is a modified version of the Environmental Policy Integrated Climate (EPIC) crop growth component (Williams et al., 1984, 1989). The WEPP crop growth component has been further modified in GPFARM and incorporates some elements from the Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC) model (Kiniry et al., 1992). A single model is used for simulating multiple crops by changing input parameter values. Stress factors for water and N are computed using inputs from other independent models within GPFARM. The crop growth component can be characterized as using the energy- or carbon-driven approach common in plant growth modeling. Potential daily biomass accumulation is based on the interception of light by the canopy (as represented by the LAI and light extinction coefficients) and an energy-to-biomass conversion factor. Limiting abiotic resources are reflected in growth constraint factors (temperature, water, and N) reducing the potential daily biomass accumulation. Currently GPFARM is parameterized for winter wheat (*Triticum aestivum* L.), corn (*Zea mays* L.), proso millet (*Panicum miliaceum* L.), sunflower (*Helianthus annuus* L.), sorghum (*Sorghum bicolor* L.), and foxtail/hay millet (*Setaria italica* (L.) Beauv.).

2.2. Climatic gradient, topographic gradient, and experimental cropping systems

Experimental data used for GPFARM model evaluation were obtained from an on-going sustainable dryland agroecosystems project (DAP) in eastern Colorado, USA. The DAP experiment was initiated in 1985 to evaluate the effect of cropping intensity on total biomass production, water-use efficiency, and other selected soil chemical and physical properties (Peterson et al., 1993) and has three major variables: (1) climatic gradient (e.g., precipitation, PET), (2) soil properties (e.g., plant available water) across landscape position, and (3) cropping intensity under no-till management across landscape position. Climatic variability was represented by three experimental locations in eastern Colorado, USA representing different levels of PET from north to south: Sterling (north location/low ET; 40.37°N, 103.13°W), Stratton (central location/medium ET; 39.18°N, 102.26°W), and Walsh (south location/high ET; 37.23°N, 102.17°W). Selected climatic properties for these locations are given in Table 1.

The DAP topographic variable is represented by summit, sideslope, and toeslope landscape positions along a catenary sequence (Fig. 1a–c). Along with PET differences, the topography across the locations is quite different. These differences in slope and elevation provide evidence for water relationships that are observed in the field but are extremely difficult to model. The Sterling location has a catenary sequence that has a maximum elevation difference of 5.9 m with two transition zones between the summit/sideslope and sideslope/toeslope along a north facing slope (Fig. 1a). The largest slope (5.8%) found along this 305 m length is on the west side of the sideslope landscape position. There is a slight ridge that is found in the transition zone between the sideslope and toeslope that can act as a water catchment resulting in lateral surface flow during some rainfall events. The Stratton location has the most complex topography of the three locations (Fig. 1b). The catenary sequence starts with the summit position to the west with a transition zone before the sideslope position followed by another transitional wedge that has a 14% maximum slope before the toeslope position for a total slope length of 198 m. The toeslope then transitions into another sideslope and summit which are not part of the experimental data collection area (although strips continue up to the second summit). The sideslope

Table 1
Elevation and selected climatic properties at the Sterling (40.37°N, 103.13°W), Stratton (39.18°N, 102.26°W), and Walsh (37.23°N, 102.17°W) DAP experimental locations in eastern Colorado[a].

Experimental location	Elevation (m)	Mean annual temperature (°C)	Mean annual precipitation (1985–2007) (mm)	Days above 32 °C (days)	Growing season open pan evaporation (mm)	Deficit water[b] (mm)	Relative PET
Sterling	1341	9.3	425	42	1600	−1175	Low
Stratton	1335	10.8	405	54	1725	−1320	Medium
Walsh	1134	12.2	400	64	1975	−1575	High

[a] Adapted from Sherrod et al. (2005).
[b] Deficit water = precipitation − open pan evaporation.

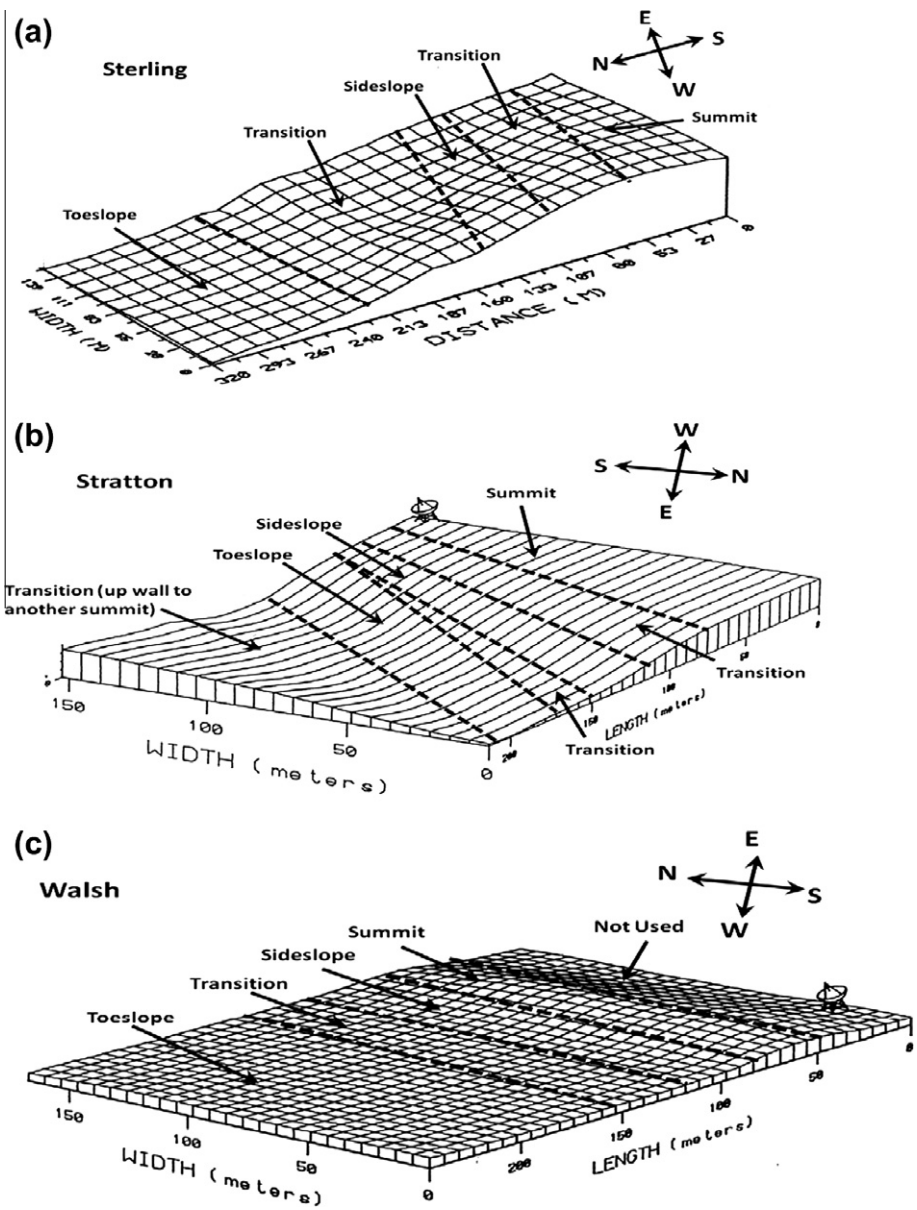

Fig. 1. Catenary sequence as represented by summit, sideslope, and toeslope landscape positions for the Sterling (a), Stratton (b), and Walsh (c) DAP experimental locations in eastern Colorado.

is east facing with a steep slope (~13%) bottoming into a narrow toeslope that is a three-way drainage area from east, south, and west slopes. The north side of the plot is along the edge of a road running east and west. This funnel effect delivers run-on water to the toeslope which has produced the highest crop yields across the three experimental locations. The high PET location at Walsh has a moderate elevation change of 1.1 m along the 183 m of the catenary sequence with a maximum slope of 5.3% on the west facing sideslope soil (Fig. 1c). This location has transition zones before the summit and between the sideslope and toeslope landscape positions with an average slope of 0.6% across the catena.

Soil physical and hydraulic properties for the top two soil horizons across landscape positions at the DAP experimental locations are given in Table 2, along with soil hydraulic properties estimated by GPFARM. Each landscape position represents a unique soil series common to the geographic area (Peterson et al., 1993). At the summit, the surface (Ap) horizons of the experimental location soils represent a range of textures that result in differing plant available water (PAW) holding capacities and saturated hydraulic conductivity rates (Table 2). Further examination of the horizons below the surface reveals additional differences between DAP experimental location soils. The summit soil profile at Sterling changes from a clay content of 21% at the surface (Ap) to 31% in the 8–20 cm depth (Bt1). Around the 85 cm depth (2Bk1), there is a marked increase in lime content (lime data not shown). The high clay and lime mixture creates a partially cemented zone that is slowly permeable to water, but relatively impermeable to plant roots. At Stratton, the summit soil profile is highest in clay at the surface (34% in the Ap horizon) and then decreases steadily to 14% clay below the 96 cm depth (Bk3). There are few restrictions to surface water infiltration or to plant root development throughout the profile as compared to summit soil at Sterling. The Stratton toeslope soil contains approximately two times the amount of total organic C and total N found on toeslope soils at the other two DAP experimental locations (Table 2). The summit and sideslope soils at Walsh have very sandy textures (>60% sand) in the top two soil horizons compared to the Sterling and Stratton summit soils, thus no restrictions to surface water infiltration or root penetration occur in this profile. There is, however, an abrupt increase in clay content at 135 cm (from 21% in the Bk4 horizon to 40% in the Btk horizon, data not shown) that represents a type of "plug" in the summit soil profile. That is, water can infiltrate rapidly in the coarse-textured surface horizons, but does not drain rapidly beyond the root zone due to the high clay content of the deepest horizon at 135 cm (data not shown). PAW at the Walsh summit soil surface horizon is 3.0 cm, which is the highest for all Ap horizons across experimental locations and landscape positions (Table 2). The amount of total organic C and total N found at the Walsh location are substantially lower relative to similar slope positions at Sterling and Stratton.

With respect to catena landscape positions across the DAP experimental locations, total C in the Ap horizon, total C in the soil profile, total N in the Ap horizon, and total PAW in the soil profile are shown in Fig. 2a–d. Fig. 2 shows that, in general, the toeslope landscape positions have greater levels of C, N, and PAW than the summit and sideslope landscape positions. However, as previously stated this is misleading due to the cemented zone at 85 cm for the Sterling summit. The Stratton location, with the exception of PAW at the summit, generally has higher levels of C, N, and PAW across landscape positions than the other two experimental locations (Fig 2). The high levels of total N in the Ap horizon and organic C in both the profile and the Ap horizon at Stratton toeslope can largely be explained by sediment deposition coming in from multiple slopes. In summary, Table 2 and Fig. 2 show that the experimental locations and landscape positions have unique characteristics that should be carefully considered when performing a comprehensive modeling study such as this.

The DAP experiment is a split–split–block design, with location as the first block and landscape position the sub-block with three cropping systems evaluated: wheat–fallow [WF], wheat–corn (or sorghum for the Walsh location)–fallow [WC(S)F], and wheat–corn (or sorghum for the Walsh location)–millet–fallow [WC(S)MF]. The cropping systems (all managed with no-till techniques to maximize water storage potential) were randomly assigned in strips within each block at the summit landscape position, and represent

Table 2
Soil physical and hydraulic properties for the top two soil horizons across landscape positions at the DAP experimental locations in eastern Colorado.

Soil horizon name	Soil horizon depth (cm)	Bulk density (BD) (33 kPa) (g cm^{-3})	Sand (%)	Clay (%)	Total organic carbon (kg ha^{-1})	Total nitrogen (kg ha^{-1})	Field capacity (FC) water content (33 kPa) (%)	Wilting point (WP) water content (1500 kPa) (%)	Plant available water[a] (cm)	K_{sat} [b] (cm h^{-1})
Sterling summit (Weld loam – fine-silty, mixed, mesic Aridic Argiustoll)										
Ap	0–8	1.37	45	21	11,674	900	0.21	0.10	1.2	3.3
Bt1	8–20	1.35	33	31	14,592	1670	0.28	0.13	2.3	1.2
Sterling sideslope (Satanta loam – fine-loamy, mixed, mesic Aridic Argiustoll)										
Ap1	0–11	1.47	54	21	15,642	1321	0.22	0.09	2.0	2.6
Ap2	11–20	1.34	44	26	11,144	1060	0.25	0.12	1.5	2.5
Sterling toeslope (Albinas loam – fine-loamy, mixed, mesic Pachic Argiustoll)										
Ap1	0–7	1.31	42	18	15,009	1223	0.22	0.10	1.2	4.7
Ap2	7–18	1.49	47	20	12,210	1139	0.20	0.09	1.7	5.0
Stratton summit (Norka clay loam – fine-silty, mixed, mesic Aridic Argiustoll)										
Ap	0–13	1.35	25	34	20,553	1874	0.27	0.17	1.8	0.23
Bt	13–39	1.26	20	36	33,987	3517	0.31	0.22	2.7	0.27
Stratton sideslope (Richfield loam – fine, montmorillonitic, mesic Aridic Argiustoll)										
Ap1	0–10	1.36	41	20	14,994	1323	0.26	0.10	2.2	3.2
Ap2	10–18	1.33	35	28	8928	918	0.28	0.14	1.5	1.9
Stratton toeslope (Kuma loam – fine-silty, mixed, mesic Pachic Argiustoll)										
Ap	0–15	1.28	25	26	41,040	3866	0.28	0.14	2.8	1.3
Ab1	15–30	1.26	23	25	44,838	4738	0.30	0.13	3.3	1.4
Walsh summit (undefined loamy sand – fine-loamy, mixed, mesic Aridic Ustochrept)										
Ap	0–18	1.48	65	14	9954	1024	0.17	0.05	3.0	5.2
Bk1	18–40	1.49	66	18	7944	967	0.14	0.07	2.5	4.3
Walsh sideslope (undefined sandy loam – fine, montmorillonitic, mesic Ustollic Haplargid)										
Ap	0–10	1.55	72	10	6552	588	0.15	0.05	1.6	5.5
BAk	10–20	1.50	57	20	6519	731	0.15	0.08	1.0	2.7
Walsh toeslope (Nunn sandy clay loam – fine, montmorillonitic, mesic Aridic Argiustoll)										
Ap	0–13	1.32	38	24	17,391	1569	0.28	0.11	2.9	2.7
Ab	13–24	1.34	32	26	27,090	2752	0.27	0.12	2.2	1.6

[a] Plant available water calculated as $[(FC * BD) - (WP * BD)] * $ soil horizon depth.
[b] K_{sat}, saturated hydraulic conductivity (estimated in GPFARM from Brooks–Corey parameters).

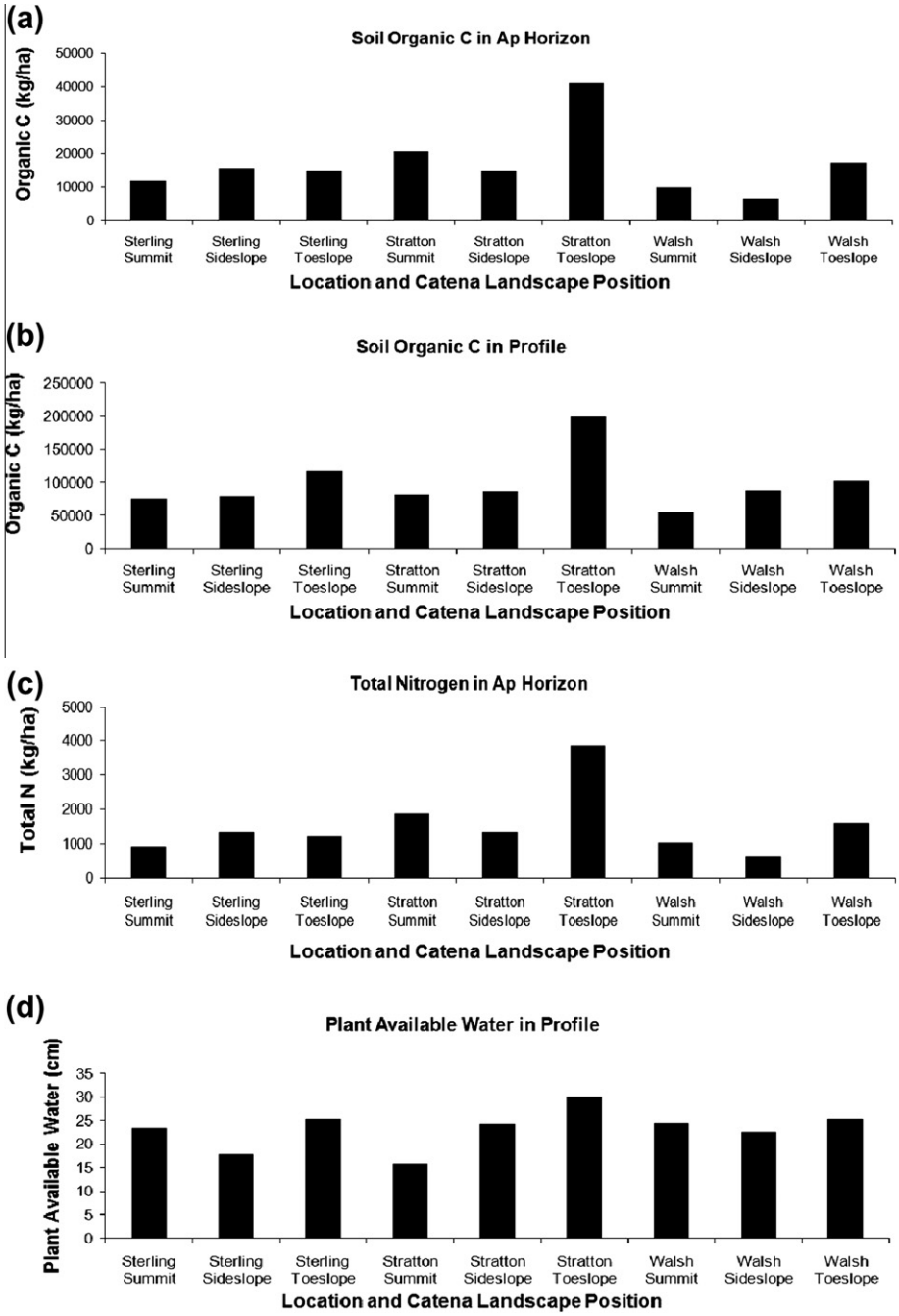

Fig. 2. Soil organic carbon (C) in the Ap horizon (a), soil organic C in the profile (b), total nitrogen (N) in the Ap horizon (c), and plant available water (PAW) in the profile (d) across landscape positions for the DAP experimental locations in eastern Colorado.

a continuum with increasing cropping intensity resulting in less summer fallow frequency. Although landscape positions were not randomized, a split block analysis of each location was used as if they had been (Steel and Torrie, 1997). For each year and landscape position, all rotation phases were present in experimental units within two replications. An experimental unit is a particular phase of a cropping system at a particular landscape position at a location with varying size, i.e., all units are 6.1 m wide but vary in length with the particular location (ranging from 183 to 305 m long). Fertilizer N was applied to each experimental unit according to soil tests obtained from each soil within each rotation and targeted for the crop present in a given year. The N fertilizer source, urea–NH_4NO_3 solution (32-0-0), was applied at planting with a dribble method directly behind the planter (Peterson et al., 1993). Phosphorus (10-34-0) was band-applied at planting of all crops near the seed (Peterson et al., 2000). Phosphorus (P) was applied on one-half of each wheat (until 1992), corn and proso millet plot over all soils, but applied to the entire wheat plot since the 1993 crop year. The P application rate was 9.5 kg/ha each year. Grain yield response to P is not currently simulated in GPFARM but it was found to be small to negligible in experimental data.

2.3. Evaluation data set

Measurements relevant to the evaluation of GPFARM included daily weather data, dry matter biomass and grain yields, crop residue dry mass, soil water content, and soil residual NO_3–N. Additional variables were measured, as described by Peterson et al.

(1993), but were not considered in this evaluation study. An automated weather station at each location measured daily maximum and minimum air temperature, mean relative humidity, precipitation, total solar radiation, wind direction, and mean wind speed. Soil water content at planting and harvest was measured in each cropping system by use of a neutron attenuation probe. Soil residual NO_3–N (at varying increments down to a depth of 150 cm) was measured (using site-specific probe calibrations) prior to planting for making fertilizer N calculations. Dry mass grain yields were measured with a plot combine (approximately 30 m × 1.2 m in the middle of each experimental unit) while total above-ground biomass was measured at harvest by hand sampling a small area in each experimental unit. Harvest indices (dry mass grain yield/total biomass) were determined from the hand samples. Surface crop residue dry mass was measured at planting and just before harvest for each crop in each cropping system. With the exception of climate variables, all measurements from a particular cropping system were obtained from two field replicates. The replicates were then averaged for comparison with simulation results from GPFARM.

2.4. GPFARM parameterization

The GPFARM simulation model was initialized using observed data for crop residue, soil profile water content, and soil profile residual NO_3–N corresponding to the simulation start dates. Observed bulk density, texture, and organic matter content of the soil layers (Table 2) were also input into GPFARM. From these properties, GPFARM estimated the soil water retention curve, soil porosity (or saturated water content), soil water content (WC) at field capacity [WC(33 kPa)], soil water content at wilting point [WC(1500 kPa)], and saturated/unsaturated hydraulic conductivity (Rawls and Brakensiek, 1985; Ahuja et al., 1989, 1999). Actual soil horizons (Table 2) and N application rates (data not shown) were used in the simulations. Weather inputs into GPFARM included observed daily precipitation (mm), maximum and minimum air temperatures (°C), solar radiation (Langleys d^{-1}), wind speed (m s^{-1}), and relative humidity (%). All weather inputs were measured on-site except for daily precipitation data for Sterling, which were downloaded from the Colorado Climate Center (CCC) website (http://ccc.atmos.colostate.edu). The CCC precipitation station near Sterling was approximately 20 km northwest of the experimental location. The complete precipitation data set (1987–1999 for Sterling) from the CCC was used in lieu of the on-site precipitation data set that had numerous gaps, especially during the winter months. For plant growth parameters of the crops involved in the study (i.e., winter wheat, corn, proso millet, and sorghum), best parameter estimates from the literature were used (Table 3) and verified to be within the ranges recommended by Arnold et al. (1995) and Kiniry et al. (1995). In addition, no calibrations were performed for the soil water, soil residual NO_3–N, and crop residue decomposition processes.

2.5. GPFARM evaluation procedure

The simulation periods for GPFARM evaluation began in 1988 and ended in 1997, 1999, and 1993 for the WF, WC(S)F, and WC(S)MF rotations, respectively. The WF simulations ended in 1997 because this system was subsequently converted to wheat–corn–proso millet rotation (Peterson et al., 2000). For WC(S)MF, sunflower was planted in place of proso millet after 1993 (Peterson et al., 2000) but the sunflower crops produced little or no yields, which limited efforts to calibrate the crop growth model for sunflower grain yield. Thus, the WC(S)MF simulations were ended in 1993. Average (i.e., from the two replicates) dry mass grain yield, crop residue, total soil profile water content, and total residual soil profile NO_3–N observed during the above periods were pooled by landscape position across all rotation phases at each experimental location and compared with corresponding GPFARM simulation outputs. The following model evaluation statistics were calculated to quantify the accuracy of the GPFARM simulations: (1) relative error (RE) which shows bias of the predicted mean relative to the observed mean; (2) a normalized objective function (NOF), based on the root mean square error (RMSE) which shows the average deviation between predicted and observed values, regardless of sign; and (3) index of agreement (d) which indicates how well model predictions agree with observations, relative to the one-to-one line. The simulated and observed coefficient of variation, CV, which shows whether or not simulated and observed variability are similar, was also calculated. Relative error (RE, %) was expressed as:

Table 3
Critical crop parameter values used in GPFARM DAP simulations.

Parameter	Definition	Units	Parameter value			
			Winter wheat	Corn	Proso millet	Sorghum
GDDMAX	Growing degree days (GDD) from planting to maturity/harvest	°C days	1700	1500	1300	1800
HI	Harvest index	0–1 ratio	0.45	0.56	0.45	0.50
HMAX	Maximum canopy height	m	0.91	2.60	1.20	1.01
LAI_{max}	Maximum potential leaf area index (LAI)	m^2 m^{-2}	3.0	3.5	2.4	3.5
BEINP	Biomass to energy conversion ratio for a crop	kg MJ^{-1}	35.0	30.0	35.0	25.0
BN1	Normal fraction of nitrogen in crop biomass at emergence	0–1 ratio	0.060	0.040	0.044	0.044
BN2	Normal fraction of nitrogen in crop biomass at mid-season	0–1 ratio	0.023	0.016	0.016	0.016
BN3	Normal fraction of nitrogen in crop biomass at maturity	0–1 ratio	0.013	0.013	0.013	0.013
BTEMP	Base air temperature used in calculating crop GDD	°C	4.0	10.0	5.0	10.0
CRIT	Growing degree days from planting to emergence	°C days	140.0	60.0	65.0	60.0
DLAI	Heat unit index when LAI starts to decline (fraction of GDDMAX)	0–1 ratio	0.65	0.80	0.80	0.85
EXTNCT	Radiation extinction coefficient	Unitless	0.65	0.65	0.65	0.60
OTEMP	Optimal temperature for plant growth	°C	20.0	25.0	20.0	27.5
RDMAX	Maximum rooting depth	m	1.5	1.5	1.0	1.5
RSR	Root biomass to shoot biomass ratio	0–1 ratio	0.25	0.25	0.25	0.25
SPRIOD	Period over which senescence occurs	Days	14	30	30	40
RLAD	Rate of LAI decline	Unitless	1.0	1.0	1.0	1.0
PPOP1	Plant density at FMLAI1	Plants m^{-2}	125	4	125	5
FMLAI1	Fraction of XMXLAI corresponding to PPOP1	0–1 ratio	0.60	0.47	0.60	0.43
PPOP2	Plant density at FMLAI2	Plants m^{-2}	250	7	250	15
FMLAI2	Fraction of XMXLAI corresponding to PPOP2	0–1 ratio	0.95	0.80	0.80	0.79

$$\mathrm{RE} = \frac{(\bar{P} - \bar{O})}{\bar{O}} * 100 \tag{2}$$

where $\bar{P}$ is the predicted mean and $\bar{O}$ is the observed mean. The RMSE was calculated by:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{3}$$

where P_i is the ith predicted value, O_i is the ith observed value, and n is the number of data pairs. The NOF (unitless), which is similar to the coefficient of variation (Pennell et al., 1990; Costa et al., 1994) was calculated as:

$$\mathrm{NOF} = \frac{\mathrm{RMSE}}{\bar{O}} \tag{4}$$

where RMSE and $\bar{O}$ are as previously defined. The NOF should be interpreted as a relative value to compare model performance of simulating different data sets. NOF = 0 indicates a perfect fit between experimental data and simulated results; NOF < 1 may be interpreted as simulation error of less than 1 standard deviation around the experimental mean. The index of agreement (d, unitless) was calculated as proposed by Willmott (1981) and Willmott and Wicks (1980):

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i'| + |O_i'|)^2}\right], \quad 0 \leqslant d \leqslant 1 \tag{5}$$

where P_i, O_i, and n are as previously defined, $P_i' = P_i - \bar{O}$ and $O_i' = O_i - \bar{O}$ where $\bar{O}$ is as previously defined, and the enclosing bars (| |) indicate absolute values. A d value of one indicates complete agreement between model predictions and observations. The NOF and d values indicate the average event-by-event (short-term) prediction errors, as opposed to the RE which is an arithmetic average over the duration of data (i.e., shows long-term bias). Additional statistical analysis using a one-way, fixed-effects ANOVA was performed to assess the influence of landscape position on observed data and GPFARM simulation model output responses. Mean values were separated using Tukey's least significant difference (LSD) with $P \leqslant 0.05$ considered significant. The ANOVA and Tukey's analysis were conducted using SigmaStat 3.11 (Systat, 2006).

As a final note, the evaluations of soil water and soil residual NO_3–N simulations in this study were limited to total soil profile amounts, and observed grain yields affected by severe weed infestation, poor or erratic emergence due to hard surface soil conditions, hail damage, or killing frost were excluded from comparisons with simulated grain yields since the model was not designed to account for these extreme events. Steiner et al. (1987) and Cabelguenne et al. (1999) used similar approaches of data screening to limit evaluations to the validity domain of the models. GPFARM does include a weed module (Canner et al., 2002, 2009), but there were insufficient quantitative observations of infestation to allow for weed module calibration.

3. Results and discussion

3.1. Trend analysis – crop grain yield and residue

For all crops and experimental locations, observed grain yield data showed statistically significant differences ($P \leqslant 0.05$) between either the summit and sideslope or the sideslope and toeslope landscape positions (Table 4). However, statistically significant difference tendencies between the two landscape position combinations were somewhat varied. Except for proso millet at Walsh, observed grain yield was always statistically different between the summit and toeslope landscape positions across all crops and locations (Table 4). This was not the case comparing summit and sideslope landscape positions at most experimental locations where observed grain yields and crop residue amounts were usually statistically the same. For all experimental locations, observed grain yields and crop residue amounts at the toeslope landscape position were significantly greater than at the summit or sideslope landscape positions, except for proso millet grain yields at Sterling and Walsh (Table 4). This was expected given the greater inherent fertility at this depositional slope as evidenced by the higher amounts of organic C and total N (Fig. 2b and c). In addition to differences within and across locations in organic matter levels (C and N), there are dynamic differences in PAW within locations and across landscape positions with the toeslope having the highest PAW levels (Fig. 2d). It is of interest that the sideslope landscape position grain yields and crop residue amounts were usually greater than at the summit landscape position, with Stratton as an exception where mean winter wheat/corn grain yields and crop residue amounts at the summit were greater (but not significantly different) than corresponding grain yields and crop residue amounts at the sideslope (Table 4). This may be explained by the degree of slope and slope length between the summit and sideslope positions. For example, the sideslope at Sterling has a bowl formation with an outcrop feature in the transition zone between sideslope and toeslope that tends to backup runoff water.

GPFARM simulation results were mixed in accurately distinguishing statistically significant differences between landscape positions across locations. For example, GPFARM correctly predicted statistically significant differences between the summit and toeslope landscape positions for winter wheat and sorghum grain yield across locations with the only discrepancy being winter wheat grain yield at Stratton (Table 4). However, GPFARM simulations showed no statistically significant difference in productivity across landscape positions for corn grain yield at Stratton and proso millet grain yield at all locations. For proso millet, the comparatively low number of observations (a maximum of five at any landscape position) contributed to the inability of GPFARM to simulate productivity differences between landscape positions. In general, GPFARM simulated grain yields and crop residues were not usually significantly different at the summit and sideslope landscape positions across locations which correlated with observed trends (Table 4). Also in agreement with observed trends, GPFARM predicted significantly lower amounts of crop residue at the summit landscape position and simulated mean grain yields (and crop residue amounts) were greatest at the toeslope landscape position.

Examination of observed trends for the "All Locations" data set (i.e., data pooled across all experimental locations for each landscape position) showed that mean crop grain yields and residue amounts at the toeslope landscape position were significantly greater than at the summit or sideslope landscape positions (Table 4). Observed mean grain yields and crop residue amounts at the summit and sideslope landscape positions were not significantly different, although grain yields and crop residue amounts at the sideslope landscape position were slightly higher than corresponding grain yields and amounts at the summit landscape position. Overall, the observed grain yield data exhibited a general trend towards increased productivity downslope across the landscape catena, i.e., going from the summit to the sideslope to the toeslope landscape positions. Again, this trend is likely due to the greater amounts of C, N, and PAW found at the toeslope landscape position (Fig. 2). Under semi-arid conditions or dry years, yields are generally lowest at the summit and increase downslope (Kosmas et al., 1993; Rockström et al., 1999) because of downslope water movement and better toeslope soil conditions (Peterson et al., 1993). For the "All Locations" data set, GPFARM reproduced observed landscape position trends for winter wheat, corn, and sorghum grain yields. However, in contrast to observed data, GPFARM predicted no significant differences in mean proso millet

Table 4
Observed and simulated mean and coefficient of variation (CV) across landscape positions for simulated grain yield, crop residue, total soil profile water content, and total residual soil profile NO_3–N at the DAP experimental locations in eastern Colorado[a].

Experimental location	Observed						GPFARM simulated					
	Summit landscape position		Sideslope landscape position		Toeslope landscape position		Summit landscape position		Sideslope landscape position		Toeslope landscape position	
	Mean (kg·ha^{-1})	CV (%)	Mean (kg·ha^{-1})	CV (%)	Mean (kg·ha^{-1})	CV (%)	Mean (kg·ha^{-1})	CV (%)	Mean (kg·ha^{-1})	CV (%)	Mean (kg·ha^{-1})	CV (%)
Winter wheat grain yield												
Sterling	2063[a]	26	2129[a]	25	2727[b]	23	2222[a]	11	2339[ab]	9	2569[b]	11
Stratton	2433[a]	21	2274[a]	23	3467[b]	25	2166[a]	29	2457[a]	34	2493[a]	29
Walsh	1876[a]	24	2082[ab]	23	2541[b]	22	1471[a]	31	1652[b]	25	2218[c]	33
All locations	2140[a]	25	2169[a]	23	2955[b]	27	1959[a]	30	2159[a]	31	2434[b]	26
Corn grain yield												
Sterling	3184[a]	22	4124[b]	24	5048[b]	23	3854[a]	31	4040[a]	25	4416[b]	21
Stratton	3908[a]	39	3568[a]	35	5299[b]	24	3822[a]	38	3991[a]	40	4270[a]	36
All locations	3518[a]	34	3871[a]	29	5164[b]	24	3839[a]	33	4018[a]	32	4348[b]	28
Proso millet grain yield												
Sterling	1810[a]	22	1944[a]	34	2227[b]	30	2031	12	1951	7	2048	16
Stratton	1554[b]	28	1676[a]	12	2161[a]	29	1994	47	1788	59	2602	19
Walsh	814[a]	0.7	1266[a]	20	1861[a]	13	1403	49	1451	10	1908	3
All locations	1538[a]	33	1719[a]	29	2139[b]	27	1911	35	1800	37	2256	21
Sorghum grain yield												
Walsh	2264[a]	33	2453[a]	27	3165[b]	39	1937[a]	38	2507	28	2919[b]	32
Crop residue												
Sterling	3234[a]	49	3620[ab]	53	4319[b]	42	3898[a]	41	4104[a]	40	4481[a]	37
Stratton	3081[a]	62	2998[a]	63	3938[b]	62	4113[a]	49	4286[ab]	48	4623[b]	49
Walsh	1753[a]	66	1945[a]	72	2976[b]	61	3059[a]	53	3195[a]	54	3988[b]	49
All locations	2634[a]	65	2797[a]	67	3658[b]	59	3674[a]	50	3845[b]	49	4347[b]	47
Total soil profile water content	(mm)	(%)	(mm)	(%)	(mm)	(%)	(mm)	(%)	(mm)	(%)	(mm)	(%)
Sterling	247[a]	19	241[a]	22	328[b]	21	298[b]	18	260[a]	23	279[c]	21
Stratton	284[b]	20	247[a]	21	390[c]	25	291[a]	17	324[b]	19	329[b]	17
Walsh	294[a]	16	287[a]	16	326[b]	15	224[a]	19	316[b]	21	327[b]	18
All locations	274[b]	20	258[a]	21	350[c]	24	276[b]	21	302[a]	23	308[c]	20
Total soil profile residual NO_3–N	(kg·ha^{-1})	%	(kg·ha^{-1})	%	(kg·ha^{-1})	%	(kg·ha^{-1})	%	(kg·ha^{-1})	%	(kg·ha^{-1})	%
Sterling	68[a]	43	62[a]	56	68[a]	55	45[a]	56	40[a]	40	47[a]	49
Stratton	67[a]	38	57[a]	40	104[b]	42	50[a]	60	50[a]	65	76[b]	63
Walsh	60[a]	51	76[b]	62	68[a]	78	29[a]	51	33[a]	61	60[b]	53
All locations	65[a]	44	65[a]	57	81[b]	60	42[a]	62	41[a]	62	62[b]	62

[a] Within-row observed and GPFARM simulated means followed by the same letter are not significantly different using Tukey's LSD at $P \leqslant 0.05$.

grain yields across landscape positions and simulated mean crop residue at the sideslope landscape position was significantly different than at the summit landscape position. With the exception of proso millet grain yield, GPFARM simulations for the "All Locations" data set were in agreement with the observed general trend towards increased yield productivity and crop residue amounts downslope across the landscape catena. In general, GPFARM estimation of crop grain yield coefficient of variability (CV) produced mixed results, i.e., there were no strong tendencies toward underestimation or overestimation. However, there was a strong tendency for GPFARM to underestimate crop residue CVs across all locations and landscape positions (Table 4) due to the fact that GPFARM consistently overestimated crop residues and could not simulate low residue values. Also, the smaller range in simulated crop residues resulted in smaller standard deviations.

3.2. Trend analysis – total soil profile water content and soil residual NO_3–N

Similar to observed grain yield data, observed data for total soil profile water content and soil profile residual NO_3–N showed statistically significant differences ($P \leqslant 0.05$) between the summit and toeslope landscape positions across all locations (Table 4). The only exception was for observed total soil profile residual NO_3–N at Sterling where no significant differences were observed between landscape positions. This finding is confirmed by Fig. 2c which shows very little difference in total N in the Ap horizon between landscape positions at Sterling. At all locations, observed total soil profile water contents were significantly greater at the toeslope landscape position than at the summit or sideslope landscape positions. Mean total soil profile water content at the summit landscape position was greater than at the sideslope landscape position, although the difference was only significant at Stratton (Table 4). In addition, residual NO_3–N at the toeslope landscape position was significantly greater than at the summit and sideslope landscape positions for only the Stratton location and not Sterling or Walsh. Again, Fig. 2c shows a large difference between toeslope and summit/sideslope total N in the Ap horizon at Stratton but not at the other two experimental locations. GPFARM was able to reproduce observed trends across landscape positions for total soil profile water content and residual NO_3–N except for the inability to predict significant differences between the summit and toeslope landscape positions for total soil profile water content at Stratton and total residual NO_3–N at Sterling. Converging flow from two upslopes that directly contribute run-on water to the toeslope is a probable reason that GPFARM

underpredicted total soil profile water content at Stratton. Predicting residual NO_3–N levels within a profile has several factors that could be interacting to cause this level of discrepancy between observed and predicted values. For example, GPFARM overestimation of corn yields would lead to greater stover additions that would tie up more residual NO_3–N during decomposition.

GPFARM predicted trends for total soil profile water content were similar to observed trends at Stratton and Walsh, with mean amounts greatest at the toeslope landscape position and least at the sideslope landscape position (Table 4). Unlike the observed data, GPFARM predicted mean water content at Sterling was greatest at the summit. In addition, except for Sterling, GPFARM was unable to reproduce the observed trend of lower soil water content at the sideslope landscape position for all locations. Because GPFARM generally overpredicts sideslope and underpredicts toeslope soil water content (Table 4), this may be an indication that it is not fully accounting for surface runoff or lateral subsurface flow from the sideslope to toeslope landscape positions. However, specific reasons for this are difficult to identify since observations of these water balance components are unavailable. Furthermore, the magnitude of the prediction differences is not dramatic with the exception of the toeslope at Stratton. GPFARM simulated trends of total soil profile residual NO_3–N were similar to observed trends at Sterling and Stratton, with mean amounts greatest at the toeslope landscape position and least at the sideslope landscape position (Table 4).

Examination of observed trends for the "All Locations" data set showed that mean total soil profile water contents were significantly different across all landscape positions (Table 4). Overall, total soil profile water content was greatest at the toeslope landscape position and least at the sideslope landscape position. The observed mean of total soil profile residual NO_3–N was significantly greater at the toeslope landscape position than at the summit and sideslope landscape positions; however, mean total soil profile residual NO_3–N values at the summit and sideslope landscape positions were not significantly different. GPFARM reproduced observed trends with predicted total soil profile water content significantly greatest at the toeslope landscape position and significantly lowest at the sideslope landscape position (Table 4). Also similar to observed data, GPFARM simulated mean total soil profile residual NO_3–N was significantly greater at the toeslope landscape position than at the summit and sideslope landscape positions. Analysis of observed total soil profile water content and soil profile residual NO_3–N variability for the "All Locations" data set showed that observed CVs across landscape positions ranged from 20% to 24% for total soil profile water content and 44% to 60% for total soil profile residual NO_3–N (Table 4). GPFARM simulated variability across landscape positions was very close to observed for total soil profile water content (20–23%), but not quite as good for total soil profile residual NO_3–N (62% for all landscape positions).

3.3. GPFARM performance evaluation – crop grain yield and residue amount

Long-term trends in overprediction and underprediction are manifested in the relative error (RE) statistics presented in Table 5. The REs in GPFARM simulated winter wheat grain yield for the experimental locations and landscape positions were generally less than ±20%, with REs ranging from −28% (Stratton toeslope) to 10% (Sterling sideslope). Mean winter wheat grain yields were mostly underpredicted by GPFARM at the summit and toeslope landscape positions (Table 5 and Fig. 3a) as the model tended to underpredict winter wheat harvest index (HI) in most years (data not shown). This may also explain the overpredictions in crop residue, as HI is used in the model to partition above-ground biomass into grain yield and remaining plant biomass that contributes to crop residues. Similar to RE, high normalized objective function (NOF) values typically indicate either strong overprediction/underprediction or considerable scatter when observed data are plotted against simulated model output response. The lowest (best) and highest (worst) NOF values were at the Sterling and Stratton toeslope landscape position; however, NOF values were less variable and very similar for the summit and sideslope landscape positions across locations (Table 5). Index of agreement (d) values for winter wheat grain yield were slightly better for the summit landscape position and ranged from a low of 0.40 (Sterling – all landscape positions) to a high of 0.67 (Walsh summit).

The REs for proso millet grain yield simulations were extremely variable, ranging from a low of 0.40% at the Sterling sideslope landscape position to a high of 72% at the Walsh summit landscape position (Table 5). The evaluation statistics at Walsh are questionable because of the very limited number of observations across landscape positions at that location (due to consistently low yields, proso millet at Walsh was replaced by forage sorghum beginning in 1993). GPFARM consistently overpredicted proso millet grain yield at the summit and sideslope landscape positions, however, this trend was less prominent for the toeslope landscape position (Fig. 3b). Overprediction in proso millet grain yield at Stratton and Walsh may again be due to the inability of the GPFARM crop growth model to sufficiently respond to soil water deficits during critical growth periods. Similar to predictions for corn grain yield, the NOF range for proso millet grain yield at the toeslope landscape position across experimental locations (0.07–0.39) was much lower than for the sideslope and summit landscape positions (Table 5). Agreement between observed and GPFARM simulated values showed the most variability among all crops, with d ranging from a low of 0.01 (Walsh summit and Stratton sideslope landscape positions) to a high of 0.59 (Walsh toeslope position).

GPFARM simulated corn grain yield REs were similar to simulated wheat grain yield REs, ranging from underprediction of −19% to overprediction by 21% at the Stratton sideslope and Sterling summit landscape positions, respectively (Table 5 and Fig. 3c). GPFARM underpredicted corn grain yield at the toeslope landscape position; however, Fig. 3c shows general overprediction of corn yield by GPFARM at the summit and sideslope landscape positions. Corn is very sensitive to water deficits and water stress during tasseling, silking, and early grain filling. Using long-term on-farm records (32–88 years) at five locations in northeastern Colorado, Nielsen (1996) showed a strong correlation between precipitation and corn grain yield during the 6-week period of July 15 to August 25. Corn grain yield NOF values for the summit and sideslope landscape positions were generally higher than NOF values for the toeslope position. In general, agreement (d) between simulated and observed corn grain yields was somewhat lower than that for winter wheat, with corn grain yield index of agreement values ranging from a low of 0.29 (Sterling toeslope) to a high of 0.61 (Stratton toeslope). For sorghum, which was planted only at Walsh, the RE was less than 15% across all landscape positions with a slight tendency towards underprediction (Fig. 3c). Sorghum grain yield NOF values across all landscape positions were comparable to winter wheat grain yield NOF values, and sorghum grain yield index of agreement (d) values across landscape positions were the highest for all crops.

GPFARM simulation results for crop residue were noticeably poor compared to crop grain yield simulation results. Table 5 shows that crop residue amounts were strongly overpredicted by GPFARM at all locations; however, GPFARM crop residue predictions were much better for Sterling than for Stratton or Walsh. This may be due to the ET gradient of the DAP experiment, i.e., cooler temperatures and lower ET (Table 1) mean that residue remains longer at Sterling than at Stratton or Walsh (where the higher temperatures and increased ET accelerate residue decomposition).

Table 5
Relative error (RE), normalized objective function (NOF), and index of agreement (*d*) model evaluation statistics for simulated grain yield, crop residue, total soil profile water content, and total residual soil profile NO_3–N across landscape positions at the DAP experimental locations in eastern Colorado.

Experimental location	Summit landscape position			Sideslope landscape position			Toeslope landscape position		
	RE (%)	NOF (unitless)	*d* (unitless)	RE (%)	NOF (unitless)	*d* (unitless)	RE (%)	NOF (unitless)	*d* (unitless)
Winter wheat grain yield									
Sterling	8	0.27	0.40	10	0.27	0.40	−6	0.24	0.40
Stratton	−11	0.27	0.58	8	0.33	0.63	−28	0.40	0.50
Walsh	−22	0.29	0.67	−21	0.30	0.61	−13	0.31	0.61
All locations	−8	0.28	0.63	−0.4	0.30	0.62	−18	0.34	0.52
Corn grain yield									
Sterling	21	0.49	0.30	−2	0.28	0.57	−13	0.33	0.29
Stratton	−2	0.42	0.60	12	0.54	0.39	−19	0.33	0.61
All locations	9	0.46	0.52	4	0.40	0.46	−16	0.33	0.49
Proso millet grain yield									
Sterling	12	0.32	0.21	0.4	0.33	0.08	−8	0.31	0.41
Stratton	28	0.63	0.41	7	0.64	0.01	20	0.39	0.43
Walsh	72	0.94	0.01	15	0.27	0.20	3	0.07	0.59
All locations	24	0.52	0.50	5	0.48	0.23	6	0.33	0.43
Sorghum grain yield									
Walsh	−15	0.42	0.57	2	0.30	0.67	−8	0.32	0.75
Crop residue									
Sterling	21	0.49	0.73	13	0.54	0.65	4	0.37	0.76
Stratton	34	0.64	0.75	43	0.80	0.66	17	0.66	0.66
Walsh	75	1.17	0.51	64	1.08	0.58	34	0.83	0.53
All locations	40	0.73	0.71	38	0.78	0.66	19	0.64	0.65
Total soil profile water content									
Sterling	21	0.27	0.64	8	0.24	0.72	−15	0.23	0.68
Stratton	2	0.15	0.83	31	0.35	0.62	−16	0.29	0.57
Walsh	−24	0.28	0.53	10	0.22	0.67	0.5	0.16	0.75
All locations	0.8	0.23	0.62	17	0.27	0.68	−12	0.25	0.63
Total soil profile residual NO_3–N									
Sterling	−34	0.50	0.67	−36	0.62	0.56	−31	0.54	0.67
Stratton	−26	0.57	0.52	−14	0.60	0.58	−27	0.61	0.53
Walsh	−52	0.72	0.46	−56	0.84	0.45	−13	0.79	0.50
All locations	−36	0.60	0.56	−37	0.73	0.48	−24	0.66	0.60

GPFARM also overpredicted crop residue amounts across all landscape positions (Table 5), but especially for the summit and sideslope landscape positions. This level of variability was demonstrated by Cantero-Martinez et al. (2006) in that the highest CVs were found in the summit and sideslope positions. Cantero-Martinez et al. (2006) also noted that crop residue variability was reduced as cropping system intensity increased from a wheat–fallow system to a wheat–corn–fallow or a wheat–corn–millet–fallow system. As previously stated, HI is used to partition total above-ground biomass into grain yield and vegetative biomass in the GPFARM crop growth model. Unharvested vegetative biomass contributes to the amount of crop residue, thus, overpredictions of crop residues likely result from overprediction of total above-ground biomass, underprediction of HI, or a combination of both. Crop residue NOF values were also much higher compared to grain yield NOF values, exceeding 1.0 for the Walsh summit and sideslope landscape positions. Interestingly, crop residue agreement was higher compared to grain yield agreement, ranging from a low of 0.51 at the Walsh summit landscape position to a high of 0.76 at the Sterling toeslope landscape position.

Additional statistical evaluation of crop grain yields and residue amounts for the "All Locations" combined data set (excluding sorghum grain yield at Walsh) are shown in Table 5 and Fig. 4. The RE values were generally within a range of ±20% or better with the exception being proso millet grain yield at the summit landscape position. For all crops, Fig. 4 shows that the lowest RE was obtained with winter wheat grain yield at the sideslope landscape position and the highest RE was found for proso millet grain yield at the summit landscape position. The NOF values ranged from a low of 0.28 for winter wheat grain yield to high of 0.52 for proso millet grain yield, both at the summit landscape position. Index of agreement (*d*) values ranged from a low of 0.23 for proso millet grain yield at the sideslope landscape position to a high of 0.63 for winter wheat grain yield at the summit landscape position (Table 5). The REs for crop residue were very high, up to 40% across all landscape positions (Fig. 4). NOF values for crop residue were similarly high (0.64–0.78) compared to crop grain yield NOF values, and d values for crop residue ranged from 0.65 to 0.71. In general, Fig. 4 shows a tendency for GPFARM to underpredict crop grain yield at the toeslope landscape position. This is consistent with underpredictions in total soil profile water content and residual NO_3–N at the toeslope (Table 5) which in turn may be related to GPFARM inability to simulate water and chemical movement across the landscape catena. In addition, the toeslopes have higher residue levels that reduce the amount of soil surface evaporation.

In analyzing the grain yield simulation results, GPFARM crop growth model prediction errors may be a consequence of the lack of varietal-specific parameterization, insufficient characterization of soil water content across the catena, crop growth component process representation (e.g., simplified algorithms for phenology, water stress calculations, etc.) or a combination of these. The tendency towards overprediction of proso millet and corn grain yields (Fig. 3b and c, respectively) at the summit and sideslope landscape positions may illustrate the need for better corn and proso millet parameterization of the GPFARM crop growth model across the entire landscape catena. Kiniry et al. (1995) observed that EPIC can give reasonable mean yield simulations for the major crops and forages in the Great Plains, but was unable to adequately simulate yield in dry low-yielding years. Andales et al. (2003) concluded that errors in prediction of biomass seem to be the major reason for errors in simulated grain yield for corn, whereas in winter wheat, the contribution of HI to error in simulated grain yields

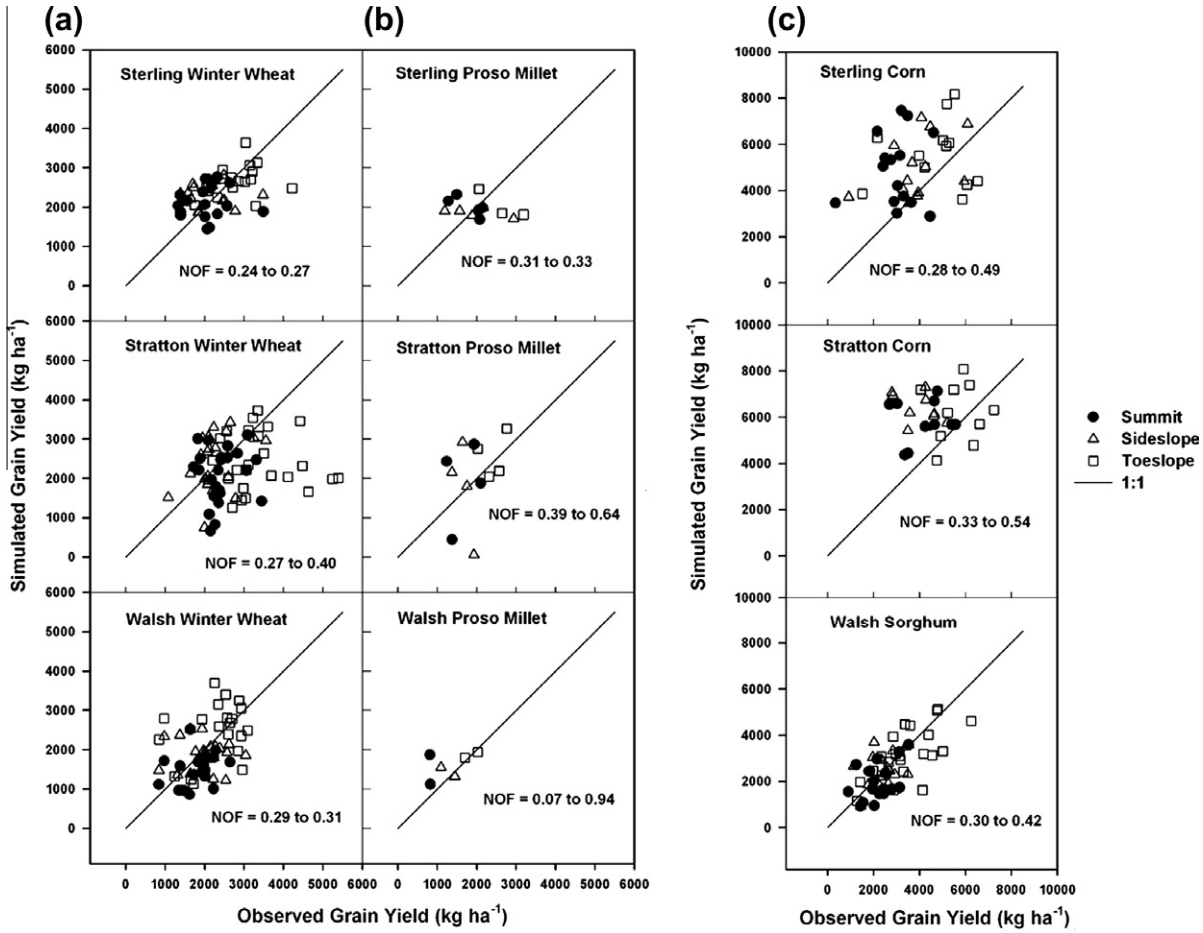

Fig. 3. Simulated against observed dry mass grain yield values across landscape positions for winter wheat (a), proso millet (b), and corn/sorghum (c) for the DAP experimental locations in eastern Colorado. NOF is the normalized objective function; additional model evaluation statistics are given in Table 5.

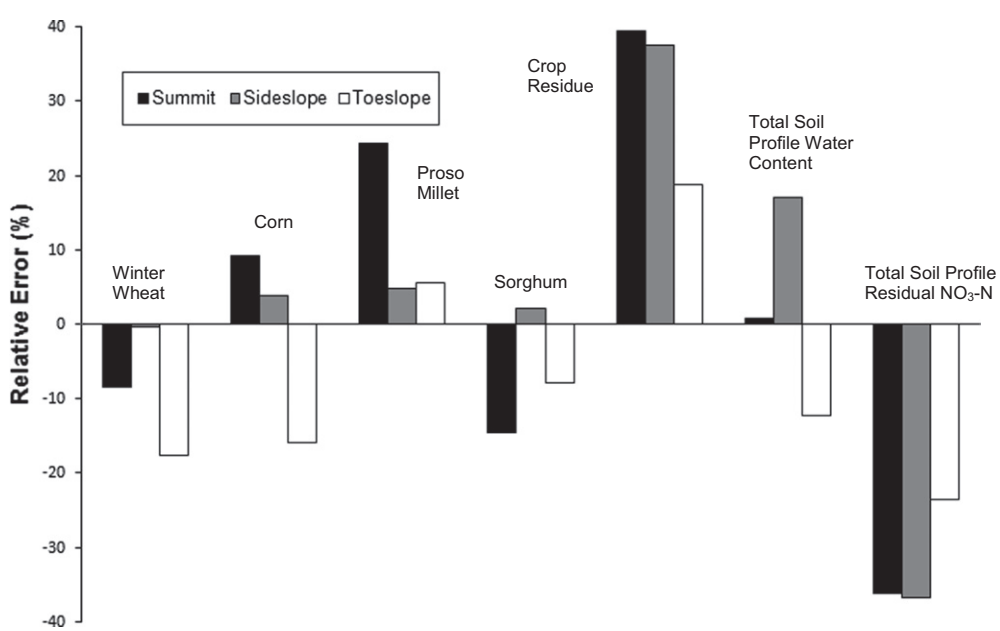

Fig. 4. GPFARM simulated dry mass grain yield, crop residue, total soil profile water content, and total soil profile residual NO_3–N relative error (RE) for the "All Locations" landscape catena data set combined across the DAP experimental locations in eastern Colorado.

was the dominant factor. Cabelguenne et al. (1999) also confirmed that EPIC overestimated vegetative biomass and grain production, especially under conditions of pronounced water stress. Andales et al. (2003) also suggested that the dryland conditions in eastern Colorado, which are characterized by periods of extreme water and temperature stresses, may be outside the validity domain of the

EPIC crop growth model. This finding was echoed by Kiniry et al. (1995) and Jara and Stockle (1999). Based on the above evaluation statistics, the EPIC-based crop growth model in GPFARM seems more suited for estimating long-term average crop yields or trends in yields rather than simulating year-to-year variability in crop yields. Other researchers who have evaluated the EPIC crop growth model or its implementation in GPFARM have reported similar results (e.g., Kiniry et al., 1995; Jara and Stockle, 1999; Cabelguenne et al., 1999; Andales et al., 2003).

3.4. GPFARM performance evaluation – total soil profile water content and soil residual NO_3–N

GPFARM total soil profile water content simulations were much better at the toeslope landscape position with lower REs, lower NOF values, and higher index of agreement values across all locations. The REs for total soil profile water content simulations were quite variable, ranging from a low of 0.50% at the Walsh toeslope landscape position to a high of 31% at the Stratton sideslope landscape position (Table 5). GPFARM total soil profile water content simulations are interesting in that model performance was erratic across all landscape positions (Fig. 5a), e.g., total soil profile water content was both underpredicted and overpredicted at the summit landscape position, strongly overpredicted at the sideslope landscape position, and underpredicted at the toeslope landscape position. Again, not accurately accounting for water movement from the summit and sideslope landscape positions to the toeslope landscape position could explain these results; however, additional experimental data is necessary to fully test this hypothesis. It is important to note that in addition to the severe ET gradient, physiographic (e.g., changes in physical properties between soil horizons across locations and landscape as shown in Table 2) and topographic (e.g., varying potentials for surface and lateral flow across the landscape catena at the experimental locations) complexities render the modeling of soil water content in this study a very difficult task. However, GPFARM simulated the correct timing for most of the observed drying and wetting events over time for all experimental locations (detailed data not shown). The NOF range for total soil profile water content at the toeslope and summit landscape positions were quite similar and lower than for the sideslope landscape position across experimental locations (Table 5). GPFARM simulations of total profile soil water content were comparable in accuracy to those of other agricultural system models, including the RZWQM which simulates the soil water balance with much greater process detail. The index of agreement values between GPFARM and observed total soil profile water content ranged from 0.53 to 0.83 across locations and landscape positions with the majority of d values greater than 0.60. In comparison, Wu et al. (1999) reported lower d values (0.54 and 0.59) for total water content simulations of the RZWQM during two seasons in a sandy soil near Princeton, Minnesota. In addition, Farahani et al. (1999) applied the RZWQM at the Sterling and Stratton locations and reported soil water depletion RE values ranging from −18% (Sterling summit) to 195% (Stratton toeslope). The errors in soil water content simulations are possibly well within the range of spatial variability considering that only two point measurements were taken per treatment (1500 m^2 average plot area per treatment), although the point measurements are in close agreement. Further-

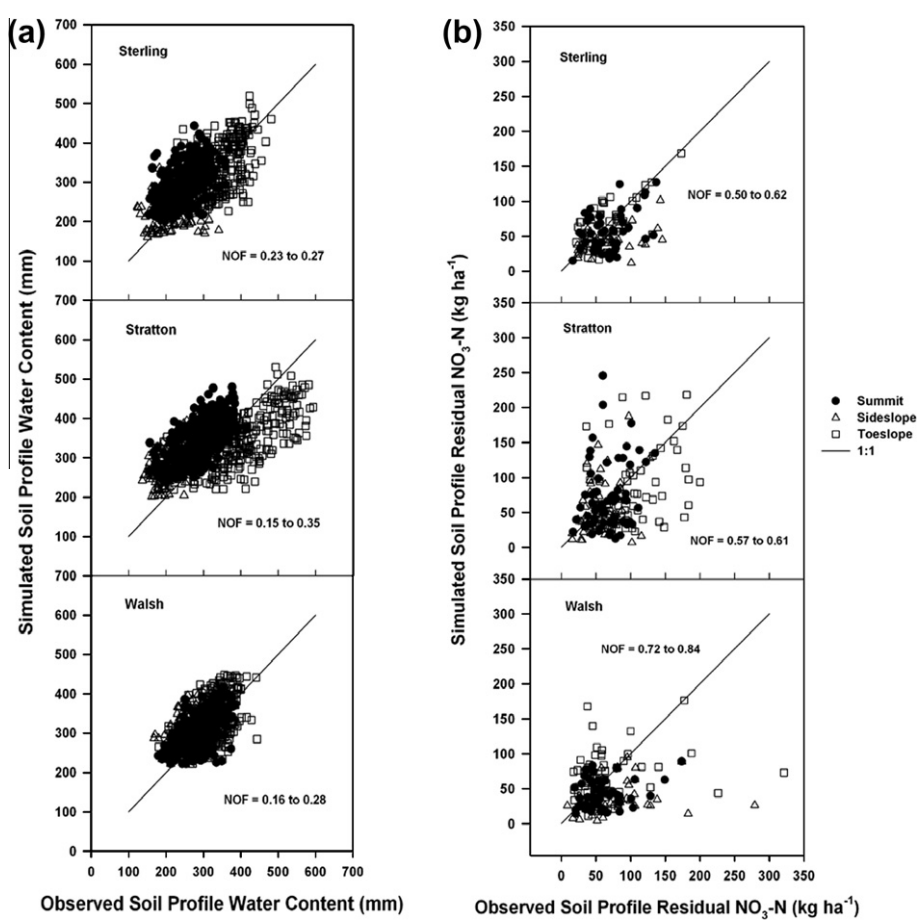

Fig. 5. Simulated against observed values across landscape positions for total soil profile water content (a) and total soil profile residual NO_3–N (b) for the DAP experimental locations in eastern Colorado. NOF is the normalized objective function; additional model evaluation statistics are given in Table 5.

more, GPFARM assumes fixed (2-h) durations for all storms and the use of actual storm intensities from breakpoint rainfall data would almost certainly improve simulation of soil water content.

Total soil profile residual NO_3–N REs ranged from a magnitude of −13% (Walsh toeslope landscape position) to −56% (Walsh sideslope landscape position), and were generally lower at the toeslope landscape position (Table 5). Simulated total soil profile residual NO_3–N means were consistently underestimated across all landscape positions (Fig. 5b), and NOF values ranged from a low of 0.50 (Sterling summit landscape position) to a high of 0.84 (Walsh sideslope landscape position). The highest *d* value was obtained at the Sterling summit and toeslope landscape positions, while *d* values were much lower for other landscape positions and locations. Predicted total soil profile residual NO_3–N was highly sensitive and positively correlated to the amount of organic matter (Table 2) in the soil and negatively correlated to crop leaf area index (Table 3). Numerous interrelated plant–soil–environment factors that influence N cycling in the soil make prediction of residual soil profile NO_3–N a difficult task. Predicting NO_3–N amounts over an extended number of years is an even greater challenge, e.g., a lack of within-season residual NO_3–N data collection prevented year-to-year evaluation of NO_3–N root uptake. Sherrod et al. (2003) offer key insights concerning N variability across the landscape catena for the three eastern Colorado experimental locations. Total soil N on the sideslopes was found to be significantly lower than summits with the toeslopes having the highest levels and cropping intensity also positively impacting surface soil total N. In addition, the largest REs for total soil profile NO_3–N were found at the summit and sideslope soils at Walsh which have the highest sand content profiles in this study (Table 2). Sherrod et al. (2005) found the highest particulate organic matter (the source material for N mineralization and resultant nitrification) levels in the toeslope soils at the experimental locations with no significant difference between the summit and sideslope soils. Total soil profile residual NO_3–N may be inversely related to increases in total N due to cropping intensity since immobilization of nitrates by microbes (which decomposes surface residues) is more of a factor in no-till surface soils (Sherrod et al., 2005). The above insights could help lead to further improvements in GPFARM modeling of crop NO_3–N uptake and N dynamics for the experimental conditions in this study.

Additional analysis of the "All Locations" data set for total soil profile water content and soil profile residual NO_3–N is presented in Table 5 and Fig. 4. Fig. 4 clearly illustrates GPFARM underprediction of both total soil profile water content at the toeslope landscape position and total soil profile residual NO_3–N at all landscape positions, and also reveals that REs were much lower for total soil profile water content (±20% or better) than for total soil profile residual NO_3–N (−20% to −40%). Correspondingly, Table 5 shows that NOF values were much better for total soil profile water content than for total soil profile residual NO_3–N. Index of agreement values were also slightly better for total soil profile water content than for total soil profile residual NO_3–N.

3.5. GPFARM performance evaluation – landscape position analysis

A secondary objective of this study was to determine whether the predictive performance of GPFARM was impacted by landscape position within the catena. As a synthesis of Table 5, the landscape positions where GPFARM performed the best for each model evaluation statistic (i.e., lowest absolute RE value, lowest NOF value, and highest *d* value) are shown in Table 6. As previously discussed, the NOF and *d* model evaluation statistics indicate the average event-by-event (short-term) prediction errors and should be considered more robust indicators of model performance. Focusing on the NOF and *d* evaluation statistics and the "All Locations" data set, GPFARM performed best at the summit or sideslope landscape positions for the majority of output response variables. As expected, much more variability in GPFARM performance for each evaluation statistic is evident when location is individually examined. With the *d* evaluation statistic as an example, for crop residue and total soil profile water content GPFARM performed the best at a different landscape position for each experimental location (Table 6). Furthermore, for corn grain yield and the "All Locations" data set, the sideslope position had the lowest RE, the toeslope position had the lowest NOF, and the summit landscape position had the highest index of agreement.

Table 6
Catena landscape positions where GPFARM performed best according to relative error (RE), normalized objective function (NOF), and index of agreement (*d*) model evaluation statistics.

Location	Evaluation statistic		
	RE	NOF	*d*
Winter wheat grain yield			
Sterling	Toeslope	Toeslope	All positions equal
Stratton	Sideslope	Summit	Summit
Walsh	Toeslope	Summit	Summit
All	Sideslope	Summit	Summit
Corn grain yield			
Sterling	Sideslope	Sideslope	Sideslope
Stratton	Summit	Toeslope	Toeslope
All	Sideslope	Toeslope	Summit
Proso millet grain yield			
Sterling	Sideslope	Sideslope	Toeslope
Stratton	Sideslope	Toeslope	Toeslope
Walsh	Toeslope	Toeslope	Toeslope
All	Sideslope	Toeslope	Summit
Sorghum grain yield			
Walsh	Toeslope	Sideslope	Toeslope
Crop residue			
Sterling	Toeslope	Toeslope	Toeslope
Stratton	Toeslope	Summit	Summit
Walsh	Toeslope	Toeslope	Sideslope
All	Toeslope	Toeslope	Summit
Total soil profile water content			
Sterling	Sideslope	Toeslope	Sideslope
Stratton	Summit	Summit	Summit
Walsh	Toeslope	Toeslope	Toeslope
All	Summit	Summit	Sideslope
Total soil profile residual NO_3–N			
Sterling	Toeslope	Summit	Summit/Toeslope
Stratton	Sideslope	Summit	Sideslope
Walsh	Toeslope	Summit	Toeslope
All	Toeslope	Summit	Toeslope

Table 6 illustrates that different interpretations of GPFARM (and perhaps any agroecosystem model) performance across the landscape catena can be made depending on the evaluation statistic of interest. This finding seems self-evident but differences in model evaluation statistics are rarely pointed out in the literature. In addition, the results strongly indicate that modelers must be aware of the strengths, weaknesses, and general predictive capability of selected evaluation criteria in order to objectively assess model performance. For example, it is important to remember that RE is an arithmetic average over the duration of data, i.e., the RE shows long-term bias and the simulated against observed deviations can be cancelled out, especially if the model both overpredicts and underpredicts with similar frequency. The NOF and d values, however, indicate the average event-by-event (short-term) prediction errors and should be considered more robust indicators of model performance, e.g., the index of agreement accounts for individual simulated against observed deviations. The *d* statistic accounts for variability of predicted and observed values around the observed mean while the NOF does not. Thus, *d* values will tend to

be higher when the variability of predicted and/or observed values is high.

4. Conclusions

Given the simplifying assumptions inherent in many of the GPFARM simulation model components, and bearing in mind the specified purpose of GPFARM (to serve as a agricultural management DSS for strategic, long-term planning), the model appears to have reasonably simulated dry mass grain yield, crop residue, total soil profile water content, and total soil profile residual NO_3–N across a catenary sequence at the eastern Colorado DAP experimental locations. GPFARM simulations of total soil profile residual NO_3–N were less accurate than simulations of total soil profile water content, although the use of actual storm intensities from breakpoint rainfall data would almost certainly improve simulation of soil water content. Values of the RE evaluation statistic suitably demonstrate GPFARM efficacy in quantifying long-term (strategic) interactions between the environment and alternative crop management systems, but the NOF and *d* evaluation statistics show the simulation model may be lacking in accuracy for predictions on a short-term (tactical) planning basis. With a few exceptions (e.g., Stratton toeslope), GPFARM successfully simulated observed trends in grain yield, crop residue, total soil profile water content, and total soil profile residual NO_3–N at the DAP experimental locations, in both the short- and long-term. It is important to re-emphasize that GPFARM was developed to operate at the field scale where both model input parameters and output responses represent conditions averaged over a fairly large area. On the other hand, the observed data used in this study to evaluate GPFARM were collected at the plot scale, which is typically subject to much greater variability and may partly explain inadequacies in GPFARM simulation of the four output response variables. It is difficult to single out specific GPFARM model deficiencies using observed experimental data representing a high degree of temporal and spatial variability. However, some model deficiencies were expectedly magnified at different landscape positions, e.g., errors in simulated plant water and N stress were greater at the summit landscape position than at the toeslope where water status is more favorable and plant stress is reduced.

For both experimental and simulation studies, the sideslope and toeslope landscape positions had the uncertainty of receiving unmeasured runoff from upslope areas. A key limitation of GPFARM is the inability to simulate surface and subsurface movement of water and chemicals across a landscape catena. GPFARM overpredicted mean profile soil water content at the sideslope landscape position across all locations and underpredicted mean profile soil water content at the Sterling and Stratton toeslope landscape positions. Based on GPFARM simulated results, this difference across landscape positions provides some evidence that hydrologically significant runoff–runon events were occurring at the DAP experimental locations. Addition of a spatially-distributed water and chemical routing component to GPFARM should not only improve characterization of soil spatial variability (and its influence on soil water availability, fertility, and root distribution), significant improvements due to hydrologic spatial interaction across the catenary sequence should be realized as well. Another important limitation of GPFARM is a potential lack of accuracy for predictions on a short-term planning basis, especially for grain yield. More thorough testing and enhancement of the EPIC-based crop growth model in GPFARM is needed under dryland conditions in eastern Colorado using detailed observations of soil water content at depth, biomass, LAI, phenology, harvest index and grain yield for various crops. Additional evaluation and improvement of the C and N cycling component is needed as well. Finally, additional application of GPFARM to extend the geographic area of consideration to the entire Great Plains is being considered. This effort will incorporate additional crops (e.g., soybeans, alfalfa, etc.) and improvements in crop model response to water, temperature, and N stress (and their interactions). It is anticipated that enhancements in the crop growth and environmental components of the GPFARM simulation model, including more robust parameterization, will improve model accuracy for both strategic and tactical applications, and result in a GPFARM DSS useful for real-time cropping system management.

Acknowledgments

The authors would like to recognize all members of the GPFARM Development Team at the USDA-ARS Agricultural Systems Research Unit at Fort Collins, Colorado. In particular, Bruce Vandenberg, Pat Bartling, and Debbie Edmunds made extraordinary efforts towards developing the GPFARM interface, simulation framework, and databases; Gale Dunn and Daniel Palic spent countless hours working with producers on GPFARM evaluation and improvement. Sincere appreciation is also extended to the Colorado State University Department of Soil and Crop Sciences for their role in obtaining and processing the experimental data from the Dryland Agroecosystem Project.

References

Ahuja, L.R., Cassel, D.K., Bruce, R.R., Barnes, B.B., 1989. Evaluation of spatial distribution of hydraulic conductivity using effective porosity data. Soil Sci. 148, 404–411.

Ahuja, L.R., Rawls, W.J., Neilsen, D.R., Williams, R.D., 1999. Determining soil hydraulic properties and their field variability from simpler measurements. In: Agricultural Drainage, Agronomy Monograph No. 38. American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, Wisconsin, pp. 1207–1233.

Ahuja, L.R., Rojas, K.W., Hanson, J.D., Shaffer, M.J., Ma, L. (Eds.), 2000. Root Zone Water Quality Model: Modeling Management Effects on Water Quality and Crop Production. Water Resources Publications, LLC, Highlands Ranch, Colorado.

Andales, A.A., Ahuja, L.R., Peterson, G.A., 2003. Evaluation of GPFARM for dryland cropping systems in eastern Colorado. Agron. J. 95, 1510–1524.

Arnold, J.G., Weltz, M.A., Alberts, E.E., Flanagan, D.C., 1995. Plant growth component. In: Flanagan, D.C., Nearing, M.A., Laflen, J.M. (Eds.), USDA-Water Erosion Prediction Project: Hillslope Profile and Watershed Model Documentation. NSERL Report No. 10, ARS National Soil Erosion Research Laboratory, West Lafayette, IN. pp. 8.1–8.41.

Ascough II, J.C., Hoag, D.L., Frasier, W.M., McMaster, G.S., 1999. Computer use in agriculture: an analysis of Great Plains producers. Comput. Electron. Agric. 23, 189–204.

Ascough II, J.C., Shaffer, M.J., Hoag, D.L., McMaster, G.S., Dunn, G.H., Ahuja, L.R., Weltz, M.A., 2002. GPFARM: an integrated decision support system for sustainable Great Plains agriculture. In: Stott, D.E., Mohtar, R.H., Steinhardt, G.C. (Eds.), Sustaining the Global Farm – Local Action for Land Leadership: Selected Papers from the 10th International Soil Conservation Organization (ISCO) Conference, May 24–29, 1999, Purdue University, West Lafayette, Indiana. International Soil Conservation Organization in Cooperation with the USDA and Purdue University, West Lafayette, Indiana. pp. 951–960.

Ascough II, J.C., McMaster, G.S., Andales, A.A., Hansen, N.C., Sherrod, L.A., 2007. Evaluating GPFARM crop growth, soil water, and soil nitrogen components for Colorado dryland locations. Trans. ASABE 50 (5), 1565–1578.

Brooks, R.H., Corey, A.T., 1964. Hydraulic Properties of Porous Media. Colorado State Univ. Hydrology Paper 3.

Cabelguenne, M., Debaeke, P., Bouniols, A., 1999. EPICphase, a version of the EPIC model simulating the effects of water and nitrogen stress on biomass and yield, taking account of developmental stages: validation on maize, sunflower, sorghum, soybean and winter wheat. Agric. Syst. 60, 175–196.

Campbell, G.S., 1974. A simple method for determining unsaturated conductivity from moisture retention data. Soil Sci. 117, 311–314.

Canner, S.R., Wiles, L.J., McMaster, G.S., 2002. Weed reproduction model parameters may be estimated from crop yield loss data. Weed Sci. 50 (6), 763–772.

Canner, S.R., Wiles, L.J., Erskine, R.H., McMaster, G.S., Dunn, G.H., Ascough II, J.C., 2009. Modeling with limited data: the influence of crop rotation and management on weed communities and crop yield loss. Weed Sci. 2009 (57), 175–186.

Cantero-Martinez, C., Westfall, D.G., Sherrod, L.A., Peterson, G.A., 2006. Long-term crop residue dynamics in no-till cropping systems under semi-arid conditions. J. Soil Water Conserv. 61 (2), 84–95.

Costa, J.L., Knighton, R.E., Prunty, L., 1994. Model comparison of unsaturated steady-state transport in a field plot. Soil Sci. Soc. Am. J. 58, 1277–1287.

Deer-Ascough, L.A., McMaster, G.S., Ascough II, J.C., Peterson, G.A., 1998. Application of Generic Crop Growth Model Technology to Great Plains Conservation Systems. ASAE Paper No. 98-2133 Presented at the 1998 International Meeting of the American Society of Agricultural Engineers, Orlando, Florida, July 12–16.

Delgado, J.A., 1998. Sequential NLEAP simulations to examine effect of early and late planted winter cover crops on nitrogen dynamics. J. Soil Water Conserv. 53, 241–244.

Delgado, J.A., Follett, R.F., Shaffer, M.J., 2000. Simulation of NO_3–N dynamics for cropping systems with different rooting depths. J. Soil Sci. Soc. Am. 64, 1050–1054.

Farahani, H.J., Ahuja, L.R., 1996. Evapotranspiration modeling of partial canopy/residue-covered fields. Trans. ASAE 39 (6), 2051–2064.

Farahani, H.J., Buchleiter, G.W., Ahuja, L.R., Peterson, G.A., Sherrod, L.A., 1999. Seasonal evaluation of the Root Zone Water Quality Model in Colorado. Agron. J. 91, 212–219.

Green, W.H., Ampt, G.A., 1911. Studies on soil physics. 1. Flow of air and water through soils.. J. Agric. Sci. 4, 1–24.

Hoag, D.L., Ascough II, J.C., Frasier, W.M., 1999. Farm computer adoption in the Great Plains. J. Agric. Appl. Econ 31 (1), 57–67.

Jara, J., Stockle, C.O., 1999. Simulation of water uptake in maize, using different levels of process detail. Agron. J. 91, 256–265.

Kiniry, J.R., Williams, J.R., Gassman, P.W., Debaeke, P., 1992. A general, process-oriented model for two competing plant species. Trans. ASAE 35, 801–810.

Kiniry, J.R., Major, D.J., Izaurralde, R.C., Williams, J.R., Gassman, P.W., Morrison, M., Bergentine, R., Zentner, R.P., 1995. EPIC model parameters for cereal, oilseed, and forage crops in the northern Great Plains region. Can. J. Plant Sci. 75, 679–688.

Kosmas, C.S., Danalatos, N.G., Moustakas, N., Tsatiris, B., Kallianou, C., Yassoglou, N., 1993. The impacts of parent material and landscape position on drought and biomass production of wheat under semi-arid conditions. Soil Technol. 6, 337–349.

McMaster, G.S., Ascough II, J.C., Dunn, G.H., Weltz, M.A., Shaffer, M.J., Palic, D., Vandenberg, B.C., Bartling, P.N.S., Edmunds, D.A., Hoag, D.L., Ahuja, L.R., 2002. Application and testing of GPFARM: a farm and ranch decision support system for evaluating economic and environmental sustainability of agricultural enterprises. Acta Horticulturae 593, 171–177.

McMaster, G.S., Ascough II, J.C., Shaffer, M.J., Deer-Ascough, L.A., Byrne, P.F., Nielsen, D.C., Haley, S.D., Andales, A.A., Dunn, G.H., 2003. GPFARM plant model parameters: complications of varieties and the genotype $\times$ environment interaction in wheat. Trans. ASAE 46 (5), 1337–1346.

Nielsen, D.C., 1996. Estimating Corn Yields from Precipitation Records. Conservation Tillage Fact Sheet No. 2-96. USDA-ARS and Colorado Conservation Tillage Association, Akron, Colo.

Pennell, K.D., Hornsby, A.G., Jessup, R.E., Rao, P.S.C., 1990. Evaluation of five simulation models for predicting aldicarb and bromide behavior under field conditions. Water Resour. Res. 26 (1990), 2679–2693.

Peterson, G.A., Westfall, D.G., Cole, C.V., 1993. Agroecosystem approach to soil and crop management research. Soil Sci. Soc. Am. J. 57, 1354–1360.

Peterson, G.A., Westfall, D.G., Peairs, F.B., Sherrod, L.A., Poss, D., Gangloff, W., Larson, K., Thompson, D.L., Ahuja, L.R., Koch, M.D., Walker, C.B., 2000. Sustainable Dryland Agroecosystem Management. Agric. Exp. Stn. Tech. Bull. TB00-3. Colorado State Univ., Fort Collins.

Rawls, W.J., Brakensiek, D.L., 1985. Prediction of soil water properties for hydrologic modeling. In: Proc. Watershed Manage. In the Eighties, Denver, CO, 30 April–1 May, ASCE, New York.

Rockström, J., Barron, J., Brouwer, J., Galle, S., de Rouw, A., 1999. On-farm spatial and temporal variability of soil and water in pearl millet cultivation. Soil Sci. Soc. Am. J 63, 1308–1319.

Shaffer, M.J., Halvorson, A.D., Pierce, F.J., 1991. Nitrate Leaching and Economic Analysis Package (NLEAP): model description and application. In: Follett, R. et al. (Eds.), Managing Nitrogen for Groundwater Quality and Farm Profitability. Soil Science Society of America, Madison, WI, pp. 285–322 (372pp).

Shaffer, M.J., Bartling, P.N.S., Ascough II, J.C., 2000. Object-oriented simulation of integrated whole farms: GPFARM framework. Comput. Electron. Agric. 28, 29–49.

Shaffer, M.J., Lasnik, K., Ou, X., Flynn, R., 2001. NLEAP internet tools for estimating NO_3–N leaching and N_2O emissions. In: Shaffer, M.J. et al. (Eds.), Modeling Carbon and Nitrogen Dynamics for Soil Management. CRC Press LLC, Boca Raton, FL, pp. 403–426 (651pp).

Shaffer, M.J., Bartling, P.N.S., McMaster, G.S., 2004. GPFARM modeling of corn yield and residual soil nitrate-N. Comput. Electron. Agric. 43 (2), 87–107.

Sherrod, L.A., Peterson, G.A., Westfall, D.G., Ahuja, L.R., 2003. Cropping intensity enhances soil organic carbon and nitrogen in a no-till agroecosystem. Soil Sci. Soc. Am. J. 67, 1533–1543.

Sherrod, L.A., Peterson, G.A., Westfall, D.G., Ahuja, L.R., 2005. Soil organic carbon pools after 12 years in no-till dryland agroecosystems. Soil Sci. Soc. Am. J. 69, 1600–1608.

Steel, R.G.D., Torrie, J.H., 1997. Principles and Procedures of Statistics: A Biometrical Approach, third ed. McGraw-Hill, New York, NY.

Steiner, J.L., Williams, J.R., Jones, O.R., 1987. Evaluation of the EPIC simulation model using a dryland wheat–sorghum–fallow crop rotation. Agron. J. 79, 732–738.

Systat, 2006. SigmaStat 3.11 for Windows, Systat, Inc., Chicago, Ill.

Williams, J.R., Jones, C.A., Dyke, P.T., 1984. A modeling approach to determining the relationship between erosion and soil productivity. Trans. ASAE 27 (1), 129–144.

Williams, J.R., Jones, C.A., Kiniry, J.R., Spanel, D.A., 1989. The EPIC crop growth model. Trans. ASAE 32, 497–511.

Willmott, C.J., 1981. On the validation of models. Phys. Geogr. 2, 184–194.

Willmott, C.J., Wicks, D.E., 1980. An empirical method for the spatial interpolation of monthly precipitation within California. Phys. Geogr. 1, 59–73.

Wu, L., Chen, W., Baker, J.M., Lamb, J.A., 1999. Evaluation of the Root Zone Water Quality Model using field-measured data from a sandy soil. Agron. J. 91, 177–182.