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Research paper

Modelling forage yield and water productivity of continuous crop sequences in the Argentinian Pampas

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ABSTRACT

In recent years, the use of forage crop sequences (FCS) has been increased as a main component into the animal rations of the Argentinian pasture-based livestock systems. However, it is unclear how year-by-year rainfall variability and interactions with soil properties affect FCS dry matter (DM) yield in these environments. Biophysical crop models, such as Agricultural Production Systems Simulator (APSIM), are tools that enable the evaluation of crop yield variability across a wide of environments. The objective of this study was to evaluate the APSIM ability to predict forage DM yield and water productivity (WP) of multiple continuous FCS. Thirteen continuous FCS, including winter and summer crops, were simulated by APSIM during two/three growing seasons in five locations across the Argentinian Pampas. Our modelling approach was based on the simulation of multiple continuous FCS, in which crop DM yields depend on the performance of the previous crop in the same sequence and the final soil variables of the previous crop are the initial conditions for the next crop. Overall, APSIM was able to accurately simulate FCS DM yield (0.93 and 3.2 $Mg\,ha^{-1}$ for concordance correlation coefficient [CCC] and root mean square error [RMSE] respectively). On the other hand, the model predictions were better for annual (CCC = 0.94; RMSE = 0.4 $g\,m^{-2}\,mm^{-1}$) than for seasonal WP (CCC = 0.71; RMSE = 1.9 $g\,m^{-2}\,mm^{-1}$), *i.e.* at the crop level. The model performance to predict WP was associated with better estimations of the soil water dynamics over the long-term, *i.e.* at the FCS level, rather than the short-term, *i.e.* at the crop level. The ability of APSIM to predict WP decreased as seasonal WP values increased, *i.e.* for low water inputs. For seasonal water inputs, < 200 mm, the model tended to under-predict WP, which was directly associated with crop DM yield under-predictions for frequently harvested crops. Even though APSIM showed some weaknesses in predicting seasonal DM yield and WP, *i.e.* at the crop level, it appears as a potential tool for further research on complementary forage crops based on multiple continuous FCS in the Argentinian livestock systems.

1. Introduction

Worldwide food demand is expected to increase by 60–100% by 2050 (Tilman et al., 2011; Valin et al., 2014), which include the growing demand for meat and milk (Bouwman et al., 2005; Zhang et al., 2017). This will drive an increase in forage production to supply animal feed. This increase could be achieved, at least in part, through forage crop intensification, *i.e.* the production of more fodder crop per unit of cultivated land (Mueller et al., 2012; Teixeira et al., 2014). Likewise, to optimize the increasingly limited land use and to avoid adverse environmental impacts, future yield increases should focus on increasing the environmental resources use efficiency, in particular

Abbreviations: APSIM, Agricultural Production Systems Simulator; AR-M, annual ryegrass-maize; B-M, barley-maize; B-M, barley-maize; B-S, barley-soybean; CCC, concordance correlation coefficient; DM, dry matter; FCS, forage crop sequences; M-M, maize-maize; O-M, oats-maize; O-S, oats-soybean; RMSE, root mean square error; W-M, wheat-maize; WP, water productivity; W-S-M, wheat-soybean-maize

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water (Caviglia et al., 2004).

The Argentinian Pampas is an important livestock production region (Solbrig and Viglizzo, 1999), in which animal feed is predominantly based on forage crops sequences (FCS, *i.e.* sequences based on annual forage crops for silage, hay or grazing) and perennial pastures (Ojeda et al., 2016). In recent years, the sowing area of forage crops (annual and perennial) has decreased significantly in the face of the advance of grain and oilseed cropping (annual crops like soybean, wheat, barley, and sunflower) in this region. However, the decreasing area of perennial pastures has been off-set by a doubling of the area sown to annual forage crops in the last 24 years (200000 *v.* 100000 ha year^{-1}, respectively) (INDEC, 1988; FAOSTAT, 2013). Likewise, the sowing area of annual silage crops has increased ~300% from 2006 to 2014, with maize (*Zea mays* L.) accounting for 67% of this increase (Opacak, F., personal communication, CACF).

Annual forage crops are fed during periods of low growth rates of perennial pastures has been widely used to improve and stabilize the balance between supply and forage demand (Rawnsley, 2007; Rawnsley et al., 2013), productivity per unit area (Garcia et al., 2008) and, water and nitrogen (N) use efficiency (Garcia et al., 2008; Neal et al., 2011). Likewise, there is an increasing interest to integrate perennial pastures with FCS in order to improve livestock systems productivity and stability under predicted scenarios of climate variability (Chapman et al., 2008a, 2011). Although the FCS are important forage resources, it is unclear how year-by-year rainfall variability and the interaction with soil type affect dry matter (DM) yield in these environments. This information is required to guide the adoption of management practices oriented to increase the livestock systems stability facing up the increasing frequency of extreme climatic events (Pembleton et al., 2016).

To study the spatio-temporal variability of FCS DM yield, long-term field experiments are needed which require considerable time and funding resources. An alternative is to use biophysical crop models to evaluate the FCS DM yield variability across a wide of environments to identify the most successful systems prior to field evaluation. Several simulation models have been used to predict crop growth for the evaluation of pasture-based livestock systems (Chapman et al., 2008a,b; Cullen et al., 2009; Rawnsley et al., 2009). The Agricultural Production Systems Simulator (APSIM) is a crop simulation model that integrates through sub-modules, agronomic management with climatic data in a mechanistic way to simulate growth and development of crops, as well as the dynamics of soil water and N (Keating et al., 2003; Holzworth et al., 2014). Although APSIM was initially created to predict crop grain yield in Australia, in the past years it has appeared to be promissory to simulate forage crop DM yield across several environments (*e.g.* Canterbury plains, New Zealand [Teixeira et al., 2010, 2015], south-eastern Australia (Pembleton et al., 2013, 2016; Islam et al., 2015) and the Argentinian Pampas (Ojeda et al., 2016)).

Crop modelling studies in the Argentinian Pampas also have been mainly focused on grain production using Decision Support System for Agrotechnology Transfer (DSSAT) (Monzon et al., 2007; Mercau et al., 2007; Caviglia et al., 2013). However, recent advances have been reported simulating perennial pastures in the last years. For example, Berger et al. (2014) examined DairyMod's ability to predict tall fescue (*Festuca arundinacea* Schreb.) DM yield under contrasting seasons, N fertilizations and soil water availability at Balcarce, Argentina. Also, a recent study reported by Laulhe (2015) demonstrated the DSSAT capacity to simulate the fescue DM yield in two locations in the south-eastern of Buenos Aires. However, there are no reported modelling studies using annual forage crop sequences for this region.

A useful approach to study the impact of the interaction between climate variability and soil type on FCS DM yield is the water productivity (WP), estimated as the ratio between DM yield and rainfall (or rainfall plus irrigation water, where relevant). This metric has been widely used in natural grasslands (Noy-Meir, 1973; Le Houerou, 1984; Sala et al., 1988; Lauenroth and Sala, 1992; Paruelo et al., 1999; Huxman et al., 2004; Verón et al., 2005), agricultural cropping systems (Pereira et al., 2002; Sadras, 2002; Molden et al., 2003; Caviglia et al., 2004; Passioura, 2006; Van Opstal et al., 2011) and could be also used in forage systems (Zhang et al., 2017).

Before APSIM could be used as a possible predictor of DM yield in multiple continuous FCS in different Argentinian Pampas environments, an exhaustive validation process is required. Particularly, the evaluation of the model ability to accurately simulate possible effects of previous crops and initial soil conditions on the following crops into the sequence. Likewise, an analysis of the WP year-by-year variability would allow the analysis of DM yield variation due to water inputs, *i.e.* rainfall and irrigation. The objective of this study was to evaluate the APSIM ability to predict forage DM yield and water productivity (WP) of multiple continuous FCS in five locations across the Argentinian Pampas under a range of inputs and crop management system.

2. Materials and methods

The model validation was carried-out following the subsequent steps: (i) climate data and practices management were provided to APSIM, (ii) soil parametrization was generated for each experiment (Table 1), (iii) graphical comparison and statistical analyses of observed and modelled crop and FCS DM yields and WP. A complete description of data used for APSIM validation is provided in Table 2.

2.1. Experimental locations and forage growth

The FCS DM yields were collected in five locations across Argentinian Pampas: Rafaela (31°11′S, 61°30′O), Pergamino (33°56′S 60°33′O), General Villegas (35°01′S 63°01′O), Trenque Lauquen (36°04′S 62°45′O) and Balcarce (37°45′S 58°18′O). Data for APSIM validation were collected from experimental stations of the Argentinian National Institute of Agriculture (INTA), except at Trenque Lauquen where were collected from experiments located at the farm level. The dataset included thirteen FCS DM yields of annual crops (annual ryegrass [*Lolium multiflorum* Lam.], oats [*Avena sativa* L.], wheat [*Triticum aestivum* L.], barley [*Hordeum vulgare* L.], soybean [*Glycine max* L.] and maize) from 2009 to 2015 (Fig. 1; Table 2). Each sequence was comprised of two crops per year except for the wheat-soybean-maize sequence at Rafaela where it included three crops per year (Fig. 1). All field experiments were carried-out under dryland conditions, except at Pergamino where some sequences were irrigated (Table 2).

2.2. Climate data

The climate characteristics of each location are provided in Fig. 2. Daily meteorological data (daily minimum and maximum air temperature [at 1.5 m height], solar radiation and rainfall) for each location were obtained from a meteorological station, except at Trenque Lauquen where they were provided by the Climate and Water Institute of INTA (CIRN) and by local researchers. Any missing daily solar radiation, minimum and maximum temperature data were obtained from the NASA Prediction of Worldwide Energy Resource (POWER) – Climatology Resource for Agroclimatology (NASA, 2013). This database provides information on historical climatic series of interest locations based on geographical coordinates (latitude and longitude). Recent assessments of NASA-POWER's predictive capacity showed good predictions of maximum and minimum air temperature in different US (White et al., 2008; Ojeda et al., 2017) and Argentinian environments (Aramburu Merlos et al., 2015).

The maximum mean air temperature range was from 4.0 to 46.3 °C and the minimum mean air temperature from −11.1 to 28.2 °C (Fig. 2). Average cumulative annual rainfall ranged from 793 to 1002 mm for Trenque Lauquen and Pergamino, respectively (Fig. 2). Similarly, the maximum soil water storage capacity between locations ranged from 113 mm at Trenque Lauquen (from 0 to 1.3 m soil depth) to more than the double at Rafaela (264 mm, from 0 to 1.6 m soil depth) (Table 1).

Table 1
Soil parameters used to configure Agricultural Production Systems Simulator (APSIM).

Location	Soil type[a]	Soil series	Depth	Texture class			BD	Air Dry	LL	DUL	SAT	PO	SWCON	OC	pH
				sand	silt	clay									
			m	%	%	%	Mg m^{-3}	mm mm^{-1}				(0–1)	day^{-1}	%	1:5
RAF	Typic Argiudoll	Rafaela	0–0.2	2	72	26	1.26	0.066	0.132	0.295	0.328	0.52	0.34	1.47	6.2
			0.2–0.35	3	69	28	1.29	0.098	0.140	0.300	0.333	0.50	0.33	0.90	6.3
			0.35–0.63	2	60	38	1.37	0.144	0.180	0.310	0.342	0.47	0.32	0.51	6.5
			0.63–0.93	2	58	41	1.35	0.165	0.183	0.319	0.352	0.48	0.31	0.37	6.7
			0.93–1.15	2	65	33	1.31	0.167	0.185	0.305	0.337	0.50	0.33	0.24	7.2
			1.15–1.4	1	68	31	1.28	0.158	0.175	0.292	0.322	0.51	0.34	0.17	7.4
			1.4–1.6	5	65	30	1.28	0.135	0.150	0.284	0.313	0.51	0.35	0.11	8.2
PER	Typic Argiudoll	Pergamino	0–0.13	13	65	23	1.27	0.089	0.178	0.326	0.362	0.51	0.31	1.69	5.9
			0.13–0.25	12	65	23	1.32	0.125	0.178	0.327	0.363	0.49	0.31	1.48	6.1
			0.25–0.34	13	57	30	1.33	0.155	0.193	0.356	0.393	0.49	0.28	0.87	6.2
			0.34–0.75	9	48	44	1.33	0.204	0.226	0.418	0.461	0.49	0.24	0.64	6.3
			0.75–0.95	13	56	30	1.33	0.174	0.193	0.355	0.392	0.49	0.28	0.35	6.5
			0.95–1.6	18	66	17	1.33	0.145	0.160	0.293	0.323	0.49	0.34	0.24	6.4
GV	Typic Hapludoll	Blaquier	0–0.2	69	19	12	1.26	0.038	0.075	0.174	0.193	0.52	0.57	1.29	6.3
			0.2–0.28	69	18	13	1.29	0.055	0.078	0.164	0.182	0.50	0.61	1.17	6.3
			0.28–0.57	66	19	15	1.37	0.061	0.076	0.163	0.180	0.47	0.61	0.60	6.0
			0.57–0.89	75	14	11	1.35	0.059	0.065	0.143	0.158	0.48	0.70	0.18	6.5
			0.89–1.25	77	14	10	1.31	0.056	0.062	0.125	0.138	0.50	0.80	0.07	6.8
			1.25–1.6	77	14	10	1.28	0.056	0.062	0.125	0.138	0.51	0.80	0.07	6.8
TL	Entic Hapludoll	Piedritas	0–0.28	61	25	15	1.37	0.035	0.070	0.170	0.189	0.47	0.59	1.29	7.1
			0.28–0.47	65	21	15	1.38	0.031	0.061	0.182	0.202	0.47	0.55	0.86	8.3
			0.47–0.84	64	24	12	1.22	0.023	0.045	0.133	0.147	0.53	0.75	0.35	8.3
			0.84–1.08	75	13	12	1.30	0.033	0.065	0.121	0.134	0.50	0.83	0.13	8.8
			1.08–1.3	70	21	9	1.22	0.049	0.097	0.209	0.231	0.53	0.48	0.09	9.3
BAL	Petrocalcic Paleudoll	Balcarce	0–0.23	33	41	26	1.15	0.085	0.169	0.280	0.393	0.56	0.36	3.28	7.0
			0.23–0.31	35	39	26	1.15	0.105	0.150	0.276	0.387	0.56	0.36	2.26	7.4
			0.31–0.54	36	29	35	1.27	0.142	0.178	0.351	0.498	0.51	0.28	1.59	7.4
			0.54–0.70	45	31	24	1.27	0.194	0.215	0.427	0.507	0.51	0.23	0.82	7.8
			0.70–1.2	50	31	19	1.35	0.179	0.199	0.396	0.450	0.48	0.25	0.64	7.8

RAF, Rafaela; PER, Pergamino; GV, General Villegas; TL, Trenque Lauquen; BAL, Balcarce; BD, Bulk density; LL, lower drainage limit (*i.e.* permanent wilting point); DUL, upper drainage limit (*i.e.* field capacity); SAT, saturated volumetric water.
[a] Soil Survey Staff, 2010.

2.3. Soil data

The configuration of soil N and C modules (*SoilN*) and water balance (*SoilWat*) were carried-out following the next steps. Soil water parameters required to the model such as drained lower limit (LL), drained upper limit (DUL), bulk density (BD) and organic carbon were provided by the Soils Institute of INTA (CIRN) (Table 1). Also, for each soil, air dry (AD), saturated volumetric water (SAT), total porosity (PO), drainage coefficient (SWCON) and soil pH were estimated according to the reported by Ojeda et al. (2017) for US environments. In addition, the water extraction coefficient (KL) was set at 0.08 mm d^{-1} (Robertson et al., 1993a,b; Dardanelli et al., 1997, 2004) for each soil layer. The root exploration factor (XF) was set as 1 for up to 1 m depth and then decreased exponentially to 0.6 at the maximum soil depth (Monti and Zatta, 2009). To initialize the soil nitrogen pool, a 10-year simulation of previous management at the experimental locations (oats-maize sequence), the location-specific climate, and soil data were used (Ojeda et al., 2017).

Initial simulations shown that was required the inclusion of soil water from water table at Rafaela. This additional water was included into the model following Ojeda et al. (2016).

2.4. APSIM configuration

All simulations were performed using APSIM (version 7.5) (Keating et al., 2003; Holzworth et al., 2014). Oats, wheat, barley, soybean and maize were simulated with the respective plant modules (APSIM-*Oats*, −*Wheat*, −*Barley*, *Soybean* and −*Maize*, respectively; Carberry et al., 1989; Keating et al., 2003; Wang et al., 2003; Peake et al., 2008). Annual ryegrass was simulated with the APSIM-*Weed* module (Deen et al., 2003; Pembleton et al., 2013) re-parameterized by Ojeda et al. (2016) using the late flowering genotype. Simulations were performed at the crop sequence level, *i.e.* the initial soil condition for a specific crop was the final soil condition of the previous crop. The sequences are shown in Fig. 2. Since genotypes used in the field experiments were not available into APSIM, we used the genotypes that best reflected the maturity type/crop development among the available genotypes in the model. The actual crop management such as sowing date, plant density, row spacing, nitrogen fertilization and irrigation were set in the model to mimic the practices applied in the field (Table 2). The harvest rule was set to remove the aerial biomass at a height of 0.03 m (Ojeda et al., 2016). Seasonal WP was calculated as the ratio between the DM yield in each crop harvest and seasonal rainfall in the same period. Likewise, the annual WP was calculated as the ratio between the annual DM yield for each FCS and the annual rainfall.

2.5. Evaluation of APSIM performance

First, the model performance was assessed to predict crop and FCS DM yield. After that, APSIM's ability to sense spatio-temporal variability in the FCS DM yield and WP was evaluated. The assessment was based on the comparison between observed and modelled values by scatter plots (Piñeiro et al., 2008) for crops and FCS DM yield in all locations.

The evaluation of model performance described in Tedeschi (2006) was used to statistically evaluate APSIM to predict crop and FCS DM yields. The statistical parameters used were: observed and modelled mean and standard deviation, coefficient of determination (R^2), root mean square error (RMSE) and the concordance correlation coefficient

Table 2
Summary of the agronomic management of forage crops sequences used for model validation.

Location	SEQ	D/I	SD	HD	Crop management			Genotype	References
					Fert N (kg N ha^{-1})	Density (plants m^{-2})	RS (m)		
annual ryegrass									
PER	S-AR	D	1-Mar-10	18-May/10-Jun/8-Jul/10-Ago/13-Sep/12-Oct-10	250	300	0.175	Barturbo	EEA Pergamino INTA
PER	M-AR	D	1-Mar-10	18-May/10-Jun/8-Jul/10-Ago/13-Sep-10	250	300	0.175	Barturbo	Ojeda et al. (2016)
PER	S-AR	D	28-Feb-11	10-May/8-Jun/21-Jul/29-Ago/6-Oct-11	250	300	0.175	Caleufú PV INTA	
PER	M-AR	D	28-Feb-11	10-May/8-Jun/21-Jul/29-Aug	250	300	0.175	Caleufú PV INTA	
PER	S-AR	D	28-Feb-12	30-May/10-Jul/23-Aug/21-Sep/12-Oct-12	250	300	0.175	Caleufú PV INTA	
PER	M-AR	D	28-Feb-12	30-May/10-Jul/23-Aug/21-Sep-12	250	300	0.175	Caleufú PV INTA	
GV	AR[a]-M	D	8-Apr-10	22-Jun/18-Aug/7-Oct-10	150	365	0.175	Bill max	EEA G. Villegas INTA
GV	AR[a]-M	D	8-Apr-10	19-Sep-10	150	400	0.175	Bill max	Ojeda et al. (2016)
GV	AR[b]-M	D	15-Apr-11	2-Sep/17-Oct-11	150	448	0.175	Bill max	
GV	AR[b]-M	D	15-Apr-11	28-Oct-11	150	400	0.175	Bill max	
oats									
PER	M-O	D/I	1-Mar-10	27-Apr/1-Jun/6-Jul/13-Sep-10	250	252	0.175	Violeta INTA	EEA Pergamino INTA
PER	M-O	D/I	1-Mar-11	26-Apr/30-May/11-Jul/25-Ago-11	250	323	0.175	Violeta INTA	unpublished data
PER	M-O	D/I	1-Mar-12	2-May/5-Jun/14-Aug/21-Sep-12	250	341	0.175	Violeta INTA	
PER	S-O	D/I	1-Mar-10	27-Apr/1-Jun/6-Jul/13-Sep/12-Oct-10	250	252	0.175	Violeta INTA	
PER	S-O	D/I	28-Feb-11	26-Apr/30-May/11-Jul/25-Aug/3-Oct-11	250	323	0.175	Violeta INTA	
PER	S-O	D/I	1-Mar-12	2-May/5-Jun/14-Aug/21-Sep/12-Oct-12	250	341	0.175	Violeta INTA	
BAL	M-O	D	7-Mar-13	16-May/29-Aug-13	150	300	0.200	Bonaerense INTA	Ojeda J.J.
BAL	M-O	D	16-Apr-14	11-Jul/20-Aug/8-Oct-14	150	300	0.200	Bonaerense INTA	unpublished data
TL	O-S	D	19-Apr-10	8-Oct-10	0	125	0.175	Victoria	AER T. Lauquen INTA
TL	O-S	D	8-Jul-11	20-Oct-11	0	125	0.175	Cristal	unpublished data
wheat									
RAF	W-M	D	21-Apr-10	25-Oct-10	75	200	0.175	–	EEA Rafaela INTA
RAF	W-S-M	D	1-Jul-10	16-Nov-10	75	200	0.175	–	unpublished data
RAF	W-M	D	19-May-11	14-Sep-11	75	200	0.175	–	
RAF	W-S-M	D	2-Jul-11	27-Oct-11	75	200	0.175	–	
barley									
GV	B-S	D	8-Apr-10	22-Jun/19-Oct-10	150	350	0.175	Scarlet	EEA G. Villegas INTA
GV	B-S	D	15-Apr-11	10-Aug/4-Nov-11	150	350	0.175	Scarlet	unpublished data
TL	B-M	D	11-Jun-10	15-Nov-10	0	120	0.175	Scarlett	AER T. Lauquen INTA
TL	B-M	D	8-Jul-11	20-Oct-11	0	120	0.175	Scarlett	unpublished data
soybean									
RAF	W-S-M	D	20-Nov-10	1-Mar-11	0	30	0.52	–	EEA Rafaela INTA
RAF	W-S-M	D	15-Nov-11	7-Feb-12	0	30	0.52	–	unpublished data
PER	S-O	D/I	10-Nov-09	25-Feb-10	13	42	0.70	ADM 50048 (5)[c]	EEA Pergamino INTA
PER	S-AR	D	10-Nov-09	25-Feb-10	13	42	0.70	ADM 50048 (5)[c]	unpublished data
PER	S-O	D/I	4-Nov-10	25-Feb-11	–	45	0.52	GAPP 890 (8)[c]	
PER	S-AR	D	4-Nov-10	25-Feb-11	0	45	0.52	GAPP 890 (8)[c]	
PER	S-O	D/I	25-Oct-11	7-Feb-12	5	34	0.52	A 5009 RG (5)[c]	
PER	S-AR	D	25-Oct-11	7-Feb-12	5	34	0.52	A 5009 RG (5)[c]	
GV	B-S	D	9-Nov-10	4-Mar-11	0	35	0.175	DM 4970	EEA G. Villegas INTA unpublished data
TL	O-S	D	9-Dec-10	16-Mar-11	0	30	0.52	DM 4970	AER T. Lauquen

(*continued on next page*)

Table 2 (*continued*)

Location	SEQ	D/I	SD	HD	Crop management			Genotype	References
					Fert N (kg N ha^{-1})	Density (plants m^{-2})	RS (m)		
TL	O-S	D	9-Dec-11	–	0	30	0.52	DM 4970	INTA unpublished data
maize									
RAF	M-M	D	20-Oct-09	20-Jan-10	75	7.5	0.52	DK Feed2 RR2	EEA Rafaela INTA
RAF	M-M	D	25-Jan-10	27-May-10	75	7.5	0.52	DK Feed2 RR2	unpublished data
RAF	W-M	D	30-Nov-10	29-Mar-11	75	7.5	0.52	DK Feed2 RR2	
RAF	W-S-M	D	3-Mar-11	14-Jun-11	75	7.5	0.52	DK Feed2 RR2	
RAF	M-M	D	19-Oct-10	17-Feb-11	75	7.5	0.52	DK Feed2 RR2	
RAF	M-M	D	25-Feb-11	24-Jun-11	75	7.5	0.52	DK Feed2 RR2	
RAF	W-M	D	16-Jan-12	16-May-12	75	7.5	0.52	DK Feed2 RR2	
RAF	W-S-M	D	10-Feb-12	11-Jun-12	75	7.5	0.52	DK Feed2 RR2	
RAF	M-M	D	11-Oct-11	14-Jan-12	75	7.5	0.52	DK Feed2 RR2	
RAF	M-M	D	16-Jan-12	16-May-12	75	7.5	0.52	DK Feed2 RR2	
PER	M-O	D/I	16-Oct-09	15-Feb-10	113	8.5	0.70	DUO 548 HX	EEA Pergamino INTA
PER	M-AR	D	16-Oct-09	15-Feb-10	113	8.5	0.70	DUO 548 HX	unpublished data
PER	M-O	D/I	27-Sep-10	18-Feb-11	207	11.5	0.52	PAN 5E 202	
PER	M-AR	D	27-Sep-10	18-Feb-11	207	11.5	0.52	PAN 5E 202	
PER	M-O	D/I	19-Sep-11	26-Jan-12	207	8.5	0.70	DK 747 VT 3P	
PER	M-AR	D	19-Sep-11	26-Jan-12	207	11.5	0.52	DK 747 VT 3P	
GV	AR[a]-M	D	10-Nov-10	9-Mar-11	150	7.7	0.52	DK 780S	EEA G. Villegas INTA
GV	AR[a]-M	D	10-Nov-10	9-Mar-11	150	7.7	0.52	DK 780S	unpublished data
GV	AR[b]-M	D	9-Nov-11	24-Apr-12	150	4	0.52	DUO 548 HX	
GV	AR[b]-M	D	9-Nov-11	24-Apr-12	150	7.7	0.52	DUO 548 HX	
TL	B-M	D	9-Dec-10	11-Mar-11	0	8	0.52	DK 780S	AER T. Lauquen INTA
TL	B-M	D	25-Oct-11	29-Feb-12	0	8	0.52	DM Duo 548 RR	unpublished data
BAL	M-O	D	26-Oct-12	26-Feb-13	220	9	0.52	DK 747 VT 3P	Ojeda J.J.
BAL	M-O	D	7-Oct-13	7-Mar-14	220	8.5	0.52	DK 747 VT 3P	unpublished data
BAL	M-O	D	17-Nov-14	12-Mar-15	200	8.5	0.52	DK 747 VT 3P	

Abbreviations: SEQ, sequence; SD, sowing date; HD, harvesting date; D/I, dry (S) or irrigated (I); ISW, initial soil water before sowing related to plant available water capacity; Fert N, nitrogen fertilization; RS, row spacing; PER, Pergamino; RAF, Rafaela; BAL, Balcarce; TL, Trenque Lauquen; GV, General Villegas; S-AR, soybean-annual ryegrass; M-AR, maize-annual ryegrass; AR-M, annual ryegrass-maize; M-O, maize-oats; S-O, soybean-oats; O-S, oats-soybean; W-M, wheat-maize; W-S-M, wheat-soybean-maize; B-S, barley-soybean; B-M, barley-maize; S-AR, soybean-annual ryegrass; M-M, maize-maize.

[a] Annual ryegrass with several harvests (grazing simulation).

[b] Annual ryegrass with only one harvest (silage simulation).

[c] Maturity group.

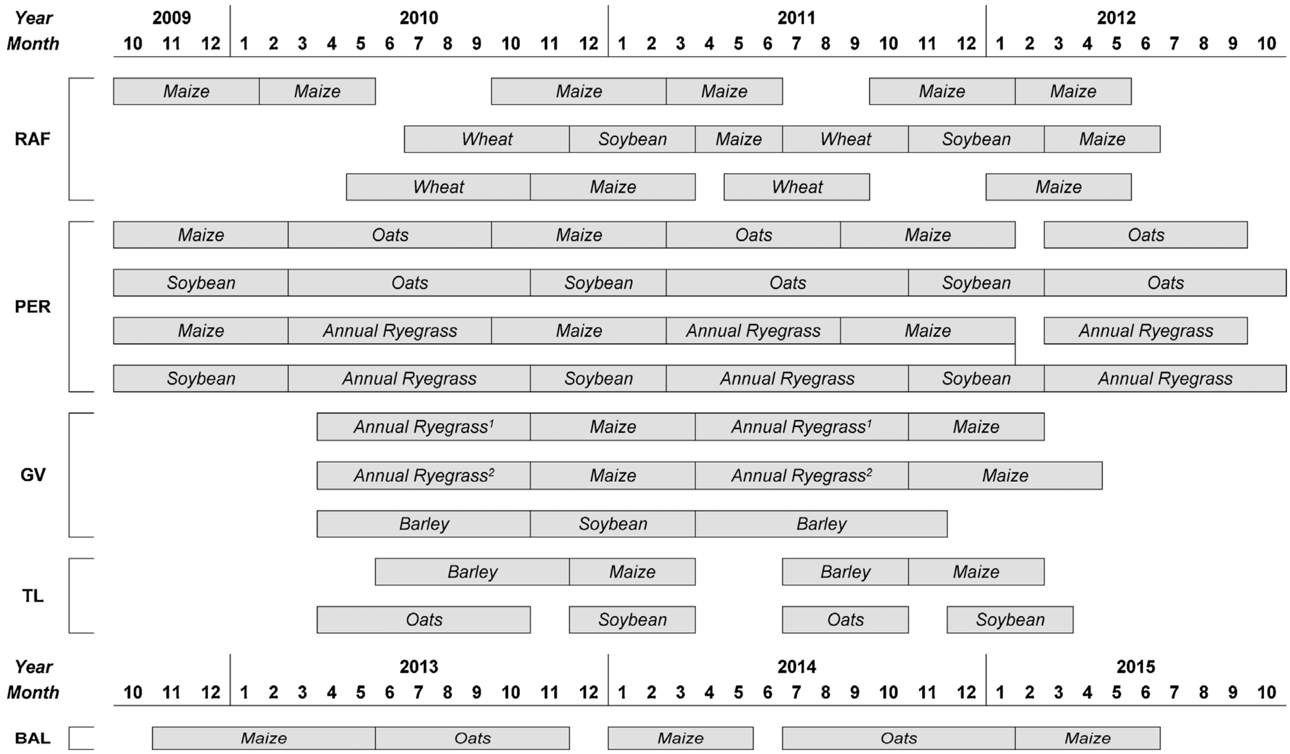

Fig. 1. Schematic representation of forage crop sequences growing in Rafaela (RAF), Pergamino (PER), General Villegas (GV), Trenque Lauquen (TL) and Balcarce from 2009 to 2015. Superscript 1 and 2 indicates annual ryegrass with successive harvests and with only one harvest, respectively.

(CCC). The CCC integrates precision through Pearson's correlation coefficient, which represents the proportion of the total variance in the observed data that can be explained by APSIM, and accuracy by bias which indicates how far the regression line deviates from the line (1:1).

The crop model performance was categorically judged based on the values of CCC as proposed by Stöckle et al. (1998). Upper and lower statistical limits were set as: "very good" when CCC > 0.90, "satisfactory" when 0.80 < CCC < 0.90, "acceptable" when 0.70 < CCC < 0.80 and "poor" with other values.

3. Results

3.1. Dry matter yield

The observed crop DM yield ranged from 1.4 Mg ha^{-1} (annual ryegrass) to 14.9 Mg ha^{-1} (maize). The difference between observed and modelled crop mean DM yield was 0.2 Mg ha^{-1}, being higher in crops with lowest number of observations (wheat and barley, Table 3). A better model accuracy to predict DM yield was found when maize DM

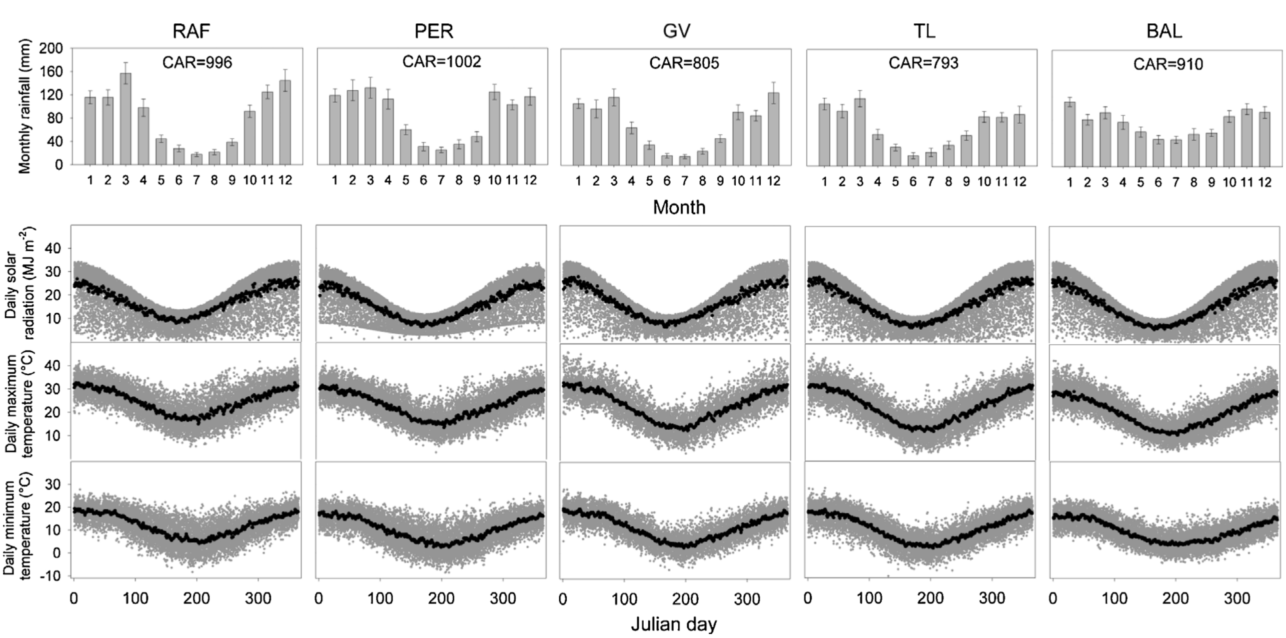

Fig. 2. Historical climate data in Rafaela (RAF), Pergamino (PER), General Villegas (GV), Trenque Lauquen (TL) and Balcarce (BAL) from 1983 to 2013. Black points indicate long-term averages. Numbers for the x-axis in panels a, b, c, d and e indicates the month of the year from January (1) to December (12) and error bars are the standard error for the period. Grey points are individual daily values during the 30-year period from 1-January (Julian day 1) to 31-December (Julian day 365). Cumulative annual rainfall (CAR).

Table 3
Statistical summary indicating the performance of the Agricultural Production Systems Simulator in predicting the crop DM yield.

	Crop						Location						Total
	annual ryegrass[a]	oats	barley	wheat	soybean	maize	RAF	PER	PERI	GV	TL	BAL	
No. Obs.	34	47	5	4	13	24	16	60	26	11	6	8	127
Observed mean (Mg ha^{-1})	1.4	1.5	2.7	4.8	5.9	14.9	12.6	2.8	4.2	1.9	2.4	8.7	4.6
Modelled mean (Mg ha^{-1})	1.2	1.2	4.4	5.9	6.5	13.7	11.0	2.7	3.9	2.5	3.6	8.9	4.4
Observed SD (Mg ha^{-1})	0.7	0.8	1.5	1.6	2.5	6.1	6.2	3.9	5.6	1.5	1.1	9.4	5.9
Modelled SD (Mg ha^{-1})	0.8	0.8	1.3	2.2	3.2	6.2	4.0	4.1	6.4	1.9	1.2	10.0	5.7
RMSE (Mg ha^{-1})	0.7	0.6	1.7	1.6	1.4	3.4	3.3	0.9	1.7	1.1	1.5	2.0	1.7
CCC	0.46	0.77	0.90	0.79	0.90	0.86	0.84	0.98	0.96	0.84	0.53	0.98	0.96

Abbreviations;: No. Obs.Number of observations; SDstandard deviation; RMSEroot mean square error; CCCconcordance correlation coefficient; RAFRafaela; PER Pergamino dryland; PERIPergamino irrigated; GVGeneral Villegas; TLTrenque Lauquen; BALBalcarce.

[a] For this analysis was used the re-parametrized APSIM *Weed* module by Ojeda et al. (2016).

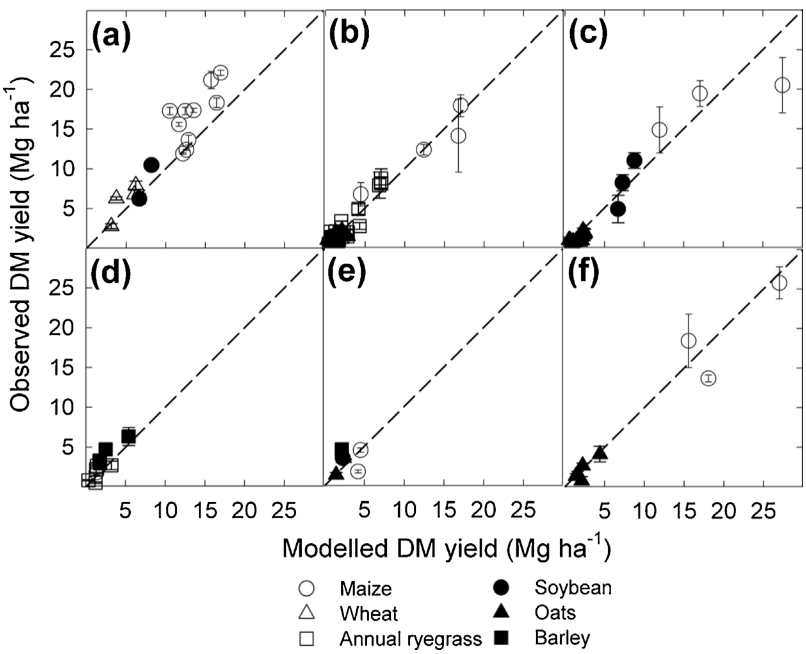

Fig. 3. Observed *v.* modelled crop dry matter (DM) yield in (a) Rafaela, (b) Pergamino dryland, (c) Pergamino irrigated, (d) General Villegas, (e) Trenque Lauquen and (f) Balcarce. The diagonal line represents the line 1:1, *i.e.* y = x. The vertical bars indicate the standard deviation of the mean.

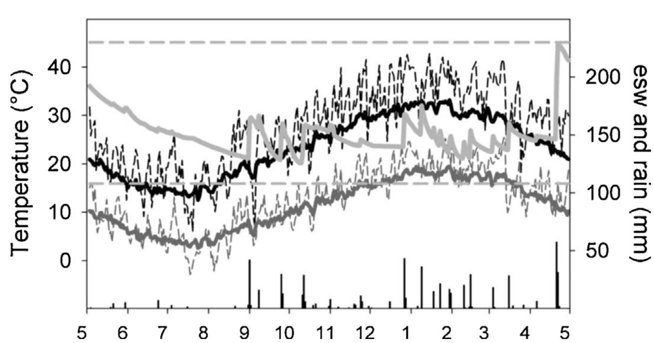

Fig. 4. Daily maximum (dotted black line) and minimum air temperature (dotted dark grey line), modelled extractable soil water (esw, solid grey line) and rain (black bars) from May-2010 to May-2011 in General Villegas. Numbers for the x-axis indicates the month of the year from January (1) to December (12). Solid black and dark grey lines represent the historical daily maximum and minimum air temperature, respectively. Dotted grey lines represent the lower and upper drainage limits for the Typic Hapludoll soil at this location.

yields from 2010/11 were deleted. In this year, the maximum temperatures during summer were extreme (> 40 °C; Fig. 2) and the extractable soil water was close to LL (Fig. 4). After removing these data, the CCC increased from 0.80 to 0.86 and the RMSE decreased from 4.1 to 3.4 Mg ha^{-1}. Likewise, better model predictions were obtained by simulating crops for silage, *i.e.* only one harvest for wheat, soybean and maize, than when crops were harvested successively (annual ryegrass, oats and barley) (Fig. 3; Table 3).

The crop DM yield at Pergamino dryland and irrigated, Rafaela and Balcarce was simulated more accurately compared to the crop DM yield modelled at General Villegas and Trenque Lauquen (Table 3; Fig. 3). Likewise, the model accuracy in simulating DM yield under irrigated conditions at Pergamino was slightly lower compared to dryland conditions. However, the observations at Pergamino irrigated (n = 26) were less than half that the observations at Pergamino dryland (n = 60).

Overall, the model had a very good ability to simulate DM yields of FCS. The performance of the model in predicting FCS DM yield is highlighted in Figs. 5 and 6 and confirmed by the summary statistics in Table 4 (CCC = 0.83–0.95, RMSE = 2.3–5.0 Mg ha^{-1}). The observed FCS DM yield ranged from 4.3 Mg ha^{-1} (Trenque Lauquen) to 28.7 Mg ha^{-1} (Rafaela) among locations (Table 4) and from 16.2 Mg ha^{-1} (third year of the sequence) to 19.1 Mg ha^{-1} (first year of the sequence) among years (Table 4). The difference between observed and modelled mean FCS DM yield was less than 0.2 Mg ha^{-1}, being the lowest under irrigation at Pergamino (0.7 Mg ha^{-1}; Table 4) and the highest at Rafaela (3.7 Mg ha^{-1}; Table 4). The sequences annual ryegrass-maize (AR-M) and barley-soybean (B-S) at General Villegas and the sequences oats-soybean (O-S) and barley-maize (B-M) at Trenque Lauquen had the lowest observed and modelled FCS DM yield

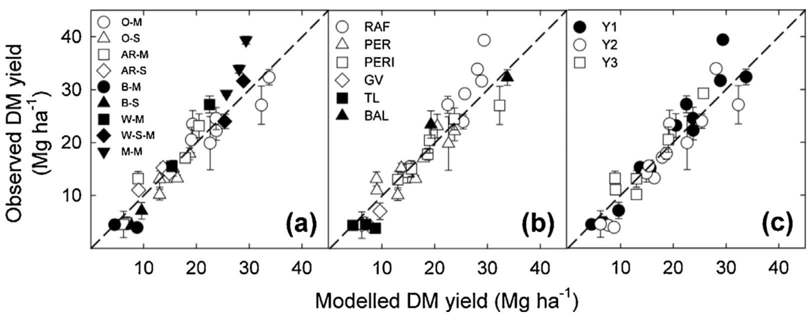

Fig. 5. Observed *v.* modelled forage crop sequences dry matter (DM) yield by (a) sequence type, (b) location and (c) year. The diagonal line represents the adjusted line 1:1, *i.e.* y = x. The vertical bars indicate the standard deviation of the mean. O-M, oats-maize; O-S, oats-soybean; AR-M, annual ryegrass-maize; AR-S, annual ryegrass-soybean; B-M, barley-maize; B-S, barley-soybean; W-M, wheat-maize; W-S-M, wheat-soybean-maize; M-M, maize-maize; RAF, Rafaela; PER, Pergamino dryland; PERI, Pergamino irrigated; GV, General Villegas; TL, Trenque Lauquen; BAL, Balcarce; Y1, year 1; Y2, year 2 and Y3, year 3.

(Fig. 5a) while the highest DM yields were found for maize-maize (M-M) and wheat-soybean-maize (W-S-M) at Rafaela and oats-maize (O-M) at Balcarce (Fig. 5a). Due to the small number of observations that were available for Trenque Lauquen and Balcarce, no statistical analyses of DM yield at the level of FCS were performed (Table 4). The FCS DM yield under irrigation at Pergamino was simulated more accurately than in the same site without irrigation, Rafaela and General Villegas (Table 4; Fig. 3). The model over-predicted the FCS DM yield at Rafaela, mainly due to the over-prediction of maize DM yield (Figs. 5 b; 6 a). There were no discernible groupings based on years in the data points for all sequences. For all FCS, DM yield was better simulated as the crops progressed in their development (Fig. 6), except in some specific cases. For example, maize into the sequence wheat-maize (W-M) at Rafaela during 2011 (Fig. 6a) and barley into the sequence barley-maize (B-M) at Trenque Lauquen during 2010 (Fig. 6d).

3.2. Water productivity

Very good agreement between observed and modelled seasonal WP was found at Balcarce (CCC = 0.90, RMSE = 0.7 g m^{-2} mm^{-1}; Table 5). However, the model's ability to predict seasonal WP was acceptable at Pergamino under both dryland and irrigated conditions (CCC = 0.73–0.74, RMSE = 2.0–2.5 g m^{-2} mm^{-1}; Table 5) and poor at Rafaela (CCC = 0.55, RMSE = 1.3 g m^{-2} mm^{-1}), Trenque Lauquen (CCC = 0.51, RMSE = 1.0 g m^{-2} mm^{-1}) and General Villegas (CCC = 0.42, RMSE = 1.4 g m^{-2} mm^{-1}) (Table 5). At Pergamino, dryland and irrigated, the observed seasonal WP shown extreme values because seasonal rainfall between oats and annual ryegrass harvests was scarce (< 20 mm, Fig. 8a). For seasonal water inputs (*i.e.* rainfall + irrigation) less than 200 mm, the model under-predicted WP values more than over-predicted (Fig. 7a). However, the model predictions on an annual basis were very good (Fig. 7b).

The model predicted annual WP with very good accuracy, as demonstrated by CCC = 0.91–0.96 and RMSE = 0.2–0.5 g m^{-2} mm^{-1} for the total observations (Table 5), except for Rafaela where the model under-predicted (0.5 g m^{-2} mm^{-1}; 12%) the annual WP (CCC = 0.62, RMSE = 0.7 g m^{-2} mm^{-1}). Likewise, the observed and modelled seasonal WP were on average 95 and 21% superior at Rafaela, Pergamino under both dryland and irrigated conditions and Balcarce than at General Villegas and Trenque Lauquen, except for the modelled WP at Pergamino (Table 5). However, the observed and modelled annual WP at Rafaela was higher than Pergamino and, in turn higher at Pergamino than at General Villegas and Trenque Lauquen (Table 5).

There was a better fit for the observed than for the modelled WP data (Fig. 8a; Table 6) in the regression of the WP as a function of seasonal water inputs (cumulative rainfall + irrigation) (P < 0.001; Table 6). Likewise, a better fit was found for winter crops (oats, annual ryegrass, barley and wheat) and soybean than for maize (Fig. 8a; Table 6). Similarly, there was a curvilinear relationship between annual WP and water inputs (p < 0.001) for both observed and modelled data (Fig. 8b; Table 6). At low annual water inputs (< 800 mm), in General Villegas and Trenque Lauquen the WP, on average, was only a third than in other locations (Fig. 8b).

4. Discussion

In this study, 13 FCS including winter (oats, annual ryegrass, barley and wheat) and summer crops (soybean and maize), were simulated by APSIM across five Argentinian locations. Our objective was to evaluate the APSIM ability to predict DM yield and water productivity (WP) of multiple continuous FCS. Overall, the results showed that APSIM was able to simulate better DM yield and WP on an annual basis, *i.e.* at the FCS level, than at a seasonal basis, *i.e.* at the crop level.

The ability of APSIM to predict crops DM yield in the Argentinian Pampas was similar to annual forage crop modelling efforts reported in south-eastern Australia (Pembleton et al., 2013, 2016; Islam et al., 2015) and New Zealand (Teixeira et al., 2010, 2015). The model accuracy was higher when predicting soybean and maize DM yield than the other crops. The APSIM-*Oats* module had an acceptable performance since it is has received scarce development efforts compared to the other modules used in this study (Peake et al., 2008; Pembleton et al., 2013). The very good and satisfactory model accuracy when predicting soybean and maize DM yields, respectively, was not surprising, since both modules (APSIM-*Soybean* and APSIM-*Maize*) have been widely evaluated across diverse environments for their ability to predict grain and DM yield (Robertson and Carberry, 1998; Denner et al., 1998; Shamudzarira and Robertson, 2002; Lyon et al., 2003; Teixeira et al., 2010; Mohanty et al., 2012; Liu et al., 2013; Pembleton et al., 2013; Archontoulis et al., 2014a,b). However, the model under-predicted maize DM yields at Rafaela mainly during the first year of simulation (Figs. 3 a and 6). Surprisingly, the N fertilization rate to this crop at Rafaela was relatively low (0.075 Mg N ha^{-1}) for the high recorded mean DM yield (17.5 Mg ha^{-1}). Although previous studies have reported that APSIM-*Sugarcane* module was scarcely sensitive to variations in the initial soil N at US environments (Ojeda et al., 2017), our study demonstrated a high model response for maize in this location of the Argentinian Pampas (Fig. A1 in the Supplementary material). The mentioned under-predictions of maize DM yield at Rafaela could be attributed to the under-estimation of initial soil N at this location because of the soil initialization method used in this study based on a 10-year sequence simulation of oats-maize as previous crops. In fact, Teixeira et al. (2015) reported the importance to choose representative initialization values for soil water and N in studies that often consider several soil types. On the other hand, Ojeda et al. (2017) found that APSIM predictions of Miscanthus DM yield were more sensitive to changes in the initial organic carbon on a sandy soil than in a silty soil at US. Collectively, this reinforces the importance of the initial soil conditions on the accuracy of DM yield and WP simulations of different FCS under several input intensities. Therefore, further research should be addressed to clarify the extent of under or over-estimation of initial soil parameters on the predictions of continuous FCS DM yield and WP using APSIM.

Although APSIM had a very good accuracy when predicting barley DM yield (CCC = 0.90; Table 3), the model over-predicted the barley DM yield (5 out of 5 observations) as was demonstrated by the difference between observed and modelled mean DM yield (1.7 Mg ha^{-1}; Table 3). Previous studies in southern Queensland, Australia, found that

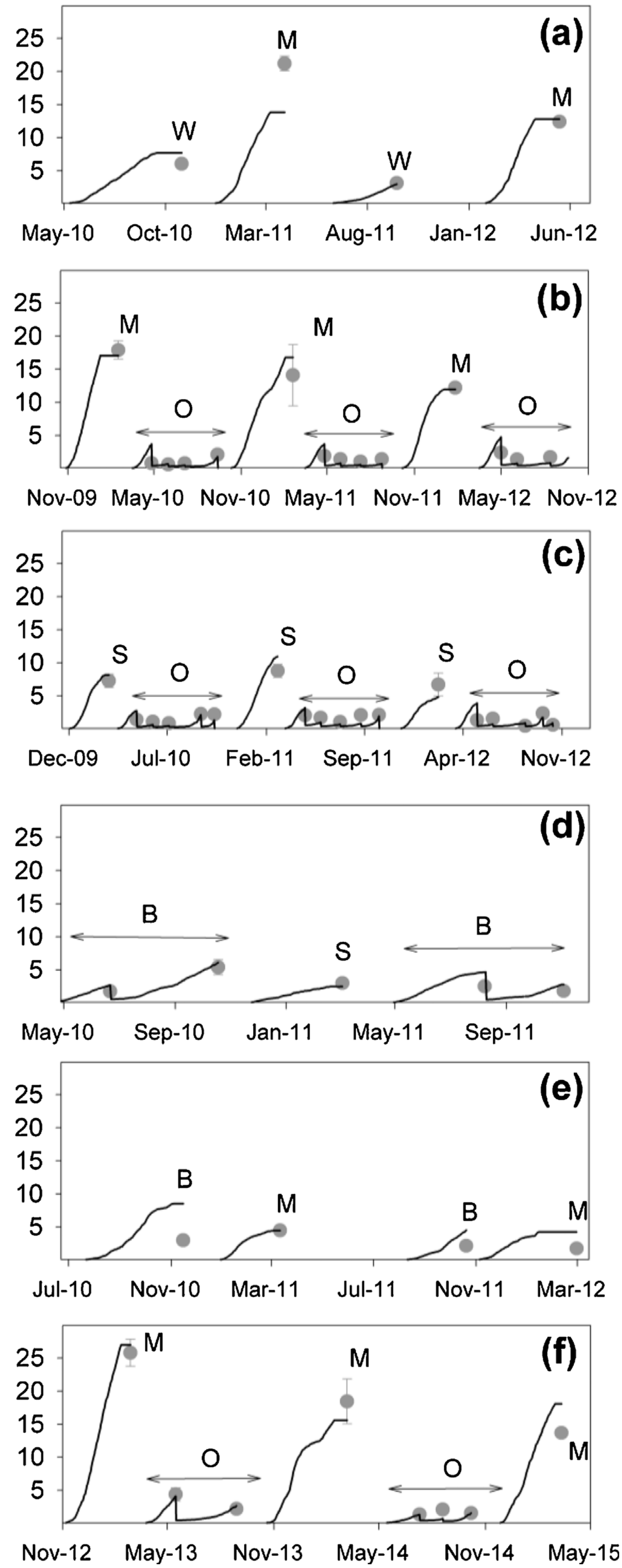

Fig. 6. Modelled (solid black line) and observed (grey points) dry matter (DM) yield for selected forage crop sequences (FCS): (a) wheat-maize in Rafaela, (b) maize-oats in Pergamino dryland, (c) soybean-oats in Pergamino irrigated (d) barley-soybean in General Villegas, (e) barley-maize in Trenque Lauquen and (f) maize-oats in Balcarce. Capped vertical bars represent the range in observed values where such data were available. W, wheat; M, maize; O, oats; B, barley.

the APSIM-*Barley* module was able to explain 91 and 82% of the variation observed in total biomass at maturity and grain yield, respectively (Manschadi et al., 2006). However, their study was based on the calibration of only one Australian barley genotype (Grimmet). Probably, the low fit between observed and modelled mean DM yield at General Villegas and Trenque Lauquen (Fig. 3d and e) would be due to genotypic differences between the currently available genotypes into the model and those used in the field experiments as well as the method of soil initialization as mentioned above.

The model accuracy to predict silage DM yield of individual crops (barley, wheat, soybean and maize), *i.e.* a single harvest by season, was better than to predict DM yield of frequently harvested crops (annual ryegrass, oats and barley), *i.e.* several harvest by season (Fig. 3). This model response was not surprising as APSIM was initially developed to simulate grain crops managed with only one final harvest at maturity. The main reason for this model's inability would be related to the absence of APSIM calibrations using forage crop phenology data and with the model settings related to the biomass remaining after each harvest which is directly involved in the following forage regrowth (Ojeda et al., 2016).

The predictions of FCS DM yield across the Argentinian Pampas were very good (Fig. 5; Table 4), which were similar to the APSIM simulations reported by Teixeira et al. (2010) in New Zealand using double crops (wheat and triticale [*X. triticosecale*, Wittmack] as winter crops and maize and kale [*Brassica oleracea* L.] as summer crops). In the same way, our results were comparable with modelling efforts reported by Islam et al. (2015) for FCS DM yield in dairy systems in south-eastern Australia. Similarly, these authors found high DM yield achieved from maize-based FCS compared with FCS based on other summer crops (soybean and forage sorghum [*Sorghum bicolor* (L.) Moench]) due to the high yield potential of maize.

Soil variables required as model inputs to initialization of the simulation (*e.g.* water, C and N) are habitually re-initialized (*i.e.* are set in each simulation using constant values based on regional knowledge) (Teixeira et al., 2015). Despite the soil variables were set only once previous to the first crop sowing into the FCS the first year of the simulation, APSIM demonstrated high robustness to simulate DM yield of several FCS (Fig. 5) in wide edaphoclimatic and temporal conditions in the Argentinian Pampas. This modelling approach considers that the crop DM yields in the FCS depend on the previous crop in the same sequence, carrying the final soil variables of the previous year as the initial ones for the next year. White et al. (2011) reported that from 166 modelling papers that considered adaptation strategies (*i.e.* sowing date, fertilization rate, irrigation, cultivars and crop rotations), only 11 papers compared crop rotations. In fact, most crop modelling assessments consider simulations of the same crop over consecutive years (White et al., 2011). However, there are only a few studies that used the FCS approach, *i.e.* simulating crop rotations. For example, Teixeira et al. (2015) evaluated the effects to use different APSIM simulation (at the individual crop and sequence level) on DM yield, soil water and N in the Canterbury plains of New Zealand. These authors reported greater model sensitivity to the simulation when the crops grown under restrictive soil water and N levels. Therefore, they proposed that a more detailed representation of the simulations at the sequences level would be key to accurately simulating crop growth under limited resources conditions, where the sequence effect would have greater influence on the subsequent crops growth.

The use of complementary forage systems based on FCS as an option to maximize WP was reported in south-eastern Australia under non-limiting N and water conditions by Garcia et al. (2008) and Islam and Garcia (2012) winter crops/maize triple crops (forage rape, persian clover [*T. resupinatum* L.], and field peas [*Pisum sativum* L.] as winter crops). These authors reported WP values ranging 3.4–6.1 g m^{-2} mm^{-1} for different N rates and sowing dates. The WP range modelled in our study (1.0–4.0 g m^{-2} mm^{-1}) was consistent with values reported by Caviglia et al. (2004, 2013) for wheat-soybean sequences at Balcarce

Table 4
Statistical summary indicating the performance of Agricultural Production Systems Simulator in predicting the dry matter yield of forage crop sequences.

	RAF	PER	PERI	GV	TL	BAL	Y1	Y2	Y3	Total
No. Obs.	7	11	6	4	3	2	14	13	6	33
Observed mean (Mg ha^{-1})	28.7	15.8	19.7	5.2	4.3	27.9	19.1	16.9	16.2	17.7
Modelled mean (Mg ha^{-1})	25.0	16.0	20.4	7.6	6.7	26.5	18.2	18.0	14.8	17.5
Observed SD (Mg ha^{-1})	7.6	4.3	5.4	1.3	0.4	6.3	11.4	9.1	7.4	9.7
Modelled SD (Mg ha^{-1})	4.9	4.9	6.9	1.5	2.1	10.2	9.3	7.8	6.5	8.1
RMSE (Mg ha^{-1})	5.0	2.4	2.3	2.5	3.1	–	3.4	3.2	2.7	3.2
CCC	0.83	0.86	0.93	0.86	–	–	0.95	0.93	0.93	0.93

Abbreviations: No. Obs., Number of observations; SD, standard deviation; RMSE, root mean square error; CCC, concordance correlation coefficient; RAF, Rafaela; PER Pergamino dryland; PERI, Pergamino irrigated; GV, General Villegas; TL, Trenque Lauquen; BAL, Balcarce; Y1, year 1; Y2, year 2; Y3, year 3.

(calculated using DM yield on an annual basis). However, there is no study in the literature on modelling that analyze the WP variations of FCS in the Argentinian Pampas, despite that WP has been widely reported for grain crops sequences in this region.

The results showed that APSIM was able to predict with better accuracy the annual (very good) than seasonal WP (acceptable) (Table 5) as was demonstrated by the CCC and RMSE for the annual (0.71; 0.4 g m^{-2} mm^{-1}) and seasonal WP (0.94; 1.9 g m^{-2} mm^{-1}), respectively (Table 5). This model response could be due to the annual estimation which considers the rainfall in a year period (from 1 July to 31 May) while seasonal estimation only considers rainfall occurred in short-time periods, *i.e.* from sowing to harvest and between two consecutive harvests (in some cases < 20 d), and therefore the soil water storage is not accounted. Likewise, the model's ability to predict seasonal WP was not acceptable for all locations (Table 5). These results suggest that, in environments such as Trenque Lauquen characterized by a low cumulative annual rainfall (793 mm) and low maximum soil water storage capacity (113 mm), soil water conditions carried by the model from one crop to the next, would play an important role to obtain better FCS DM yield predictions, even more under soil water stress conditions.

The highest seasonal WP, both observed and modelled, were obtained at Rafaela (Table 5), which can be attributed to the highest proportion of maize in the FCS (Fig. 1), which is a C4 species with a high-water use efficiency (Neal et al., 2011; Zhang et al., 2017). The use of the double crop maize-maize (M-M) in this location was related with the climate characteristics, where the optimal solar radiation and temperature conditions allow to grow two summer crops (Monzon et al., 2014) in the same season (Fig. 2).

The lowest observed and modelled WP values at General Villegas and Trenque Lauquen (Fig. 8b) were probably associated with the reduction in DM yield of maize due to the high temperatures and low rainfall during the spring-summer period (Fig. 4). Therefore, the FCS DM yield was highly dependent on maize performance in these locations. In fact, the WP was lower in these locations than in Rafaela or Balcarce (Fig. 8b), which had more favourable climate conditions during spring-summer period (not shown). Thus, maize DM yield seems to be critical to maximize WP in FCS.

The model's accuracy decreased when seasonal WP values were higher, *i.e.* for low water inputs (Fig. 7a). For seasonal water inputs (rainfall + irrigation) less than 200 mm, the model tended to under-predict WP (Fig. 7a). This model response was directly associated with crop DM yield under-predictions for crops with frequent harvests. Similarly, high APSIM under-predictions were reported by Ojeda et al. (2016) for the first harvest of annual ryegrass in the period during the crop establishment at Pergamino and General Villegas, Argentina. This model weakness to under-predict DM yield of frequently harvested crops directly affect the model performance to predict WP at this environments. A deeper discussion of this model limitation is provided in Ojeda et al. (2016), who mentioned the predictions of DM yield of annual ryegrass improved substantially when several key model parameters (*e.g. shoot_lag, shoot_rate, leaf_no_at_emerg* and *transp_eff_c*) were well calibrated. Therefore, important modelling efforts are still required for simulate a wide range frequently harvested crop using APSIM, since

Table 5
Statistical summary indicating the performance of Agricultural Production Systems Simulator in predicting seasonal and annual Water Productivity (WP).

Seasonal WP										
	RAF	PER	PERI	GV	TL	BAL	Y1	Y2	Y3	Total
No. Obs.	16	60	26	11	6	8	51	45	31	127
Observed mean (g m^{-2} mm^{-1})	4.3	3.4	3.3	2.3	1.2	3.5	3.6	3.7	2.3	3.3
Modelled mean (g m^{-2} mm^{-1})	3.8	2.6	2.0	3.1	1.8	3.7	2.7	3.1	2.0	2.7
Observed SD (g m^{-2} mm^{-1})	1.5	3.1	3.8	0.8	0.4	1.5	3.1	2.9	2.5	2.9
Modelled SD (g m^{-2} mm^{-1})	1.0	2.0	1.8	1.6	1.1	1.8	1.8	1.8	2.0	1.9
RMSE (g m^{-2} mm^{-1})	1.3	2.0	2.5	1.4	1.0	0.7	2.0	2.2	1.1	1.9
CCC	0.55	0.74	0.73	0.42	0.51	0.90	0.72	0.58	0.89	0.71
Annual WP										
	RAF	PER	PERI	GV	TL	BAL	Y1	Y2	Y3	Total
No. Obs.	7	11	6	4	3	2	14	13	6	33
Observed mean (g m^{-2} mm^{-1})	4.1	1.8	1.9	0.8	0.7	4.3	2.3	2.4	2.0	2.3
Modelled mean (g m^{-2} mm^{-1})	3.6	1.8	1.8	1.2	1.1	4.0	2.1	2.5	1.7	2.2
Observed SD (g m^{-2} mm^{-1})	0.7	0.5	0.9	0.3	0.2	0.1	1.5	1.4	1.3	1.4
Modelled SD (g m^{-2} mm^{-1})	0.3	0.6	1.1	0.4	0.4	0.6	1.2	1.2	1.1	1.2
RMSE (g m^{-2} mm^{-1})	0.7	0.2	0.4	0.4	0.5	–	0.4	0.4	0.4	0.4
CCC	0.62	0.96	0.93	0.91	–	–	0.95	0.94	0.98	0.94

Abbreviations: No. Obs., Number of observations; SD, standard deviation; RMSE, root mean square error; CCC, concordance correlation coefficient; RAF, Rafaela; PER Pergamino dryland; PERI, Pergamino irrigated; GV, General Villegas; TL, Trenque Lauquen; BAL, Balcarce; Y1, year 1; Y2, year 2; Y3, year 3.

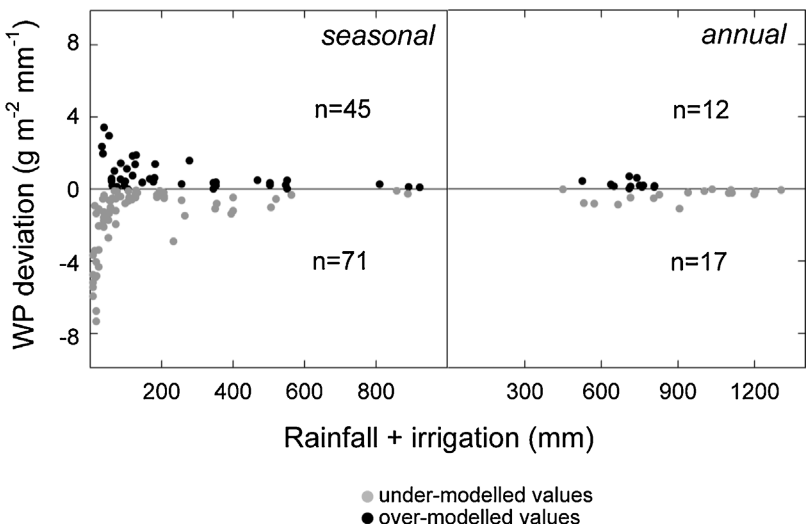

Fig. 7. Water productivity (WP) deviation values from the observed values *v.* rainfall + irrigation on a seasonal- and annual-base during 7 years (2009–2015) for different forage crop sequences growing in the Argentinian Pampas.

it model was originally developed for simulate crops with a single harvest by season.

Our results showed that APSIM predicted WP better on an annual basis (Fig. 7b) than for a seasonal basis (Fig. 7a). It is likely that the model is better at estimating soil water dynamics over the long-term rather than the short-term. Likewise, the high seasonal WP values at low water inputs (Fig. 8a) reflect more a weakness of the WP concept than of the model performance, *i.e.* high DM yields (observed or modelled), which are reached by using soil water storage, results in elevated WP values at low seasonal water inputs.

We also have presented evidence that when annual water inputs are high, the annual WP is low (Fig. 8b; Table 6). Likewise, a better fit was found for crops with photosynthetic metabolism C3 (wheat, annual ryegrass, oats, barley and soybean) than for C4 (maize; Fig. 8a; Table 6). This response was not surprising because WP reductions against water inputs increments has been well established in Bangladesh (Ali and Talukder, 2008) in the South-eastern Pampas (Caviglia et al., 2013), in the Loess Plateau region of China (Zhang et al., 2017) and in several environments across the world (Zhang et al., 2001). Also, we found higher WP values for maize than C3 species for the same water input from ~200 to 900 mm (Fig. 8a) directly linked with the high photosynthetic capacity of maize to convert water into DM yield (Neal et al., 2011). This highlights the importance of including maize as a part of FCS to increase the WP in the Argentinian livestock systems, although the impact of their inclusion may vary among locations according soil water holding capacity, rainfall and the high temperature stress during summer season.

The APSIM model will be a useful resource for further research on complementary forage crops based on multiple continuous FCS and perennial crops in the Argentinian and alike livestock systems. In addition, in this work we found evidence that the maize inclusion as a part of a FCS was very important to maximize DM yield and WP in some locations. However, it may increase the year-by-year variability of both DM yield and WP, particularly in locations with low soil water holding capacity, high temperatures stress and low rainfall during the spring-summer period, such as south-western Pampas.

5. Conclusions

In this paper, we evaluated the APSIM ability to predict forage DM yield and WP of multiple continuous FCS. Even though APSIM showed some weaknesses to reasonably predict seasonal DM yield and WP, *i.e.* at the crop level, it appears as a potential tool for further research on complementary forage crops based on multiple continuous FCS in the Argentinian livestock systems. The impact of initial soil conditions on the accuracy of DM yield and WP simulations seems to be critical to improve APSIM performance, especially under water-limited growth conditions.

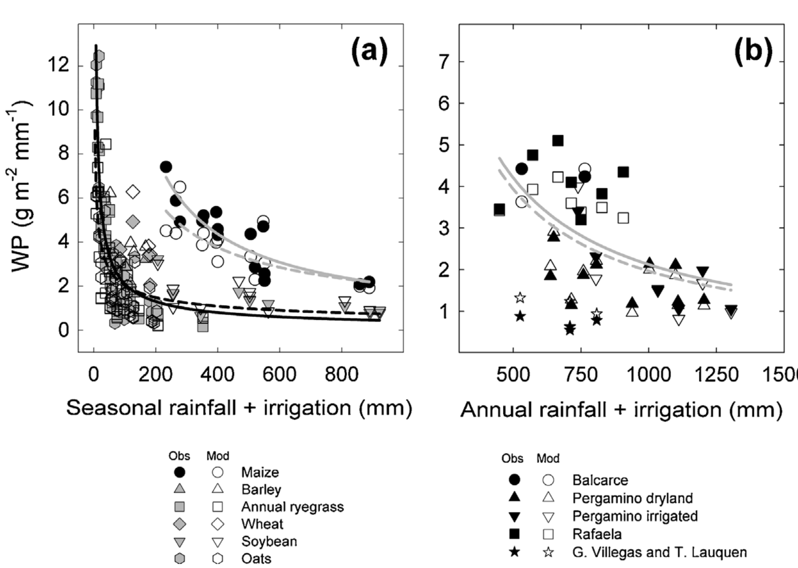

Fig. 8. Observed (closed symbols) and modelled (open symbols) Water Productivity (WP) *v.* rainfall + irrigation on a (a) seasonal- and (b) annual-base. Solid and dotted lines represent the regression lines for observed and modelled data, respectively. The regression line shown in panel b was calculated excluding data from General Villegas and Trenque Lauquen. The regression equations are shown in Table 6.

Table 6
Statistical summary of the linear regression between the observed and modelled Water Productivity (WP) of winter crops (oats, wheat, annual ryegrass and barley) and soybean, and maize *v.* cumulative seasonal annual rainfall plus irrigation and between the observed and modelled Water Productivity (WP) of forage crop sequences *v.* cumulative seasonal annual rainfall plus irrigation.

Seasonal WP v. cumulative seasonal rainfall + irrigation		
	winter crops + soybean	maize
No. Obs.	107	20
Observed data		
Adjusted logarithmic regression	$y = 385.56x^{-0.668}$	$y = 10414x^{-0.916}$
R^2	0.605	0.808
P value	< 0.001	< 0.001
Modelled data		
Adjusted logarithmic regression	$y = 151.6x^{-0.488}$	$y = 3379x^{-0.754}$
R^2	0.424	0.696
P value	< 0.001	< 0.001
Annual WP v. cumulative annual rainfall + irrigation		
	forage crop sequences	
No. Obs.	26[a]	
Observed data		
Adjusted logarithmic regression	$y = 8.65e^{-0.002x}$	
R^2	0.448	
P value	< 0.001	
Modelled data		
Adjusted logarithmic regression	$y = 9.12e^{-0.002x}$	
R^2	0.531	
P value	< 0.001	

Abbreviations: No. Obs., Number of observations.
[a] The regression functions were calculated excluding data from General Villegas and Trenque Lauquen (see Fig. 8).

The model accuracy to predict silage DM yield of individual crops (barley, wheat, soybean and maize), *i.e.* a single harvest by season, was better than to predict DM yield of frequently harvested crops (annual ryegrass, oats and barley), *i.e.* several harvest by season.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.eja.2017.10.004.

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