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CROP PRODUCTION

Parameterization of the APSIM-Oats model for simulating the growth of black oat cultivated for forage purposes under cut-and-carry management

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ABSTRACT. Studies on modeling the growth of annual crops are typically conducted for economically significant crops like soybeans, corn, and wheat. Conversely, there has been limited exploration of annual forage crops, despite their substantial importance, as they can help address forage supply shortages during periods of low production for perennial tropical forages. This study aimed to parameterize the APSIM-Oats model for simulating the growth of black oats (*Avena strigosa* Schreb cv. IAPAR 61 Ibiporã) cultivated for forage purposes and managed under a cut-and-carry system. Two experiments were conducted in 2018 and 2019 in Piracicaba, São Paulo State, Brazil, encompassing both irrigated and non-irrigated plots. Various productive, biometric, and soil moisture variables were monitored throughout the crop cycles. Parameters were manually calibrated through a trial-and-error process until the estimates closely matched the observed data. Model evaluation involved comparing observed and simulated data using statistical indices. The most favorable results were obtained for live biomass, leaf mass, and stem mass (with modeling efficiency exceeding 0.55 in the rainfed system and surpassing 0.34 for the irrigated system). Estimates of soil water content exhibited better accuracy for shallower soil layers (0 to 0.30 m). The calibration of the APSIM-Oats model for black oats yielded satisfactory estimates for live biomass under rainfed conditions. The simulations in this study represent an initial step in modeling the growth of black oats.

Keywords: decision support; forage management; crop modeling; water stress.

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Introduction

Oats are a versatile crop with multiple applications, serving as a source of cereal, feed grain, green and conserved fodder, and a winter cover crop (Suttie & Reynolds, 2004). In South America, oats are cultivated in five distinct environments: the temperate regions of Argentina and Uruguay, the temperate areas of Chile, the subtropical region of Brazil (South Brazil), certain tropical regions of Brazil (between latitudes 20° and 24° S), and specific tropical Andean regions of Bolivia, Ecuador, and Peru (Federizi & Mundstock, 2004).

Within the *Avena* genus, black oats (*Avena strigosa* Schreb) belong to the diploid subgroup of cultivated annual species (Ugrenovic et al., 2021). They possess valuable characteristics such as rusticity, adaptability to low-fertility soils, and vigorous growth (Fontaneli et al., 2012). Black oats exhibit tolerance to drought (Dial, 2014) but are less resistant to low temperatures compared to other *Avena* species (Ashford & Reeves, 2003). This species is employed for grain production for both human and animal consumption, as a forage crop for grazing or silage production, as a cover crop, and for weed control due to its allelopathic potential (Feliceti et al., 2023). Furthermore, black oats can bridge gaps in forage production in tropical pastures during the fall and winter seasons.

In a significant portion of Brazil, the seasonal period of limited growth for tropical forages is associated with low rainfall, minimum temperatures at or below 11°C, reduced photoperiod, and decreased solar radiation, which predominantly occur during the fall and winter months for most regions (Pezzopane, Santos, Cruz, Bosi, & Sentelhas, 2018; Sbrissia et al., 2017). In regions where water availability is the primary limiting factor for forage production, irrigation can enhance tropical forage productivity during the dry season. However, in areas where meteorological factors like temperature impose constraints on pasture growth, winter forages such as black oats can be integrated into exclusive systems or mixed cropping to ensure consistent forage production year-round (Sbrissia et al., 2017). This practice is widespread in South and parts of Southeast and Midwest regions of Brazil, the Argentine Pampas, South Africa, and the South and Southeast of Australia (Barth Neto et al., 2014; Fessehazion, Annandale, Everson, Stirzaker, & Tesfamariam, 2014; Kunrath et al., 2014; Ojeda, Cavigliab, Irisarrid, & Agnusdei, 2018a).

Crop models serve as valuable tools for understanding agricultural systems and the intricate interactions among soil, climate, and crops. These models can aid in the planning of forage production systems and support decision-making related to forage implementation and management. However, research on oat growth modeling has been predominantly focused on grain production.

Despite this, some studies have aimed to evaluate model simulations of annual crops for forage purposes, such as the study by Pembleton et al. (2013), who assessed the accuracy of APSIM in simulating the productivity of wheat (*Triticum aestivum* L.), white oats (*Avena sativa* L.), rapeseed (*Brassica napus* L.), sorghum (*Sorghum bicolor* L.), and annual ryegrass (*Lolium multiflorum* Lam.) in Australia. Ojeda et al. (2018b), using APSIM-Oats (Peake, Whitbread, Davoren, Braun, & Limpus, 2008), simulated the yield of white oats cultivated in sequence with soybean and corn. Notably, these studies primarily focused on white oats using APSIM, while no prior research involving crop models had been conducted for the simulation of black oats. Hence, there exists a need to parameterize the APSIM-Oats model specifically for this species.

In this context, this study aimed to parameterize the APSIM-Oats model for the simulation of the growth of black oats (*Avena strigosa* Schreb cv. IAPAR 61 Ibiporã) when cultivated for forage purposes and managed under a cut-and-carry management.

Material and methods

Experimental data

This study used data from two consecutive experiments conducted in 2018 and 2019, both carried out in the same experimental area at *Escola Superior de Agricultura "Luiz de Queiroz"* (ESALQ), located in Piracicaba, São Paulo State, Brazil (22°42'15" S, 47°37'23" W, 546 m a.s.l.). The growth cycles of these experiments occurred between May and November 2018 (Experiment 1) and between May and October 2019 (Experiment 2).

In both experiments, black oats (*Avena strigosa* Schreb cv. IAPAR 61 Ibiporã) were sown using original seeds from the Instituto de Desenvolvimento Rural do Paraná (IDR-Paraná). Two treatments were employed: irrigated and rainfed, each occupying an area of approximately 90 m², with a vegetated space of 33.7 m² separating them. Within each treatment, the usable area within the plots was subdivided into four repetitions, each with an individual area of 9 m².

Sprinkler irrigation was applied to the irrigated treatment, with soil moisture being monitored using a capacitance probe FDR (Frequency Domain Reflectometry) Diviner 2000 (SENTEK Pty Ltd., Stepney, SA, Australia). This probe measured moisture levels in the soil layer from 0 to 0.70 m, with four repetitions per treatment. Additionally, tensiometers were installed in the irrigated area at three depths (0.15, 0.30, and 0.60 m) with three repetitions. The FDR probe was also used to measure soil water content in the rainfed treatment.

Before conducting the experiments, soil samples were collected for chemical analysis at depths ranging from 0 to 0.40 m to assess the need for soil fertility correction. Physical analyses, including granulometry, soil water content at saturation point (SAT), and bulk density (BD), the same adopted by Souza et al. (2022) The limits of lower limit (LL15) and drained upper limit (DUL) were calibrated based on soil moisture data measured by the FDR probe for each depth, following the approach described by Bosi, Pezzopane, and Sentelhas (2019). DUL was adjusted considering the maximum soil moisture measured at each depth, excluding events of heavy rainfall, while LL15 was defined as the lowest soil moisture value measured after the longest interval without rain. The permanent wilting point for oats (OatsLL) was adopted as equal to LL15, and the water extraction coefficient of oats (OatsKL) was adjusted to best fit the measured and observed soil moisture. The root exploration factor (OatsXF) was considered as 1 for all depths since the soil did not present any impediments to root growth. Table S1[1] provides the physical characteristics for each soil layer.

Prior to sowing, a new soil chemical characterization was conducted in each experimental year, analyzing organic matter, organic carbon, base saturation, sum of bases, macronutrients, micronutrients, nitrate NO_3,

[1] The supplementary material (Tables S1, S2, S3, and S4) and software file simulations are available at https://github.com/deborapdsouza/ActaScientiarum.Agronomy.

and ammonium NH_4^+, for samples collected at intervals of 0.20 m, up to 0.60 m. Additionally, soil electrical conductivity and pH (in water) analyses were performed. Nitrogen fertilization was carried out immediately after each cutting during the growth cycles, with urea applied at a rate of 50 kg ha^{-1} of N, a value falling within the range of 20 to 62 kg ha^{-1} of N used in other studies (Kunrath et al., 2014; Ojeda, Pembleton, Islam, Agnusdei, & Garcia, 2016; Zhang et al., 2019).

Forage cuts were conducted when the black oats covered the entire ground or when they reached the initial reproductive phenological phase, as grain filling was not the objective when using oats for forage.

Experiment 1

Experiment 1 was sown on April 28, 2018, in rows spaced 0.20 m apart, with a sowing rate of 70 kg ha^{-1} of seeds. Soil collection for chemical characterization (Table S2) was conducted on the day preceding sowing.

The duration of the first growth cycle was 47 days, with the subsequent five cycles lasting between 30 and 32 days. In the last cycle, evaluations were conducted solely in the rainfed plots, as the plants in the irrigated plots did not recover after the previous cut (October 18, 2018).

Irrigation management considered a depth of 0.50 m and a depletion factor of 30% of the available water capacity, as these conditions were found to be optimal for oat growth (Allen, Pereir, Raes, & Smith, 1998). The moisture limits, derived from the soil water retention curve, were field capacity (θ_{FC}) at 44% and lower limit point (θ_{PWP}) at 33%. These values were used to calculate the irrigation level, and measurements with tensiometers were performed every four days.

Daily climatic data (rainfall, air temperature, solar radiation, wind) for model input were obtained from the ESALQ/USP automatic weather station, located 100 m from the experimental area, as presented in Table S3, along with irrigation data.

Crop assessments were conducted four times per growth cycle. After each cycle, a cut was performed, maintaining a stubble height of 0.07 m, in accordance with the recommendation of George et al. (2013) to ensure good regrowth and tillering for stubble heights between 0.05 and 0.10 m. Forage was cut at the stubble height within four sampling rectangles, each with an area of 0.25 m², situated in the central area of the experimental plot, avoiding edge effects. Tillers were counted in this area, and after cutting, the samples were taken to the laboratory for morphological separation. All replicates were divided into leaves, stems, inflorescences, and dead material, and dried in a forced air circulation oven to determine the percentage of dry matter. At the conclusion of each growth cycle, the entire plot's crop canopy was cut to the predefined stubble height.

The specific leaf area (SLA) was determined in all forage assessments by separating 0.05 kg of leaves from each repetition. The leaf area of these samples was measured using a leaf area meter (LI-3100C, Li-Cor®). These leaves were subsequently dried and weighed to calculate SLA.

Stubble mass below 0.07 m was assessed at the end of cycles 2, 5, and 6, collected with pruning shears and cut at the soil surface. In the laboratory, the stubble forage samples were evaluated following the same procedure employed for the forage.

Experiment 2

Between the two experiments, the experimental area was maintained under fallow management, with chemical control of invasive plants. Experiment 2 was sown on April 27, 2019, with rows spaced 0.17 m apart and a sowing rate of 100 kg ha^{-1} of seeds.

Irrigation management for Experiment 2 was consistent with that of Experiment 1. The first growth cycle had a duration of 47 days, while the remaining four cycles ranged from 30 to 36 days. The last cycle (Cycle 5) was assessed only in plots without irrigation, as the plants in the irrigated plots did not recover after the previous cut (September 24, 2019). After the last cycle in the plots without irrigation, the tillers remained alive for approximately eight days (November 1, 2019). Climatic data from the ESALQ/USP automatic weather station, provided in Table S3, were used for Experiment 2 as well.

Experiment 2 followed the same evaluation protocol as Experiment 1, with the exception that, in the first cycle, four forage assessments were conducted, while in subsequent cycles, the crop was assessed only at the end of the cycle. Stubble mass was quantified at the end of each cycle, starting from the second cycle, for both rainfed and irrigated plots.

Description of the APSIM-Oats model

Peake et al. (2008) developed the APSIM-Oats model by adapting the wheat crop model. This model was incorporated into the APSIM Next Generation version (Holzworth et al., 2018) using the Plant Modeling Framework (PMF). This framework enables the coupling of models and sub-models in a tree structure, with child branches, facilitating the construction of simulations. In the case of oats, sub-models encompass Arbitration (Structural, metabolic, reserve biomass, and nitrogen), Phenology, Structural, and those related to plant organs (Grain, Leaf, Stem, Root, and Panicle).

The phenology of the APSIM-Oats model is primarily driven by temperature, utilizing the concept of thermal time. Transitions between phenological phases are determined based on the accumulated thermal sum for each phase. Additionally, the rate of leaf appearance, calculated from the number of leaves and factors defining the cultivar's sensitivity to vernalization and photoperiod during the vegetative and initial reproductive stages, influences phenological development (Jamieson, Brooking, Porter, & Wilson, 1995).

The development of oats from sowing to maturity is divided into eight phases, marked by phenological stages: germination, emergence, end of the juvenile stage, floral initiation, flowering, the start of grain filling, end of grain filling, and physiological maturity (Zhang et al., 2019; Peake, Brown, Zyskowski, Teixeira, & Huth, 2020). Each of these phases begins and ends in specific sub-phases, as shown in Table S4.

The Structural sub-model simulates plant development based on sowing density, using information on leaf appearance, calculated from Haun's phenological stage model (Haun, 1973), to determine the number of leaves in development. The tillering rate values are also used to calculate the current stalk quantity, up to the formation of the terminal spikelet.

Model parameterization

Parameterization of the APSIM-Oats model to estimate the growth of black oats cultivar IAPAR 61 Ibiporã was conducted using data from the two experiments conducted in different years (2018 and 2019). Initially, a preliminary investigation was carried out on the cultivars previously calibrated by other authors, available in the Oats model, to identify cultivars suitable for forage use and capable of regrowth after cutting. Information was sought in cultivar catalogs to determine which cultivars met these criteria.

After identifying potential cultivars, a preliminary simulation was performed without changing any parameters. The cultivar that exhibited the closest responses to black oats was *Avena byzantina* cv. Algerian. Parameters were then calibrated using a trial-and-error approach within the Phenology, Structural, and plant organs sub-models (Leaf, Panicle, Grain, and Root).

This study also assessed the parameters corresponding to the APSIM-SoilWat model to determine their appropriateness for use in this study. SoilWat is a cascade water balance model derived from CERES (Jones & Kiniry, 1986) and PERFECT (Littleboy et al., 1992).

Model evaluation

Model performance was evaluated using various statistical measures, including the coefficient of determination (R^2) from regression analysis, the coefficient of modeling efficiency (NSE) (Nash & Sutcliffe, 1970), mean error (ME), mean absolute error (MAE), root mean square error (RMSE), Willmott's agreement index (d) (Willmott et al., 1985), and Camargo's confidence index (c) (Camargo & Sentelhas, 1997).

Results

Calibrated parameters

The first parameter value that was modified falls within the Structural sub-model, specifically related to the tillering rate during the vegetative phases, known as "Potential branching rate vegetative," which influences leaf appearance. By analyzing tiller counting data from the experiments, it became evident that the observed values in the field were lower than the response pattern provided by the standard model. Consequently, the values were adjusted, as detailed in Table 1. Additionally, adjustments were made to account for the impact of crop soil cover on the tillering rate, referred to as the "Cover effect on branching rate." The values adopted for this effect were aligned with those of the Algerian cultivar, as indicated in Table 1. Notably, potential tillering was linearly reduced when the crop cover fraction exceeded 40%, ultimately reaching 70%.

Table 1. Phenology and structural submodels parameters of APSIM-Oats, calibrated for IAPAR 61 Ibiporã black oat, evaluated between 2018 and 2019 in Piracicaba, São Paulo State, Brazil, and the original values calibrated for Algerian red oat.

Parameter	Unit	Algerian	IAPAR 61 Ibiporã
Minimum Leaf Number	Leaves	9	9
Vrn Sensitivity	Leaves	12	13
Vrn Lag	-	1	2
Pp Sensitivity	Leaves	6	6
Early Reproduct. Pp Sensitivity	Leaves	4	2
Pot. Branching Rate Vegetative	X: Leaf tips	X: 1, 2, 3, 4, 5, 6, 7, 8	X: 1, 2, 3, 4, 5, 6, 7, 8
	Y: Branching rate	Y: 0, 0, 1, 2, 4, 7, 12, 20	Y: 0, 0, 0.8, 0.5, 0.5, 0.2, 0, 0
Cover Effect on Branching Rate	X: Cover fraction	X: 0, 0.4, 0.7	X: 0, 0.4, 0.7
	Y: Age value	Y: 1, 1, 0	Y: 1, 1, 0

Parameters with several values represent a range of values for a given variable (x) and their correspondent factor values (y). The parameters presented here were those modified from the standard Oats model parameters. Vrn: vernalization, Pp: photoperiod, Pot.: Potential.

Within the Phenology sub-model, several parameter modifications were implemented. The first pertained to the minimum number of leaves parameter. In the standard APSIM-Oats model, this parameter is set at 7 leaves. However, for the Algerian cultivar, it stands at 9 leaves. The latter value was deemed the most appropriate for the black oat cultivar IAPAR 61 Ibiporã, as detailed in Table 1. Two additional parameters in the Phenology sub-model underwent adjustments. The first was related to vernalization sensitivity (Vrn Sensitivity), and the second concerned the vernalization response concerning the transition between vegetative and reproductive phases (Vrn Lag). Black oats exhibited a later onset of the reproductive phase compared to other oat species, thus necessitating a change in the Vrn Lag value from 1 to 2. This modification introduced a delay twice as long in Vegetative phase 3 (Table 1), resulting in a 21-day start date for the differentiation of the terminal spikelet or phase 4 (Table S4). Furthermore, in the Phenology sub-model, alterations were made to the parameters related to sensitivity to photoperiod (Pp Sensitivity) and sensitivity to photoperiod in the reproductive phase. The standard Oats model assigns a value of 3 leaves for Pp Sensitivity, whereas for black oats, the same value as that adopted for the Algerian cultivar, i.e., 6 leaves, was used. In the reproductive phase, the value chosen was 2 leaves, in contrast to the 4 leaves associated with the Algerian cultivar, and the standard Oats model, which considers 3 leaves (Table 1).

The values for radiation use efficiency (RUE) and the light extinction coefficient were retained at the standard values of APSIM-Oats, namely, 1.6 g MJ^{-1} and 0.45, respectively. The base temperature (Tb) was set to 0°C. Additionally, other calibrated parameters were deemed satisfactory since they enabled accurate estimation of crop variables. Some plant organ parameters were calibrated and are presented in Table 2, with no parameter changes introduced for the stem sub-model. The remaining parameters retained their original values as per the standard Oats model.

Table 2. Plant organs (Leaf, Panicle, Grain, Root) submodels parameters of APSIM-Oats, calibrated for IAPAR 61 Ibiporã black oat and the original values calibrated for Algerian red oat.

Parameter	Unit	Algerian	IAPAR 61 Ibiporã
Area Largest Leaves	mm^2	5000	5000
SLA Max.	X: Phen. stage	X: 2, 3, 4	X: 2, 3.05, 3.1, 4, 6, 7, 8
	Y: SLA mm^2 g^{-1}	Y: 25000, 30000, 40000	Y: 100, 3200, 45000, 25000, 12000, 8000, 6000
SLA Min.	X: Leaf Fn	X: 0.4, 1	X: 0.4, 1
	Y: SLA mm^2 g^{-1}	Y: 10000, 18000	Y: 6000, 6000
Multiplier for Leaf Growth Duration	-	1.75	4
Panicle Max. Organ Weight	g	0.4	0.17
Max. Potential Grain Size	g	0.032	0.015
Pre-Flowering Age Factor on root	X: Phen. stage	X; 3, 4	X; 3, 4
DM demand	Y: Fraction (0-1)	Y: 0.5, 0.2	Y: 0.2, 0.2

Parameters with several values represent a range of values for a given variable (x) and their correspondent factor values (y). The parameters presented here were those modified from the standard Oats model parameters. SLA: specific leaf area.

Noteworthy differences were observed in the experimental data for black oat morphological characteristics. One such difference concerned the maximum leaf area for the largest leaves, which was adjusted to 5000 mm^2, mirroring the value for the Algerian cultivar (Table 2). Variations were also identified in the maximum specific leaf area (SLA) for black oat, with values adjusted based on phenological phases (Table 2). Another distinct characteristic related to the minimum SLA as a function of leaf nitrogen content, with lower values compared to the Algerian cultivar. Consequently, it was modified to 6000 mm^2 g^{-1}, regardless of the amount of nitrogen present in the leaf. The last modification within the leaf sub-model pertained to leaf growth duration, with multipliers adjusted from 1.75 to 4 (Table 2).

Adjustments were also made to the maximum panicle weight and maximum grain size, drawing on experimental information and referencing the characteristics of the cultivar IAPAR 61 Ibiporã, as described by its developer (Instituto Agronômico do Paraná [IAPAR], 2000).

In the root sub-model, the demand for structural dry matter was subdivided into three phases: pre-emergence, pre-flowering, and post-flowering. The pre-flowering phase was influenced by age and phenological stage as determining factors. Initial model settings led to a decrease in value between stages 3 and 4. However, upon examining our data, it became evident that the cultivar IAPAR 61 Ibiporã exhibited late flowering. Consequently, a single value was adopted for this parameter in both phases to enhance the simulations (Table 2).

Within the APSIM-SoilWat model, adjustments were necessary for coefficients related to water evaporation in the soil (U) and the drainage coefficient (ConA). These coefficients play a crucial role in calculating soil evaporation in two stages: the first stage involves complete saturation of the soil with water, leading to soil evaporation rates matching the potential rate of evaporation. Over time, as soil water content decreases, the second stage ensues, characterized by soil evaporation rates falling below potential evaporation rates (termed the second stage) (Dalgliesh, Hochman, Huth, & Holzworth, 2016). The standard simulation values for the Oats model set U and ConA at 5, with no variation based on the time of year (summer and winter). In our study, due to the black oat plots being sown in rows, the soil surface was intermittently exposed as the crop cover varied. Consequently, adjustments were required. U values were set at 4 mm for summer, starting from October 1st, and 2 mm for winter, starting from April 1st. Concurrently, ConA values were adjusted to 2 for summer and 1.5 for winter. These adjustments aimed to account for variations in soil surface cover throughout the year. The water diffusivity constant in the soil and the diffusivity gradient were maintained in line with standard values for clay soils (averaging 54.6% clay content; Table 1), with values of 40 mm^2 day^{-1} and 16 mm^{-1}, respectively (Dalgliesh et al., 2016).

Plant variables estimates

Simulations demonstrated notable improvements following model calibration (Table 3), with particular enhancements in Stem mass, SLA, and Stem population variables. Estimates of live mass proved to be more precise (R^2) in the non-irrigated system compared to the irrigated system. When evaluating accuracy (the d index), it was consistently higher for nearly all variables in the rainfed system, except for LAI and SLA, as observed in Table 3.

For the non-irrigated system, the d index ranged from 0.54 to 0.95, the R^2 coefficient from 0.14 to 0.81, and the c index from 0.20 to 0.85. According to the classification by Camargo and Sentelhas (1997), the latter was rated as 'very bad' to 'very good,' respectively. The values of NSE were generally below 0.78 (Table 3). The least satisfactory results were evident in the simulations of LAI, dead mass, and tiller population (Table 3).

In contrast, for the irrigated system, the APSIM-Oats model struggled to predict the productive potential of live mass observed in both experiments, exhibiting a mean error of -613.4 kg ha^{-1} and an RMSE of 861.9 kg ha^{-1} (Table 3). The statistical indices indicated low agreement between estimated and observed data, with d values ranging from 0.49 to 0.83, R^2 from 0.17 to 0.82, and the 'c' index from 0.23 to 0.73. These values were classified as 'terrible' to 'very good,' respectively, following Camargo and Sentelhas (1997). The NSE values equaled or fell below 0.47 (Table 3). Similarly, as in the rainfed system, the least accurate simulations pertained to LAI.

Observing the estimates of dead mass, errors in simulations occurred throughout the entire crop cycle in both rainfed and irrigated areas, with the greatest discrepancies between observed and estimated data occurring toward the end of the cycle. These estimations generated RMSE values of 23.44 and 30.80 g m^{-2} in rainfed and irrigated areas, respectively.

Overall, it was evident that the parameterized model failed to reach the productive potential for live mass observed under irrigation during the initial two growth cycles (Figure 1a). This is corroborated by the RMSE values of 861.9 kg ha^{-1} in the irrigated system and 389.8 kg ha^{-1} in the rainfed system (Table 3).

The most significant errors in LAI estimation were observed during the first two cycles in Experiment 1 and during the 3rd and 4th cultivation cycles in Experiment 2. In the first experiment, the model was unable to reach the maximum observed LAI values, while in the second experiment, estimated values exceeded the observed ones (Figure 1b), resulting in an RMSE of 0.97 in the rainfed system and 1.15 in the irrigated system.

Table 3. Statistical indexes, coefficients, and errors for the comparison between observed data and those estimated by the APSIM-Oats model for black oat variables, before (with Algerian cultivar) and after parameterization assessed in Experiments 1 and 2, conducted between 2018 and 2019, in Piracicaba, São Paulo State, Brazil.

Variable/Unit	Data	d	R^2	c	ME	MAE	RMSE	NSE
Unit		--	--	--	g m^{-2} ou cm^2 g^{-1} (SLA)			--
Values before parameterization using Algerian cultivar								
Total mass (g m^{-2})	Rainfed	0.86	0.62	0.68	21.37	41.80	60.72	0.35
	Irrigated	0.85	0.76	0.75	-63.58	69.39	89.47	0.51
Live mass (g m^{-2})	Rainfed	0.87	0.64	0.69	13.16	37.84	52.17	0.38
	Irrigated	0.87	0.73	0.74	-51.05	58.21	78.89	0.53
Leaf mass (g m^{-2})	Rainfed	0.73	0.46	0.50	16.32	35.97	50.23	-0.83
	Irrigated	0.87	0.62	0.68	-14.64	37.91	49.80	0.44
Stem mass (g m^{-2})	Rainfed	0.85	0.59	0.65	-8.06	15.28	22.73	0.51
	Irrigated	0.75	0.62	0.59	-36.99	36.99	49.67	0.11
Leaf area index (m^2 m^{-2})	Rainfed	0.34	0.27	0.18	1.34	1.45	2.41	-15.78
	Irrigated	0.64	0.38	0.39	0.84	1.30	2.31	-1.78
Specific leaf area (cm^2 g^{-1})	Rainfed	0.54	0.18	0.23	109.057	118.543	148.636	-1.72
	Irrigated	0.76	0.52	0.54	38.144	90.408	105.061	0.43
Dead mass (g m^{-2})	Rainfed	0.36	0.07	0.10	8.20	32.31	46.28	-4.64
	Irrigated	0.66	0.23	0.32	-12.53	18.53	27.35	-0.29
Tiller population (number m^{-2})	Rainfed	0.04	0.01	0.00	2776.32	2847.71	4143.89	-515.25
	Irrigated	0.01	0.02	0.00	6684.64	6737.91	9621.55	-6677.8
Values after parameterization								
Total mass (g m^{-2})	Rainfed	0.95	0.81	0.85	1.11	26.55	36.06	0.77
	Irrigated	0.80	0.82	0.73	-83.58	83.71	103.40	0.34
Live mass (g m^{-2})	Rainfed	0.93	0.81	0.83	14.20	26.52	38.98	0.65
	Irrigated	0.83	0.74	0.71	-61.34	63.45	86.19	0.44
Leaf mass (g m^{-2})	Rainfed	0.91	0.79	0.81	8.63	16.52	25.02	0.55
	Irrigated	0.81	0.62	0.64	-32.42	39.54	52.24	0.39
Stem mass (g m^{-2})	Rainfed	0.91	0.73	0.78	4.51	14.49	20.09	0.62
	Irrigated	0.82	0.78	0.73	-29.20	29.20	39.66	0.43
Leaf area index (m^2 m^{-2})	Rainfed	0.71	0.66	0.57	0.60	0.60	0.97	-1.72
	Irrigated	0.80	0.44	0.53	-0.07	0.74	1.15	0.31
Specific leaf area (cm^2 g^{-1})	Rainfed	0.81	0.48	0.56	16.39	56.10	67.99	0.43
	Irrigated	0.78	0.52	0.56	-26.27	83.46	101.21	0.47
Dead mass (g m^{-2})	Rainfed	0.54	0.14	0.20	-13.09	16.60	23.44	-0.45
	Irrigated	0.49	0.56	0.36	-22.24	22.24	30.80	-0.63
Tiller population (number m^{-2})	Rainfed	0.67	0.54	0.49	-119.42	145.88	177.93	0.05
	Irrigated	0.54	0.17	0.23	-143.62	144.71	180.16	-1.34

Agreement index (d), coefficient of determination (R^2), Confidence index (c), mean error (ME), mean absolute error (MAE), root mean square error (RMSE), and Nash-Sutcliffe efficiency (NSE).

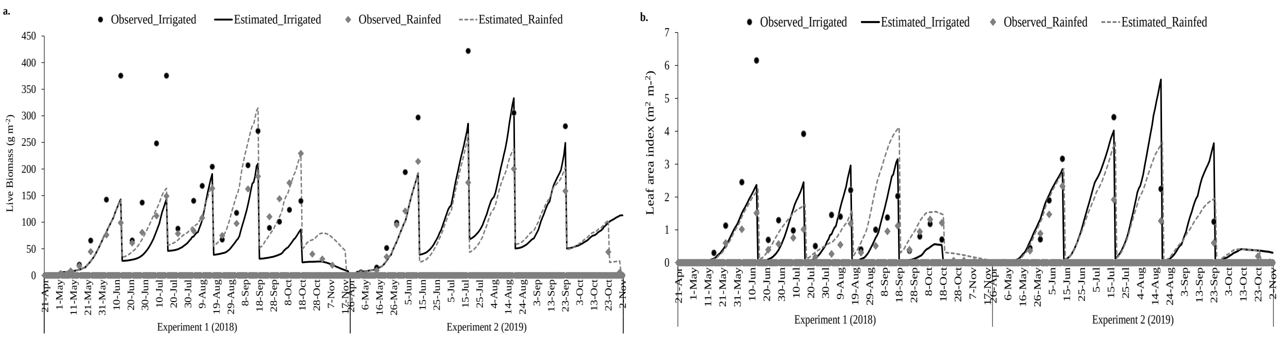

Figure 1. Time series of observed and estimated of IAPAR 61 Ibiporã black oat for the treatments irrigated and rainfed of the experiments 1 and 2, conducted in 2018 and 2019, respectively, in Piracicaba, São Paulo State, Brazil. a. live biomass; b. leaf area index.

In the rainfed system, the poorest simulations were for estimates of tiller population, consistently underestimated, with an average error of 120 tillers m^{-2} for the rainfed system and 144 tillers m^{-2} for the irrigated system (Table 3). Variables such as total mass, live mass, leaf mass, and stem mass exhibited the most accurate estimates. The model evaluation revealed larger errors for the irrigated system, characterized by underestimations. In this system, the estimates also yielded NSE indices ranging between 0.34 and 0.44 (Table 3).

The observed values of inflorescence mass (panicle + grains) remained low and were only present at the end of the final growth cycles. This was due to the primary goal of cultivating forage, with harvests occurring at the onset of the reproductive phase. Consequently, there was an insufficient amount of observed data to establish a correlation, making it impossible to calibrate the model adequately for estimating this variable. However, it is worth noting that the beginning of the panicle formation period observed in Experiment 1 (October 7, 2018) coincided with the model's predictions. In contrast, for Experiment 2, the field-observed onset of flowering (September 23, 2019) occurred earlier than the model's prediction. Nevertheless, both periods fell within the stem elongation range on the Zadock scale, from 30 to 39 (Zadoks, Chang, & Konzak, 1974).

The Zadock scale represents growth stages for cereal species and is also employed in the APSIM-Oats model. The Zadok growth stage value was calculated based on the current phenological growth stage within the model. The model uses information on germination, emergence, leaf appearance, and tiller appearance for the initial growth stages (0 to 30). For the reproductive stages, it relies on phenological stages, commencing at stem elongation and extending to stage 3, as shown in Table S4, represented on the Zadok scale by the value 30, eventually reaching 100 (maturation).

In the analysis of all data (Irrigated + Rainfed) combined, as presented in Table 4, improved results were evident for coefficients d, R^2, c, and NSE in variables such as total, live, leaf, and stem mass, as well as SLA. In correlation graphs between observed and estimated data, illustrated in Figure 2, the most substantial deviations were observed in samples with higher mass, resulting in R^2 values exceeding 0.60 for Total and Live mass.

Table 4. Statistical indexes, coefficients, and errors for the comparison between observed data and those estimated by the APSIM-Oats model for black oat variables in Experiments 1 and 2, conducted between 2018 and 2019, in Piracicaba, São Paulo State, Brazil.

Variable/Unit	d	R^2	c	ME	MAE	RMSE	NSE
Unit	--	--	--	g m^{-2} ou cm^2 g^{-1} (SLA)			--
Total mass (g m^{-2})	0.84	0.64	0.68	-37.51	52.62	74.73	0.52
Live mass (g m^{-2})	0.86	0.60	0.67	-20.25	43.36	64.93	0.55
Leaf mass (g m^{-2})	0.85	0.55	0.63	-10.09	27.02	39.82	0.49
Stem mass (g m^{-2})	0.85	0.60	0.66	-10.86	21.20	30.61	0.53
Leaf area index (m^2 m^{-2})	0.77	0.42	0.50	0.29	0.66	1.05	0.08
Specific leaf area (cm^2 g^{-1})	0.82	0.53	0.60	-3.08	68.56	84.75	0.53
Dead mass (g m^{-2})	0.50	0.12	0.17	-17.26	19.17	27.04	-0.54
Tiller population (number m^{-2})	0.64	0.42	0.41	-130.27	145.35	178.93	-0.27

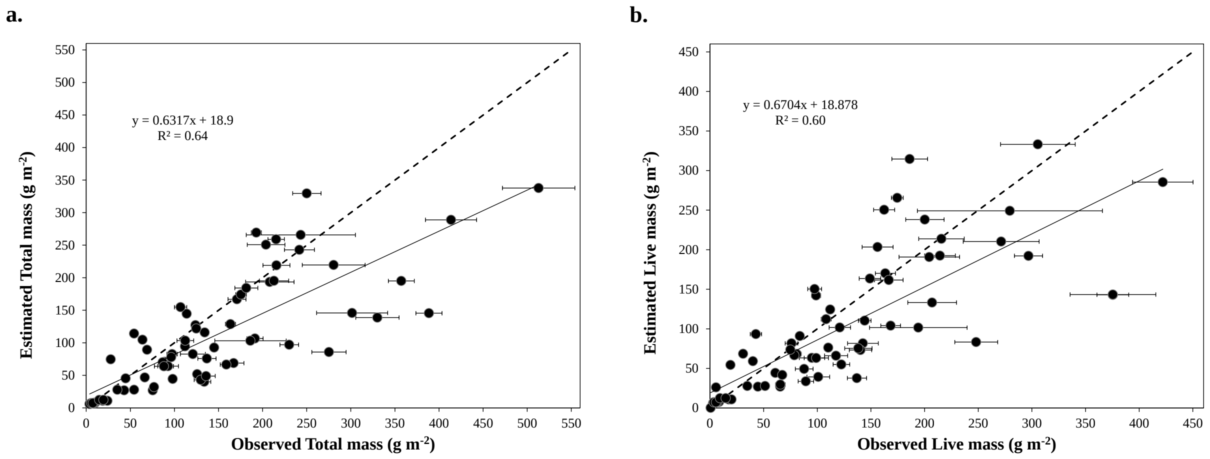

Figure 2. Relationships between observed and estimated data of IAPAR 61 Ibiporã black oat for all treatments irrigated and rainfed of experiments 1 and 2, conducted in 2018 and 2019, respectively, in Piracicaba, São Paulo State, Brazil. (a) Total mass, with regression equation: y = 0.6317x + 18.9; (b) Live mass, with regression equation: y = 0.6704x + 8.878. With a standard deviation bar.

Soil water content

Soil water contents were simulated for each 0.10 m soil layer, encompassing the profile from 0 to 0.70 m. The estimates generated by the APSIM-SoilWater model for the irrigated system, when compared to data collected by capacitive sensors in the soil, did not exhibit strong correlations when analyzed on a layer-by-layer basis, particularly at the deeper layers.

A detailed depth analysis revealed Willmott's 'd' index ranging from 0.84 to 0.96, R^2 values between 0.61 and 0.86, NSE index values from 0.08 to 0.84, and RMSE values spanning 0.95 to 3.27 cm^3 cm^{-3} (Table 5).

Moreover, in the uppermost soil layers (0 to 0.40 m), the simulations demonstrated greater efficiency compared to the layers from 0.40 to 0.70 m (Table 5).

Table 5. Statistical indexes, coefficients, and errors for the comparison between observed and estimated by the APSIM model values of soil water, for Experiments 1 and 2, conducted between 2018 and 2019, in Piracicaba, São Paulo State, Brazil.

Depth	d	R^2	c	ME (mm)	MAE (mm)	RMSE (mm)	NSE
0 - 0.10 m	0.93	0.75	0.80	0.20	2.48	3.27	0.74
0.10 - 0.20 m	0.96	0.86	0.89	0.61	1.44	1.88	0.84
0.20 - 0.30 m	0.93	0.80	0.83	0.73	1.44	1.86	0.73
0.30 - 0.40 m	0.92	0.71	0.78	0.15	0.95	1.25	0.68
0.40 - 0.50 m	0.86	0.61	0.67	0.88	1.19	1.75	0.43
0.50 - 0.60 m	0.84	0.65	0.68	-0.71	1.27	1.79	0.08
0.60 -0.70 m	0.90	0.70	0.75	0.34	0.73	0.95	0.62
0 - 0.30 m	0.97	0.89	0.91	1.54	3.76	4.97	0.88
0 - 0.70 m	0.97	0.91	0.93	2.33	5.64	6.98	0.89

Agreement index (d), coefficient of determination (R^2), Confidence index (c), mean error (ME), mean absolute error (MAE), root mean square error (RMSE), and Nash-Sutcliffe efficiency (NSE).

However, when evaluated collectively, considering the dataset from both the irrigated and rainfed systems for statistical analysis, more favorable results were obtained. In the 0 to 0.30 m layers, R^2 reached 0.89, and NSE stood at 0.88 (Table 5). In the 0 to 0.70 m layer, R^2 values of 0.91 and NSE of 0.89 were achieved, albeit with an RMSE of 6.98 $cm^3 cm^{-3}$ (Table 5).

When examining the time series of observed and estimated soil water content data in the rainfed system, certain patterns became evident (highlighted in red in Figure 3). Notably, in the layer from 0.30 to 0.70 m, soil water recharge did not align precisely with the model's simulations. In events featuring daily precipitation exceeding 38 mm, the predicted infiltration surpassed the observed values.

Upon reviewing the soil water content time series, it became apparent that the simulations exhibited increased errors starting from 08/04/2018 in Experiment 1. This coincided with a rainfall event of 59 mm and marked the commencement of a series of overestimations. These simulation errors were attributed to the APSIM-SoilWat model's inability to accurately estimate the temporal duration of this rainfall event within the day, given its time step lower than 24 hours. This, in turn, had an impact on runoff amounts (Figure 3).

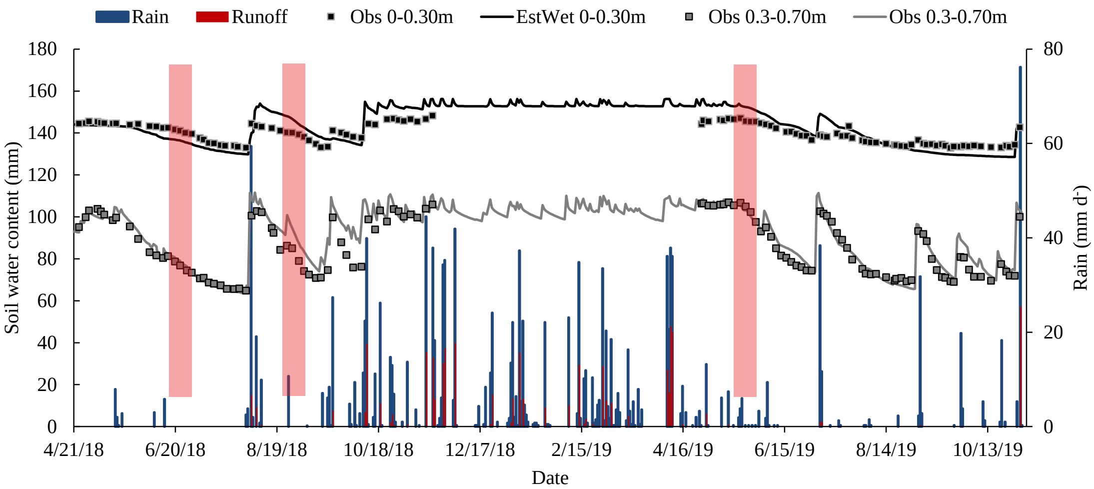

Figure 3. Time series of soil water content observed (Obs) and estimated (Est) by APSIM-*SoilWat*, in depths from 0 to 0.30 m and 0.30 to 0.70 m, in the rainfed system of Experiments 1 (2018) and 2 (2019) and rain and runoff (mm day^{-1}), conducted in Piracicaba, São Paulo State, Brazil. Arrow shows high precipitations events.

Discussion

The APSIM-Oats model was able to simulate the biomass yield of IAPAR 61 Ibiporã black oats under cut-and-carry management. However, simulations performed better for the rainfed system than for the irrigated one. These results suggest that the model can be improved to better represent crop growth in these systems.

Regarding the parameters calibrated in our study, Tb (base temperature), radiation use efficiency (RUE), and light extinction coefficient values were in line with those found in other studies. For instance, Sonego, Jamieson, Moot, and Martin (1999) and Alves (2003) reported that Tb is consistently found to be 0°C, while Alves (2003) and Zhang et al. (2019) noted that RUE ranges between 1.56 and 1.86 g MJ^{-1}. As estimated by Alves (2003) for IAPAR 61 Ibiporã black oat, light extinction coefficient varies between 0.451 and 0.677 during crop establishment and between 0.515 and 0.674 during regrowth.

For the sensitivity to photoperiod, we adopted a value of 6, which was consistent with the calibration for the Algerian cultivar and higher than that used for white oats by Zhang et al. (2019). Although both species belong to the same genus, different oat genotypes exhibit variations in their response to photoperiod regarding flowering (Locatelli, Federizzi, Milach, & McElroy, 2008).

Temperature increases can accelerate plant development, potentially reducing photoassimilate accumulation and grain filling (Liu et al., 2013), which can impact the yield of winter species cultivated for grain and seed production. However, for winter species like black oats, which are primarily grown for biomass production, temperature increases or cultivation in regions with mild winters, as in our study, may enhance biomass yields.

In a separate experiment conducted in Piracicaba, São Paulo State, Brazil, Tonato, Pedreira, Pedreira, and Pequeno (2014) monitored the yield of the black oat cultivar Common over three growth cycles. They observed similar biomass production levels in the first two growth cycles (from 1907 to 2000 kg ha^{-1}), contributing to 77% of the total crop yield, 1200 kg ha^{-1} in the third cycle. In our study, we were able to conduct four growth cycles in the irrigated plots, with the first two cycles being more productive in Experiment 1, and the second and third cycles being more productive in Experiment 2.

The cutting management strategy employed for black oats in our experiment had a noteworthy influence on crop phenology and tiller regrowth. APSIM-Oats uses thermal time to drive phenological events (Peake et al., 2020). The cutting events induced the plants to remain in the same phenological phase for an extended period, allocating photoassimilates to regrow leaves and stems. Future studies should aim to adapt the model to simulate these delays in the phenological cycle, ideally through experiments involving both cut and uncut plots to assess the duration of each phenological phase under different conditions.

Tiller population was not well estimated in our study, highlighting the need for improved simulation responses related to tillering. Black oats are annual forage crops that are frequently cut or grazed, practices known to influence regrowth potential and tillering.

Deen et al. (2003) tested the capacity of APSIM to simulate LAI and biomass in wheat and rigid ryegrass (*Lolium rigidum* Gaudin) under irrigated and rainfed conditions. The estimates for the irrigated system exhibited lower agreement with observed data than those for the rainfed system. Similarly, Ojeda et al. (2018b) evaluated crop rotations involving white oats (*Avena sativa* L.) with corn and soybeans and annual ryegrass (*Lolium multiflorum* Lam.) in sequence with corn and soybeans. They observed better biomass yield simulations under rainfed conditions, with RMSE differences of 800 kg ha^{-1} between irrigated and rainfed systems. Oat crop estimates showed a correlation coefficient of 0.77, higher than that for ryegrass and lower than that for corn and soybean. Our study aligns with these results, as black oat variables were better simulated in the rainfed system than in the irrigated one. The challenges in simulating irrigated black oats could be related to differences in partitioning between root and shoot. To investigate this hypothesis, further studies are required, with a focus on evaluating not only aboveground biomass but also root mass.

In our study, we observed that adjustments made to the parameter of sensitivity to vernalization (Vrn sensitivity) promoted a delay in the start of the reproductive phase, aligning the simulations with the panicle emergence in field experiments. However, the crop cuttings resulted in fewer panicles observed in the field than those simulated by the model. This issue could potentially be addressed in APSIM-Oats by introducing new parameters and functions to account for the effect of cutting on regrowth and reproductive development. However, this would necessitate additional experimental data.

Soil water content simulations exhibited precision and accuracy for surface soil layers up to 0.30 m but lower efficiency for deeper layers. Santos, Boote, Faria, and Hoogenboom (2019) observed a similar pattern using the CSM-CROPGRO-Perennial Forage model, estimating soil moisture in experiments with Marandu palisadegrass, with better results up to 0.20 m depth and lower efficiency for deeper layers, with a maximum error of 0.078 cm^3 cm^{-3}.

Jing et al. (2021) estimated soil moisture in wheat cultivations for several years using three models from the DSSAT platform (CERES, CROPSIM, and NWHEAT). They reported a modeling efficiency of 0.54 for the 0-1.2 m layer in continuous wheat crop cultivations and a modeling efficiency of 0.23 for cultivations with a fallow period. In our study, the simulation was continuous, encompassing the fallow period within the two crop cycles. However, the initial soil water was not adjusted for Experiment 2, leading to some estimation errors at the beginning (Figure 3). Errors in soil water estimates can influence simulation results related to biomass estimates, particularly under water deficit conditions (Ojeda et al., 2018b).

It is important to note that the results presented here are limited to the specific climatic conditions of our study location. Validation efforts in other locations could provide new perspectives and adaptations to enhance the APSIM-Oats model's performance.

Data availability statement

The data supporting this study are available in the article, accompanying online supplementary material, and software file simulations (see https://github.com/deborapdsouza/ActaScientiarum.Agronomy). Other details can be requested from the corresponding author.

Conclusion

The APSIM-Oats model can simulate IAPAR 61 Ibiporã black oat cultivation under cut-and-carry management. However, it encounters challenges in accurately estimating key parameters such as leaf area index, dead mass, and tiller population. Notably, the model exhibits higher efficiency when applied to rainfed systems compared to irrigated ones. To enhance its performance, the model requires refinements in capturing the nuances of phenology, tillering dynamics, and growth disparities between irrigated and rainfed systems. Encouragingly, the model demonstrates better accuracy in simulating soil water content within the critical depth range of 0 to 0.30 meters, which is particularly pertinent for annual crops with shallow root systems, such as black oats.

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References

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration:* Guidelines for computing crop requirements. Rome, IT: FAO. (FAO Irrigation and Drainage Paper, 56).

Alves, S. J. (2003). Dinâmica de crescimento da aveia preta sob diferentes doses de nitrogênio e ajuste de modelo matemático de rendimento potencial em função de parâmetros climáticos. *Scientia Agraria*, *4*, (1-2), 81-96, DOI: http://dx.doi.org/10.5380/rsa.v4i1.1080

Ashford, D. L., & Reeves, D. W. (2003). Use of a mechanical roller-crimper as an alternative kill method for cover crops. *American Journal of Alternative Agriculture*, *18*(1), 37-45. DOI: http://doi.org/10.1079/AJAA200232

Barth Neto, A., Savian, J. V., Schons, R. T., Bonnet, O. J. F., Canto, M. W., Moraes, A., … Carvalho, P. C. F. (2014). Italian ryegrass establishment by self-seeding in integrated crop – livestock systems: Effects of grazing management and crop rotation strategies. *European Journal of Agronomy*, *57*, 77-83. DOI: http://doi.org/10.1016/j.eja.2014.04.005

Bosi, C., Pezzopane, J. R. M., & Sentelhas, P. C. (2019). Soil water availability in a full sun pasture and in a silvopastoral system with eucalyptus. *Agroforest Systems*, *94*(2), 429-440. DOI: http://doi.org/10.1007/s10457-019-00402-7

Camargo, A. P., & Sentelhas, P. C. (1997). Avaliação do desempenho de diferentes métodos de estimativas da evapotranspiração potencial no Estado de São Paulo. *Revista Brasileira de Agrometeorologia*, *5*(1), 96-97.

Dalgliesh, N., Hochman, Z., Huth, N., & Holzworth, D. (2016). *Field Protocol to APSoil characterisations*. Version 4. Camberra, AU: CSIRO Agriculture and Food Australia.

Deen, W., Cousens, R., Warringa, J., Bastiaans, L., Carberry, P., Rebel, K., … Wang, E. (2003) An evaluation of four crop: Weed competition models using a common data set. *Weed Research*, *43*(2), 116-129. DOI: http://doi.org/10.1046/j.1365-3180.2003.00323.x

Dial, H. L. (2014). *Plant guide for black oat* (*Avena strigosa Schreb.*) (USDA-Natural Resources Conservation Service). Tucson, AZ: Tucson Plant Materials Center.

Federizi, L. C., & Mundstock, C. M. (2004). *Fodder oats*: an overview for South America. In J. M. Suttie, & S. G. Reynolds (Eds.), *Fodder oats: A world overview* (FAO Plant production and protection Series, 33). Rome, IT: FAO.

Feliceti, M. L., Possenti, J. C., Bahry, C. A., Zuanazzi, N., Ghisi, N., Santos, I. N. T., & Quisini, R. (2023). Genetic improvement of black oats: a scientometric review. *Acta Scientiarum. Agronomy*, *45*(1), 1-11. DOI: https://doi.org/10.4025/actasciagron.v45i1.60016

Fessehazion, M. K., Annandale, J. G., Everson, C. S., Stirzaker, R. J., & Tesfamariam, E. H. (2014). Evaluating of soil water balance (SWB-Sci) model for water and nitrogen interactions in pasture: Example using annual ryegrass. *Agricultural Water Management*, *146*, 238-248. DOI: https://doi.org/10.1016/j.agwat.2014.08.018

Fontaneli, R. S., Santos, H. P., Fontaneli, R. S., Oliveira, J. T., Lehmen, R. I., & Dreon, G. (2012). *Gramíneas forrageiras anuais de inverno*. Brasília, DF: Embrapa.

George, M. R., Larson-Praplan, S., Doran, M., & Tate, K. W. (2013). Grazing nassella. *Rangelands*, *35*(2), 17–21. DOI: https://doi.org/10.2111/RANGELANDS-D-12-00077.1

Haun, J. R. (1973). Visual quantification of wheat development. *Agronomy Journal*, *65*(1), 116-119. DOI: https://doi.org/10.2134/agronj1973.00021962006500010035x

Instituto Agronômico do Paraná [IAPAR]. (2000). *Aveia Preta IAPAR 61 IBIPORÃ*. Londrina, PR: IAPAR.

Jamieson, P. D., Brooking, I. R., Porter, J. R., & Wilson, D. R. (1995). Prediction of leaf appearance in wheat: a question of temperature. *Field Crops Research*, *41*(1), 35-44. DOI: https://doi.org/10.1016/0378-4290(94)00102-I

Holzworth, D., Huth, N. I., Fainges, J., Brown, H., Zurcher, E., Cichota, R., Verrall, S., Herrmann, N.I., Zheng, B., Snow, V. (2018). Environmental Modelling & Software APSIM Next Generation : Overcoming challenges in modernising a farming systems model. *Environmental Modelling and Software*, 103, 43–51. DOI: https://doi.org/10.1016/j.envsoft.2018.02.002

Jing, Q., Mcconkey, B., Qian, B., Smith, W., Grant, B., Shang, J., Liu, J., ... Luce, M. St (2021). Assessing water management effects on spring wheat yield in the Canadian Prairies using DSSAT wheat models. *Agricultural Water Management*, *244*, 106591. DOI: https://doi.org/10.1016/j.agwat.2020.106591

Jones, C. A., & Kiniry J. R. (1986). *CERES-Maize: A simulation model of maize growth and development*. College Station. Austin, TX: Texas A&M University Press.

Kunrath, T. R., Cadenazzi, M., Brambilla, D. M., Anghinoni, I., Moraes, A., Barro, R. S., & Carvalho, P. C. F. (2014). Management targets for continuously stocked mixed oat × annual ryegrass pasture in a no-till integrated crop – livestock system. *European Journal of Agronomy*, *57*, 71-76. DOI: https://doi.org/10.1016/j.eja.2013.09.013

Littleboy, M., Silburn, D. M., Freebairn, D. M., Woodruff, D. R., Hammer, G. L., & Leslie, J. K. (1992). Impact of soil erosion on production in cropping systems. Development and validation of a simulation model. *Soil Research*, *30*(5), 757-774. DOI: https://doi.org/10.1071/SR9920757

Liu, W., Yu, K., He, T., Li, F., Zhang, D., & Liu J. (2013). The low temperature induced physiological responses of avena nuda L., a cold-tolerant plant species. *The Scientific World Journal*, *2013*(1), 1-7. DOI: https://doi.org/10.1155/2013/658793

Locatelli, A. B., Federizzi, L. C., Milach, S. C. K., & McElroy, A. R. (2008). Flowering time in oat: Genotype characterization for photoperiod and vernalization response. *Field Crops Research*, *106*(3), 242-247. DOI: https://doi.org/10.1016/j.fcr.2007.12.006

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I - A discussion of principles. *Journal of Hydrology*, *10*(3), 282-290. DOI: https://doi.org/10.1016/0022-1694(70)90255-6

Ojeda, J. J., Pembleton, K. G., Islam, M. R., Agnusdei, M. G., & Garcia, S. C. (2016). Evaluation of the agricultural production systems simulator simulating Lucerne and annual ryegrass dry matter yield in the Argentine Pampas and south-eastern Australia. *Agricultural Systems*, *143*, 61-75. DOI: https://doi.org/10.1016/j.agsy.2015.12.005

Ojeda, J. J., Caviglib, O. P., Irisarrid, J. G. N., & Agnusdei, M. G. (2018a). Modelling inter-annual variation in dry matter yield and precipitation use efficiency of perennial pastures and annual forage crops sequences. *Agricultural and Forest Meteorology*, *259*(2017), 1-10. DOI: https://doi.org/10.1016/j.agrformet.2018.04.014

Ojeda J. J, Pembleton, K. G., Caviglia, O. P., Islam, M. R., Agnusdei, M. G., & Garcia, S. C. (2018b). Modelling forage yield and water productivity of continuous crop sequences in the Argentinian Pampas. *European Journal of Agronomy*, *92*, 84-96. DOI: https://doi.org/10.1016/j.eja.2017.10.004

Peake, A., Whitbread, A., Davoren, B., Braun, J. & Limpus, S. (2008). The development of a model in APSIM for the simulation of grazing oats and oaten hay. In M. Unkovich (Ed.), *"Global Issues. Paddock Action." Proceedings of 14th Agronomy Conference*. Adelaide, AU: South Australian Agronomy Conference.

Peake, A., Brown, H., Zyskowski, R., Teixeira, E. I., & Huth, N. (2020). *The APSIM oats model*. Retrieved on Aug. 10, 2023 from https://apsimdev.apsim.info/ApsimX/Releases/2020.11.20.5818/Oats.pdf

Pembleton, K. G., Rawnsley, R. P., Jacobs, J. L., Mickan, F. J., Cullen B. R., & Ramilan, T. (2013). Evaluating the accuracy of the Agricultural Production Systems Simulator (APSIM) simulating growth, development, and herbage nutritive characteristics of forage crops grown in the south-eastern dairy regions of Australia. *Crop & Pasture Science*, *64*(2), 147-164. DOI: https://doi.org/10.1071/CP12372

Pezzopane, J. R. M., Santos, P. M., Cruz, P. G., Bosi, C., & Sentelhas, P. C. (2018). An integrated agrometeorological model to simulate Marandu palisade grass productivity. *Field Crops Research*, *224*, 13-21. DOI: https://doi.org/10.1016/j.fcr.2018.04.015

Santos, M. G., Boote, K. J., Faria, R. T., & Hoogenboom, G. (2019). Simulation of productivity and soil moisture under Marandu palisade grass using the CSM-CROPGRO-Perennial Forage model. *Crop and Pasture Science*, *70*(2), 159-168. DOI: https://doi.org/10.1071/CP18258

Sbrissia, A. F., Duchini, P. G., Echeverria, J. R., Miqueloto, T., Bernardon, A., & Américo, L. F. (2017). Animal production on cultivated pasturelands in regions of temperate climate of Latin America. *Archivos Latinoamericanos de Producción Animal*, *25*(1-2), 45-58.

Sonego, M., Jamieson, P. D., Moot, D. J., & Martin, R. J. (1999). Development and growth of oat leaves at different temperatures and nitrogen levels. *Agronomy New Zeland*, *29*, 75-81.

Souza, D. P. de, Mendonça, F. C., Bosi, C., Pezzopane, J. R. M., & Santos, P. M. (2022). APSIM-Tropical Pasture model parameterization for simulating Marandu palisade grass growth and soil water in irrigated and rainfed cut-and-carry systems. *Grass and Forage Science*, 77(3), 216–231. DOI: https://doi.org/10.1111/gfs.12560

Suttie, J. M., & Reynolds, S. G. (2004). *Fodder oats: a world overview* (FAO Plant Production and Protection Series, 33). Rome, IT: FAO.

Tonato, F., Pedreira, B. C., Pedreira, C. G. S., & Pequeno, D. N. L. (2014). Aveia preta e azevém anual colhidos por interceptação de luz ou intervalo fixo de tempo em sistemas integrados de agricultura e pecuária no Estado de São Paulo. *Ciência Rural*, *44*(1), 104-110. DOI: https://doi.org/10.1590/S0103-84782014000100017

Ugrenovic, V., Popovic, V., Ugrinovic, M. Filipovic, V., Mackic, K., Ljubicic, N., ... Lakic, Ž. (2021). Black Oat (*Avena strigosa* Schreb.) ontogenesis and agronomic performance in organic cropping system and pannonian environments. *Agriculture*, *11*(1), 1-14. DOI: https://doi.org/10.3390/agriculture11010055

Willmott, C. J., Ackleson, S. G., Davis, R. E., Feddema, J. J., Klink, K. M., Legates, D. R., ... Rowe, C. M. (1985). Statistics for the evaluation and comparison of models. *Journal of Geophysical Research*: *Oceans*, *90*(C5), 8995-9005. DOI: https://doi.org/10.1029/JC090iC05p08995

Zadoks, J. C., Chang, T. T., & Konzak, C. F. (1974). A decimal code for the growth stages of cereals. *Weed Research*, *14*(6), 15-421. DOI: http://dx.doi.org/10.1111/j.1365-3180.1974.tb01084.x

Zhang, Y., Zhang, L., Yang, N., Huth, N., Wang, E., Werf, W., ... Anten, N. P. R. (2019). Optimized sowing time windows mitigate climate risks for oats production under cool semi-arid growing conditions. *Agricultural and Forest Meteorology*, *266-267*, 84-197. DOI: https://doi.org/10.1016/j.agrformet.2018.12.019.