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EDITED BY
Maura Silva,
Federal Rural University of Rio de Janeiro, Brazil

REVIEWED BY
Karun Kaniyamattam,
Texas A&M University, United States
Fabiana Pereyra-Goday,
Instituto Nacional de Investigación Agropecuaria (INIA), Uruguay
Régio Marcio Toesca Gimenes,
Federal University of Grande Dourados, Brazil

*CORRESPONDENCE
Antônio Carlos Reis de Freitas
carlos.freitas@embrapa.br

†These authors have contributed equally to this work

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Carbon footprint of beef cattle production in integrated systems of the Brazilian Cerrado

Antônio Carlos Reis de Freitas[1*†], Roberto Giolo de Almeida[2†], Manuel Claudio Motta Macedo[2†], Rodrigo da Costa Gomes[2†], Davi José Bungenstag[2†], Valdemir Antônio Laura[2†], Caroline Carvalho de Oliveira[3†], Eliane Gonçalves Gomes[4†], Vanderley Porfírio-da-Silva[5†], Bruno José Rodrigues Alves[6†] and Beata Emoke Madari[7†]

[1]Embrapa Maranhão, São Luis, Brazil, [2]Embrapa Beef Cattle, Campo Grande, Brazil, [3]Federal University of Pernambuco, Recife, Brazil, [4]Embrapa Soils, Rio de Janeiro, Brazil, [5]Embrapa Forestry, Colombo, Brazil, [6]Embrapa Agrobiology, Rio de Janeiro, Brazil, [7]Embrapa Rice and Beans, Santo Antônio de Goiás, Brazil

Prediction of soil organic carbon (SOC) stocks, tree carbon stocks, enteric emissions, and beef production is essential for evaluating low-carbon livestock systems. However, there is still limited information regarding the use of mechanistic models capable of simultaneously integrating these components under tropical integrated production systems. This study evaluated the performance of the Manure-DeNitrification-DeComposition (Manure-DNDC) model to simulate SOC stocks and estimate the emission intensity of beef production in integrated crop-livestock-forest (ICLF) systems of the Brazilian Cerrado. Methods: Experimental data collected from 2008 to 2016 at the Embrapa Beef Cattle experimental site in Campo Grande, Mato Grosso do Sul, Brazil, were used to evaluate native vegetation (NV), integrated crop-livestock (ICL), and integrated crop-livestock-forest systems (ICLF14 and ICLF22). The Manure-DNDC model was applied to simulate SOC dynamics, beef production, and enteric emissions, and model estimates were compared with measured field data. Results: The model showed good agreement between simulated and measured SOC stocks, beef production, and enteric emissions across the evaluated systems. Annual additional SOC stocks were estimated at -0.025 Mg CO2e ha^{-1} year-1 for NV, +1.06 Mg CO_2e ha^{-1} year^{-1} for ICL, +0.83 Mg CO_2e ha^{-1} year^{-1} for ICLF22, and +0.30 Mg CO_2e ha^{-1} year^{-1} for ICLF14. Emission intensity was estimated at 7.7 kg CO_2e kg^{-1} live weight gain (LWG) for ICL, whereas negative net values were observed for ICLF22 (-31.5 kg $CO2_2$ kg^{-1} LWG) and ICLF14 (-69.5 kg CO_2e kg^{-1} LWG).Discussion: The Manure-DNDC model satisfactorily represented greenhouse gas (GHG) emissions and carbon sequestration under Brazilian Cerrado conditions. The findings highlight the potential of ICLF systems to mitigate GHG emissions and reduce the carbon footprint of beef production.

KEYWORDS
beef production, enteric emissions, food systems, greenhouse gases, process model

1 Introduction

Integrated crop-livestock-forestry (ICLF) systems are designed to enhance synergy and circularity relative to specialized systems, improving economic performance by combining crop, livestock, and tree components with complementary short-, medium-, and long-term returns (Alves et al., 2017). Increased above- and below-ground residue inputs in these intensified systems promote the capture of atmospheric CO2 and its storage into the soil (Ribeiro et al., 2023).

Enhanced cattle performance on improved pastures through integrated systems allows higher stocking rates and reduces time to slaughter. As a result, the reduction in GHG emission intensity of livestock products has been a focus of investigation within this production strategy (Figueiredo et al., 2017).

In general, the greenhouse gas (GHG) emission intensity, or carbon footprint, of beef has been shown to decline due to greater increases in animal performance compared to the rise in GHG emissions from the inputs and operations required to intensify pasture production (Cardoso et al., 2016; Figueiredo et al., 2017; Oliveira et al., 2024). Nonetheless, absolute GHG emissions per unit of land increase significantly, and the urgent need to mitigate emissions to keep the global temperature rise below 2 °C (IPCC, 2014) is often overlooked, despite a more environmentally efficient food supply. However, a complete or partial assessment of livestock carbon footprint requires accounting for the potential offset of enteric CH4 emissions, while also considering other sources such as N2O emissions from excreta and fertilizer use. In addition, soil carbon sequestration or carbon storage in tree biomass may reduce net GHG emissions per unit of land and contribute to more sustainable production systems (Souza Filho et al., 2019).

Diet quality directly affects CH_4 production in the rumen by influencing fermentation pathways and hydrogen production. There is also a strong relationship between dry matter intake (DMI) and enteric emissions (EEs), with higher intake generally leading to greater absolute CH4 production. Indeed, DMI alone can explain up to 64% of the variability in methane emissions (Evangelista et al., 2024). At the same time, diets with higher digestibility and greater proportions of concentrates tend to reduce enteric CH4 emissions per unit of animal product, whereas low-quality forages generally increase emissions (Congio et al., 2021; Tseten et al., 2022).

Enteric emissions refer to methane (CH_4) produced during the fermentation process in the ruminant digestive system (e.g., cattle). The main factors influencing enteric emissions are: animal species and class, diet composition, dry matter intake (DMI), physiological phase, genetic factors, environmental conditions, and the use of additives and supplements. There is a direct correlation between the amount of feed consumed and methane production (Evangelista et al., 2024).

Soil carbon (soil C) accumulation may partially offset GHG emissions. However, its magnitude depends on edaphoclimatic conditions and land-use history, in addition to the current use, making mechanistic models the most suitable tools for prediction. In contrast, carbon stored in trees can be more easily estimated using allometric models (Latifah et al., 2021). The DeNitrification-DeComposition (DNDC) simulation model computes C and N biogeochemistry in agricultural ecosystems (DNDC, 2017). It predicts crop yield, soil nutrient fluxes, reservoirs, and GHG emissions (DNDC, 2017). Since its initial release, the model has undergone modifications to adapt to different agroecosystems, which have been incorporated into various versions, as summarized by Gilhespy et al. (2014). As these authors observed, the model is widely adopted due to its user-friendly interface, despite reported difficulties in accessing the source code for deeper modifications beyond the standard calibration process, which are required in certain situations, among other, less critical issues. Nonetheless, successful model validations have been conducted for different regions and production systems in Brazil, but primarily for simulating N_2O and CH_4 emissions (Costa et al., 2014; Bogaerts et al., 2017).

In this paper, we evaluated the performance of Manure-DNDC version 9.5 for predicting soil organic carbon (SOC) stocks, GHG emissions, and beef production across different integration systems at a single location in the Brazilian Cerrado biome. In addition to this evaluation, we propose a performance score that combines these three outputs and identifies the best-performing integrated system according to this metric. Furthermore, we consider the contribution of carbon stocks from the tree component to reducing emission intensity in ICLF systems.

2 Materials and methods

2.1 Study area

We used data from the Low Carbon Livestock Platform (Macedo et al., 2021), as listed in Table 1, from 2008 to 2016. The experiment was conducted at the Embrapa Beef Cattle site in Campo Grande City, Mato Grosso do Sul (MS), Brazil (20°24′54.9″ S, 54°42′25.8″ W, altitude 530 m), which included an area of native vegetation (NV), an integrated crop-livestock (ICL) system and two integrated crop-livestock-forestry systems (ICLF22 and ICLF14, respectively). The ICLF systems were planted with eucalyptus trees (*Eucalyptus grandis* ×

TABLE 1 Soil properties at 0–20 cm under NV, ICL, ICLF22, and ICLF14 at the Embrapa site in Campo Grande, Mato Grosso do Sul (MS), Brazil.

System	pH	Texture (%)			Soil density (g cm^{-3})		C (%)		SOC stocks (Mg C ha^{-1})	
	(H_2O)	Clay	Silt	Sand	2008	2016	2008	2016	2008	2016
NV	4.18	40.3	9.2	50.5	1.04	1.06	2.23	2.19	46.2	46.2
ICL	4.68	42.6	13.4	44.0	1.11	1.15	1.79	2.03	37.1	43.0
ICLF22	4.62	38.6	11.7	49.8	1.18	1.20	1.64	1.79	34.0	37.8
ICLF14	4.60	31.1	11.2	57.7	1.29	1.36	1.49	1.43	30.9	30.3

Source: adapted from Macedo et al. (2021).

Eucalyptus urophylla; H13 clone) in a single row, with the following arrangements: ICLF14 (14 m × 2 m) with 357 trees ha^{-1} and ICLF22 (22 m × 2 m) with 227 trees ha^{-1}. The tree rows are oriented at 69.6°, heading northwest (NW). In both systems, the forage component is *Brachiaria brizantha* cv. BRS Piatã. The trial had four 1.4 ha paddocks for each system.

2.2 Description of the beef production systems

Nellore cattle with a mean age of 8–10 months and an initial live weight of 160–210 kg were used. Each system had 24 animals, managed under continuous grazing and variable stocking rate, targeting a forage offer of 6% of live weight (6 kg of dry matter per 100 kg of live weight per day). Two tester animals were kept per paddock (eight per system) throughout the experimental period, and buffer animals were added according to the pasture support capacity at the time of weighing, using the "put-and-take" technique (Mott and Llucas, 1952). All paddocks were equipped with a trough for dry minerals as well as drinking troughs in adequate quantity and size for supply ad libitum. To evaluate performance and adjust the stocking rate, animals were weighed on a digital scale at 28-day intervals after a 12-h fast. Table 2 presents data on pasture sward height (PSH), forage dry mass (FDM), forage crude protein (CP) content, stocking rate (SR), average daily gain (ADG), and live weight gain (LWG) by area measured in each of the integrated systems (ICL, ICLF22, and ICLF14) for the rainy and dry seasons.

2.3 Soil sampling and soil C stock calculation

Soil sampling was conducted annually from 2008 to 2016 to a depth of 20 cm. In the NV and ICL system, samples were collected along a single transect in each replicate, consisting of 10 single soil samples. In the ICLF systems, one transect close to the tree rows and another in the middle of the pasture strip between tree rows were established, each composed of 10 single soil samples. All samples were analyzed for total C using an automated analyzer (Sumika/Shimadzu). Soil bulk density (SD) was measured in all paddocks down to 100 cm in 2014 and 2016. From this sampling campaign, a pedotransfer function based on soil texture, pH ($CaCl_2$), and C content was developed to estimate SD for all years. The estimated soil density values showed strong agreement with measured data (not shown), with Pearson correlation coefficients exceeding 0.80 (Macedo et al., 2021). The equation used is presented below, and was applied to calculate soil C stocks in the 0–20 cm soil layer for each land use.

$$\text{SD} = 1.2898 - \left(0.0131^{*}\text{Clay}\right) - \left(0.10868^{*}\text{Carbon}\right) + \left(0.1240^{*}\text{pH CaCl}_2\right)$$

Soil C stocks in the 0–20 cm soil layer were calculated for each treatment using a soil mass correction approach (Sisti et al., 2004). This correction accounts for differences in soil mass among treatments due to tillage-induced compaction and cattle trampling, using soil mass under native vegetation as a reference (Carvalho et al., 2009). Standardized emissions estimates were expressed as CO_2 equivalents (CO_2e), based on a 100-year global warming potential (IPCC, 2014).

2.4 Tree measurement and fixed carbon estimates

The annual dendrometric inventory was conducted from 2010 through 2016, with a sampling intensity of 10% of each plot. Tree height (Ht) was measured using a digital hypsometer (Haglöf HEC-2), and diameter at breast height (DBH, 1.30 m) was measured using a mechanical caliper. Descriptive statistics for tree height and DBH, including mean, standard deviation, and variance, are presented in Table 3 and indicate a normal distribution by the Shapiro–Wilk test. Wood volume and C content in tree biomass were estimated using the Sis_ILPF software (de Oliveira et al., 2018; Oliveira, 2021). This tool estimates wood volume based on tree DBH and Ht, as well as stand characteristics such as spatial arrangement, tree density, planting uniformity, volume equations, site index, tree age, assortment equations, and thinning and harvesting schedules The *p*-values of the *t*-test statistic in Table 3 indicate the absence of evidence of a significant difference in the tree stock CO_2 stock and also in the volume of wood per hectare in booth ICLF systems analyzed (p-values $\geq$ 0.05). Additionally, the equality of variances test (using F-statistic) does not indicate a significant difference in the two variances for the tree carbon stock (TCS) variable in both situations (p-value $\geq$0.335).

2.5 DNDC model

The DeNitrification-DeComposition (DNDC) model is a process-based simulation model that describes C and N dynamics in

TABLE 2 Animal production parameters of integrated systems (ICL, ICLF22, and ICLF14), in the period 2013–2016 at the Embrapa site in Campo Grande, Mato Grosso do Sul (MS), Brazil.

System	PSH (cm)	FDM (kg ha^{-1})	CP (%)	SR (AU ha^{-1})	ADG (kg day^{-1})	LWG (kg ha^{-1})
Rainy season (October–April)						
ICL	64.67	2,718	10.43	2.23	0.505	303
ICLF22	65.67	1,897	12.73	1.89	0.437	234
ICLF14	62.33	1,209	13.47	1.47	0.437	148
Dry season (May–September)						
ICL	52.00	2,268	6.65	1.89	0.243	99
ICLF22	47.00	1,283	8.83	1.28	0.211	40
ICLF14	43.70	633	9.00	0.79	0.180	18

Source: adapted from Almeida et al. (2021).

TABLE 3 Tree measurement and fixed carbon estimates in ICLF22 and ICLF14 systems at the Embrapa site in Campo Grande, Mato Grosso do Sul (MS), Brazil.

System	DBH (cm)			Ht (m)			Vol. ha^{-1} (m^3)			TCS (Mg·CO$_2$e ha^{-1})			*F*
	Mean ± SE	Variance	*p*	Mean ± SE	Variance	*p*	Mean ± SE	Variance	*p*	Mean ± SE	Variance	*p*	
ILPF 14	20.5 ± 2.95	61.00	0.321	20.3 ± 2.82	55.60	0.514	124.6 ± 34.63	8,395.1	0.834	97.8 ± 27.17	5,168.6	0.836	1.01
LPF 22	20.8 ± 2.99	62.60	0.472	20.5 ± 2.85	56.90	0.495	82.6 ± 23.46	3,853.3	0.868	64.8 ± 18.42	2,374.8	0.868	

SE, standard error.

agroecosystems. In this study, the Manure-DNDC version was applied to estimate SOC stocks, GHG emissions, and beef production in the integrated systems, allowing the calculation of emission intensity (EI) of beef production on an annual basis:

$$\mathrm{EI} = \left[\begin{array}{c} \text{kg CO}_2\text{e} \\ \text{emitted} - \end{array} \left(\begin{array}{l} \text{kg CO}_2\text{e} \\ \text{stored in soil} \\ +\text{kg C stock in} \\ \text{aboveground} \\ \text{tree biomass} \end{array} \right) \right]^{*} \begin{array}{l} \text{kg live} \\ \text{weight gain}\,(\text{LWG})^{-1} \end{array}$$

We applied the model yearly.

The Manure-DNDC model was parameterized and calibrated using an initial configuration developed to represent manure dynamics at the farm scale. Model calibration was performed by comparing simulated outputs with measured data and iteratively adjusting input variables to minimize the differences between the measured and simulated values (Table 4). Model performance was evaluated using root mean squared error (RMSE) and the coefficient of determination (r).

To evaluate the performance of the DNDC model in the present case study, we assessed whether simulated values of SOC stocks, GHG emissions, and beef production were representative of field measurements, across the three integrated production systems (ICL, ICLF22, and ICLF14) over the period of 2008–2016.

Input data required for site-scale simulations included: (a) daily climate data collected at the on-site weather station; (b) soil properties, including bulk density, clay content, initial SOC content, and pH; (c) farm management practices, including planting date, harvest date, and fertilization time; (d) animal type and population; meat production; intake protein and feed quality.

2.6 Uncertainty analysis

The complete dataset, considering simulated and measured variables and the four plots in each of the three integrated production systems, should comprise 585 observations. However, SOC stocks were not measured in 2011, 2013, and 2015. In 2008 and 2009, beef production and GHG emissions were neither simulated nor measured because the animals were introduced to the system only in May 2010. After excluding years with missing paired simulated-measured values, the dataset was reduced to 96 observations (48 in each category) for 2010, 2012, 2014, and 2016.

We run statistical tests of group differences to determine whether simulated and measured values are similar. Group means comparison tests assess whether the values obtained in each group are independent (i.e., significantly different means), assuming that the values are normally distributed within each group. As there were only two groups, we ran the *t*-test for each variable (Morettin and Singer, 2023).

We calculated a performance score that aggregated the three outputs of the evaluated production systems into a single measure using Data Envelopment Analysis (DEA) models. As Gomes et al. (2008) point out, although statistical methods can handle multidimensional responses, defining a one-dimensional response makes interpretation easier. DEA was originally proposed to measure the efficiency of production units considering their multiple inputs and multiple outputs, by constructing an empirical efficient frontier. Here, we used DEA

TABLE 4 Inputs and outputs parameters for Manure-DNDC simulation.

Inputs parameters	
Category	Description
Climate	Daily weather data: maximum and minimum air temperature, precipitation
stock	Livestock type (beef and cow) and heads (animal ha^{-1}) Feed rate (kg dry matter/head/day) and crude protein and P concentration (%) in feed
Pasture and crop field	Pasture type, areas (ha), and planting/harvest dates Fertilization: fertilizer types (urea), application dates, application rate (kg N ha^{-1}) Crop types (corn and soybean), areas (ha), planting/harvest dates, and crop rotation Fertilization: fertilizer types (urea), application dates, and application rate (kg N ha^{-1})
Trees	Tree age Site index Stand density Diameter at breast height (DBH) Spatial arrangement of trees (spatial design)

Outputs parameters	
Category	Description
Livestock	Daily beef production and/or weight gain
	Daily fluxes of enteric CH_4 and N_2O
Pasture and crop field	Daily fluxes of CO_2 from animal respiration Daily fluxes of CH_4, N_2O, NH_3, NO, N_2 and CO_2 from field soil Daily fluxes of nitrate leached from field soil Daily fluxes of P loss from field soil through runoff Daily N, P, and water uptake by crops Daily soil temperature, moisture, oxygen, pH, and Eh profiles Daily soil ammonium, nitrate, and P profiles Daily soil organic carbon (SOC) profiles Daily net ecosystem C exchange (C sequestration)
Trees	Basal area (m^2), Total volume (m^3) Annual volume (m^3), Tree carbon stock (Mg·CO_2e)

Source: adapted from Li et al. (2012) and Oliveira (2021).

according to the approaches of Caporaletti et al. (1999) and Lovell and Pastor (1999). We formulated a DEA model without inputs, that is, with a single unitary input. For each of the k observations (DMU in DEA jargon) the mathematical programming model of DEA is calculated as follows (Caporaletti et al., 1999): Max $\theta_0 = \sum_r u_r y_{r0}$, subjected to $\sum_r u_r y_{rk} \leq 1, \forall k, u_r \geq 0, \forall r$, where: θ_0 is the efficiency (or performance score) of the observation under evaluation (DMU 0); y_{rk} is the output r of DMU k, $r = 1\ldots s$, and u_r is the weight assigned to the output r. Each observation k maximizes its performance score (the weighted average of the outputs for the DMU 0), subject to the constrained that the weighted average of all DMUs' outputs must be at most 1 (first constraint), with all weights non-negative (second constraint). The adaptation of these models for evaluating experimental designs is discussed in Gomes et al. (2008) and was used, for instance, by Gomes et al. (2012) and Freitas et al. (2022).

We considered only the years for which there was a complete data set for all output variables in both groups. We also assumed that each plot is an observation. For example, in 2010, for the ICL production system, there were four plots, so we treated them as four independent observations. The years with valid data for both groups are 2010, 2012, 2014, and 2016, with four plots in each of the three production systems, yielding 48 observations per group.

The outputs of the DEA models are the three response variables of the experiment: beef production, SOC stocks, and GHG emissions. The latter is seen in DEA as an undesirable output, that is, a product that should be minimized. This type of output can be modeled in DEA in different ways (Halkos and Petrou, 2019). Here, we have chosen the approach in which this variable is modeled as its inverse value. It has the advantage of not having to choose between increasing production and reducing environmental impacts when calculating the efficiency score, since all variables are treated as outputs (variables that we want to maximize). It is worth mentioning that, as discussed by Lovell and Pastor (1999), in the unitary input DEA formulation, as in our case, we do not need to choose between constant and variable returns to scale, as the measures are coincident in this case.

To test the effects of years and production systems on the performance scores, we fit a fractional regression model, as defined by Papke and Wooldridge (1996). The fractional regression in our case assumes

TABLE 5 Tests for equal group means and equal variances: *p*-value results.

Tests	Variables	Global	ICL	ICLF14	ICLF22
Equal means	Beef production	0.8729	0.9139	0.9746	0.8580
	SOC stocks	0.0177	0.0593	0.0014	0.3974
	GHG emissions	0.0005	0.0028	0.1683	0.0843
Equal variance	Beef production	0.8007	0.7935	0.971	0.9858
	SOC stocks	<0.0001	<0.0001	0.9803	0.0306
	GHG emissions	<0.0001	0.0009	0.0063	0.0005

$E\left(\hat{\theta}_n\left(y_j|z_j\right)\right)=G\left(\delta' z_j\right)$, where $G(.)$ is a non-linear function with values in (0, 1], θ is the DEA score, y is the vector of outputs, z is the vector of effects to be assessed and δ is a vector of parameters. The recommendation is to use a distribution function to model $G(.)$. As the $G(.)$ function is monotonic, the model provides an easy interpretation of the response function as a function of the linear construct. Here, we assumed a Probit function. The model can be estimated by non-linear least squares or quasi-maximum likelihood. Here, the covariates z are dummy variables representing year and production system.

2.7 Statistical analyses

Considering the set of 96 observations (48 simulated and 48 measured) for the years 2010, 2012, 2014, and 2016 across the three integrated production systems, we performed t-tests to compare group means. In Table 5, we summarized the p-value results for each case. We considered here a significance level of 10%. The p-values of the group test statistic for equality of means reported in Table 5 indicate a lack of evidence for a significant difference between simulated and measured beef production in any of the cases analyzed, and for SOC in the ICLF22 and GHG in ICLF14 systems (p-values $\geq$0.10). The other comparisons appear to be different. Additionally, the equality of variances test (considering the folded F-statistic) does not indicate a significant difference in the two variances for the beef variable in any situation (p-values $\geq$0.10). GHG and SOC (except in the ICLF14 for the SOC case) show differences in variances when comparing simulated and measured values. In Tables 5, 6, "Global" refers to the whole set of data for each variable (ICL + ICLF14 + ICLF22). The other comparisons appear to be different. Additionally, the equality-of-variances test does not indicate a significant difference in the two variances for the beef variable in any situation. GHG and SOC (except in the ICLF14 for the SOC case) show differences in variances when comparing simulated and measured values.

Table 6 presents the R^2, root mean squared error (RMSE), and mean absolute error (MAE) values to summarize the differences between simulated and measured values. RMSE, MAE, and Mean are expressed in the same units as the variable under evaluation, which facilitates a direct interpretation of the model's mean error. While the MAE provides a linear average of absolute errors, the RMSE penalizes errors of greater magnitude due to its quadratic formulation. R^2 was obtained from the linear fit between these values. Beef production is the case in which the simulation model appears closest to the real values (mean/MAE = 4.3%), followed by SOC stocks (15.9%) and GHG emissions (51.1%). R-Square values for beef production in all cases ratify the association (linear) between simulated and measured values. Such observations are in line with the findings presented in Table 5, where simulated and measured beef production values did not differ.

As from the previous discussion, there is no strong evidence that simulated values reproduce measured values, except for beef production. We run two separate DEA models, one for the measured values and one for the simulated values. Each model has 48 DMUs, a single unitary input, and three outputs (beef, SOC, 1/GHG). As we previously discussed, this efficiency score is a single performance measure that aggregates the three responses from the experimental plots.

The mean efficiency was 88.2% [68.7, 100.0%] for the measured case and 91.0% [71.8, 100.0%] for the simulated data. The box plots shown in Figure 1 summarize these results. In Figure 2, the box plots of the DEA efficiency scores are shown by year and by production system. These plots give us some insights into differences in performance over the years and among the systems, and the profiles appear similar between the two types of data. We confirmed such findings by fitting fractional regressions, as explained in Section 2. We reported these fit in Tables 5, 6 for measured and simulated data, respectively.

From Tables 7, 8, we observe statistically significant differences between the production systems. At these tables, the columns $p > |z|$ show the p-values of the z-test (Wald test), and values less than 0.10 indicate statistically significant differences (significance level of 10%). ICL is the best performer, followed by ICLF22 and ICLF14. There are also significant differences between years. The exception is for the simulated data between 2012 and 2016. The years' order of performance is 2014 > 2012 > 2010 > 2016 for measured data and 2014 > 2012 = 2016 > 2010 for the simulated case. It is worth noting that, as the contextual variables we used were modeled as dummy variables, we should interpret the partial effects (expressed in terms of the regression coefficients) in relation to the constant term, as one of the categories is omitted (Gujarati and Potter, 2008). The correlation between observed and predicted values is 83.3% for the fit of Table 6 and 85.6% for the regression with simulated data (Table 7).

From all the results we presented here, we may assume that although there are differences between measured and simulated data, specifically for SOC stocks and GHG emissions, the conclusions regarding performance are the same: ICL appears to be the best-performing production system, followed by ICLF22 and ICL14.

3 Results and discussion

3.1 Soil carbon content and tree carbon stock

The DNDC-estimated annual SOC stock change for NV, ICL, ICLF22, and ICLF14 systems in the period 2008 to 2016 is presented in Table 9. Among the production systems, ICL presented the highest annual increase (1.06 Mg·CO_2e ha^{-1} year^{-1}), followed by ICLF22 (0.83 Mg·CO_2e ha^{-1} year^{-1}) and ICLF14 (0.30 Mg·CO_2e ha^{-1} year^{-1}), which exhibited the lowest increase among the integrated systems. In

TABLE 6 R^2, RMSE, MAE—measured and simulated values.

Variables	Performance metrics	Global	ICLS	ICLFS14	ICLFS22
Beef production (kg beef ha^{-1} year^{-1})	R^2	0.9710	0.9738	0.9969	0.9480
	RMSE	25.88	30.91	5.78	31.94
	MAE	10.40	12.19	4.44	14.56
	Mean (measured values)	239.35	182.94	247.56	287.56
SOC stocks (kg C ha^{-1})	R^2	0.0021	0.0232	0.0727	0.1370
	RMSE	12,143.52	20,472.63	3,124.30	3,674.95
	MAE	5,714.13	11,320.69	2,610.63	3,211.06
	Mean (measured values)	35,933.33	33,175.00	39,975.00	34,650.00
GHG emissions (kg CO_2e ha^{-1} year^{-1})	R^2	0.3990	0.2007	0.3545	0.6209
	RMSE	3,458.47	4,899.49	1,793.88	2,942.78
	MAE	2,150.17	3,601.69	1,080.31	1,768.50
	Mean (measured values)	4,208.65	2,481.50	3,990.63	6,153.81

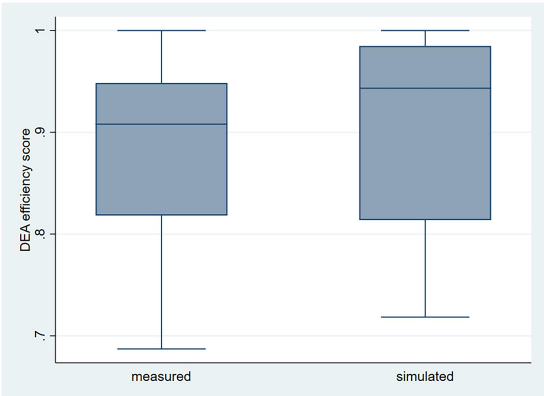

FIGURE 1
Box-plot of the efficiency scores for the DEA models run with measured and simulated data.

contrast, soil C stock change under NV was small and negative (−0.025 Mg·CO_2e ha^{-1} year^{-1}). These results are consistent with those reported for the integrated system by Carvalho et al. (2010), which ranged from 0.82 to 2.58 Mg·CO_2e ha^{-1} year^{-1}.

Annual SOC stocks under NV remained relatively stable over time, as expected, despite being slightly negative. In contrast, integrated systems showed a marked increase from 2011 onwards, likely associated with increased pasture production. Forage production appears to be a key driver of differences in soil C accumulation, as it is directly related to fresh C inputs to the soil. Systems with higher tree densities (ICLF14 > ICLF22) exhibit lower forage production due to competition for light, water, and nutrients. This also resulted in reduced animal productivity, as reported by Pereira et al. (2021), and consequently, lower enteric CH4 emissions.

Although Table 9 indicates that pastures can act as important carbon sinks, their capacity to offset GHG emissions from ruminant systems is rather limited (Wang et al., 2023). In this context, climate variability, especially rainfall, can constrain soil carbon sequestration. Conversely, the inclusion of trees in pasture systems, as in integrated crop-livestock-forestry (ICLF) systems, can increase the storage capacity in production systems (Pacheco et al., 2013).

Table 10 shows results for calculating of tree carbon stock (TCS) under ICLF22 and ICLF14 systems. Annual additional carbon stock in the tree was 18.99 Mg·CO_2e ha^{-1} year^{-1} for the ICLF22 system and 27.80 Mg·CO_2e ha^{-1} year^{-1} for the ICLF14 system. This finding is particularly noteworthy because, despite its superior performance on carbon biomass accumulation in the tree, the ICLF14 system simultaneously exhibited the lowest soil carbon stock (Table 9). This apparent paradox underscores the complexity of carbon dynamics in integrated livestock–tree production systems. While tree growth contributes substantially to aboveground carbon sequestration, such gains do not necessarily translate into enhanced soil carbon pools or reduced GHG emissions. From a broader perspective, these contrasting outcomes highlight the importance of systemic approaches to evaluating sustainability and climate-mitigation strategies within integrated systems. An exclusive focus on carbon gains in a single compartment can obscure critical trade-offs inherent to the functioning of the production system as a whole. Consequently, management strategies aimed at climate mitigation must simultaneously integrate above and belowground carbon processes, as well as emission profiles, to ensure net benefits.

Eucalyptus species and their hybrids are the most planted trees in Brazil, for both forestry and integrated systems such as ICLF, due to their wide adaptability to climate and soil conditions, rapid growth rate, and the possibility of multiple uses of the wood. Since 2010, Brazil has been promoting integrated systems as one of the alternatives to mitigate agricultural emissions, particularly through the recovery of degraded pastures (Brazilian Ministério da Agricultura, Pecuária e Abastecimento, 2012; Brazilian Ministry of Agriculture, Livestock and Food Supply, 2021).

Alves et al. (2017) developed guidelines for beef cattle production in integrated systems with trees, which reconcile animal welfare and quality beef production, offsetting emissions through carbon immobilized in wood produced within the system and destined for sawmills, such as the Carbon Neutral Brazilian Beef branded concept. For these systems, the challenge is to reconcile beef production with timber production, so that beef production is not limited by competition from trees intercropped with pasture.

The ICLF14 system produced an annual volume of wood and CO_2e removed 1.46 times greater than ICLF22 (Table 10); however, beef production was inversely proportional, and in both systems it was lower than in ICL. This volume of CO_2e removed by the trees can be used to reduce the carbon footprint of the system, considering the immobilization of C with the use of higher value-added wood.

3.2 Carbon footprint

Beef production was calculated using Manure-DNDC in kg live weight gain (LWG) in the farm scale area (ha) and period (year). Observe that Table 11 shows a wide range of annual beef production in the integrated systems in this case study, which is due to the dynamism of the intensification of beef cattle farming in the Cerrado (i.e., the seasonality of the entry and exit of animals of the system).

Table 11 shows that the ICL system has obtained the highest productivity, 477.1 kg LWG ha^{-1} $year^{-1}$, compared to the ICLF22 system (389.1 kg LWG ha^{-1} $year^{-1}$) and the ICLF22 system (283.8 kg LWG ha^{-1} $year^{-1}$). Considering that the average stocking rate of Brazilian pastures is around 1.0 animal unit (AU) for area (ha.), with a yield around 150 kg LWG ha^{-1} $year^{-1}$ (ABIEC, 2025), in the present study, the least productive system, ICLF14, presented an average stocking rate of 1.19 AU ha^{-1} (Table 2) and almost double the yield (283.8 kg LWG ha^{-1} $year^{-1}$). However, the potential for intensifying beef production with the ICL system is evident. In this context, the choice of tree density in the system is crucial for defining its purpose: a greater focus on beef production, as in ICLF22, or on timber production, as in ICLF14.

Systems with tree densities between 100 and 250 ha^{-1}, such as ICLF22, show good production potential for both beef and timber,

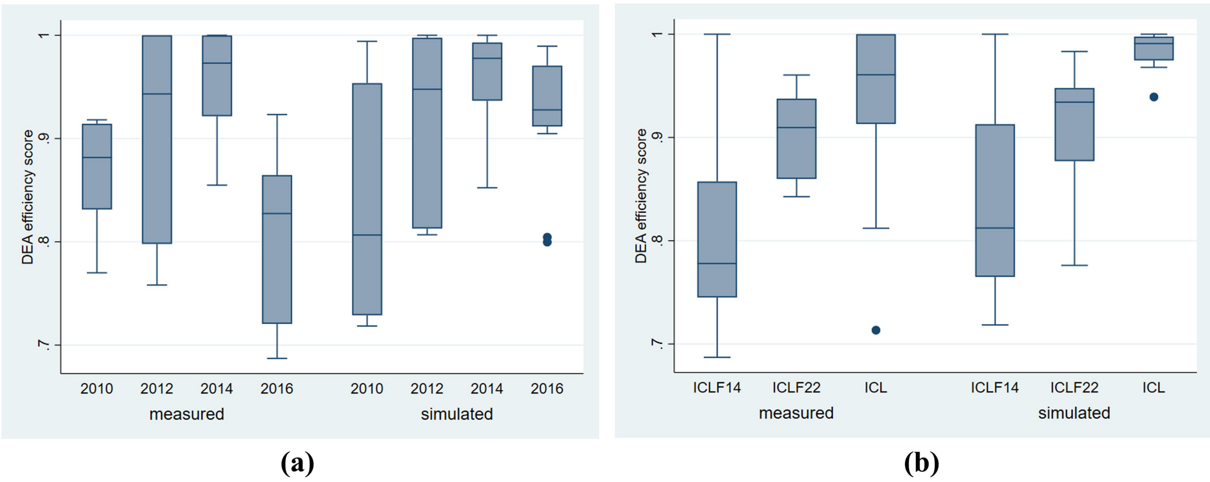

FIGURE 2
Box-plots of the efficiency scores for the DEA models run with measured and simulated data, by year **(a)** and production system **(b)**.

TABLE 7 Fractional regression fit for measured data.

Predictor	Coefficient	Standard error	*Z*	*p* > |*z*|	95% Confidence interval	
ICLF14	−0.7157	0.1251	−5.72	0.000	−0.9609	−0.4704
ICLF22	−0.3097	0.1280	−2.42	0.015	−0.5605	−0.0589
2010	0.2856	0.0814	3.51	0.000	0.1260	0.4452
2012	0.5374	0.1169	4.6	0.000	0.3082	0.7666
2014	0.8655	0.1694	5.11	0.000	0.5334	1.1976
constant	1.2151	0.1453	8.36	0.000	0.9302	1.4999

TABLE 8 Fractional regression fit for simulated data.

Predictor	Coefficient	Standard error	*Z*	*p* > |*z*|	95% Confidence interval	
ICLF14	−1.2637	0.1088	−11.62	0.000	−1.4769	−1.0505
ICLF22	−0.8638	0.1022	−8.45	0.000	−1.0642	−0.6635
2010	−0.5005	0.0950	−5.27	0.000	−0.6868	−0.3143
2012	−0.0084	0.1087	−0.08	0.938	−0.2215	0.2047
2014	0.3626	0.1458	2.49	0.013	0.0768	0.6484
Constant	2.3107	0.1242	18.6	0.000	2.0673	2.5542

TABLE 9 Modeling SOC stocks under NV, ICL, ICLF22, and ICLF14 at the Embrapa site in Campo Grande, Mato Grosso do Sul (MS), Brazil.

Year	SOC stocks (Mg·CO_2e ha^{-1} $year^{-1}$)			
	NV	ICL	ICLF22	ICLF14
2008	46.35	36.38	35.00	32.98
2009	46.29	36.35	34.61	32.71
2010	46.22	36.06	34.45	32.53
2011	46.17	35.84	34.41	32.19
2012	46.40	46.88	43.64	37.14
2013	46.34	46.94	43.62	37.02
2014	46.26	46.36	43.10	36.45
2015	46.20	46.18	42.76	36.02
2016	46.13	45.95	42.49	35.68
Annual additional SOC stocks	−0.025	1.06	0.83	0.30

TABLE 10 Modeling tree carbon stock under NV, ICL, ICLF22, and ICLF14 at the Embrapa site in Campo Grande, Mato Grosso do Sul (MS), Brazil.

Year	TCS (Mg·CO_2e ha^{-1} $year^{-1}$)			
	NV	ICL	ICLF22	ICLF14
2008	NA	NA	0	0
2009	NA	NA	0	0
2010	NA	NA	2.3	3.3
2011	NA	NA	12.7	18.9
2012	NA	NA	45.4	71.7
2013	NA	NA	66.3	104.0
2014	NA	NA	82.5	124.4
2015	NA	NA	109.3	164.2
2016	NA	NA	135.2	197.9
Annual additional tree carbon stock in aboveground biomass	–	–	18.99	27.80

NA, not applicable.

TABLE 11 Modeling beef production in ICL, ICLF22, and ICLF14 at the EMBRAPA site in the Campo Grande, Mato Grosso do Sul (MS), Brazil.

Year	kg LWG ha^{-1} $year^{-1}$		
	ICL	ICLF22	ICLF14
2008	NA	NA	NA
2009	NA	NA	NA
2010	90.8	179.8	346.8
2011	551.6	432.9	265.3
2012	726.8	654.2	426.1
2013	405.4	321.4	273.5
2014	309.6	250.6	103.7
2015	698.6	502.6	407.9
2016	556.6	381.8	163.0
Mean	477.1	389.1	283.8

NA, not applicable.

TABLE 12 Emissions intensity (kg CO_2e kg LWG^{-1}) under ICL, ICLF22 and ICLF14 at the Embrapa site in Campo Grande, Mato Grosso do Sul (MS), Brazil.

Period	kg CO_2e kg LWG^{-1}		
	ICL	ICLF22	ICLF14
2012–2008	6.6	−23.2	−49.5
2016–2013	8.8	−39.9	−89.4
Emissions intensity mean	7.7	−31.5	−69.5

in addition to providing better thermal comfort, forage nutritive value, and offsetting emissions from grazing animals (Karvatte et al., 2016; Santos et al., 2025). They are also suitable for regions prone to frost, such as the Central-South region of Brazil, thereby helping protect pastures and animals (Porfírio-da-Silva, 1994; Santos et al., 2012).

In Table 12, we present the emission intensity for each production system. The mean value for ICL (7.7 kg CO_2e kg LWG^{-1}) was greater than the value for ICLF22 and the value for ICLF14. This reveals that ICL emits more than the other integrated systems. Although more productive, the ICL exhibits a higher emission intensity due to its lower removal capacity, demonstrating lower environmental efficiency than ICLF22 and ICLF14.

Integrated systems with trees, like ICLF14 and ICLF22, in addition to emitting less methane due to lower animal stocking rates, also exhibit higher rates of annual carbon removal by trees, contributing to a negative carbon footprint compared to conventional pasture systems. However, the ICL system can reduce the carbon footprint by intensifying pasture use and removing carbon from the soil, making it more productive and efficient than conventional pastoral systems in Brazil.

Results from other studies on beef's carbon footprint are presented below. However, the functional unit considered in our study was 1 kg of live weight gain (LWG), whereas many authors present their results in carcass weight (CW) or in live weight (LW).

The results for the carbon footprint of beef cattle by Figueiredo et al. (2017) were 18.5 kg CO_2e kg CW^{-1} in the degraded pasture (DP), followed by 12.6 kg CO_2e kg CW^{-1} in the ICLF (with 476 eucalyptus trees/ha) and 9.4 kg CO_2e kg CW^{-1} in the managed pasture (MP). When soil and tree removals were factored, the carbon footprint of beef was reduced to 7.7 and −31.5 kg CO_2e kg LW^{-1} in MP and ICLF, respectively.

Cardoso et al. (2016), using Tier 2 methodologies of the IPCC, evaluated five scenarios of beef cattle production in the Cerrado with different levels of intensification and estimated annual emissions ranging from 16.92 to 51.66 CO_2e kg CW^{-1}. In contrast, MicNicol et al. (2024) observed that farms exhibit varying efficiencies, with product emissions intensities ranging from 13.8 to 38.5 kg CO_2e kg CW^{-1}. However, to achieve efficiency gains per farm, it is necessary to understand the magnitude of emissions across the different segments of the sector under analysis. This increases the likelihood of achieving environmental goals by recommending low-carbon agricultural practices.

Dick et al. (2015) compared an extensive system and an intensive system characterized by improved pastures, introduction of other forage species, and rotational grazing and found, respectively, values of 22.52 kg CO_2e kg LW^{-1} and 9.16 kg CO_2e kg LW^{-1} for the emissions intensity of these systems. This research shows that greenhouse gas emissions in extensive systems were higher than those in intensive systems, due to the longer time animals spend in each system and the quality and productivity of the pastures.

Ruviaro et al. (2015) compared several pasture-based systems under different beef cattle intensification scenarios in the south of Brazil. They found carbon footprints ranging from 18.3 to 42.6 kg CO_2e kg LWG^{-1}.

In a national assessment of beef cattle produced in the United States, Rotz et al. (2019) found total carbon footprint ranged from 17 to 40 kg CO_2e kg CW^{-1}. However, as highlighted by Persson et al. (2015), lower livestock emissions could be achieved by adopting measures to improve feed efficiency, such as feed additives to reduce methane emissions. In addition, increasing the efficiency of nitrogen fertilization by introducing legumes into pastures (Paris et al., 2009) can also contribute to reducing emission intensity.

4 Final remarks

The Manure-DNDC model performed satisfactorily in predicting beef production in integrated systems. Nonetheless, the results for SOC stocks and for GHG emissions require further improvement. Implementing integrated crop-livestock-forestry systems mitigates GHG emissions more effectively. Integrated systems using trees mitigate GHG emissions more efficiently when accounting for carbon stock above and below ground, though beef production per area might be reduced.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The animal studies were approved by the Ethics Committee on the Use of Animals (CEUA) of Embrapa Beef Cattle (Protocol CEUA No. 004/2022). The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent was obtained from the owners for the participation of their animals in this study.

Author contributions

AF: Methodology, Writing – original draft, Writing – review & editing. RA: Writing – review & editing, Writing – original draft. MM: Writing – original draft, Writing – review & editing. RC: Writing – review & editing, Writing – original draft. DB: Writing – review & editing, Writing – original draft. VL: Writing – original draft, Writing – review & editing. CO: Writing – review & editing, Writing – original draft. EG: Writing – original draft, Writing – review & editing. VP-d-S: Writing – review & editing, Writing – original draft. BA: Writing – original draft, Writing – review & editing. BM: Writing – review & editing, Writing – original draft.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Correction note

This article has been corrected with minor changes. These changes do not impact the scientific content of the article.

Generative AI statement

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