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Prediction of aboveground biomass and dry-matter content in *brachiaria* pastures by combining meteorological data and satellite imagery

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Abstract

Aboveground biomass (AGB) data are important for profitable and sustainable pasture management. In this study, we hypothesized that vegetation indexes (VIs) obtained through analysis of moderate spatial resolution satellite data (Landsat-8 and Sentinel-2) and meteorological data can accurately predict the AGB of *Brachiaria* (syn. *Urochloa*) pastures in Brazil. We used AGB field data obtained from pastures between 2015 and 2019 in four distinct regions of Brazil to evaluate (i) the relationship between three different VIs—normalized difference vegetation index (NDVI), enhanced vegetation index 2 (EVI2) and optimized soil adjusted vegetation index (OSAVI)—and meteorological data with pasture aboveground fresh biomass (AFB), aboveground dry biomass (ADB) and dry-matter content (DMC); and (ii) the performance of simple linear regression (SLR), multiple linear regression (MLR) and random forest (RF) algorithms for the prediction of pasture AGB based on VIs obtained through satellite imagery combined with meteorological data. The results highlight a strong correlation (r) between VIs and AGB, particularly NDVI (r = 0.52 to 0.84). The MLR and RF algorithms demonstrated high potential to predict AFB (R^2 = 0.76 to 0.85) and DMC (R^2 = 0.78 to 0.85). We conclude that both MLR and RF algorithms improved the biomass prediction accuracy using satellite imagery combined with meteorological data to determine AFB and DMC, and can be used for *Brachiaria* (syn. *Urochloa*) AGB prediction. Additional research on tropical grasses is needed to evaluate different VIs to improve the accuracy of ADB prediction, thereby supporting pasture management in Brazil.

KEYWORDS
biomass, machine learning, remote sensing, satellite, tropical grasslands, vegetation index

1 | INTRODUCTION

Grasslands occupy the majority of global agricultural lands and play essential roles in livestock production systems worldwide (Li et al., 2015). In Brazil, pastures occupy approximately 160 million hectares (IBGE, 2017). Most national livestock systems are based on pastures of tropical grasses, mainly *Brachiaria* (syn. *Urochloa*), thereby making management of this type of grasslands essential for profitability and sustainability. The genus *Brachiaria* (syn. *Urochloa*) comprises 85% of cultivated pastures in Brazil (Jank et al., 2014) generally because of its high resistance to acid soils, wide adaptation and good productive potential in the rainy season (Correa et al., 2020; Machado et al., 2020).

Aboveground biomass (AGB) knowledge is essential for adjusting stocking rates and grazing cycles, as overgrazing or sub-grazing conditions cause soil degradation, compromise perenniality and reduce the harvest efficiency of the forage (Carnevalli et al., 2006; de Oliveira et al., 2004; Santos et al., 2013). The traditional methodologies used to quantify pasture AGB are based on obtaining pasture samples by cutting within frames encompassing a known area, followed by weighing and laboratory analysis (Barbero et al., 2015; Delevatti et al., 2019; Sanderson et al., 2001). However, at the field level, this pasture monitoring method is laborious, time-consuming and expensive. In addition, pasture areas often show considerable soil, relief and species heterogeneity. Therefore, the AGB quantification by direct cutting, besides being destructive, often does not represent the spatial variability of the area, which reduces the accuracy of the collected data.

Currently, one technology used in pasture management improvement is remote sensing (RS). Several studies have demonstrated the potential of RS for leaf area index (LAI), height and AGB estimates of pasture. Batistoti et al. (2019) and Lussem et al. (2019) used unmanned aerial vehicles (UAV) for biomass and canopy height estimates in Brazilian and temperate grassland respectively. Insua et al. (2019) also used UAV to estimate the spatial and temporal variability of pasture growth and digestibility, whereas Wijesingha et al. (2020) used UAV equipped with a hyperspectral camera to access the crude protein (CP) and acid detergent fibre (ADF) content of forage in eight different pasture areas in Germany, demonstrating that it is also possible to use RS to monitor pasture nutritive value. Similarly, Edirisinghe et al. (2012), Wang et al. (2017), Punalekar et al. (2018) and Otgonbayar et al. (2019) demonstrated the satellite data potential to predict pasture biomass in New Zealand, China, England and Mongolia respectively. Wang et al. (2019) also demonstrated reasonable prediction of the seasonal dynamics and spatial heterogeneity of LAI and AGB by satellite-based RS in the United States. The main limitations of satellite-based RS are low temporal resolution and frequent cloud coverage. The combined use of Landsat-8 and Sentinel-2 satellites offers the possibility for free, high-frequency and long-term pasture monitoring. Mandanici et al. (2016) compared images obtained by the Landsat-8 and Sentinel-2 satellites in different study areas and found strong correlations and high regression coefficients between all corresponding bands and spectral indices calculated with the different sensors, indicating that data from both satellites can be accurately combined. Wang et al. (2019) and Chakhar et al. (2020) also demonstrated the possibility of combining Landsat-8 and Sentinel-2 images to improve the accuracy of pasture biomass estimates and crop classification respectively.

Tong et al. (2019) used different vegetation indexes (VIs) obtained through a proximal sensor to predict pasture biomass at peak production. Several other recent studies have demonstrated that VIs are accurate in predicting pasture AGB and can be used in pasture monitoring (Guerini Filho et al., 2020; Hill et al., 2017; Michez et al., 2019; Otgonbayar et al., 2019). The NDVI (normalized difference vegetation index) is the most widely used VI for monitoring crops and pastures; however, this index loses sensitivity in areas of high biomass and leaf area index or the presence of exposed soil patches in the pasture. Several other indices have been proposed to minimize these problems (Fern et al., 2018; Gitelson & Merzlyak, 1994; Gu et al., 2013; Jiang et al., 2008; Liu & Huete, 1995; Mutanga & Skidmore, 2004; Rondeaux et al., 1996).

Brazilian pastures are predominantly formed by grasses of the genus *Brachiaria* (syn. *Urochloa*) and are characterized by high spatial variability in terms of canopy structure, ground cover and relief. In addition, the grass growth pattern demonstrates great temporal variability in response to changes in weather conditions (i.e. precipitation, temperature and radiation, among others), requiring additional studies combining spectral and meteorological data to predict the AGB of these pastures in tropical regions (Fontana et al., 2018; Santana et al., 2017; Terra et al., 2020). The development of methodologies that provide highly accurate, low cost and timely information is vital for decision making in farm management. In this context, several methods have been proposed to potentially improve AGB prediction accuracy, such as regression models and machine learning tools, and the latter have been particularly successful in increasing the AGB prediction accuracy due to their ability to process large numbers of inputs and work with non-linear problems (Ali et al., 2015). Among machine learning methods, the random forest (RF) algorithm, which is a combination of multiple decision trees, has substantial promise for grassland biomass prediction because it is fast, potentially more effective than traditional regression approaches (Idowu et al., 2016), and requires fewer training samples than the artificial neural networks (ANN) method (Ali et al., 2015). In summary, RF combines the base principles of bagging with random feature selection to add additional diversity to the decisions of the predictive models.

In this study, we hypothesized that VIs obtained through analysis of data from satellites providing moderate spatial resolution (Landsat-8 and Sentinel-2), combined with meteorological data, can accurately predict the AGB of *Brachiaria* (syn. *Urochloa*) pastures in Brazil. We used pasture AGB data obtained in the field between 2015 and 2019 in four different regions of Brazil. We evaluated (i) the relationships between three different VIs and meteorological data with pasture aboveground fresh biomass (AFB), aboveground dry biomass (ADB) and dry-matter content (DMC); and (ii) the performance of simple linear regression (SLR), multiple linear regression (MLR) with backward elimination and an RF algorithm with variable selection in the prediction of pasture AGB based on VIs obtained using satellite imagery combined with meteorological data to determine which method is the more robust and accurate for our study conditions.

2 | MATERIALS AND METHODS

2.1 | Study areas

Field sampling for the AGB calculation was conducted in forty total paddocks: 24 owned by the Unidade de Ensino, Pesquisa e Extensão em Gado de Corte (UEPE-GC) of the Universidade Federal de Viçosa, in Minas Gerais (Field 1), five owned by Embrapa Gado de Leite, in Coronel Pacheco-MG (Field 2), eight located in Patrocínio Paulista–SP (Field 3) and three owned by Embrapa Agrossilvipastoril, located in Sinop-MT (Field 4). Figure 1 shows study area locations, and Table 1 provides pasture details. The four experimental areas were located in three Brazilian biomes, with different weather characteristics, and were formed predominantly (over 90%) by species of the genus *Brachiaria* (syn. *Urochloa*). According to Köppen's classification, the climate type of fields 1 and 2 is Cwa (mesothermal), field 3 is Aw and field 4 is monsoon Am. The paddocks covered a total area of approximately 164 ha of pasture, and the four areas were monitored between the summer of 2015 and the summer of 2019.

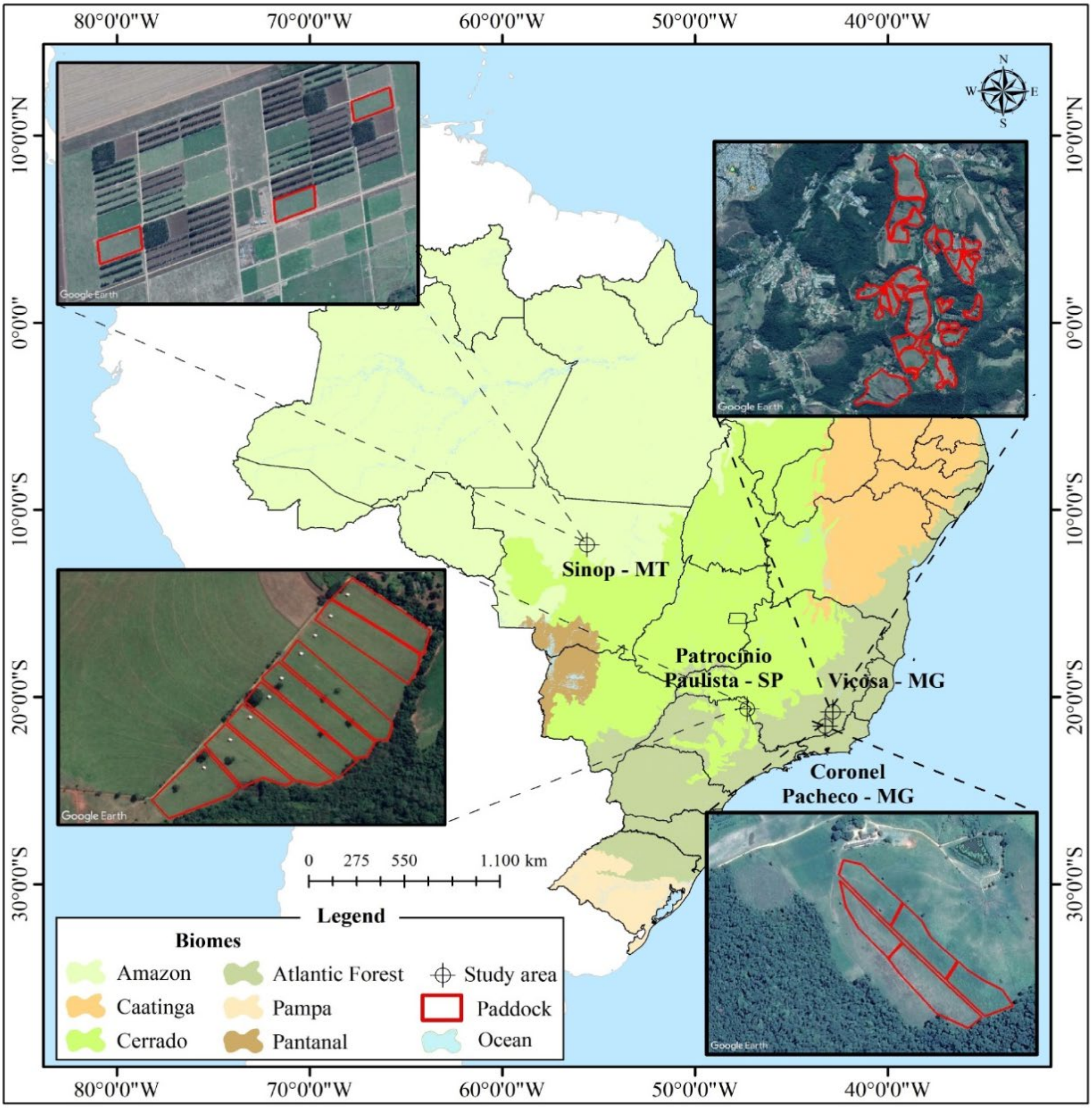

FIGURE 1 Map of Brazilian biome distribution and aboveground biomass field sampling locations

TABLE 1 Location and other information of pastures utilized for field data collection

Field ID	Location	Predominant vegetation	Relief	Biome
1	Viçosa-MG	*Brachiaria decumbens*	Mountainous	Atlantic Forest
2	Coronel Pacheco-MG	*Brachiaria decumbens/ ruziziensis*	Undulating	Atlantic Forest
3	Patrocínio Paulista-SP	*Brachiaria brizantha* cv. Marandu	Flat	Cerrado
4	Sinop-MT	*Brachiaria brizantha* cv. Marandu	Flat	Amazon

2.2 | Field data collection

To quantify the pasture AGB in the field, several points were selected randomly within each paddock, and the forage contained in the area bounded by a frame (0.25–0.64 m^2) was cut close to the ground and packed in plastic bags. The number of sampled points varied according to the area and uniformity of the paddock, with an average of twenty points per hectare. Field samplings were performed periodically throughout all seasons at intervals of 20 to 28 days in fields 1, 2 and 4, according to the duration of grazing cycles, and weekly in field 3, according to the pre- and post-grazing canopy height targets. Immediately after cutting, each sample obtained was weighed to determine the AFB, then partially dehydrated in an oven with forced air circulation at 55°C for 72h. They were then dried in an oven without forced air circulation at 105°C for 16h to determine the ADB and DMC in the samples. The forage biomass contained in the respective paddocks was expressed in kg/ha.

Precipitation, insolation (duration of solar brightness) and average temperature data for the sampling locations were obtained from the Meteorological Database for Teaching and Research (BDMEP) of the Instituto Nacional de Meteorologia (INMET). The rainfall, insolation and average temperature in the 10 days preceding the pasture sampling were calculated cumulatively to estimate the grass growth dynamic in response to weather conditions.

AGB data obtained in the field by cutting and weighing were used to assess the correlation between AGB and VIs, as well as with meteorological variables. Subsequently, field data were used for calibration and validation of pasture AGB prediction models using satellite imagery.

2.3 | Imagery acquisition

The satellites providing the images were Landsat-8, operated by NASA (National Aeronautics and Space Administration) with a spatial resolution of 30m and a 16-day temporal resolution, and Sentinel-2, operated by ESA (European Space Agency) with a spatial resolution of 10m and temporal resolution of 5 days. The only images utilized were those obtained prior to the date of biomass field data collection and with a maximum difference between data and image collection of eight days during the rainy season and twelve days during the dry period. This difference between the dates was allowed for modelling due to the period required by satellites to revisit the same location, and the recurring problem of cloud coverage in the images, ensuring a greater number of images for evaluation and observing the period of growth and morphological change of the paddock. In total, a database containing 120 observations was used for modelling. The dates of field sampling, imagery acquisition and the corresponding dataset obtained for modelling are shown in Data S1. Additionally, we evaluated the relationship between VIs obtained from Landsat-8 and Sentinel-2 on the same date and paddock to ensure the interoperability between both sources.

TABLE 2 Vegetation indices calculated and respective references

Index	Equation	Reference
NDVI	(NIR-RED) / (NIR + RED)	Rouse et al. (1974)
OSAVI	(NIR-RED) / (NIR + RED+0.16)	Rondeaux et al. (1996)
EVI2	2.5*((NIR-RED) / (NIR + 2.4*RED + 1))	Jiang et al. (2008)

Abbreviations: NIR, Reflectance of Near-Infrared wavelength; RED, Reflectance of Red wavelength.

The spectral bands of visible red (~ 665 nm) and near-infrared (~ 840 nm) referring to the selected orthorectified images were downloaded for free from the United States Geological Survey (USGS) website (Lansat-8) and ESA website (Sentinel-2) using the Semi-Automatic Classification Plugin (SCP) of the free software QGIS 3.4®. After the respective spectral bands were downloaded, they were pre-processed in the QGIS software, including reprojection of the coordinates using the DATUM WGS84 system, atmospheric correction by the dark-object subtraction (DOS1) method and radiometric correction. The atmospheric and radiometric corrections of the images were also performed using the SCP. The digital numbers of the images were converted to reflectance. From the reflectance values of the respective spectral bands, the NDVI, EVI2 (enhanced vegetation index 2) and OSAVI (optimized soil adjusted vegetation index) indices were calculated according to the equations shown in Table 2 and using the "raster calculator" tool of QGIS software.

NDVI was chosen as it is the most commonly used index to estimate biomass of several crops, including pastures. Still, it loses sensitivity

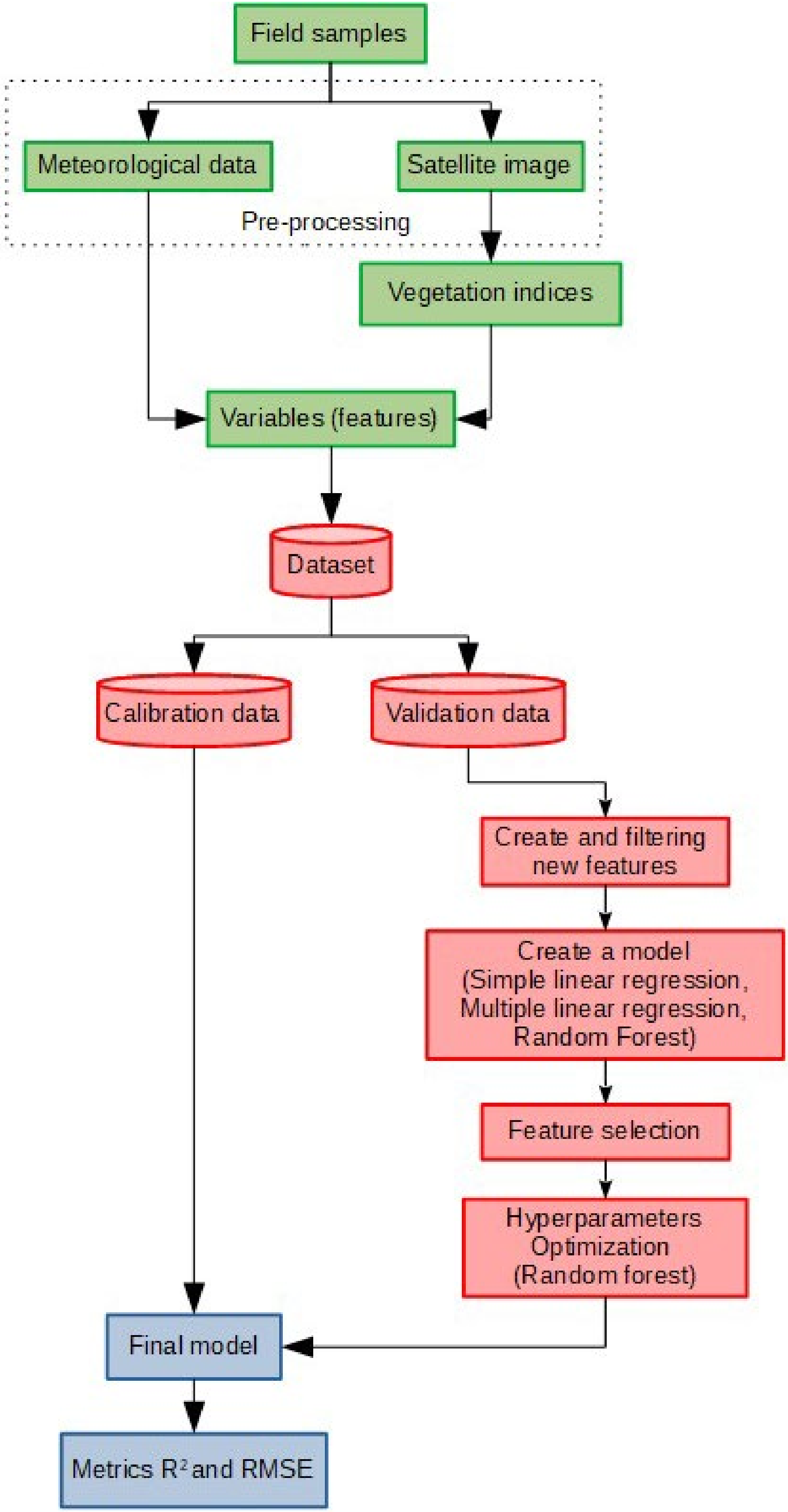

FIGURE 2 Flow chart of data processing and statistical analyses for biomass and dry-matter content prediction

under conditions of high green biomass and the presence of exposed soil (Fern et al., 2018; Mutanga & Skidmore, 2004). Therefore, EVI2 was chosen to minimize the problem of index saturation in conditions of high biomass (Jiang et al., 2008), and OSAVI was chosen to minimize soil interference (Rondeaux et al., 1996) due to the great spatial heterogeneity of the evaluated areas.

The vector layer corresponding to the paddock was inserted into the QGIS software interface to determine the average value and standard deviation of each index within each paddock. The average index between the pixels contained in the vector was obtained using the "zonal statistics" tool. The calculated average index was then used to correlate with the data obtained in the field on dates corresponding to the date of image acquisition for later biomass prediction (Data S1).

2.4 | Statistical analysis

To assess the different prediction methods, the original database (n = 120) was randomly split into calibration (n = 96) and validation (n = 24) datasets. The calibration dataset was used to perform all modelling steps (pre-processing data, selection of variables and optimization of hyperparameters). After all modelling steps, the validation dataset was applied to the final model to predict biomass.

For better model calibration, new variables were created from the combination of all variables (2x2), subtracting one from the other. All new variables created were filtered by the correlation of the new feature with the target variables. The new variable was selected to integrate the original variables if the correlation was greater than each single variable correlation.

To predict the pasture AFB, ADB and DMC, three methods were used: SLR, using NDVI, EVI2 or OSAVI as a baseline biomass predictor (reference model), MLR with backward elimination, starting with all variables and eliminating the highest p-value variables until all had p-values < 0.05 and RF with variable selection, removing the variables of minor importance (backward elimination) based on k-fold cross-validation (5 k-folds) performance. After variable selection, using k-fold cross-validation in the calibration dataset, the RF model hyperparameters were optimized by using the Bayesian optimization function from the *scikit-optimize library* (version 0.7.4).

The accuracy of the prediction models was then assessed by predicting the variables of interest for the validation dataset through the determination coefficient (R^2; Equation 1), and root-mean-square error (RMSE; Equation 2). All statistical analyses were run in Python 3 (version 3.7), and the flow chart of data processing and statistical analyses for biomass and DMC prediction are shown in Figure 2.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(V_{obs}^{i} - \hat{V}_{est} \right)^2}{\sum_{i=1}^{n} \left(V_{obs}^{i} - \ddot{V}_{obs} \right)^2} \quad (1)$$

in which V_{obs}^{i} is the observed variables, $\hat{V}_{est}$ is the model prediction and $\ddot{V}_{obs}$ is the average of the observed variables.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\hat{V}_{est} - V_{obs}^{i} \right)^2} \quad (2)$$

in which n is the number of observed variables.

3 | RESULTS

3.1 | Correlation between variables

Significant correlations were found between most of the variables analysed, including, notably, a strong positive correlation between VIs and AFB, and a negative between VIs and DMC (Figure 3). Among the VIs, EVI2 had the lowest correlation coefficient, although significant, with AFB (r = 0.74) and DMC (r = 0.77), whereas NDVI and OSAVI showed a stronger and similar correlation (r > 0.82). Among the meteorological variables, the accumulated average temperature of the period presented the weakest correlation with AFB (r = 0.44) and DMC (r = 0.47), whereas the accumulated rainfall and insolation moderately correlated with pasture variables (r > 0.55). Both VIs and meteorological variables were better correlated with AFB and DMC than ADB, although all correlations were significant.

The satellite used for image acquisition (Landsat-8 or Sentinel-2) was not significantly correlated with any other variable (Figure 3), and the VIs obtained from both image sources showed a strong correlation, with R^2 values ranging from 0.82 to 0.92 (Figure 4).

3.2 | Prediction models results

The prediction of AFB and DMC based on the SLR using different VIs (NDVI, EVI2 or OSAVI) as predictor variables demonstrated good accuracy, although lower than that of other methods, with R^2 and RMSE for the validation data ranging from 0.72 to 0.73 and 4,241.1 to 4,272.4 kg/ha, respectively, for AFB prediction (Table 3). For DMC prediction, the R^2 ranged from 0.70 to 0.73 and RMSE ranged from 10% to 11% (Table 3). The difference in performance between the predictor variables was negligible. The models for AFB and DMC prediction by SLR are shown in Table 3.

MLR demonstrated intermediate predictive performance compared to other methods. After backward selection, the variables selected for the prediction of AFB were the type of satellite used for image acquisition, OSAVI index and the combinations between temperature x insolation, EVI2 x insolation and NDVI x insolation. The R^2 and RMSE for the MLR model for prediction of validation data were 0.76 and 3,976.1 kg/ha, respectively, and 0.78 and 9.5%, respectively, for AFB and DMC prediction (Figure 5).

The models for AFB and DMC prediction by MLR are shown in Equations (3) and (4).

$$AFB = -24850 + 3128\ Satellite + 45120\ OSAVI - 803.40\ Inso_{Temp} + 14690\ Inso_{EVI2} - 13940\ Inso_{NDVI} \quad (3)$$

in which *Satellite* represents a value assigned to the sensor type used for acquire images, $Inso_{Temp}$ is the combination between insolation and temperature, $Inso_{EVI2}$ is the combination between insolation and EVI2 and $Inso_{NDV1}$ is the combination between insolation and NDVI.

	ND	Satellite	Rainfall	Inso	Temp	NDVI	EVI2	OSAVI	Inso-NDVI†	Inso-EVI2‡	Inso-Temp§	AFB	ADB
	-												
Satellite	0.10	-											
Rainfall	-0.08	0.18	-										
Inso	0.27	-0.07	-0.71	-									
Temp	-0.20	0.12	0.25	-0.02	-								
NDVI	-0.31	-0.07	0.54	-0.65	0.26	-							
EVI2	-0.35	-0.15	0.52	-0.54	0.44	0.86	-						
OSAVI	-0.35	-0.09	0.54	-0.62	0.35	0.97	0.95	-					
Inso-NDVI†	0.27	-0.07	-0.71	1.00	-0.03	-0.65	-0.55	-0.62	-				
Inso-EVI2‡	0.27	-0.07	-0.71	1.00	-0.03	-0.65	-0.55	-0.62	1.00	-			
Inso-TEMP§	0.30	-0.09	-0.73	0.99	-0.16	-0.67	-0.59	-0.66	0.99	0.99	-		
AFB	-0.35	0.14	0.55	-0.56	0.44	0.82	0.74	0.82	-0.57	-0.57	-0.62	-	
ADB	-0.32	0.03	0.34	-0.38	0.20	0.52	0.47	0.54	-0.38	-0.38	-0.40	0.76	-
DMC	0.35	-0.08	-0.65	0.63	-0.47	-0.84	-0.77	-0.82	0.64	0.64	0.69	-0.76	-0.36

FIGURE 3 Pearson correlation map of variables. ND: number of days between image acquisition and field sampling dates; Satellite: sensor type used for acquiring images; Inso: insolation; Temp: temperature; †combination between insolation and NDVI; ‡combination between insolation and EVI2; §combination between insolation and temperature; AFB: aboveground fresh biomass; ADB: aboveground dry biomass; DMC: dry-matter content. All coloured correlations are significant by test t ($p < .05$)

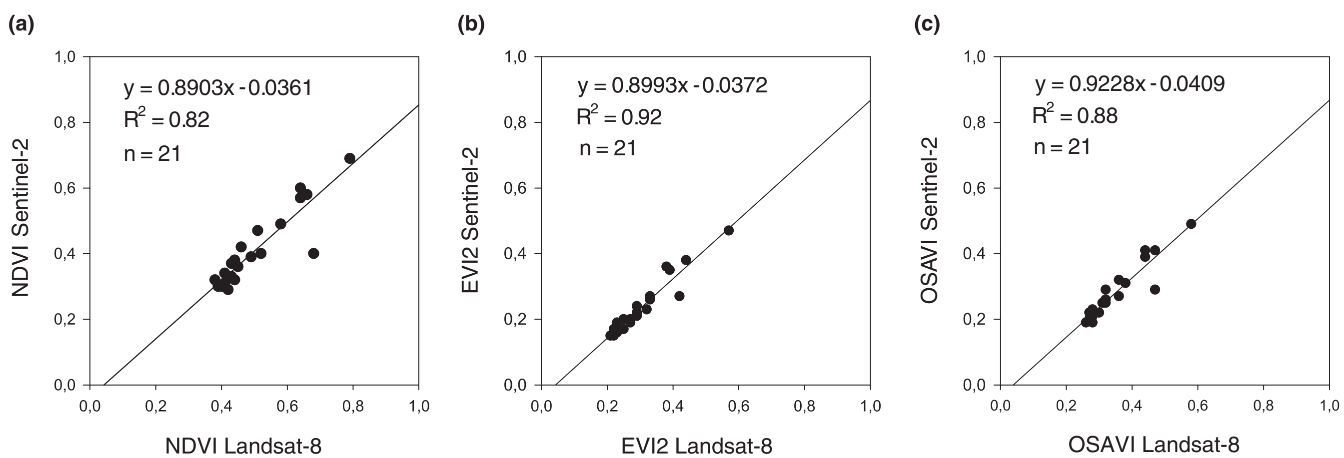

FIGURE 4 Relationship between (a) NDVI, (b) EVI2 and (c) OSAVI values obtained with Landsat-8 and Sentinel-2 images on the same date and paddock

$$\begin{aligned} DMC = {} & 124.73 + 0.65\ nd - 0.07\ Rainfall - 48.75\ Insolation \\ & - 25.40\ Temperature - 120.92\ NDVI - 64.85\ EVI2 \\ & + 239.97\ OSAVI - 23.35\ Inso_{Temp} + 72.17\ Inso_{NDVI} \end{aligned} \tag{4}$$

in which *nd* is the number of days between image acquisition date and field sampling date and *Rainfall*, *Insolation* and *Temperature* represents the respective values accumulated in ten days.

The best prediction performance of pasture AFB and DMC was achieved with the RF algorithm. During the modelling, the most important attributes selected for the construction of the RF model for the prediction of AFB and DMC were NDVI, EVI2, OSAVI, accumulated precipitation and average accumulated temperature, with emphasis on the importance value attributed to the VIs (Figure 6).

TABLE 3 Simple Linear Regression analysis for aboveground fresh biomass (AFB) and dry-matter content (DMC) prediction

Predictor variable	Model	R^2	RMSE
AFB prediction (kg/ha)			
NDVI	y = 42,340 NDVI - 10,450	0.73	4,241,1
EVI2	y = 34,860 EVI2	0.72	4,248,3
OSAVI	y = 53,220 OSAVI - 8,081.8025	0.73	4,272,4
DMC prediction (%)			
NDVI	y = −88.8984 NDVI + 92.3287	0.70	11
EVI2	y = −82.8979 EVI2 + 75.0537	0.72	11
OSAVI	y = −108.9412 OSAVI + 86.2398	0.73	10

The RF algorithm R^2 and RMSE were 0.85 and 2,947.1 kg/ha, respectively, and 0.85 and 7.9% for AFB and DMC prediction, respectively, for the validation data (Figure 7).

Despite the significant correlations between the main predictor variables and ADB, none of the three methods were efficient in predicting ADB, with R^2 values ranging from 0.19 to 0.35 (Figure 8). We chose to represent only the NDVI index in Figure 8 because both VIs performed similarly and it is the VI most widely used for estimates of vegetation cover.

4 | DISCUSSION

The results of our study are consistent with several other studies in demonstrating a strong correlation between VIs obtained by RS through satellites and pasture biomass. Edirisinghe et al. (2012) found a strong positive correlation (r = 0.81) between pasture biomass and NDVI in a study conducted in New Zealand. Barrachina et al. (2015) also found a strong correlation (R^2 = 0.82) between the biomass of mountain pastures and the EVI and NDVI index. In contrast, Ferreira et al. (2013) found weaker, but significant correlations between green biomass and NDVI (r = 0.65) or EVI (r = 0.62), whereas Fern et al. (2018) demonstrated that in areas with scarce vegetation or the presence of exposed soil patches, the OSAVI index may be more suitable for estimating green biomass because it minimizes the variability caused by soil reflectance. This index is appropriate for use in this study since tropical pasture areas present considerable spatial variability in terms of grass coverage and, consequently, the percentage of exposed soil. Consistent with this study, Guerini Filho et al. (2020), also in Brazil, found a strong correlation between different VIs obtained via the Sentinel-2 satellite and pasture biomass, demonstrating that it is possible to use spectral information obtained through the multi-spectral instrument (MSI) sensor to predict pasture biomass in this region.

The significant correlations between biomass and meteorological data demonstrate the importance of rainfall, insolation and temperature data in the prediction of pasture biomass in our study. According

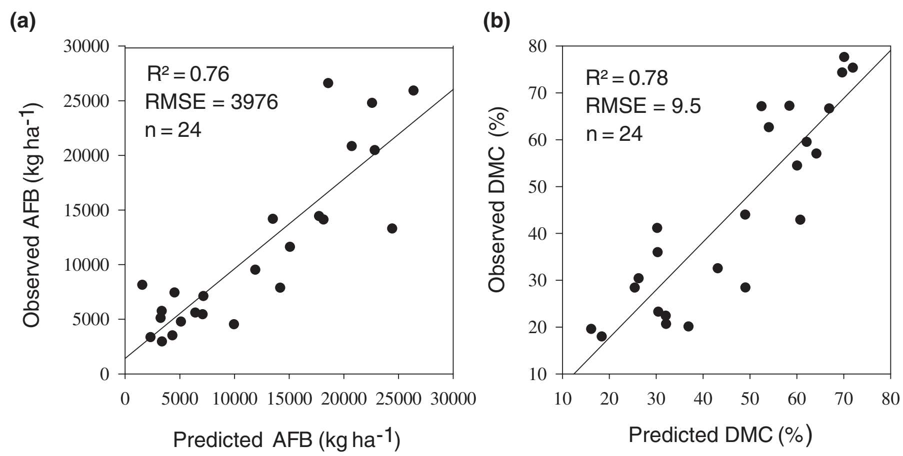

FIGURE 5 Prediction by multiple linear regression for (a) aboveground fresh biomass (AFB) and (b) dry-matter content (DMC)

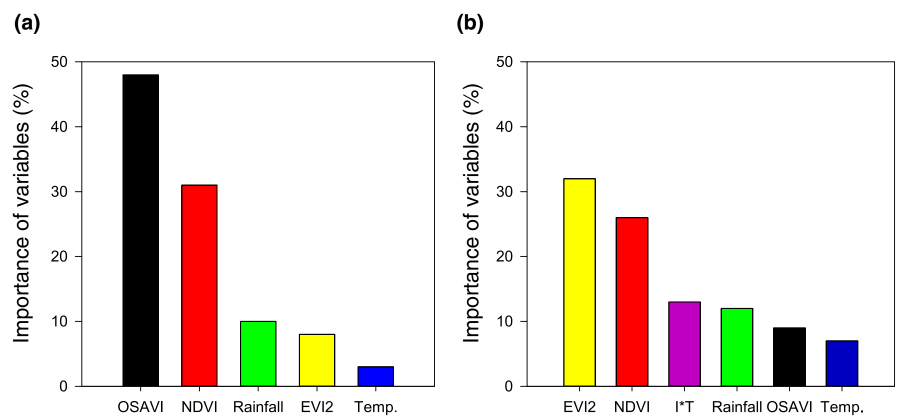

FIGURE 6 Importance of variables attributed by the random forest algorithm for (a) aboveground fresh biomass (AFB) and (b) dry-matter content (DMC) prediction. Temp.: Temperature; I*T: Combination between insolation and temperature

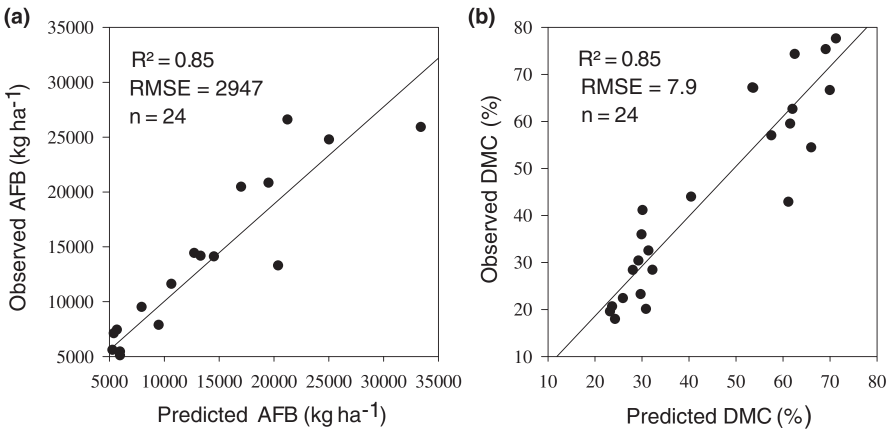

FIGURE 7 Prediction by random forest algorithm for (a) aboveground fresh biomass (AFB) and (b) dry-matter content (DMC)

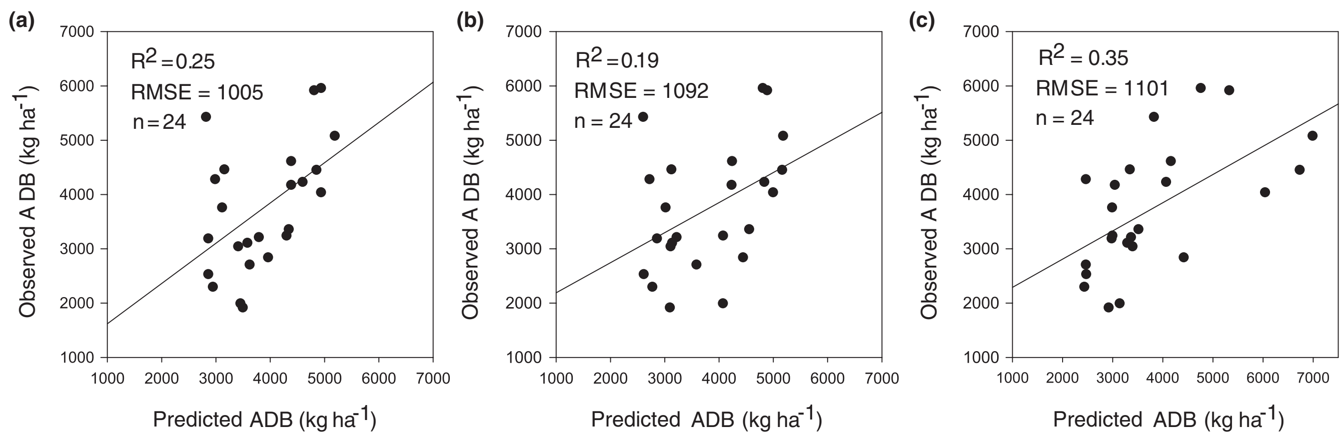

FIGURE 8 Aboveground dry biomass (ADB) prediction using (a) simple linear regression with NDVI, (b) multiple linear regression and (c) random forest algorithm

to Xu et al. (2018), precipitation, temperature and the interaction between precipitation and temperature explain 65.5, 14.5 and 9.8%, respectively, of the variation in the LAI of pastures. Studies by Hill et al. (2004) and Donald et al. (2010) also demonstrated that climatic data, combined with VIs obtained by RS, allow for accurate prediction of the growth rate of the pasture, and can play an important role in the prediction of biomass. Similarly, Fontana et al. (2018), working on natural pastures in a subtropical climate in Brazil, recommended the combination of meteorological data and spectral indexes to adjust forage accumulation models.

Strong correlations were identified between VIs obtained by the different satellites. Chakhar et al. (2020) used Landsat-8 and Sentinel-2 images for crop classification and identified that there is a strong correlation between IVs obtained by both image sources and that the linear calibration of the VIs does not contribute to improve crop classification, demonstrating the interoperability between satellites. No significant correlations were identified between the satellite used for image acquisition (Landsat-8 or Sentinel-2) and any variable of interest. In addition, the importance value attributed by the RF algorithm to the type of sensor used was negligible, suggesting that both sensors (Operational Land Imager and MSI) can be used in the prediction of *Brachiaria* (syn. *Urochloa*) pasture biomass in Brazil. Wang et al. (2019) also demonstrated the potential of integrating Sentinel-2 and Landsat-8 imagery into the monitoring of the seasonal dynamic of grasslands, consistent with our study.

We conducted a SLR analysis between the variables of interest (AFB, ADB and DMC) predicted by VIs (NDVI, EVI2 or OSAVI) and variables measured in the field to use as a reference in our study, as it is the simplest method (baseline) for predicting such variables. Goswami et al. (2015) reported a strong exponential relationship between NDVI and biomass (R^2 = 0.70) for six different species in Canada and indicated saturation of the index at biomasses above 100 g/m^2. Similarly, Pezzopane et al. (2019), using VIs to monitor pastures formed by grasses of the genus *Brachiaria* (syn. *Urochloa*), found a strong exponential relationship between NDVI and LAI, as well as between NDVI and leaf biomass for different systems. We identified a strong linear relationship between the variables estimated through the VIs and measured in the field (Table 3), suggesting that there was no index saturation effect in this study.

This study demonstrates that the RF algorithm is more accurate than MLR for predicting pasture biomass in Brazil. Consistent with our study, Mutanga et al. (2012) also compared the performance of the RF with that of the stepwise MLR in the prediction of pasture biomass and found a higher accuracy with the RF algorithm. Wang et al. (2017) also used meteorological data and images from two different satellites to predict pasture biomass in China using different prediction algorithms and determined the RF algorithm was superior to the others. Similarly, Wu et al. (2016) and Li et al. (2017) indicated that the RF algorithm associated with Landsat imagery provided accurate estimates of AGB and grasslands LAI.

Otgonbayar et al. (2019) used VIs calculated from Landsat-8 imagery to develop pasture biomass prediction models and found the RF algorithm demonstrated good predictive performance ($R^2 = 0.76$; RMSE = 98 kg/ha). The estimated error for biomass prediction in this study was well above the reported by Otgonbayar et al. (2019); however, these authors collected data in an arid climate, with low temperatures and precipitation, and studied forages with a lower production potential (mean biomass value of 257 kg DM ha^{-1}) than the tropical grasses evaluated in our study, of which the average biomass was 12,978 kg FB ha^{-1} and 3,890 kg DM ha^{-1} during the evaluated years. Considering the pasture biomass measured in the two studies, our RMSE was approximately 23% and 28% of the average AFB and ADB measured, respectively, whereas Otgonbayar et al. (2019), using RF for prediction, obtained an RMSE of approximately 38% of the average ADB observed. Pezzopane et al. (2019) analysed data from climatic conditions similar to ours, with tropical grasses of the genus *Brachiaria* (syn. *Urochloa*) in Brazil, and used NDVI to estimate forage biomass in two different production systems. The RMSE for the total biomass estimates were 961 kg DM ha^{-1}, approximately 30% of the average biomass observed (3,134 kg DM ha^{-1}). Cisneros et al. (2020) also estimated the biomass productivity of several tropical grasses and showed $R^2 = 0.54$ and RMSE = 1,800 kg/ha for estimates. In contrast, Mutanga et al. (2012) estimated the RMSE of the prediction of pasture biomass in South Africa was approximately 13% of the average biomass observed, whereas Mundava et al. (2014) observed that better estimates of VI-based biomass were obtained when the areas were grouped in terms of similar botanical composition than estimates combining different forages. This observation demonstrates the need for further development of specific prediction models for each location and type of predominant forage.

None of the three methods was efficient in predicting ADB. This result was not expected, but it can be explained by the lower variability in ADB data in the database used (a minimum of 1,129 kg/ha and a maximum of 9,080 kg/ha), whereas the variability of the AFB data was much greater (2,320 to 42,240 kg/ha), which may have reduced the R^2 of the ADB prediction models and increased the RMSE of the AFB prediction models. This small variation in ADB data relative to the variation in AFB can be explained by the seasonal variation in the structural composition of the pasture, and consequently, in the DMC. During the rainy months of the years 2015 to 2019, the average DMC was 26.2%, whereas the average DMC for the dry months was 63.3% (Appendix S1). Thus, during the pasture growing season, we had a substantial increase in the AFB of the pasture, leading to an increase in the VIs obtained in this period, which was not accompanied by a proportional increase in ADB due to the reduced DMC in the period. Likewise, during dry periods, the reduction in AFB and VIs was not accompanied by a proportional reduction in ADB due to the high DMC of the pasture. The high DMC of the grasses during the dry period may have resulted from modifications in the plant morphological composition due to changes in climatic conditions and the consequent increase in senescent material. Pezzopane et al. (2019) reported poorer VIs performance in estimating total forage biomass than estimating leaf mass and explained this observation by differences in structural composition and the senescent material proportion between different areas. Similarly, Tong et al. (2019) used MLR model for estimating AFB and ADB at two locations and also observed better predictive performance for AFB compared to ADB. Mundava et al. (2014) in a previous study tested the relationship between VIs obtained by Landsat (ETM +) imagery and biomass from different pasture areas in Australia and also found better relationships between VIs and green biomass than dry biomass.

Despite this, AFB can be used to characterize the herbage yield of a grassland and the high prediction accuracy of AFB and DMC identified in our study indicates that it is possible to quantify the forage biomass using the AFB and DMC to assess the ADB, thereby assisting the grazing management of tropical grasses in Brazil. Notably, our study was conducted in pastures in different regions of Brazil, with high heterogeneity of climate, relief and soil and high spatial variability of species, typical of our pasturelands, indicating that the RF model can be used to quantify biomass on the Brazilian *Brachiaria* (syn. *Urochloa*) pastures.

5 | CONCLUSIONS

The NDVI, EVI2 and OSAVI indices strongly correlated with biomass and DMC of *Brachiaria* (syn. *Urochloa*) pastures and can be used as tools for monitoring tropical grasslands in Brazil.

The MLR and RF algorithms improved the accuracy of biomass prediction using both Landsat-8 and Sentinel-2 imagery, combined with meteorological data to assess AFB and DMC of *Brachiaria* (syn. *Urochloa*) pastures in Brazil. Further research on tropical grasses is needed to evaluate different VIs, as well as other machine learning techniques, to improve the accuracy of prediction of ADB and to support pasture management in Brazil.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTION

Igor Lima Bretas: Conceptualization (supporting); Data curation (lead); Investigation (supporting); Methodology (supporting);

Software (supporting); Validation (supporting); Visualization (lead); Writing-original draft (lead). Domingos Sárvio Magalhães Valente: Conceptualization (supporting); Formal analysis (lead); Methodology (lead); Software (lead); Validation (lead); Writing-review & editing (equal). Fabyano Fonseca e Silva: Conceptualization (supporting); Formal analysis (supporting); Resources (supporting); Software (supporting); Validation (supporting); Visualization (supporting); Writing-review & editing (equal). Mario Luiz Chizzotti: Conceptualization (supporting); Resources (supporting); Visualization (supporting); Writing-review & editing (equal). Mário Fonseca Paulino: Data curation (supporting); Investigation (supporting); Resources (supporting); Writing-review & editing (equal). André P D'Áurea: Data curation (supporting); Investigation (supporting); Writing-review & editing (equal). Domingos Sávio Campos Paciullo: Data curation (supporting); Investigation (supporting); Writing-review & editing (equal). Bruno Carneiro e Pedreira: Data curation (supporting); Investigation (supporting); Writing-review & editing (equal). Fernanda Helena Martins Chizzotti: Conceptualization (lead); Data curation (supporting); Methodology (supporting); Project administration (lead); Resources (supporting); Supervision (lead); Visualization (supporting); Writing-review & editing (equal).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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