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Data Article

A dataset for pasture parameter estimation based on satellite remote sensing and weather variables

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A R T I C L E I N F O

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A B S T R A C T

Estimating pasture parameters is essential for decision-making in the management of livestock and agriculture. Despite that, the time-consuming acquisition of outdoor forage samples and the high cost of laboratory analysis make it infeasible to predict parameters of quality and quantity forage recurrently and with great accuracy. Previous work has shown that multispectral and weather data have correlation with forage parameters, enabling the design of supervised machine learning models to predict forage conditions. Nevertheless, datasets with pasture yield and nutritional parameters, remote sensing and weather information are scarce and rarely available, limiting the design of prediction models. This paper presents a dataset with more than 300 samples of pasture laboratory analyses collected over nearly twelve months from two paddocks. Latitude and longitude coordinates were collected for each sample using GPS coordinates, and this data helped acquire multispectral band signals and eight vegetation index values extracted from Google Earth Engine (Sentinel-2 satellite) for each pixel of each sample. Furthermore, the dataset has weather data from APIs and a meteorological station. These data can also motivate new

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studies that aim determine pasture behaviour, joining this dataset with larger datasets that have similar information.

Specifications Table

Subject	Agronomy and Crop Science
Specific subject area	Satellite Remote Sensing and Laboratory chemical data for estimation of pasture quality and quantity parameters
Data format	Raw, Filtered, and Processed
Type of data	Table
Data collection	*Approximately every 15 days, pasture samples (1m²) were collected from two paddocks (one with 4 cattle animals and one without animals) with Brachiaria Decumbens forage for nearly 12 months. After each collection, the samples were taken to the laboratory, and the estimation of pasture parameters was performed. We acquire spectral data from the Sentinel-2 satellite and weather parameters values from a meteorological station and APIs. Raw data from multispectral images were acquired, filtered (for cloud removal and atmospheric correction), and processed to transform to obtain the vegetation indices.*
Data source location	The data were collected in the School Farm of the Federal University of Mato Grosso do Sul (UFMS). UFMS is in the Midwest region of Brazil (Mato Grosso do Sul State). The school farm is located at -20.44168668512919, -54.84680916199159. This data was accessed via two APIs: Open Weather MAP [9] and Open-Meteo [10].
Data accessibility	Repository name: Mendeley Data Data identification number: 10.17632/8tjgtkktky.5 Direct URL to data: https://data.mendeley.com/datasets/8tjgtkktky/5

1. Value of the Data

- The value of the data relies on the relationship between the collected samples and the forage quantity and quality values coming from the chemical analysis process. Acquiring pasture parameters is time-consuming and costly once the pasture samples collection on different dates requires great manual effort, and chemical laboratory analysis is necessary to process and transform forage samples into pasture parameters.
- The value of the data is also in the process of acquiring, filtering, and processing multispectral and weather parameters. Eleven multispectral bands from sentinel-2 were acquired and filtered (cloud removal and atmospheric correction). Eight vegetation indices were processed based on the sentinel bands. In addition, this dataset contains weather parameters from two APIs and a meteorological station. Both multispectral and weather data are powerful parameters for estimating pasture nutrients in beef cattle production systems.
- This data can help studies aiming at understanding the pastures' standard growth and nutritional behaviours. Researchers and students can join this data into larger datasets to help the design of the trace trend lines that can characterize the pasture parameters along the time.
- Machine learning models are commonly used to estimate pasture parameters based on remote sensing and weather data [1,2]. However, independent, and dependent variables are scarce, making model development difficult. This data can be valuable in research involving the design of machine learning models to estimate pasture parameters. Furthermore, this data could also be used in research involving pre-trained artificial intelligence models. As more data for machine learning models becomes available, the opportunities for model learning and generalization to new problems are greater.
- To the best of our knowledge, this is the first dataset that makes available satellite remote sensing data related to pasture quality and quantity parameters, linking each pixel of a satel-

lite image directly to the forage collection point, containing more than 300 samples. Even if other datasets with the same characteristics are created, this one can still compose more robust datasets.

2. Background

Pasture is the primary food source in cattle grazing systems. Despite that, the standard method to monitor the pasture parameters is performing laboratory analysis of the forage, which is costly and time-intensive activity. Previous work [1,2,3] have shown that satellite remote sensing and meteorological data are significant parameters in composing supervised machine learning models to estimate pasture quantity and quality parameters. However, the design of prediction models depends on previous pasture parameter information to train the models, and the processes of pasture sample collection and forage sample laboratory analysis are essential to generate this information. This work presents a dataset with more than 300 samples of pasture laboratory analyses collected over nearly twelve months from two paddocks. We also collected latitude and longitude data for each sample using GPS coordinates. This data helped acquire multispectral band signals and eight vegetation indices values, extracted from the Google Earth Engine (Sentinel-2 satellite), for each pixel of the samples. Additionally, the dataset is comprised of weather data from APIs and a meteorological station.

3. Data Description

The dataset comprises two folders: “data” and “src”. Folder “data” contains four CSV files called “Table 1 - Field_Experiment_Data.csv”, “Table 2 - Multispectral_Data.csv,” “Table 3 - Weather_Data.csv” and “Complete_DataSet.csv”. All the files have 312 samples, the first three files are parts of the complete data, and the index of each row corresponds to data of the same sample. For example, rows 0 from files “Table 1 - Field_Experiment_Data.csv”, “Table 2 - Multispectral _Data.csv and “Table 3 - Weather _Data.csv” correspond to data from the same sample. These three subsets are sub tables of the file “Complete_DataSet.csv”, that integrates data from all other files.

Two scripts can be found in folder “src: “Search_Images_and_Weather_Data.ipynb” and “weatherapi.py”. The first script searches for multispectral data using Google Earth Engine and weather data using two APIs (Open Weather MAP and Open-Meteo). File “weatherapi.py” is an API that integrates the data of the Open Weather MAP and Open-Meteo. This file is called by “Search_Images_and_Weather_Data.ipynb” to acquire weather data. Fig. 1 illustrates the folders and files hierarchy and the repository structure.

File “Table 1 - Field_Experiment_Data.csv” includes a set of data parameters presented in Table 1. Data related to the type of paddock (with or without animals), sample coordinates, DOY (Day of Year), and the date on which each sample was acquired are included in this file. Two quantity parameters (Biomass and Dry Matter Content) and five quality parameters (Neutral Detergent Fiber, Acid Detergent Fiber, Mineral Matter, Crude Protein, and Total Digestible Nutrient) are also included in this file and were calculated from laboratory chemical analysis for each collected sample in the experimentation period.

The data of “Table 2 - Multispectral_Data.csv” is presented in Table 2. Eleven spectral bands and eight spectral indices were acquired for each local, and each sample was collected using Sentinel-2 Satellite. The acquisition date of each image (Table 2, column “Satellite_Images_Dates”) was based on the earliest date closest to each collection date, under the limitation of the percentage of clouds in the image (column “Date”, see Fig. 2). The choice of spectral bands and vegetation indices presented in Table 2 is related to the results of previous work [1, 2, and 3], which showed that vegetation indices have moderately-strongly effects on designing machine learning models to estimate pasture parameters.

Table 1
Sample characteristics and nutritional parameters estimated through chemical analysis for each sample acquired from pasture.

Column Name	Description	Variable Type
Date	Date on which each sample was collected. Format: (YYYY-mm-dd)	Date
DOY	Day of Year in which each sample was collected	Numerical/Categorical
Sample	ID of the sample	Numerical/Categorical
Sub-Sample	ID of the replicate of a sample	Numerical/Categorical
Lat	Latitude of the coordinate where the collection was performed	Numerical
Long_	Longitude of the coordinate where the collection was performed	Numerical
Sample_type	it identifies the type of sample. Paddock with animals: • Q1 - Q4: square 1 - 4 • G1 - G4: cage 1 - 4 Paddock without animals:S1 or S2: square 1 or 2	Categorical
Animals	A categorical variable that characterizes if the sample was collected from a paddock with animals (value = 1) or without animals (value = 0)	Numerical/Categorical
Biomass	Biomass of forage: quantity of forage weight in a place.	Unit of measurement: kg/ha
DM	Dry Matter Content: the weight of forage other than water that characterizes the portion of pasture nutrients [4].	Unit of measurement: percentage relative to Biomass
MM	Mineral Matter Content: a measure of total mineral content; is a residue after burning a sample [4].	Unit of measurement: percentage relative to DM
NDF	Neutral Detergent Fiber: parameter comprising the ADF and hemicellulose. Impact the animal consumption of forage [5].	Unit of measurement: percentage relative to DM
ADF	Acid Detergent Fiber: cell wall proportions of forage that relate to the ability to digest the forage [5].	Unit of measurement: percentage relative to DM
CP	Crude Protein: is 6.25 times the nitrogen content of forage and includes two types of protein: true and non-true protein nitrogen [5].	Unit of measurement: percentage relative to DM
TDN_based_NDF and TDN_based_ADF	Total Digestible Nutrient estimated on NDF and Total Digestible Nutrient calculated from ADF: these data were estimated based on both parameters - NDF and ADF. They are the sum of crude protein, non-structural carbohydrates, and digestible NDF [4].	Unit of measurement: percentage relative to DM

File “Table 3 - Weather _Data.csv” has eight columns related to weather parameters acquired from two APIs: Open Weather MAP [9] and Open-Meteo [10] (TEMP_MAX, TEMP_MIN, RAD_SOL, RAIN, WIND_SPD, EVAPOT, PRES_ATM, and HUM_REL). The other columns of this table have weather data acquired via a meteorological station located in the experimentation site (-20.446834076092262, -54.83913599788673). Each weather data was acquired in the same day the satellite image was acquired (Column “Satellite_Images_Dates”, Table 2). Finally, the File “Complete_DataSet.csv” has 312 rows and 51 columns. This file has data from Tables (1, 2) and data from Table 3.

Table 2
Sentinel-2 bands and vegetation indices acquired from each sample location.

Column Name	Description	Observations, Reference
Satellite_Images_Dates	Images acquisition date. Format: (YYYY-mm-dd)	Date
B1	Sentinel-2 Coastal and Aerosol Band	Resolution: 60m, Central Wavelength: 442.7nm, [6]
B2	Sentinel-2 Blue Band	Resolution: 10m, Central Wavelength: 492.4nm, [6]
B3	Sentinel-2 Green Band	Resolution: 10m, Central Wavelength: 559.8nm, [6]
B4	Sentinel-2 Red Band	Resolution: 10m, Central Wavelength: 664.6nm, [6]
B5	Sentinel-2 Visible and Near Infrared (NIR) Band	Resolution: 20m, Central Wavelength: 705nm, [6]
B6	Sentinel-2 Red Edge Band	Resolution: 20m, Central Wavelength: 740.5nm, [6]
B7	Sentinel-2 Red Edge Band	Resolution: 20m, Central Wavelength: 782.8nm, [6]
B8	Sentinel-2 NIR Band	Resolution: 10m, Central Wavelength: 832.8nm, [6]
B8A	Sentinel-2 Narrow NIR Band	Resolution: 20m, Central Wavelength: 864.7nm, [6]
B9	Sentinel-2 Water Vapour Band	Resolution: 60m, Central Wavelength: 945.1nm, [6]
B11	Sentinel-2 Short Wave Infrared (SWIR) Band	Resolution: 20m, Central Wavelength: 1613.7nm, [6]
B12	Sentinel-2 Short Wave Infrared (SWIR) Band	Resolution: 20m, Central Wavelength: 2202.4nm, [6]
NDVI	Normalized Difference Vegetation Index	$NDVI = \frac{B8 - B4}{B8 + B4}$, [7]
NDWI	Normalized Difference Water Index	$NDWI = \frac{B8A - B11}{B8A + B11}$, [7]
EVI	Enhanced Vegetation Index	$EVI = \frac{2.5x(B8 - B4)}{B8 + 2.4xB4 + 1}$, [7]
LAI	Leaf Area Index	$LAI = 3.618xEVI - 0.118$, [8]
DVI	Difference Vegetation Index	$DVI = B8 - B4$, [8]
GCI	Green Chlorophyll Index	$GCI = \frac{B8}{B3} - 1$, [8]
GEMI	Global Environmental Monitoring Index	$GEMI = eta\ x\ (1 - 0.25\ x\ eta) - \frac{B4 - 0.125}{1 - B4}$ $eta = \frac{2 * (B8 - B4) + 1.5 * B8 * 0.5 * B4}{B8 + B4 + 0.5}$, [8]
SAVI	Soil Adjusted Vegetation Index	$SAVI = \frac{1.5x(B8 - B4)}{B8 + B4 + 0.5}$, [8]

Table 3
Weather parameters acquired via APIs and a meteorological station.

Column Name	Description	Observations, Reference
TEMP_MAX	Maximum temperature value registered in the day	Unit of Measurement:°C, [9] - [10]
TEMP_MIN	Minimum temperature value registered in the day	Unit of Measurement:°C, [9] - [10]
RAD_SOL	Average solar radiation registered during the day	Unit of Measurement: J/M², [9] - [10]
RAIN	Average rainfall registered during the day	Unit of Measurement: mm, [9] - [10]
WIND_SPD	Average wind speed registered during the day	Unit of Measurement: m/s, [9] - [10]
EVAPOT	Average evapotranspiration estimated of the soil during the day	Unit of Measurement: mm, [9,10]
PRES_ATM	Average Atmospheric Pressure registered during the day	Unit of Measurement: hPa, [9] - [10]
HUM_REL	Average Relative humidity registered during the day	Unit of Measurement: %, [9] - [10]
TP_SFC_AVG	Average of Surface Temperature	Unit of Measurement:°C
Wind_Dir	Average of Wind Direction	Unit of Measurement: degrees
Dew_Point	Average of Dew Point Temperature	Unit of Measurement:°C
Radiative_Dif_AVG	Radiative Diffuse Average	Unit of Measurement: W/meter²
Radiative_Direct_AVG	Radiative Direct Average	Unit of Measurement: W/meter²
PPFD	Photosynthetic Photon Flux Density	Unit of Measurement : $\frac{\mu Mols}{s * meter}$
Longwave_Rad_AVG	Longwave Calculated Average (infrared radiation energy per unit area)	Unit of Measurement: W/meter²

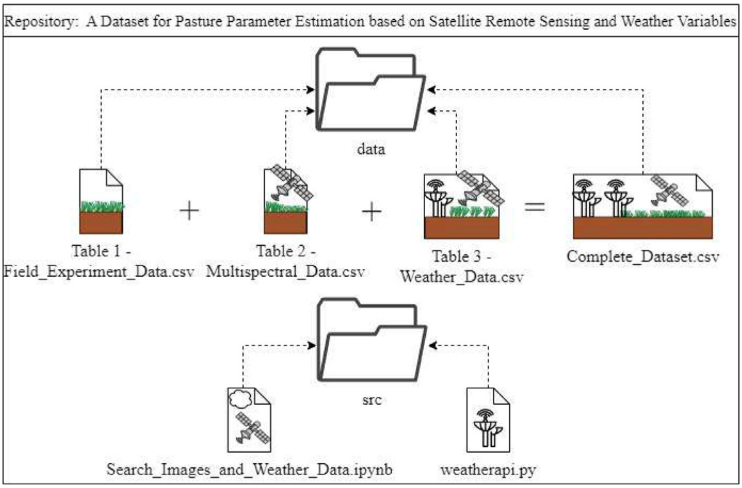

Fig. 1. Folders and files structure in the repository.

4. Experimental Design, Materials and Methods

The experimentation to perform the data acquisition can be summarized in two sub-processes: one responsible for acquiring forage samples and performing chemical analysis of nutritional parameters, and another for acquiring spectral data from satellite remote sensing and weather data from APIs and meteorological stations. Fig. 2 presents a Business Process Model Notation Diagram (BPMN) that illustrates the main data acquisition process.

A - Paddock Forage Sample Acquisition and Chemical Data Estimation

The experiments on forage sample acquisition were conducted from April 6, 2022, until March 1, 2023, in the School Farm of the Federal University of Mato Grosso do Sul, Brazil (EPSG: 4674, -54.8389411,-20.4465849), for a collection staff. The collection was carried out in two paddocks with Brachiaria Decumbens forage: one without the presence of animals (Paddock 1, size 1.343 ha) and another with four animals (Paddock 2, size 0.1531 ha). The animals in Paddock 2 were Nellore heifers, with an average live weight of 203 kg and nine months of age. Four forage samples of 1 m^2 in Paddock 1 were collected (cut flush to the ground) every 15 days at randomized representative area points and weighed to determine biomass. In addition, in the same paddock, every 30 days, four additional forage samples were collected from animal containment cages of one cubic meter. The location of those cages were randomly changed every 30 days in the paddock. In Paddock 1, only two replicates were collected; once the forage in this paddock had a more standardized growth pattern. Fig. 3. shows a satellite image from the two paddocks where experiments were carried out and the dates when the sample collections were performed.

After all replicates in both paddocks were collected, the data were sent to a laboratory. The samples were weighed, dried, ground, and forage nutritional parameters were estimated using chemical analysis. The samples were dried in a greenhouse with forced air circulation at a temperature of 55°C for 72 hours and grinding process was carried out using a laboratory Whiley knife mill. In the laboratory, the nutritional parameters estimated were Crude Protein (CP), Dry Matter Content (DM), Mineral Matter (MM), Biomass Content, Acid Detergent Fiber (ADF), Neutral Detergent Fiber (NDF), and Total Digestible Nutrients (TDN).

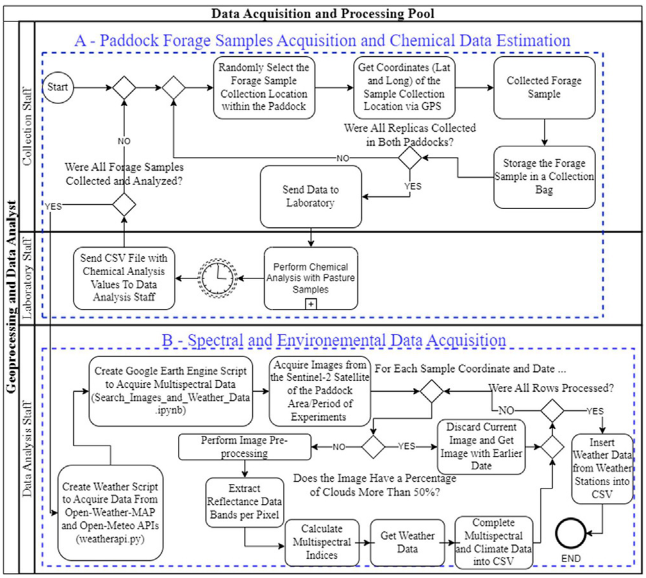

Fig. 2. BPMN Diagram with two sub-processes constituting the main data acquisition process.

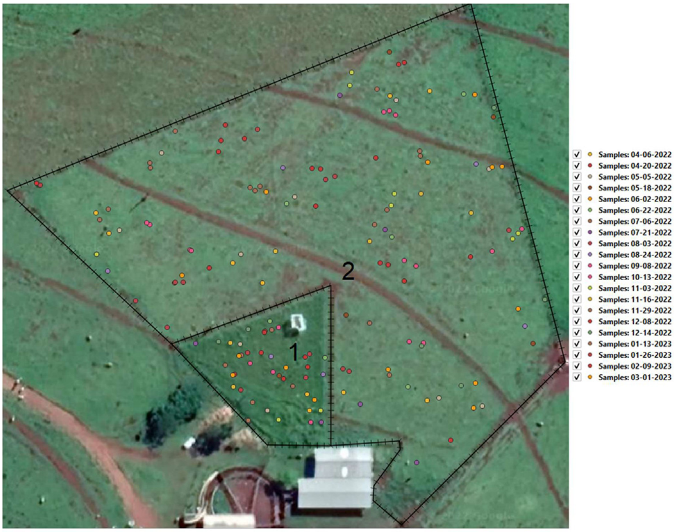

Fig. 3. Satellite Image of Paddock 1 (without animals) and Paddock 2 (with animals) and the date when each sample and replicates were collected.

CP was determined via Kjeldahl method that is based in three distinct analytical steps: digestion, distillation, and titration [11,12]. DM was estimated via the gravimetric method, consisting of weighing, drying, and weighing samples to determine DM [12]. Biomass content was estimated via quadrat sampling (square frames), consisting of randomly laughing squares onto the field, removing the grass portion from the site using gardening shears, and then weighting it to determine the biomass content [12]. ADF and NDF were estimated based on Van Soest method [13], which is the recovery of insoluble fibrous residue in a neutral or acidic medium, using extraction in an aqueous medium, applying heat and the action of an anionic (sodium lauryl sulfate) or cationic (cetyltrimethylammonium bromide) detergent [12,13,14]. TDN was estimated from NDF and ADF based on [15]. Lastly, to estimate MM, the M-001/2 [12,16] method was used. The method consists of incinerating the sample at high temperatures long enough for total combustion of the organic matter in the sample to occur, resulting in MM. After all the samples had been chemically analysed, the data analyst staff began sub-process B: “Spectral and Weather Data Acquisition.”

B - Spectral and Weather Data Acquisition

Spectral data were acquired based on the coordinate points of each sample collected in the paddock. Fig. 4. presents the process of building the complete dataset.

Fig. 4 shows that “Table 1 - Field_Experiment_Data.csv” (Table 1) is the input to a Python script (Search_Images_and_Weather_Data.ipynb). The data was collected in scenes with only 50% of clouds (see Fig. 2) and atmospheric correction. Under conditions where too many clouds were found in the image (>50%), a new image (with the same coordinates) with a previous date was provided until the condition was met (Fig. 2, subprocess B). Furthermore, eight well-known spectral indexes were calculated (Table 2), and both data sets are joined into the same data structure.

Next, the acquisition of weather parameters is carried out in two ways: based on data acquired from two APIs (Open Weather MAP [9] and Open-Meteo [10]) and data from an existing meteorological station at the data collection site (Table 3). Integrating weather data from APIs is carried out by “Search_Images_and_Weather_Data.ipynb “ and “weatherapi.py” scripts. The Data Analysis Staff used the script “Search_Images_and_Weather_Data.ipynb” to join the “Table 1 – Field_Experiment_Data.csv” with “Table 2 – Multispectral_Data.csv” and weather data acquired

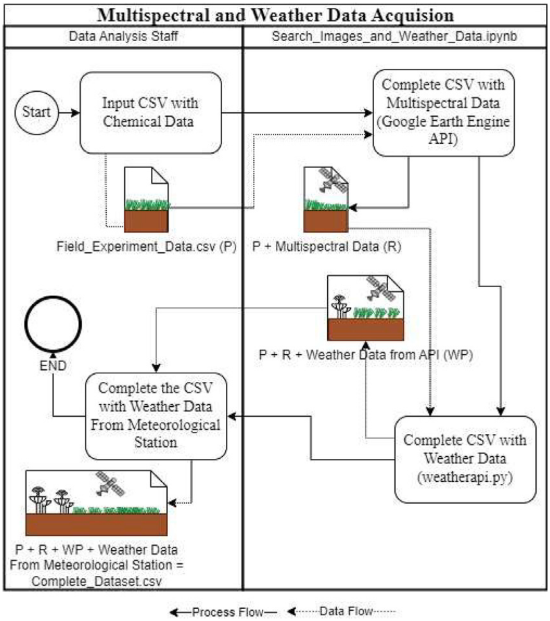

Fig. 4. Complete CSV with Multispectral and Weather Data.

from APIs existing in the "Table 3 – Weather_Data.csv". The Data Analysis Staff manually carried out the final data integration, joining the weather data acquired from the meteorological station with the other data, joining the lines according to the column "Dates", thus building the "Complete_DataSet.csv" file.

Limitations

None

Ethics Statement

This work is registered in the UFMS Animal's Ethics Committee under No. 1.227/2022, and the experiments complied with the ARRIVE guidelines and carried out in accordance with the U. K. Animals Act, 1986. The acquisition process of primary data (pasture samples) was also permitted by the UFMS Animal's Ethics Committee under No. 1.227/2022.

Data Availability

A Dataset for Pasture Parameter Estimation based on Satellite Remote Sensing and Weather Variables (Original data) (Mendeley Data).

CRediT Author Statement

Guilherme Defalque: Conceptualization, Methodology, Software, Validation, Investigation, Data curation, Writing – review & editing; **Pedro Arfux:** Software; **Marcio Pache:** Writing –

review & editing; **Gumercindo Franco:** Investigation, Methodology, Writing – review & editing; **Ricardo Santos:** Conceptualization, Methodology, Validation, Investigation, Writing – review & editing, Supervision, Project administration.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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