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Leveraging Earth Observation services for enhanced livestock farming productivity

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Abstract

Under the European Space Agency's Global Development Assistance (GDA) programme, GMV leads a pilot project in Paraguay with the World Bank and FECOPROD to enhance livestock farming using Earth Observation (EO) services. By integrating EO-derived data into FECOPROD's digital systems, the project optimizes grazing, monitors water availability, and prevents overgrazing, improving resource management and reducing environmental impact. Dry matter biomass is estimated using the Carnegie-Ames-Stanford Approach (CASA) model, which leverages Sentinel and Landsat data, meteorological inputs, and environmental stress factors. These insights predict pastureland condition and yield, aligning feed production with seasonal cycles for efficient, cost-effective operations.

The EO-based approach provides farmers with detailed land condition data, enabling informed decisions on breeding, health, and farm management. This scalable solution fosters sustainability in livestock farming, reducing environmental pressures while boosting productivity and resilience for Paraguay's agricultural sector and beyond.

Introduction

Two principal methodologies exist for estimating dry matter biomass (DMB): direct modelling using vegetation indices and productivity models (Wenquan et al., 2024). Productivity models, particularly net primary productivity (NPP)-based approaches, are divided into three categories: climate-based models, physiological/ecological models, and light use efficiency (LUE) models (Pei et al., 2024). The widely used CASA model exemplifies LUE models, leveraging remote sensing data for broad applicability (Wang et al., 2022).

This study emphasizes the use of multispectral imagery, with the Moderate-Resolution Imaging Spectroradiometer (MODIS) onboard Terra and Aqua satellites being historically dominant. Since the Sentinel-2 (S2) missions began in 2017, the CASA model has been employed to generate NPP maps at higher spatial resolution (Fang et al., 2021). In addition to EO data, the CASA model requires climate inputs, such as the ERA5-Land dataset, which provides global climate reanalysis data with high spatial and temporal resolution.

The NPP calculation using CASA involves several key steps, notably the estimation of the fraction of Absorbed Photosynthetically Active Radiation (fAPAR). Traditional fAPAR derivation relies on long-term Normalized Difference Vegetation Index (NDVI) data. However, red-edge bands in S2 data improve on NDVI by addressing saturation issues in crop biomass estimations (Fang et al., 2021). While previous studies focus on seasonal or annual NPP calculations, this study targets 10-day intervals. Shorter intervals increase gaps caused by cloud cover, necessitating gap-filling techniques to preserve phenological trends in fAPAR time series. Such approaches also enhance cumulative DMB estimates (Chen et al., 2004).

To mitigate NDVI saturation, this study applies the Beer-Lambert law to fAPAR calculation, linking it to Leaf Area Index (LAI). The Simple Sentinel-2 LAI Index (SeLI), derived from near-infrared and red-edge bands, is used for LAI estimation (Pasqualotto et al., 2019). Reflectance composites over 10-day periods, integrating bands from blue to shortwave infrared (SWIR), are generated by selecting the day with maximum NDVI, ensuring consistent data quality.

Like fAPAR, albedo is integral to CASA's NPP computation, particularly in Photosynthetically Active Radiation (PAR) estimation (Wang et al., 2022). Using S2 reflectance composites and methods from Landsat-8/9 OLI data processing, S2 albedo is calculated (He et al., 2018). As OLI and Sentinel-2 MSI sensors provide comparable imagery, harmonization between the missions is feasible.

The LUE parameter, crucial in NPP estimation, reflects the relationship between biomass accumulation and solar radiation use efficiency. It is influenced by multiple factors and can be derived empirically from photosynthetic responses or simulated using ground-based or global datasets (Propastin et al., 2012).

Converting cumulative NPP into DMB requires field data specific to vegetation types, such as carbon allocation capacity ($C_{allocation}$) and root-to-shoot biomass ratios (Fu et al., 2023). In the absence of local data, global or regional studies may be used (Bolinder et al., 2006).

This study aims to produce 10-day DMB estimates, resulting in 36 maps annually. Such time-series data provide sufficient temporal resolution for phenometric analysis, offering an alternative to spectral indices commonly used in phenology studies. The detailed 10-day DMB profiles facilitate identification of critical phenological events and their corresponding biomass values.

Methods

The study area covers 1,260 km² in Paraguay's Central Chaco region, spanning longitudes 59° 58' 12" to 59° 37' 4.8" west and latitudes 22° 35' 38" to 22° 16' 44" south. It includes parts of the municipalities of Loma Plata, Filadelfia, Tte 1º Manuel Fernández, and Mariscal José Félix Estigarribia (Figure 1). This predominantly pasture area hosts trial plots managed by FECOPROD and two dairy farms.

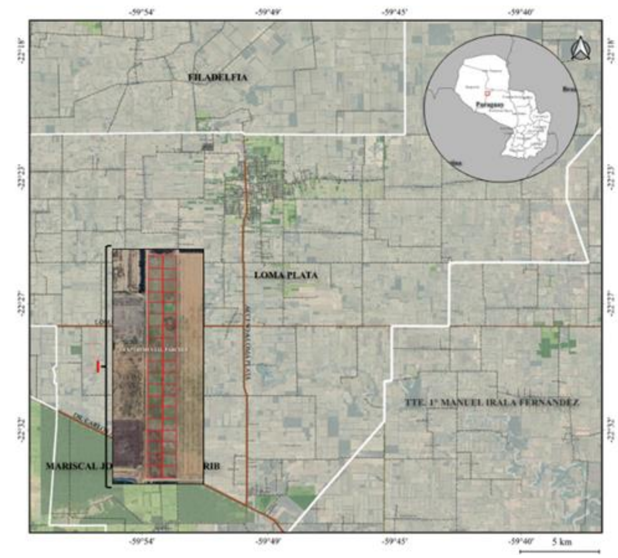

Figure 1 Study area.

The methodology includes four main stages: data collection, time-series preparation, NPP calculation, and DMB calculation with phenometric analysis (PA). The workflow is illustrated in Figure 2 and detailed below.

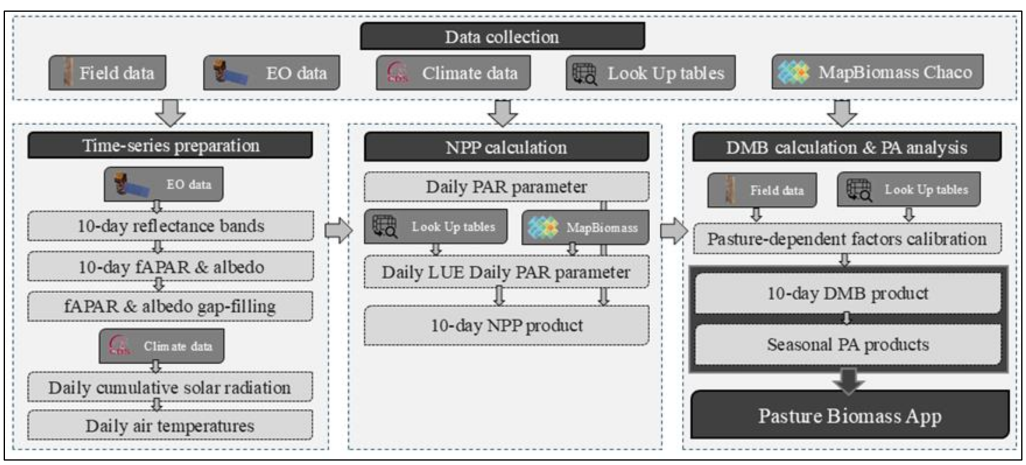

Figure 2 Workflow employed in this study.

Data collection

Data collection involved field data, EO data, climate data, and look-up tables. Field data from FECOPROD included 38 trial plots with forage species' sowing and mowing dates for the 2022 season and average bale weights per species. S2 Level 2A data (2016 onward) provided the EO dataset, while climate data came from the ERA5-Land dataset via Copernicus Climate Data Store (CDS). Look-up tables included global sources like the Biome-Property-Look-Up-Table for MODIS GPP/NPP (Zhao et al., 2005) and $C_{allocation}$ parameters from Bolinder et al. (2006). Pasture maps were sourced from MapBiomas Chaco.

Time series preparation

Daily S2 scenes were used to calculate the NDVImax-day product, which identifies the optimal day within each 10-day period based on maximum NDVI. Using the NDVImax-day, 10-day composites were created for blue to SWIR narrow-bands by assigning reflectance values directly from the sensor rather than averaging. These composites formed the basis for calculating 10-day fAPAR and albedo using equations (1) and (2):

$$\text{fAPAR} = 1 - \exp(-k\,(5.405 \cdot (\text{SeLI} - 0.114)) \qquad (1)$$

$$\text{albedo} = 0.0134 + 0.246\ \text{blue} + 0.146\ \text{green} + 0.191\ \text{red} + 0.304\ \text{nir} + 0.105\ \text{swir1} + 0.008\ \text{swir2} \qquad (2)$$

Here, SeLI (Pasqualotto et al., 2019) was used to estimate fAPAR, and the albedo equation for OLI sensors (He et al., 2018) was adapted for S2. Time-series gaps in fAPAR and albedo were addressed through outlier removal, a combination of interpolation and forward-fill methods, and Savitsky-Golay smoothing (Chen et al., 2004). Climate data, including solar radiation (SSRD) and minimum air temperature (TMIN), were generated daily from CDS.

NPP calculation

The CASA model calculated NPP using equations (3) to (6):

$$\text{PAR}\ [\text{MJ/m}^2\text{/day}] = \text{SSRD}\ (1 - \text{albedo}) \qquad (3)$$

$$tmin_{\text{LUE}}\ [^{\circ}\text{C}] = (\text{TMIN} - tmin_{\text{min}})\ ((1 / (tmin_{\text{max}} - tmin_{\text{min}}))) \qquad (4)$$

$$\text{LUE}\ [\text{gC/MJ/day}] = \text{LUE}_{\text{max}}\ tmin_{\text{LUE}} \qquad (5)$$

$$\text{NPP}\ [\text{gC/m}^2] = \text{fAPAR LUE PAR} \qquad (6)$$

Parameters $tmin_{\text{min}}$, $tmin_{\text{max}}$, and LUE_{max} were derived from the Biome-Property-Look-Up-Table (Zhao et al., 2005).

DMB calculation

DMB was calculated using equation (7):

$$\text{DMB} = \sum \text{NPP}\ (\text{root-shoot ratio} / \text{C}_{\text{allocation}}) \qquad (7)$$

Field trials were conducted to calibrate the root-to-shoot ratio parameter. NPP time-series data were accumulated throughout the 2022 season, and by grouping field trials with the same forage species, average total NPP values were compared to ground-truth bale weights. At this stage, the $C_{allocation}$ value was adopted from Bolinder et al. (2006), and the root-to-shoot ratio was calibrated for each forage species.

Since no forage species map was available outside the field trials, the root-to-shoot ratio used to infer DMB in the Chaco region was approximated as the average value of all calibrated forage species. This average ratio (0.4136) aligns with previous findings for the Chaco region (Baldassini et al., 2020).

The following table compares ground-truth bale weights (kg/ha) with DMB estimates from the CASA model (LUE approach) for each forage species in the 2022 field trials, applying the average root-to-shoot ratio instead of the species-specific calibrated values. During model calibration, the accuracy achieved was a coefficient of determination (R^2) of 0.87 and a root mean square error of 29.03%.

Table 1 Ground-truth bale weights (kg/ha) vs. CASA model DMB estimates using the average root-to-shoot ratio in 2022 field trials

Forage species	DMB - Bale weights [kg/ha]	DMB - LUE approach [kg/ha]
Callide	4,735	4,712
Cayman	2,438	2,605
Dicantio	2,705	2,968
Gatton panic	2,475	2,484
Lucero	3,370	3,127
Paiaguas	3,800	3,306
Quenia	2,525	3,017
Ruziziensis	3,860	3,555
Tamani	2,103	2,254

Using the calibrated root-to-shoot ratio, 10-day DMB products were generated for the entire study area, enabling phenometric analysis with high temporal resolution. This approach allows tracking of phenological events and biomass trends in pastures at 10-day intervals. While ground-truth data from FECOPROD field trials ensured proper model calibration, additional in-situ DMB data from other locations within the inference region were unavailable. As a result, DMB estimates could not be validated outside the Chaco region, except for the comparison shown in the previous table.

Results

The catalogue of products from this study is available through the Pasture Biomass Production App (last accessed November 2024). The products, at a 10-meter resolution, include:

- 10-day DMB
- Total DMB annually
- PA products such as start, peak, and end of season (times and DMB values)
- Daily DMB increase or decrease rates from start to peak times or from peak to end times

These products can be compared using the 'Split Map' mode. Additionally, by activating the contextual layer for Pastures experimental plots and selecting 'Display timeseries for selected product,' time-series statistics at the trial plot level are shown when clicking on each plot. Figure 3 illustrates the 10-day DMB product. The DMB products start on fixed days (1, 11, and 21), so the length of the last 10-day interval varies depending on the month.

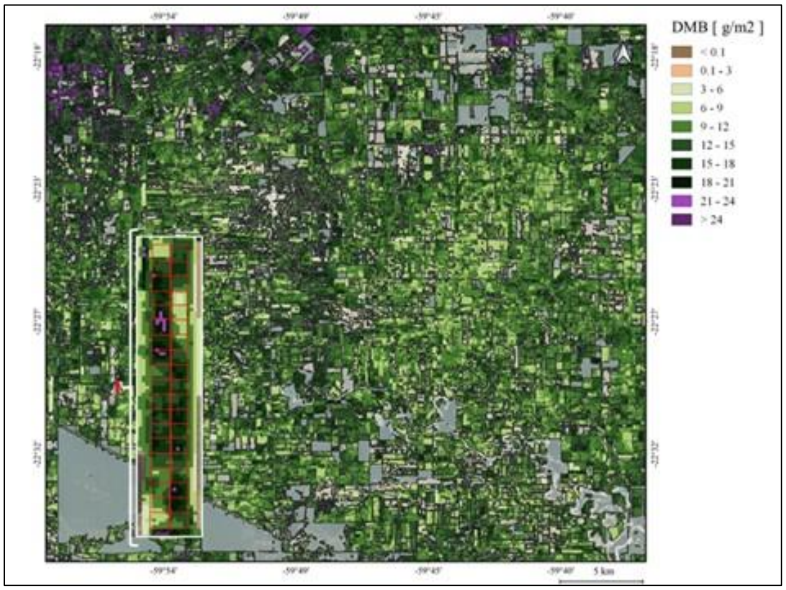

Figure 3 10-day DMB product. DMB generated in the interval 11th-20th, January 2022.

Discussion and conclusions
This study primarily uses datasets from the Copernicus services, but the processors are adaptable to other sources. The time series preparation strategy enables 10-day interval pasture monitoring. Unlike most studies that use a fixed albedo value, this study employs a detailed, updated albedo product from EO data.

The pasture map can be replaced with other maps, such as farm cartography or species-specific maps, as the root-shoot ratio parameter was calibrated for various forage species. The $C_{allocation}$ parameter and environmental stress factors in the LUE calculation were fixed based on local information, but alternative approaches can be considered.

FECOPROD, while technically advanced in data acquisition, lacked the ability to add value to the recorded information. It needed to analyse available data with EO data to generate value-added information like dry matter biomass and its variability over different time spans. The study's initial objectives were achieved, providing a scalable solution that addresses environmental concerns, promotes resource management, and enhances the sustainability of the livestock industry in Paraguay and beyond. This contributes to a more efficient, productive, and environmentally conscious agricultural sector.

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