# Estimating forage yields of rangeland in Burkina Faso's climatic zones using satellite data

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***Keywords***

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***Summary***

The assessment of forage resources is a key element for governing livestock food crises in Burkina Faso. This study aims to evaluate, for the first time, the possibility of estimating forage yields in Burkina Faso's climatic zones using uni and multivariate linear statistical models constructed from forage plant biomass data collected in the field in 2017, 2018, and 2019, and phenological satellite variables (Normalized Difference Vegetation Index (NDVI) and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR)) and agroclimatic variables (precipitation, soil moisture, evapotranspiration, surface temperature). An exhaustive search for the best linear statistical models with one to four variables was conducted, and the best models according to the Bayesian Information Criterion were identified. The performance of the uni to quadri-variate models obtained is quite low, with for all climatic zones except the Sahelian zone, RRMSE press ranging from 55% to 61% ($R^2$ press ranging from 0.07 to 0.36), and for the Sahelian climatic zone, RRMSE press ranging from 42% to 49% ($R^2$ press ranging from 0.59 to 0.69). The decrease in correlation of the majority of variables with forage plant biomass along the north-south gradient results in a decrease in model performance along this gradient. Agroclimatic variables were found to be useless, and those derived from FAPAR appeared to be generally more effective than those derived from NDVI. The results also show a very low added value of multivariate models compared to univariate models, except for the Sahelian zone, and a better performance of models developed in more homogeneous climatic zones. A series of recommendations have been identified to improve the coupling between field-collected forage plant biomass data and variables extracted from satellite images, and thereby improve the performance of the models.

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## ■ INTRODUCTION

Livestock farming is an important pillar of the economy and well-being of rural households in Sahelian countries (Nkonya *et al*., 2015; Valerio *et al*., 2020). In Burkina Faso, it constitutes the primary source of monetary income for rural households and thus enables their access to basic social services (INSD, 2007). Livestock farming is a means to combat poverty and youth unemployment in rural areas (Gning, 2005; Johnson *et al*., 2015). Since 2018, the Burkinabe government has developed an annual response and support plan for vulnerable livestock farmers (PRSEV), which aims to mobilize financial resources to support poor households

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practicing livestock farming. This plan allows for the yearly planning of management actions related to major risks affecting livestock. The contingency of agropastoral drought is one of the most important pillars of this plan (MRAH, 2020). Within this financial and advocacy tool, the cost of livestock feed is the most significant expenditure, representing more than 50% to 60% of the total plan budget. The expenditure varies depending on the performance of the agropastoral season (namely the level of vegetation development and the filling of surface water points and bodies), which influences the number of animals exposed to food crises. The cost of livestock feeding is generally estimated from the forage balance, of which a key phase is the assessment of pastures (FAO, 2020). Given the importance of forage resource assessment in the development of the PRSEV and for the governance of pastoral crises, certain Sahelian countries have agreed to harmonize methods and techniques for assessing pasture forage yields (PRAPS, 2017; PREGEC, 2019). Eventually, the results of the forage balance should be included in analyses carried out within the framework of the harmonized system.

Remote sensing products and services can contribute to the improvement of the implementation of agricultural public policies in Africa and, more specifically, to the prevention and management of pastoral crises (Bégué *et al*., 2020; Taugourdeau *et al*., 2023). With technological advancements, numerous satellite imagery products and data are freely available, such as those from Copernicus (https://land.copernicus.eu) or the US Geological Survey's Early Warning and Environmental Monitoring Program (https://earlywarning.usgs.gov). Algorithms are improving, and the quality of images is increasing (Khamala, 2017). The satellite data and products used for monitoring and evaluation of the agropastoral season are numerous and diverse (Fritz *et al*., 2019). The most commonly used relate to rainfall, soil moisture, surface temperature, evapotranspiration, and vegetation development (Adole *et al*., 2016; Fritz *et al*., 2019), such as, for example, the Normalized Difference Vegetation Index (NDVI), the Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), and dry matter productivity (DMP) (PRAPS, 2017). These are commonly used to estimate forage yields in the Sahel (Diouf *et al*., 2015; Lo *et al*., 2022; Taugourdeau *et al*., 2023), or for the yield estimation of other crops in different geographical contexts (Thao *et al*., 2022). More specifically, according to various authors (Meroni *et al*., 2014; Diouf *et al*., 2015; Olsen *et al*., 2015; Tian *et al*., 2016; Garba *et al*., 2017; Lo *et al*., 2022), the use of phenological variables derived from NDVI and FAPAR satellite images has led to increased accuracy in forage yield estimation models. Satellite products allow for both the identification of forage-deficient areas and a better understanding of drought hazard spatial distribution, as well as improved estimation of dry matter quantities potentially available for livestock feeding during the dry season. Among the available satellite products, it is necessary to identify those that can reliably estimate forage yields from Sahelian rangelands.

In Burkina Faso, there are currently no large-scale studies coupling field-collected forage plant biomass data with satellite variables. However, such an initiative has been ongoing in Senegal for more than three decades to support pastoral livestock farming (Diouf *et al*., 2015). This is because the national biomass data collection system in Burkina Faso was only established in 2017 and is still in the implementation phase for field observation sites. This activity also requires efficient technical support to improve forage yield estimation methods. In this context, the objective of this study was to evaluate, for the first time, the possibility of estimating forage yields from pastures in the climatic zones of Burkina Faso using univariate and multivariate linear statistical models constructed from forage plant biomass data collected in the field in 2017, 2018, and 2019, as well as phenological satellite variables (NDVI and FAPAR) and agroclimatic satellite variables (precipitation, soil moisture, evapotranspiration, surface temperature).

## ■ MATERIAL AND METHODS

The overall methodological framework for identifying the best statistical models to estimate forage yields from pastures in the climatic zones of Burkina Faso using satellite data is presented in Figure 1.

### *Climatic zones of Burkina Faso*

Burkina Faso is a Sahelian country crossed by two major climatic belts: the Sahelian belt and the Sudanian belt, according to the Köppen-Geiger classification (Richter, 2016). The Sudanian belt is divided into two zones, which allows the distinction of three climatic zones: Sahelian, North Sudanian, and South Sudanian. This study also considered, in addition to these three climatic zones, the grouping of the Sahelian and North Sudanian zones, the grouping of the South Sudanian and North Sudanian zones, and finally the grouping of the three initial zones into one national climatic zone, for a total of six climatic zones analyzed.

The ecological drought hazard can heterogeneously affect the different climatic zones and therefore differentially impact their forage production. In the Sahelian grazing areas of Senegal and Niger, various authors (Diouf *et al*., 2015; Garba *et al*., 2017) have shown a reduction in estimation model errors when models were developed per vegetation zone or bioclimatic zone, demonstrating the interest in working at the scale of well-defined and sub-national climatic zones. Thus, in the framework of this study, the division of Burkinabe territory into climatic zones was preferred over division into ecoregions. The division into ecoregions, considered as relatively homogeneous ecological zones (Tappan *et al*., 2016), does not follow the logic of vegetation belts or phytogeographic zones indicated in the works of Fontes and Guinko (1995). The geographical criteria used to define the ecoregions of Burkina Faso are based on the interaction and integration of numerous biophysical factors such as geology, geomorphology, pedology, hydrology, vegetation, climate, and fauna, as well as anthropogenic factors such as land use (Tappan *et al*., 2016). Therefore, to work in more homogeneous vegetation zones, ecoregions were deemed less relevant than climatic zones.

The rainfall situation in Burkina Faso over the period 2017–2019 is characterized by cumulative precipitation (from early April to late October) that was similar to or above the 1981–2010 average over much of the territory (Figure 2). Despite this overall favorable situation, there remains strong spatial and temporal heterogeneity in rainfall, and some provinces show a low level of pasture development, which can locally exacerbate forage deficits. This underscores the importance of spatially evaluating pasture forage yields at the end of the rainy season, in order to facilitate the planning of public actions supporting the livestock sector.

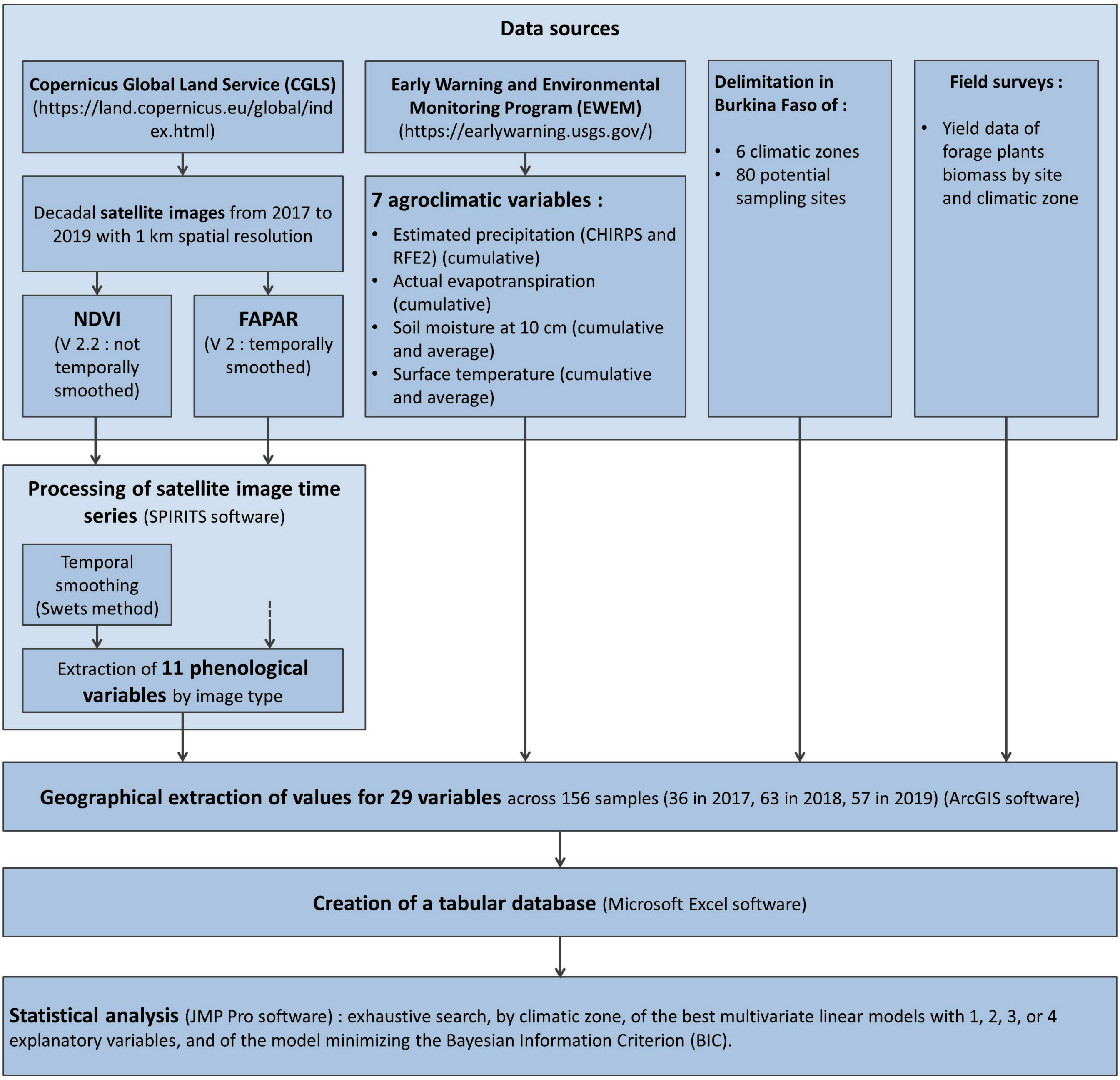


**Figure 1:** Overall methodological scheme for the search for the best linear statistical models for estimating forage yields in Burkina Faso's climatic zones using satellite data /// *Schéma méthodologique global de la recherche des meilleurs modèles statistiques linéaires d'estimation des rendements fourragers des pâturages dans les espaces climatiques du Burkina Faso à partir de données satellitaires*

Climate and anthropogenic activities are the two main factors controlling vegetation dynamics (Leroux *et al*., 2017). The spectral response of vegetation to rainfall in a given climatic zone also depends on its floristic composition and the state of soil fertility (Lind and Fensholt, 1999; Musau *et al*., 2018). In Burkina Faso, during the rainy season (May–June to September–October), vegetation consists of woody and herbaceous species, with a tendency towards the dominance of cultivated plants. The onset of the agropastoral season varies depending on the year and the climatic gradient. The period of herbaceous layer establishment enables livestock feeding and marks the end of the pastoral lean season.

The expansion of agricultural land is a phenomenon that impacts the ecological units of savannas in Burkina Faso. The annual rate of newly cleared plots is 4.2% (MAH *et al*., 2011). Between 2001 and 2014, the area of agricultural land under rainfed cultivation increased from 60,441 to 114,994 km², representing a +90% increase (Knauer *et al*., 2017). Over the same period, the area of irrigated land increased from 78 to 345 km² (+344%), and that of plantations expanded from 561 to 1,568 km² (+179%). In Burkina Faso, the density of woody vegetation decreases along the rainfall gradient, except in forest conservation areas, which show higher density (Fontes and Guinko, 1995). Herbaceous vegetation is dominated by annual herbaceous species and annual crops (Ratzmann *et al*., 2016; Abdi *et al*., 2017).

### *Forage plant biomass sampling sites*

The agricultural landscape of Burkina Faso is characterized by significant fragmentation of land use into agricultural lands (fields),

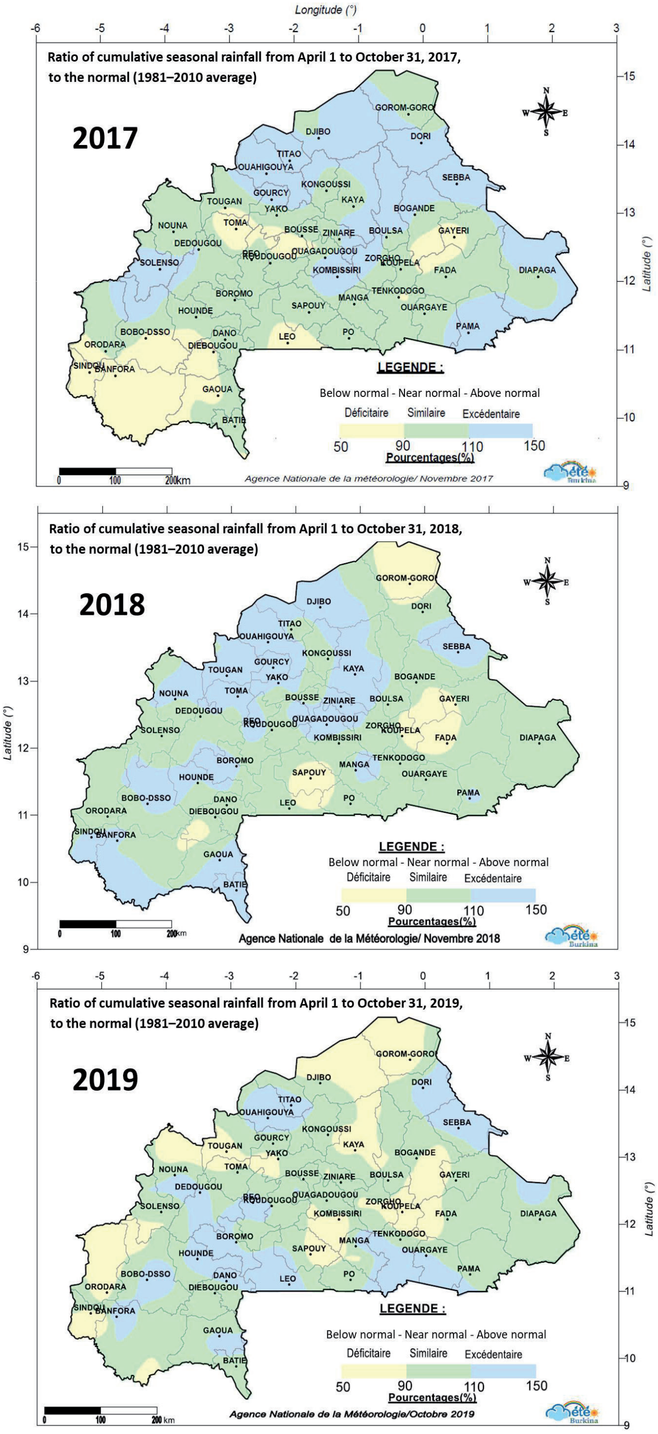


**Figure 2:** Rainfall anomalies recorded from April 1st to October 31st for the years 2017 to 2019 in Burkina Faso /// *Anomalies pluviométriques relevées du 1er avril au 31 octobre pour les années 2017 à 2019 au Burkina Faso*

Source: World AgroMeteorological Information Service (https://wamis.org/wamis/burkina-faso/)

pastures, protected forests, and tree plantations (orchards) (Knauer *et al.*, 2017). The monitoring and evaluation of forage yields requires the establishment of a field-based forage plant biomass sampling system. Furthermore, the assessment of plant resources relies on agroecological and statistical standards (Floc'h, 2007; Daget *et al.*, 2010; Picard *et al.*, 2012), which implies the establishment of sampling sites that are representative of existing ecological facies. Accordingly, the sampling sites are generally based on ecoregions (Tappan *et al.*, 2016). For this study, each ecoregion was stratified into more homogeneous zones based on soil water holding capacity (WHC) (Reynolds *et al.*, 2000). The selection of a potential sampling site was also based on accessibility criteria, with a preference for pastoral zones and former sampling sites of the Environment and Agricultural Research Institute (INERA) for safety and control reasons. In total, 80 potential sites were selected for the national monitoring system. This number is considered ideal for pasture assessment in Burkina Faso, as it is large enough to allow the substitution of a temporarily inaccessible site due to security concerns by another site within the same ecoregion.

The identification phase of potential sampling sites was followed by a validation and installation phase in the field, carried out in collaboration with local communities. The validation involved identifying the location of the sites together with local actors in natural resource management, based on specific criteria—primarily accessibility—and excluding places of worship and local conservation areas not included in the 2012 land use database (BDOT).

The size of a site was set at 1 km × 1 km and 500 m × 500 m in the Sahelian and Sudanian climatic zones, respectively. Site size was reduced in the Sudanian zone due to the significant expansion of croplands and the resulting difficulty in finding homogeneous and accessible 1 km$^2$ pasture areas during the rainy season. Between 2017 and 2019, a total of 156 field samplings were carried out: 36 in 2017, 63 in 2018, and 57 in 2019. Figure 3 shows all the sites that were sampled during this period.

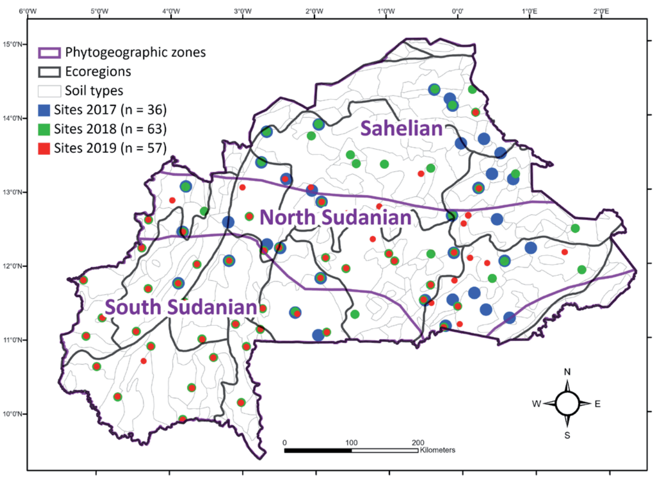


**Figure 3:** Location of forage biomass sampling sites assessed between 2017 and 2019 in Burkina Faso /// *Localisation des sites d'échantillonnage de la biomasse végétale fourragère réalisé entre 2017 et 2019 au Burkina Faso*

Sources: phytogeographic zones from the National Topographic Data Base (BNDT) 2012 of the Geographic Institute of Burkina; Ecoregions from the website https://www.usgs.gov/index.php/centers/eros/science/ecological-regions; Soil types from the FAO World Soil Map (Reynolds et al., 2000).

## *Forage plant biomass data collection*

The forage plant biomass collected at the sampling sites consisted of herbaceous plants and leaves from woody species located at a height of less than 2 meters, that is, within the reach of livestock. The optimal field collection period was determined each year by visualizing the NDVI profile of the vegetation growing season on the FEWSNET website (https://earlywarning.usgs.gov/fews). This period corresponds to the peak of vegetation and varies according to the characteristics of the agropastoral season and the climatic zone in question. It falls between the third ten-day period of September and the first ten-day period of November each year (Figure 4).

The estimation of herbaceous biomass in the field was carried out using the full harvest method described by Levang and Grouzis (1980) and Fournier (1990). A transect of 700 meters (Sudanian zone) or 1,400 meters (Sahelian zone) was established along one of the site's diagonals. At regular intervals—every 23 meters in the Sudanian zone or every 45 meters in the Sahelian zone—herbaceous biomass was harvested within a 1 m² yield quadrat. A total of 30 yield quadrats were delineated per site. The cut grass from each quadrat was weighed fresh in the field, and its weight was recorded on a data sheet. Two 250 g samples of fresh cut grass were collected and air-dried to estimate dry matter content.

The estimation of the biomass of leaves from woody species located at a height of less than 2 meters was conducted in square plots of 2,500 m² (50 m × 50 m) in the Sudanian zone and 10,000 m² (100 m × 100 m) in the Sahelian zone. In most cases, when the woody formations within a site were homogeneous, a single plot per site was used. Otherwise, a second plot per site could be used to better account for the heterogeneity of the site. Each plot was established in a representative area and the different woody species within were identified and counted. Then, a test tree per species, representative of the plot (i.e., an average tree), was selected. The foliar biomass of the test tree was estimated based on one of its branches. The proportion of the test tree's volume accessible to livestock represented by the selected branch was visually estimated (e.g., 1/10th, 1/20th, 1/100th). The leaves from the selected branch were then harvested and weighed. This weight was multiplied by the inverse of the previously estimated proportion to obtain the total weight of leaves accessible to livestock from the test tree. This weight was then multiplied by the number of trees of the species within the plot to obtain the total foliar biomass accessible to livestock for each woody species. The sum across all woody species was then calculated. Finally, the leaves were air-dried and weighed to determine the biomass expressed as dry matter.

### *Satellite data: Phenological and agroclimatic variables*

The list of satellite variables selected for this study was established based on studies related to the modeling of Sahelian rangelands (Diouf *et al*., 2015; Garba *et al*., 2015). These studies relied on a limited set of variables linked to the vegetation development cycle, representing either the causes of this development (e.g., rainfall) or its evaluation (e.g., spectral indices used to assess vegetation quantity) (Diouf *et al*., 2015; Garba *et al*., 2015; Tian *et al*., 2016). The abbreviations and definitions of the 29 variables selected for this study are presented in Table I.

For the calculation of the variables, the period from April to October was chosen for each study year in order to account for the early regrowth of perennial grasses and other woody forage species due to rainfall (Fournier, 1990; Brandt *et al*., 2019; Zhang *et al*., 2019).

The value of each satellite variable corresponds to the average of the pixels intersecting the sampling site. The ArcGIS and SPIRITS (Software for the Processing and Interpretation of Remotely sensed Image Time Series) software programs (Eerens *et al*., 2014) were used to extract the variable values from satellite imagery.

### *Phenological variables*

Twenty-two phenological variables characterizing the vegetation development profile during the rainy season were generated by processing decadal time series of NDVI (version 2.2, 11 variables) and FAPAR (version 2, 11 variables) satellite products at 1 km spatial resolution, derived from PROBA-V satellite data, and freely available on the Copernicus Global Land Service (CGLS) website (https://land.copernicus.vgt.vito.be/).

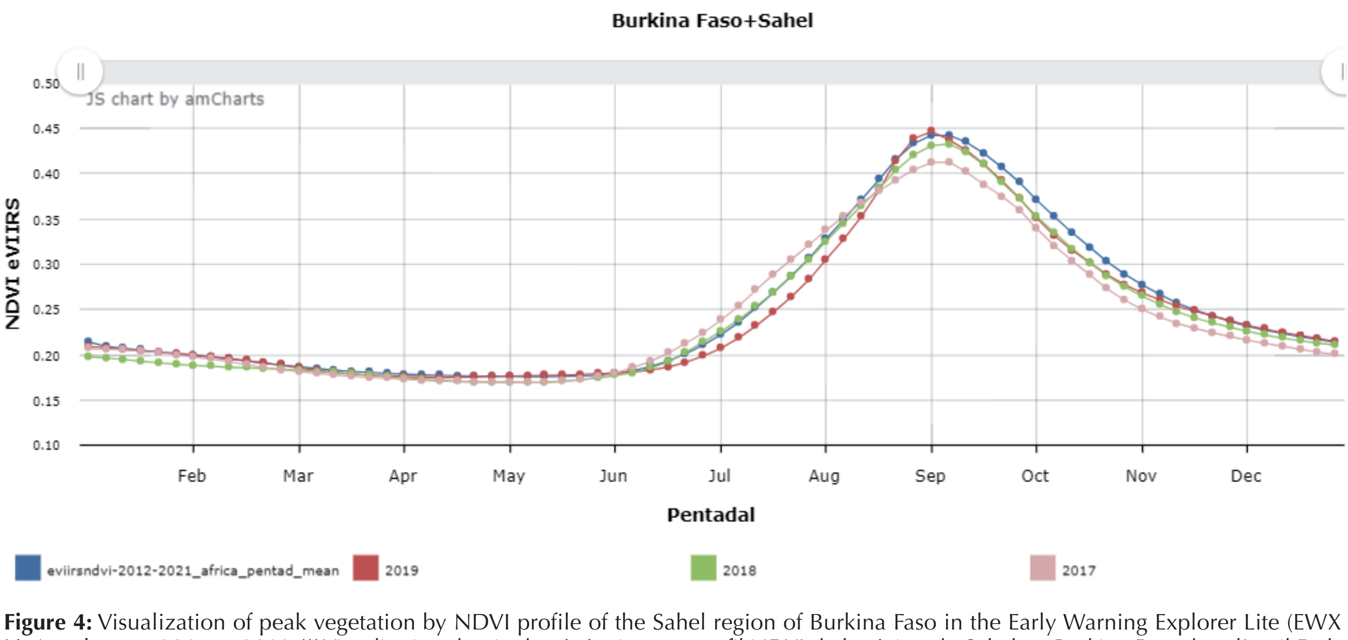


**Figure 4:** Visualization of peak vegetation by NDVI profile of the Sahel region of Burkina Faso in the Early Warning Explorer Lite (EWX Lite) tool, years 2017 to 2019 /// *Visualisation du pic de végétation par profil NDVI de la région du Sahel au Burkina Faso dans l'outil Early Warning Explorer Lite (EWX Lite), années 2017 à 2019*
Source: FEWS NET https://earlywarning.usgs.gov/fews/ewx_lite/index.html?region=af

**Table I:** Abbreviation and definition of explanatory variables for forage plant biomass calculated from time series of satellite data over the period of the agropastoral season from the beginning of April to the end of October, for the years 2017, 2018 and 2019: phenological (n = 2*11) and agroclimatic (n = 7) variables /// *Abréviation et définition des variables explicatives de la biomasse végétale fourragère calculées à partir de séries temporelles de données satellitaires sur la période de la campagne agropastorale allant de début avril à fin octobre, pour les années 2017, 2018 et 2019 : variables phénologiques (n = 2*11) et agroclimatiques (n = 7)*

| | |
|---|---|
| **Agroclimatic variables** | |
| AET_cum | Actual evapotranspiration (cumulative monthly data) |
| CHIRPS_cum | Estimated precipitation using the CHIRPS* method (cumulative monthly data) |
| RFE2_cum | Estimated precipitation using the RFE* method version 2.0 (cumulative monthly data) |
| SM10_cum | Soil moisture at 10 cm depth (cumulative monthly data) |
| SM10_moy | Soil moisture at 10 cm depth (monthly data average) |
| LST_cum | Surface temperature (cumulative monthly data) |
| LST_moy | Surface temperature (monthly data average) |
| **Phenological variables calculated from NDVI* and FAPAR* time series** (definitions adapted from Eerens et al., 2014) | |
| Vav<br>Vmn<br>Vmx | Mean value (Vav), minimum value (Vmn), or maximum value (Vmx) of the NDVI or FAPAR curve |
| Aup<br>Adn | Angle representing the greatest increase (Aup) or decrease (Adn) during the growth (Aup) or decline (Adn) phase of the NDVI or FAPAR curve between two successive dekad |
| Rrg | Vmx-Vmn |
| Rsd | Standard deviation of NDVI or FAPAR values calculated within the Rrg value range |
| Dmn | Date of the (first) Vmn |
| Dmx | Date of the (last) Vmx |
| Dup | Date of the (first) Aup |
| Ddn | Date of the (last) Adn |

* NDVI : Normalized Difference Vegetation Index ; FAPAR : Fraction of Absorbed Photosynthetically Active Radiation ; CHIRPS : Climate Hazards Group InfraRed Precipitation with Station data ; RFE : Rainfall Estimates.

The NDVI is a vegetation index calculated from the red and near-infrared spectral bands (Rouse *et al*., 1973). Chlorophyllous plant material strongly absorbs solar radiation in the red spectral band and reflects it strongly in the near-infrared band. NDVI is thus an indicator of the quantity and condition of chlorophyllous plant matter, and it is often considered, by extension, a proxy for green biomass quantity (Gamon *et al*., 1995; Western *et al*., 2015).

FAPAR images are calculated from reflectances in the visible and near-infrared spectral domains (Jacobs, 2019). FAPAR is the fraction of incident photosynthetically active solar radiation (400–700 nm) that is absorbed by vegetation (Monteith, 1972; Gitelson *et al*., 2014). It allows assessment of the vegetation's condition and its potential productivity (Gitelson *et al*., 2014).

The extraction of phenological variables was carried out using SPIRITS software, which is recommended for agropastoral season monitoring and evaluation based on satellite products (Eerens *et al*., 2014). Before extracting the phenological variables using the Pheno function of SPIRITS, the NDVI time series was temporally smoothed to reduce the effect of atmospheric disturbances on the satellite signal, using the Swets filter in SPIRITS software. This is an algorithm based on a linear regression approach using the weighted least squares method. The FAPAR time series, on the other hand, was available for download already temporally smoothed (Jacobs, 2019).

## *Agroclimatic variables*

Seven variables related to agroclimatic conditions that have played a role in the onset of past food crises were considered. These include precipitation data (monthly cumulative values, 0.05 × 0.05 degree resolution, CHIRPS and RFE2), surface temperature (monthly cumulative and average values, 0.05 × 0.05 degree resolution), and actual evapotranspiration (monthly cumulative values, 1 × 1 km resolution), all extracted from the Early Warning and Environmental Monitoring Program (EWEM) website (https://earlywarning.usgs.gov/); and soil moisture data for the 0–10 cm layer (monthly cumulative and average values, 0.1 × 0.1 degree resolution) obtained from the FEWSNET Land Data Assimilation System (FLDAS) website (https://ldas.gsfc.nasa.gov/fldas). These variables are originally derived from satellite imagery and models. The estimation methods for these variables are described in works by various authors that are freely accessible (Wan, 1999; NOAA/CPC, 2001; Savoca *et al*., 2013; Funk *et al*., 2015; McNally *et al*., 2017).

## *Statistical modeling*

The statistical approach of this study aimed to identify the best univariate and multivariate linear models for predicting forage plant biomass in each of the six climatic zones of Burkina Faso, based on the 29 satellite variables presented in the previous section.

For each climatic zone, an exhaustive search was carried out for the best linear statistical models (based on $R^2$) including one, two, three, or four explanatory variables. A maximum of four variables was chosen to limit issues related to overfitting, with four considered a reasonable upper limit for this study. Among the four best models per climatic zone, the best model was identified as the one minimizing the Bayesian Information Criterion (BIC) (Schwarz, 1978; Burnham and Anderson, 2004). The BIC penalizes the selection of models with too many variables, thereby enabling the identification of more parsimonious models.

No interaction effects between variables or variable transformations were applied prior to model selection. All available observations within a given climatic zone were used to construct the statistical models for that zone.

The quality of the models produced was evaluated using three main parameters:

RMSE: Root Mean Square Error (kg/ha), which is the square root of the mean of squared errors;

RRMSE: Relative Root Mean Square Error (%), which is the RMSE divided by the mean value of the observations;

$R^2$: Pearson's linear coefficient of determination, which indicates the proportion of the variance in forage plant biomass explained by the model.

Each of these three parameters was calculated in two ways: (i) based on the results of each model obtained (these parameters are then suffixed with "ordinary"), and (ii) in predictive mode using leave-one-out cross-validation (these parameters are then suffixed with "press", which stands for "prediction error sum of squares"). In addition, the adjusted $R^2$ was calculated for each model. The adjusted $R^2$ moderates the value of $R^2$ based on the number of parameters included in the model and thus facilitates comparison between models with different numbers of parameters.

Pearson correlation coefficients between forage plant biomass and each of the 29 potential explanatory variables were calculated for each of the six climatic zones of Burkina Faso. Pairwise correlations between variables were systematically examined for the national climatic zone.

All statistical analyses were performed using JMP Pro software.

## ■ RESULTS

### *Forage plant biomass*

Across all years combined (2017, 2018, 2019), the average forage yield values, expressed in kilograms of dry matter per hectare, from the field-assessed sites increase from north to south (Figure 5), with 732 kg/ha in the Sahelian zone, 1,452 kg/ha in the North Sudanian zone, and 1,875 kg/ha in the South Sudanian zone. However, there is a relatively significant overlap in yield values among these three climatic zones, as well as a wide range of value dispersion within each climatic zone.

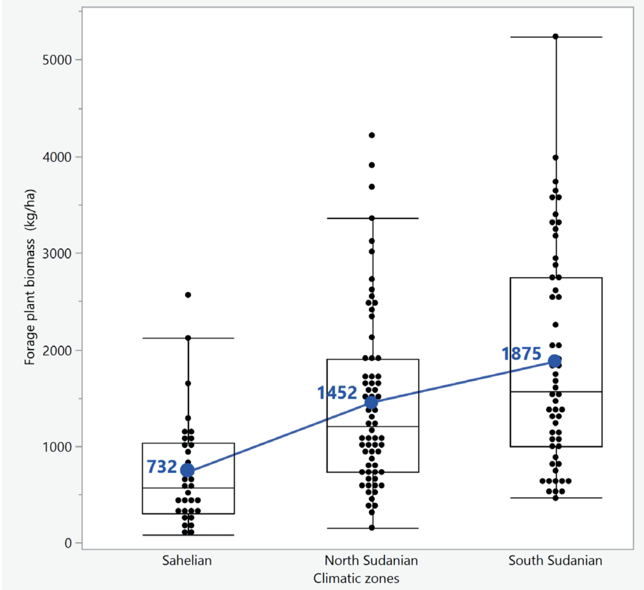


**Figure 5:** Total forage plant biomass (kg of dry matter per ha) from field-assessed sites (combined years 2017, 2018, and 2019), in the three climatic zones of Burkina Faso /// *Biomasse végétale fourragère totale (kg de matière sèche par ha) des sites évalués sur le terrain (années 2017, 2018 et 2019 confondues), dans les trois espaces climatiques du Burkina Faso*

In blue: average by climatic zone. The horizontal lines in the boxes correspond to the medians, the lower and upper limits of the boxes correspond to the 1st and 3rd quartiles, and the "whiskers" correspond to the minimum and maximum values excluding extreme values. Basic descriptive statistics for all variables studied (forage plant biomass and 29 explanatory variables) for all 156 sites sampled in Burkina Faso are presented in supplementary material I /// *En bleu : moyenne par espace climatique. Les lignes horizontales dans les boites correspondent aux médianes, les limites inférieures et supérieures des boites correspondent aux 1er et 3e quartiles, et les « moustaches » correspondent aux valeurs minimales et maximales hors valeurs extrêmes. Les statistiques descriptives de base de toutes les variables étudiées (biomasse végétale fourragère et 29 variables explicatives) pour l'ensemble des 156 sites échantillonnés au Burkina Faso sont présentées dans le matériel supplémentaire I*

### *Pearson correlation between explanatory variables at the national scale*

Figure 6 presents the matrix of Pearson correlation coefficients for all variables studied at the national scale (156 sites).

| | | | Agroclimatic variables | | | | | | | FAPAR phenological variables | | | | | | | | | | | NDVI phenological variables | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | FPB | CHIRPS_cum | RFE2_cum | SM10_cum | SM10_moy | AET | LST_cum | LST_moy | adn_fapar | aup_fapar | ddn_fapar | dmn_fapar | dmx_fapar | dup_fapar | rrg_fapar | rsd_fapar | vav_fapar | vmn_fapar | vmx_fapar | adn_ndvi | aup_ndvi | ddn_ndvi | dmn_ndvi | dmx_ndvi | dup_ndvi | rrg_ndvi | rsd_ndvi | vav_ndvi | vmn_ndvi | vmx_ndvi |
| | FPB | 1.00 | 0.39 | 0.35 | 0.40 | 0.40 | 0.33 | -0.35 | -0.35 | -0.12 | 0.29 | 0.27 | -0.27 | 0.14 | -0.24 | 0.45 | 0.35 | 0.48 | 0.29 | 0.51 | 0.04 | 0.22 | 0.08 | -0.31 | 0.08 | -0.21 | 0.41 | 0.38 | 0.48 | 0.33 | 0.47 |
| Agroclimatic var. | CHIRPS_cum | 0.39 | 1.00 | 0.88 | 0.95 | 0.95 | 0.45 | -0.73 | -0.73 | 0.08 | 0.00 | 0.51 | -0.43 | 0.25 | -0.35 | 0.36 | 0.22 | 0.82 | 0.76 | 0.78 | 0.09 | 0.25 | -0.19 | -0.45 | 0.07 | -0.21 | 0.49 | 0.41 | 0.80 | 0.74 | 0.76 |
| | RFE2_cum | 0.35 | 0.88 | 1.00 | 0.84 | 0.84 | 0.44 | -0.73 | -0.73 | 0.09 | 0.02 | 0.47 | -0.47 | 0.18 | -0.35 | 0.34 | 0.20 | 0.75 | 0.69 | 0.71 | 0.03 | 0.23 | -0.17 | -0.42 | 0.01 | -0.25 | 0.47 | 0.38 | 0.74 | 0.67 | 0.70 |
| | SM10_cum | 0.40 | 0.95 | 0.84 | 1.00 | 1.00 | 0.43 | -0.73 | -0.73 | 0.06 | 0.01 | 0.49 | -0.46 | 0.27 | -0.40 | 0.37 | 0.22 | 0.81 | 0.72 | 0.76 | 0.05 | 0.28 | -0.21 | -0.46 | 0.09 | -0.23 | 0.51 | 0.40 | 0.77 | 0.68 | 0.73 |
| | SM10_moy | 0.40 | 0.95 | 0.84 | 1.00 | 1.00 | 0.43 | -0.73 | -0.73 | 0.06 | 0.01 | 0.49 | -0.46 | 0.27 | -0.40 | 0.37 | 0.22 | 0.81 | 0.72 | 0.76 | 0.05 | 0.28 | -0.21 | -0.46 | 0.09 | -0.23 | 0.51 | 0.40 | 0.77 | 0.68 | 0.73 |
| | AET | 0.33 | 0.45 | 0.44 | 0.43 | 0.43 | 1.00 | -0.66 | -0.66 | 0.03 | 0.20 | 0.27 | -0.27 | 0.04 | -0.53 | 0.42 | 0.27 | 0.73 | 0.58 | 0.69 | -0.15 | 0.16 | -0.08 | -0.31 | 0.01 | -0.35 | 0.48 | 0.40 | 0.72 | 0.57 | 0.66 |
| | LST_cum | -0.35 | -0.73 | -0.73 | -0.73 | -0.73 | -0.66 | 1.00 | 1.00 | -0.07 | -0.09 | -0.37 | 0.42 | 0.02 | 0.54 | -0.32 | -0.14 | -0.85 | -0.77 | -0.76 | 0.07 | -0.20 | 0.20 | 0.37 | 0.09 | 0.39 | -0.47 | -0.35 | -0.82 | -0.70 | -0.72 |
| | LST_moy | -0.35 | -0.73 | -0.73 | -0.73 | -0.73 | -0.66 | 1.00 | 1.00 | -0.07 | -0.09 | -0.37 | 0.42 | 0.02 | 0.54 | -0.32 | -0.14 | -0.85 | -0.77 | -0.76 | 0.07 | -0.20 | 0.20 | 0.37 | 0.09 | 0.39 | -0.47 | -0.35 | -0.82 | -0.70 | -0.72 |
| FAPAR phenological variables | adn_fapar | -0.12 | 0.08 | 0.09 | 0.06 | 0.06 | 0.03 | -0.07 | -0.07 | 1.00 | -0.13 | -0.05 | 0.10 | 0.06 | 0.00 | -0.15 | -0.15 | 0.00 | 0.07 | -0.05 | 0.33 | -0.16 | -0.13 | 0.09 | -0.09 | 0.03 | -0.12 | -0.14 | -0.02 | 0.06 | -0.06 |
| | aup_fapar | 0.29 | 0.00 | 0.02 | 0.01 | 0.01 | 0.20 | -0.09 | -0.09 | -0.13 | 1.00 | 0.07 | -0.13 | -0.15 | -0.23 | 0.39 | 0.36 | 0.18 | -0.07 | 0.22 | -0.23 | 0.40 | -0.02 | -0.14 | -0.25 | -0.25 | 0.35 | 0.34 | 0.22 | -0.01 | 0.25 |
| | ddn_fapar | 0.27 | 0.51 | 0.47 | 0.49 | 0.49 | 0.27 | -0.37 | -0.37 | -0.05 | 0.07 | 1.00 | -0.27 | 0.33 | -0.11 | 0.45 | 0.42 | 0.43 | 0.25 | 0.49 | 0.18 | 0.07 | 0.30 | -0.56 | 0.12 | -0.08 | 0.29 | 0.29 | 0.49 | 0.53 | 0.50 |
| | dmn_fapar | -0.27 | -0.43 | -0.47 | -0.46 | -0.46 | -0.27 | 0.42 | 0.42 | 0.10 | -0.13 | -0.27 | 1.00 | -0.04 | 0.31 | -0.31 | -0.20 | -0.46 | -0.30 | -0.42 | 0.17 | -0.20 | 0.07 | 0.43 | -0.05 | 0.25 | -0.39 | -0.32 | -0.47 | -0.31 | -0.46 |
| | dmx_fapar | 0.14 | 0.25 | 0.18 | 0.27 | 0.27 | 0.04 | 0.02 | 0.02 | 0.06 | -0.15 | 0.33 | -0.04 | 1.00 | 0.08 | 0.05 | 0.10 | 0.04 | 0.05 | 0.07 | 0.14 | -0.13 | 0.02 | -0.18 | 0.60 | 0.22 | 0.01 | 0.06 | 0.05 | 0.19 | 0.12 |
| | dup_fapar | -0.24 | -0.35 | -0.35 | -0.40 | -0.40 | -0.53 | 0.54 | 0.54 | 0.00 | -0.23 | -0.11 | 0.31 | 0.08 | 1.00 | -0.31 | -0.08 | -0.59 | -0.35 | -0.46 | 0.10 | -0.08 | 0.19 | 0.33 | 0.05 | 0.63 | -0.36 | -0.20 | -0.59 | -0.37 | -0.46 |
| | rrg_fapar | 0.45 | 0.36 | 0.34 | 0.37 | 0.37 | 0.42 | -0.32 | -0.32 | -0.15 | 0.39 | 0.45 | -0.31 | 0.05 | -0.31 | 1.00 | 0.93 | 0.51 | 0.04 | 0.73 | -0.18 | 0.43 | 0.16 | -0.42 | 0.01 | -0.22 | 0.84 | 0.85 | 0.56 | 0.21 | 0.73 |
| | rsd_fapar | 0.35 | 0.22 | 0.20 | 0.22 | 0.22 | 0.27 | -0.14 | -0.14 | -0.15 | 0.36 | 0.42 | -0.20 | 0.10 | -0.08 | 0.93 | 1.00 | 0.32 | -0.10 | 0.58 | -0.20 | 0.41 | 0.25 | -0.27 | 0.03 | -0.05 | 0.78 | 0.87 | 0.38 | 0.08 | 0.61 |
| | vav_fapar | 0.48 | 0.82 | 0.75 | 0.81 | 0.81 | 0.73 | -0.85 | -0.85 | 0.00 | 0.18 | 0.43 | -0.46 | 0.04 | -0.59 | 0.51 | 0.32 | 1.00 | 0.85 | 0.94 | -0.09 | 0.33 | -0.17 | -0.48 | -0.08 | -0.39 | 0.64 | 0.51 | 0.99 | 0.82 | 0.91 |
| | vmn_fapar | 0.29 | 0.76 | 0.69 | 0.72 | 0.72 | 0.58 | -0.77 | -0.77 | 0.07 | -0.07 | 0.25 | -0.30 | 0.05 | -0.35 | 0.04 | -0.10 | 0.85 | 1.00 | 0.71 | -0.03 | 0.17 | -0.28 | -0.26 | -0.09 | -0.18 | 0.28 | 0.16 | 0.80 | 0.85 | 0.66 |
| | vmx_fapar | 0.51 | 0.78 | 0.71 | 0.76 | 0.76 | 0.69 | -0.76 | -0.76 | -0.05 | 0.22 | 0.49 | -0.42 | 0.07 | -0.46 | 0.73 | 0.58 | 0.94 | 0.71 | 1.00 | -0.14 | 0.42 | -0.08 | -0.47 | -0.06 | -0.28 | 0.78 | 0.71 | 0.94 | 0.74 | 0.96 |
| NDVI phenological variables | adn_ndvi | 0.04 | 0.09 | 0.03 | 0.05 | 0.05 | -0.15 | 0.07 | 0.07 | 0.33 | -0.23 | 0.18 | 0.17 | 0.14 | 0.10 | -0.18 | -0.20 | -0.09 | -0.03 | -0.14 | 1.00 | -0.35 | 0.10 | -0.17 | -0.08 | -0.06 | -0.42 | -0.42 | -0.08 | 0.17 | -0.21 |
| | aup_ndvi | 0.22 | 0.25 | 0.23 | 0.28 | 0.28 | 0.16 | -0.20 | -0.20 | -0.16 | 0.40 | 0.07 | -0.20 | -0.13 | -0.08 | 0.43 | 0.41 | 0.33 | 0.17 | 0.42 | -0.35 | 1.00 | -0.17 | -0.08 | -0.14 | -0.03 | 0.54 | 0.54 | 0.31 | 0.06 | 0.43 |
| | ddn_ndvi | 0.08 | -0.19 | -0.17 | -0.21 | -0.21 | -0.08 | 0.20 | 0.20 | -0.13 | -0.02 | 0.30 | 0.07 | 0.02 | 0.19 | 0.16 | 0.25 | -0.17 | -0.28 | -0.08 | 0.10 | -0.17 | 1.00 | -0.17 | 0.07 | 0.04 | -0.07 | 0.06 | -0.11 | -0.08 | -0.09 |
| | dmn_ndvi | -0.31 | -0.45 | -0.42 | -0.46 | -0.46 | -0.31 | 0.37 | 0.37 | 0.09 | -0.14 | -0.56 | 0.43 | -0.18 | 0.33 | -0.42 | -0.27 | -0.48 | -0.26 | -0.47 | -0.17 | -0.08 | -0.17 | 1.00 | 0.01 | 0.34 | -0.27 | -0.20 | -0.55 | -0.53 | -0.49 |
| | dmx_ndvi | 0.08 | 0.07 | 0.01 | 0.09 | 0.09 | 0.01 | 0.09 | 0.09 | -0.09 | -0.25 | 0.12 | -0.05 | 0.60 | 0.05 | 0.01 | 0.03 | -0.08 | -0.09 | -0.06 | -0.08 | -0.14 | 0.07 | 0.01 | 1.00 | 0.21 | 0.06 | 0.07 | -0.10 | -0.13 | -0.03 |
| | dup_ndvi | -0.21 | -0.21 | -0.25 | -0.23 | -0.23 | -0.35 | 0.39 | 0.39 | 0.03 | -0.25 | -0.08 | 0.25 | 0.22 | 0.63 | -0.22 | -0.05 | -0.39 | -0.18 | -0.28 | -0.06 | -0.03 | 0.04 | 0.34 | 0.21 | 1.00 | -0.12 | -0.03 | -0.42 | -0.27 | -0.24 |
| | rrg_ndvi | 0.41 | 0.49 | 0.47 | 0.51 | 0.51 | 0.48 | -0.47 | -0.47 | -0.12 | 0.35 | 0.29 | -0.39 | 0.01 | -0.36 | 0.84 | 0.78 | 0.64 | 0.28 | 0.78 | -0.42 | 0.54 | -0.07 | -0.27 | 0.06 | -0.12 | 1.00 | 0.95 | 0.65 | 0.23 | 0.85 |
| | rsd_ndvi | 0.38 | 0.41 | 0.38 | 0.40 | 0.40 | 0.40 | -0.35 | -0.35 | -0.14 | 0.34 | 0.29 | -0.32 | 0.06 | -0.20 | 0.85 | 0.87 | 0.51 | 0.16 | 0.71 | -0.42 | 0.54 | 0.06 | -0.20 | 0.07 | -0.03 | 0.95 | 1.00 | 0.53 | 0.13 | 0.77 |
| | vav_ndvi | 0.48 | 0.80 | 0.74 | 0.77 | 0.77 | 0.72 | -0.82 | -0.82 | -0.02 | 0.22 | 0.49 | -0.47 | 0.05 | -0.59 | 0.56 | 0.38 | 0.99 | 0.80 | 0.94 | -0.08 | 0.31 | -0.11 | -0.55 | -0.10 | -0.42 | 0.65 | 0.53 | 1.00 | 0.85 | 0.93 |
| | vmn_ndvi | 0.33 | 0.74 | 0.67 | 0.68 | 0.68 | 0.57 | -0.70 | -0.70 | 0.06 | -0.01 | 0.53 | -0.31 | 0.19 | -0.37 | 0.21 | 0.08 | 0.82 | 0.85 | 0.74 | 0.17 | 0.06 | -0.08 | -0.53 | -0.13 | -0.27 | 0.23 | 0.13 | 0.85 | 1.00 | 0.71 |
| | vmx_ndvi | 0.47 | 0.76 | 0.70 | 0.73 | 0.73 | 0.66 | -0.72 | -0.72 | -0.06 | 0.25 | 0.50 | -0.46 | 0.12 | -0.46 | 0.73 | 0.61 | 0.91 | 0.66 | 0.96 | -0.21 | 0.43 | -0.09 | -0.49 | -0.03 | -0.24 | 0.85 | 0.77 | 0.93 | 0.71 | 1.00 |

**Figure 6:** Matrix of Pearson correlation coefficients for all variables studied at national level (156 sites) /// *Matrice des coefficients de corrélation de Pearson de l'ensemble des variables étudiées à l'échelle nationale (156 sites)*

Variable name abbreviations: see Table I /// *Abréviation des noms des variables : confer Tableau I*

Color code for Pearson correlation coefficients : -1.00 0.00 1.00

Concerning agroclimatic variables, the cumulative and mean values calculated for soil moisture at 10 cm depth (SM10_cum and SM10_moy), or for surface temperature (LST_cum and LST_moy), logically exhibit a correlation of 1, making them redundant in the context of statistical model development for estimating forage plant biomass. A relatively strong correlation ($r = 0.88$) is observed between the two rainfall-related variables (CHIRPS_cum and RFE2_cum), indicating a certain convergence between these two data sources. A strong correlation is also observed between soil moisture variables and precipitation variables ($r = 0.84$ and $0.95$, respectively).

Regarding phenological variables, the FAPAR variables generally show very low mutual correlations, with the exception of the trio of variables vav, vmn, vmx, and the pair rsd and rrg. The same observation holds true for NDVI variables. Correlations between phenological FAPAR and NDVI variables (Figure 6, lower central area, and Figure 7) are mostly weak, but some variable pairs are highly to very highly correlated, particularly when comparing the same type of variable calculated from FAPAR and NDVI (e.g., $r = 0.99$ for vav_fapar and vav_NDVI).

Agroclimatic variables are weakly correlated with the majority (16 out of 22) of phenological variables ($0 \leq |r| \leq 0.54$), but exhibit stronger correlations with the six phenological FAPAR and NDVI variables of the vav, vmn, vmx types ($0.57 \leq |r| \leq 0.85$), which can be explained by the causal relationship between meteorological conditions and vegetation development.

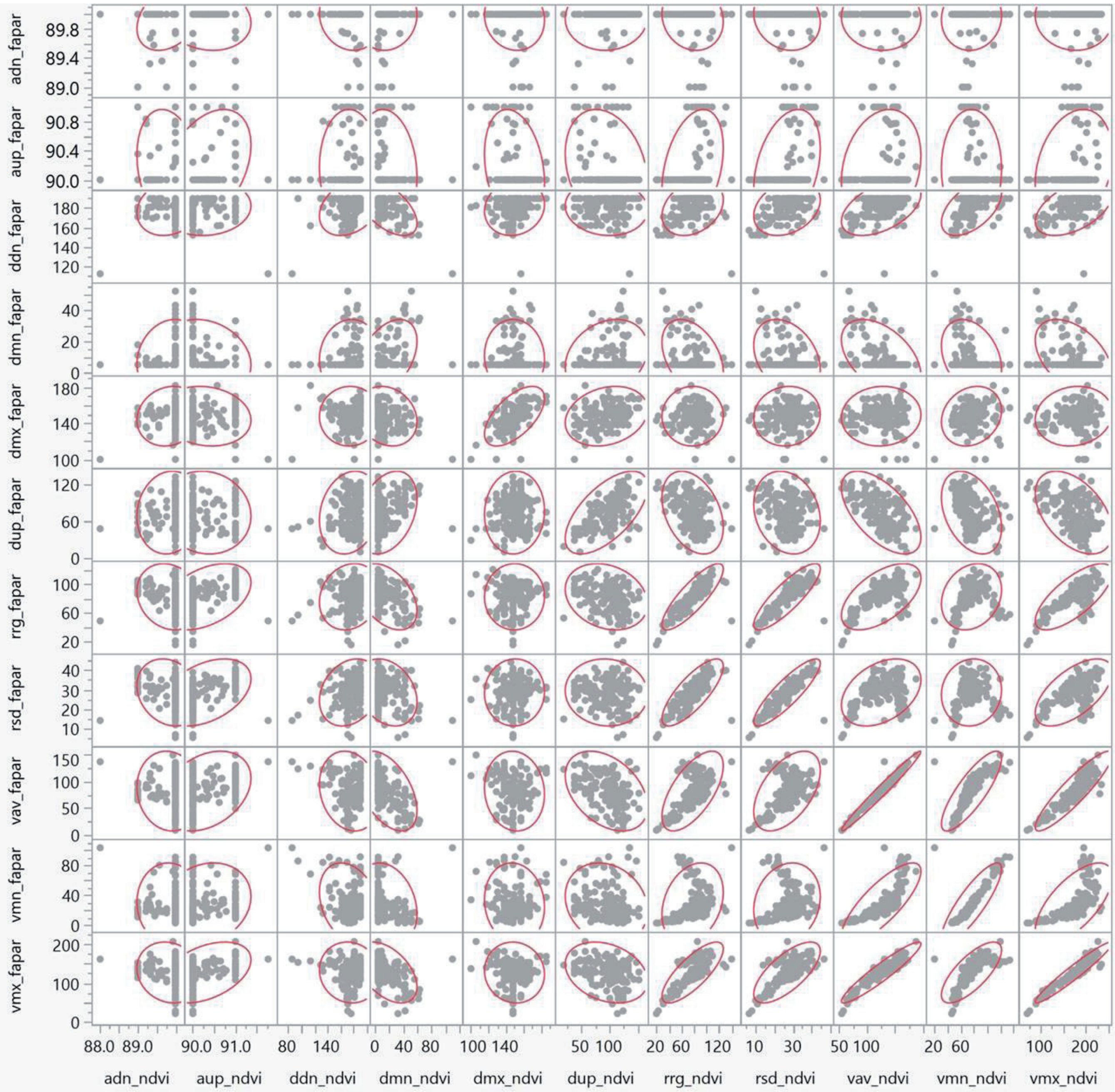


**Figure 7:** Scatterplot matrix of FAPAR-derived variables versus NDVI-derived variables at national scale (156 sites) /// *Matrice des graphiques de nuages de points des variables dérivées du FAPAR en fonction des variables dérivées du NDVI à l'échelle nationale (156 sites)*

In red: point density ellipse. Variable name abbreviations: see Table I /// *En rouge : ellipse de densité des points. Abréviation des noms des variables : confer Tableau I*

## *Pearson correlation between forage plant biomass and explanatory variables*

Figure 8 and Table II respectively present the absolute values and the actual values of the Pearson correlation coefficients of the 29 variables with forage plant biomass across the three or six considered climatic zones.

The correlation progressively decreases along the north-south latitude gradient for the majority of the variables (18 out of 29). The decrease in correlation is strong and almost systematic (27 variables out of 29) from the Sahelian zone to the North Sudanian zone. The transition from the North Sudanian zone to the South Sudanian zone is more heterogeneous, with smaller decreases or increases and, in some cases, stability. In particular, a few variables (8), including aup_fapar and rsd_fapar, show a decrease in correlation from the Sahelian zone to the North Sudanian zone, followed by an increase in correlation from the North Sudanian to the South Sudanian zone (Figure 8). It is also worth noting that two variables, dup_ndvi and adn_fapar, show an atypical north-south evolution of their correlation with forage plant biomass, with a peak correlation reached in the intermediate North Sudanian zone (Figure 8).

The ranking of climatic zones in descending order based on the average absolute values of the correlations calculated across all 29 variables is as follows: Sahelian ($r = 0.52$), Sahelian and North Sudanian ($r = 0.38$), Burkinabe (national) ($r = 0.31$), North Sudanian ($r = 0.19$), North Sudanian and South Sudanian ($r = 0.16$), South Sudanian ($r = 0.11$) (last row of Table II). The same order is observed when individually considering the groups of agroclimatic variables, FAPAR phenological variables, or NDVI phenological variables, with the exception of a minor inversion in the order for the agroclimatic variables between the North Sudanian and North Sudanian–South Sudanian zones. The average absolute correlation values are pulled upward by the Sahelian climatic zone in the three zones that include it, resulting in better correlations in the national Burkinabe zone than in the two smaller and more homogeneous zones, North Sudanian and South Sudanian, or their combination.

In the Sahelian zone, the variables vav_fapar ($r = 0.81$) and vav_ndvi ($r = 0.80$) show the highest correlation with forage plant biomass. Six other variables show correlations greater than or equal to 0.70 (Table II). In the North Sudanian zone, the variables vav_fapar ($r = 0.43$), vmx_fapar ($r = 0.38$), and vav_ndvi ($r = 0.43$) show the highest correlation values. In the South Sudanian zone, the variable aup_fapar ($r = 0.39$) shows by far the highest correlation, but this variable exhibits low correlation in the Sahelian and North Sudanian zones compared to other variables. At the national level, the FAPAR and NDVI variables of the vav and vmx types show the highest correlation with forage plant biomass ($0.47 \leq r \leq 0.51$) (Table II).

In the South Sudanian zone, four variables derived from FAPAR exhibit absolute correlation values equal to or greater than 0.2, whereas those derived from NDVI all remain below 0.2. This could possibly be explained based on two elements: (i) the South Sudanian climatic zone has greater cloud cover than the two zones further north; (ii) the FAPAR products may have better quality than the NDVI products, with this higher quality potentially stemming from better preprocessing allowing for greater attenuation of the disturbing effect of clouds on FAPAR images, and thus a greater sensitivity to changes in vegetation conditions.

The agroclimatic variables exhibit very low correlation values in the North Sudanian and South Sudanian climatic zones (Figure 8), which could be explained by the fact that these variables do not correspond to strongly limiting factors for vegetation growth in these two zones.

The ranking of variables according to their correlation value with forage plant biomass is not the same across the three climatic zones (Figure 8), reflecting the variability of their relative importance in these different zones in the context of forage plant biomass estimation.

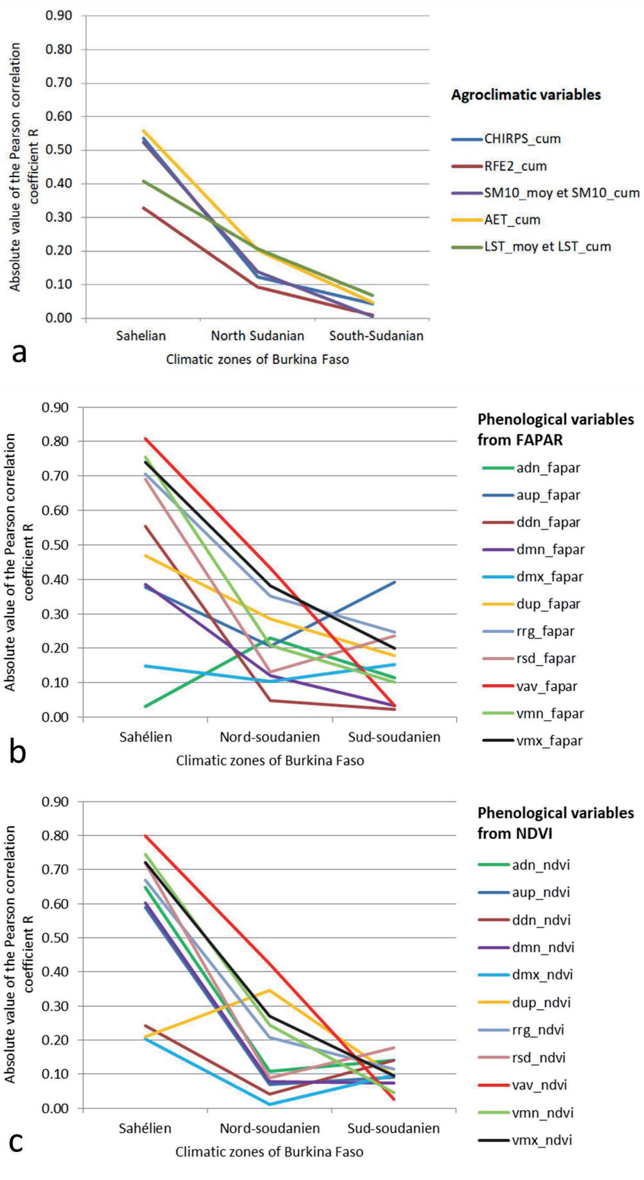


**Figure 8:** Evolution, in the 3 Sahelian, North-Sudanese, and South-Sudanese climatic zones of Burkina Faso, of Pearson correlation coefficient values between forage plant biomass of pastures and (a) the 7 agroclimatic variables, (b) the 11 phenological variables derived from FAPAR, and (c) the 11 phenological variables derived from NDVI /// *Évolution, dans les 3 espaces climatiques sahélien, nord-soudanien et sud-soudanien du Burkina Faso, des valeurs du coefficient de corrélation de Pearson entre la biomasse végétale fourragère des pâturages, et (a) les 7 variables agroclimatiques, (b) les 11 variables phénologiques issues du FAPAR et (c) les 11 variables phénologiques issues du NDVI*

Variable name abbreviations: see Table I. /// *Abréviation des noms des variables : confer Tableau I*

**Table II:** Pearson correlation coefficient between forage plant biomass from pastures and the 29 potential explanatory variables in the six climatic zones of Burkina Faso /// *Coefficient de corrélation de Pearson entre la biomasse végétale fourragère des pâturages et les 29 variables explicatives potentielles dans les six espaces climatiques du Burkina Faso*

| | Climatic zones | Sahelian | Sahelian and North Sudanian | North Sudanian | North Sudanian and South Sudanian | South Sudanian | Burkinabè (national) |
|---|---|---|---|---|---|---|---|
| | **Variables** | (n=33) | (n = 100) | (n = 67) | (n= 123) | (n= 56) | (n= 156) |
| **7 agroclimatic variables** | CHIRPS_cum | 0.54 | 0.42 | 0.12 | 0.18 | -0.04 | 0.39 |
| | RFE2_cum | 0.33 | 0.35 | 0.09 | 0.16 | -0.01 | 0.35 |
| | SM10_cum | 0.52 | 0.41 | 0.14 | 0.19 | 0.01 | 0.40 |
| | SM10_moy | 0.52 | 0.41 | 0.14 | 0.19 | 0.01 | 0.40 |
| | AET_cum | 0.56 | 0.39 | 0.20 | 0.15 | -0.05 | 0.33 |
| | LST_cum | -0.41 | -0.40 | -0.21 | -0.17 | 0.07 | -0.35 |
| | LST_moy | -0.41 | -0.40 | -0.21 | -0.17 | 0.07 | -0.35 |
| **11 FAPAR phenological variables** | adn_fapar | -0.03 | -0.26 | -0.23 | -0.08 | 0.11 | -0.12 |
| | aup_fapar | 0.38 | 0.25 | 0.21 | 0.29 | 0.39 | 0.29 |
| | ddn_fapar | 0.55 | 0.36 | 0.05 | 0.03 | -0.02 | 0.27 |
| | dmn_fapar | -0.39 | -0.28 | -0.12 | -0.13 | -0.03 | -0.27 |
| | dmx_fapar | 0.15 | 0.05 | -0.10 | 0.07 | 0.15 | 0.14 |
| | dup_fapar | -0.47 | -0.42 | -0.28 | -0.08 | 0.18 | -0.24 |
| | rrg_fapar | 0.70 | 0.54 | 0.35 | 0.26 | 0.25 | 0.45 |
| | rsd_fapar | 0.69 | 0.45 | 0.13 | 0.15 | 0.24 | 0.35 |
| | vav_fapar | 0.81 | 0.61 | 0.43 | 0.28 | -0.03 | 0.48 |
| | vmn_fapar | 0.76 | 0.47 | 0.21 | 0.13 | -0.10 | 0.29 |
| | vmx_fapar | 0.74 | 0.56 | 0.38 | 0.34 | 0.20 | 0.51 |
| **11 NDVI phenological variables** | adn_ndvi | -0.65 | -0.09 | 0.11 | 0.15 | 0.14 | 0.04 |
| | aup_ndvi | 0.59 | 0.24 | 0.07 | 0.11 | 0.09 | 0.22 |
| | ddn_ndvi | 0.24 | 0.14 | 0.04 | 0.06 | 0.14 | 0.08 |
| | dmn_ndvi | -0.60 | -0.36 | -0.08 | -0.11 | -0.07 | -0.31 |
| | dmx_ndvi | 0.20 | 0.12 | -0.01 | 0.03 | 0.10 | 0.08 |
| | dup_ndvi | -0.21 | -0.34 | -0.35 | -0.15 | 0.10 | -0.21 |
| | rrg_ndvi | 0.67 | 0.48 | 0.21 | 0.17 | 0.11 | 0.41 |
| | rsd_ndvi | 0.72 | 0.45 | 0.09 | 0.14 | 0.18 | 0.38 |
| | vav_ndvi | 0.80 | 0.60 | 0.42 | 0.29 | -0.03 | 0.48 |
| | vmn_ndvi | 0.75 | 0.51 | 0.25 | 0.15 | -0.05 | 0.33 |
| | vmx_ndvi | 0.72 | 0.52 | 0.27 | 0.27 | 0.10 | 0.47 |
| **Mean of the absolute values of the correlations** | 7 variables agroclimatiques | 0.47 | 0.40 | 0.16 | 0.17 | 0.04 | 0.37 |
| | 11 variables phénologiques FAPAR | 0.52 | 0.39 | 0.23 | 0.17 | 0.16 | 0.31 |
| | 11 variables phénologiques NDVI | 0.56 | 0.35 | 0.17 | 0.15 | 0.10 | 0.27 |
| | 29 variables | 0.52 | 0.38 | 0.19 | 0.16 | 0.11 | 0.31 |

Variable name abbreviations: see Table I; n: number of sites analyzed /// *Abréviation des noms des variables : confer Tableau I ; n : nombre de sites analysés*

| Color code for Pearson correlation coefficients : | 1.0 | 0.5 | 0.0 | -0.5 | -1.0 |
|---|---|---|---|---|---|

**Table III:** Best models for estimating forage plant biomass for each of Burkina Faso's six climatic zones, including 1 to 4 explanatory variables, and parameters for assessing the quality of these models /// *Meilleurs modèles d'estimation de la biomasse végétale fourragère pour chacun des six espaces climatiques du Burkina Faso, incluant 1 à 4 variables explicatives, et paramètres d'évaluation de la qualité de ces modèles*

| Climatic zones of Burkina Faso | Number of sites | Number of variables | Variables selected in the best models | Ordinary RMSE (kg/ha) | Press RMSE (kg/ha) | Ordinary RRMSE (%) | Press RRMSE (%) | Ordinary $R^2$ | Press $R^2$ | Adjusted ordinary $R^2$ | AICc | BIC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| National | 156 | 1 | vmx_fapar | 879 | 884 | 60.5 | 60.9 | 0.26 | 0.25 | 0.26 | 2562 | 2571 |
| | | 2 | vmx_fapar, aup_fapar | 862 | 874 | 59.4 | 60.2 | 0.30 | 0.26 | 0.29 | 2557 | 2569 |
| | | 3 | vmx_fapar, aup_fapar, dmx_ndvi | 849 | 865 | 58.5 | 59.6 | 0.32 | 0.28 | 0.31 | 2553 | 2568 |
| | | **4** | **vmx_fapar, aup_fapar, dmx_ndvi, adn_ndvi** | **832** | **851** | **57.3** | **58.6** | **0.35** | **0.30** | **0.34** | **2548** | **2566** |
| Sahelian | 33 | 1 | vav_fapar | 339 | 358 | 46.3 | 48.9 | 0.65 | 0.59 | 0.64 | 483 | 487 |
| | | 2 | ddn_ndvi, vav_ndvi | 305 | 345 | 41.7 | 47.2 | 0.73 | 0.62 | 0.71 | 478 | 482 |
| | | 3 | vav_fapar, ddn_ndvi, adn_ndvi | 277 | 321 | 37.9 | 43.9 | 0.78 | 0.67 | 0.76 | 473 | 478 |
| | | **4** | **ddn_ndvi, vav_ndvi, vmn_ndvi, LST_moy** | **266** | **309** | **36.4** | **42.2** | **0.81** | **0.69** | **0.78** | **472** | **478** |
| Sahelian and North Sudanian | 100 | 1 | vav_fapar | 703 | 712 | 57.9 | 58.6 | 0.37 | 0.34 | 0.36 | 1599 | 1607 |
| | | 2 | vav_fapar, adn_fapar | 689 | 707 | 56.7 | 58.2 | 0.40 | 0.35 | 0.39 | 1596 | 1606 |
| | | **3** | **vav_fapar, adn_fapar, adn_ndvi** | **675** | **700** | **55.6** | **57.6** | **0.43** | **0.36** | **0.41** | **1593** | **1606** |
| | | 4 | adn_fapar, adn_ndvi, vav_ndvi, vmn_ndvi | 671 | 700 | 55.2 | 57.6 | 0.44 | 0.36 | 0.42 | 1593 | 1608 |
| North Sudanian | 67 | 1 | vav_fapar | 828 | 844 | 57.0 | 58.1 | 0.19 | 0.13 | 0.18 | 1095 | 1101 |
| | | 2 | vav_fapar, adn_fapar | 808 | 836 | 55.6 | 57.6 | 0.24 | 0.15 | 0.21 | 1093 | 1101 |
| | | **3** | **adn_fapar, adn_ndvi, vav_ndvi** | **776** | **813** | **53.4** | **56.0** | **0.31** | **0.19** | **0.28** | **1089** | **1099** |
| | | 4 | adn_fapar, adn_ndvi, vav_ndvi, dmx_ndvi | 768 | 808 | 52.9 | 55.6 | 0.33 | 0.20 | 0.29 | 1089 | 1100 |
| North Sudanian and South Sudanian | 123 | 1 | vmx_fapar | 972 | 981 | 59.1 | 59.6 | 0.12 | 0.09 | 0.11 | 2046 | 2054 |
| | | 2 | vmx_fapar, aup_fapar | 947 | 964 | 57.6 | 58.6 | 0.17 | 0.12 | 0.16 | 2040 | 2051 |
| | | 3 | vmx_fapar, aup_fapar, dmx_ndvi | 930 | 952 | 56.5 | 57.9 | 0.21 | 0.14 | 0.19 | 2037 | 2051 |
| | | **4** | **vmx_fapar, aup_fapar, dmx_ndvi, adn_ndvi** | **910** | **935** | **55.3** | **56.8** | **0.25** | **0.17** | **0.22** | **2033** | **2049** |
| South Sudanian | 56 | 1 | aup_fapar | 1043 | 1075 | 55.6 | 57.3 | 0.15 | 0.07 | 0.14 | 942 | 947 |
| | | **2** | **aup_fapar, dmx_fapar** | **1013** | **1051** | **54.0** | **56.0** | **0.22** | **0.11** | **0.19** | **940** | **947** |
| | | 3 | aup_fapar, dmx_fapar, vmx_fapar | 998 | 1045 | 53.2 | 55.7 | 0.25 | 0.12 | 0.21 | 939 | 948 |
| | | 4 | aup_fapar, dmx_fapar, vmx_fapar, vmx_ndvi | 976 | 1035 | 52.0 | 55.2 | 0.30 | 0.14 | 0.25 | 938 | 949 |

In bold: the best model for each climate space (minimization of the BIC parameter). Abbreviations of variable names: see Table I /// En gras : le meilleur modèle de chaque espace climatique (minimisation du paramètre BIC). Abréviation des noms des variables : confer tableau I.

RMSE : Root Mean Squared Error ; RRMSE : Relative Root Mean Squared Error ; ordinary : parameter calculated directly from the resulting model ; press : parameter calculated using leave-one-out cross-validation; $R^2$ : Pearson's linear coefficient of determination; AICc : corrected Akaike's Information Criterion ; BIC : Bayesian Information Criterion.

### Forage plant biomass prediction models

Table III presents the best estimation models for forage plant biomass in each of the six climatic zones of Burkina Faso, including one to four explanatory variables, along with the model quality evaluation parameters.

Table IV presents the equations of the best forage plant biomass estimation model for each of the six climatic zones of Burkina Faso. The best model within a given climatic zone is defined here as the one minimizing the BIC parameter during multivariate linear regression allowing the selection of up to four explanatory variables.

Among the various model quality evaluation parameters reported in Table III, those derived from leave-one-out cross-validation (with the "press" suffix) will be prioritized to support the results analysis, as these parameters better reflect model performance under future re-use conditions. In this regard, it should be noted that the difference between ordinary and press RRMSE values is minimal for all models across all climatic zones (0 to 3%), with the exception of the Sahelian climatic zone, where this difference can reach 3 to 6%.

### Model performance

The performance of all the models obtained is rather low, with press RRMSE values ranging between 55% and 61% for all the models obtained, except for the Sahelian zone, which shows a press RRMSE ranging between 42% and 49%, clearly distinguishing it from the other zones as the location enabling the production of higher-quality models (Table III and Figure 9). The observation of $R^2$ values confirms this analysis, with a maximum press $R^2$ of 0.36 (maximum ordinary $R^2$ of 0.44) across all climatic zones except the Sahelian zone, and an average press $R^2$ of 0.23 (average ordinary $R^2$ of 0.33) for the quadrivariate models in these zones only, which contrasts with a press $R^2$ of 0.69 (ordinary $R^2$ of 0.81) for the quadrivariate model of the Sahelian zone. The decline in model quality along the north–south gradient is more clearly illustrated by the evolution of $R^2$ than of RRMSE, with the following values for the quadrivariate models: Sahelian climatic zone, press RRMSE = 42%, press $R^2$ = 0.69; North Sudanian climatic zone, press RRMSE = 56%, press $R^2$ = 0.20; South Sudanian climatic zone, press RRMSE = 55%, press $R^2$ = 0.14.

Within each of the climatic zones, except for the Sahelian zone, a very small difference in performance is observed between models using one or four variables, with differences in press RRMSE ranging from 1% for the Sahelian-and-North-Sudanian zone to 3% for the North-Sudanian-and-South-Sudanian zone. This difference is 7% for the Sahelian zone. This observation highlights the very limited added value of multivariate models compared to univariate models, except for the Sahelian zone where this added value is more significant.

The models of the three climatic zones corresponding to smaller geographic areas—namely the Sahelian, North Sudanian, and South Sudanian zones—show slightly better performance (press RRMSE for four-variable models of 42%, 56%, and 55% respectively) than those of the three larger zones—namely the national, Sahelian-and-North-Sudanian, and North-Sudanian-and-South-Sudanian zones (press RRMSE for four-variable models of 59%, 58%, and 57%, respectively).

### Relative performance of the variables

Agroclimatic variables appear to be useless in the prediction of forage plant biomass compared to variables derived from NDVI and FAPAR, given that they are never selected in the best models using one to four variables, except in the four-variable model for the Sahelian zone which includes the variable LST_moy (Table III). However, a four-variable model for the Sahelian zone based solely on phenological variables (RRMSE press = 44.6%, $R^2$ press = 0.66, results not shown in Table III) yields a model with similar, although slightly lower, performance than the model including the agroclimatic variable (RRMSE press = 42.2%, $R^2$ press = 0.69, Table III).

Variables derived from FAPAR appear to be more performant than those derived from NDVI, given that the best univariate and bivariate models for all climatic zones use only FAPAR variables (vmx, vav, aup, adn, dmx), with the exception of the bivariate model for the Sahelian zone which uses two NDVI variables (ddn and vav). The trivariate and quadrivariate models generally include a mix of FAPAR and NDVI variables, indicating a certain complementarity between these two sources of variables. Among the 22 FAPAR and NDVI variables, only five FAPAR variables (vmx, vav, adn, dmx, aup) and six NDVI variables (vmx, vav, adn, dmx, vmn, ddn) are included in the best uni- to quadrivariate models presented in Table III. The four types of variables vmx, vav, adn, and dmx are common to both FAPAR and NDVI variables included in these models.

**Table IV:** Equation of the best models* for estimating forage plant biomass for each climatic zone in Burkina Faso /// *Équation des meilleurs modèles* d'estimation de la biomasse végétale fourragère pour chaque espace climatique du Burkina Faso*

| Climatic zones of Burkina Faso | Equation of the best models for estimating forage plant biomass * |
|---|---|
| National | -125877.5 + 831.4 aup_fapar + 15.6 vmx_fapar + 537.8 adn_ndvi + 13.9 dmx_ndvi |
| Sahelian | -10922.1 + 116.3 LST_moy + 36.0 ddn_ndvi + 49.2 vav_ndvi - 59.3 vmn_ndvi |
| Sahelian and North Sudanian | 45176.9 - 976.2 adn_fapar + 23.0 vav_fapar + 471.3 adn_ndvi |
| North Sudanian | 35614.1 - 1172.1 adn_fapar + 756.6 adn_ndvi + 27.0 vav_ndvi |
| North Sudanian and South Sudanian | -140267.2 + 953.5 aup_fapar + 17.3 vmx_fapar + 570.5 adn_ndvi + 15.2 dmx_ndvi |
| South Sudanian | -138072.9 + 1526.0 aup_fapar + 15.8 dmx_fapar |

* Best model: model minimizing the Bayesian Information Criterion (BIC) parameter in multivariate linear regression, allowing selection of 1 to 4 explanatory variables at most /// *Meilleur modèle : modèle minimisant le paramètre Bayesian Information Criterion (BIC) lors de la régression linéaire multivariée autorisant la sélection de 1 à 4 variables explicatives maximum*

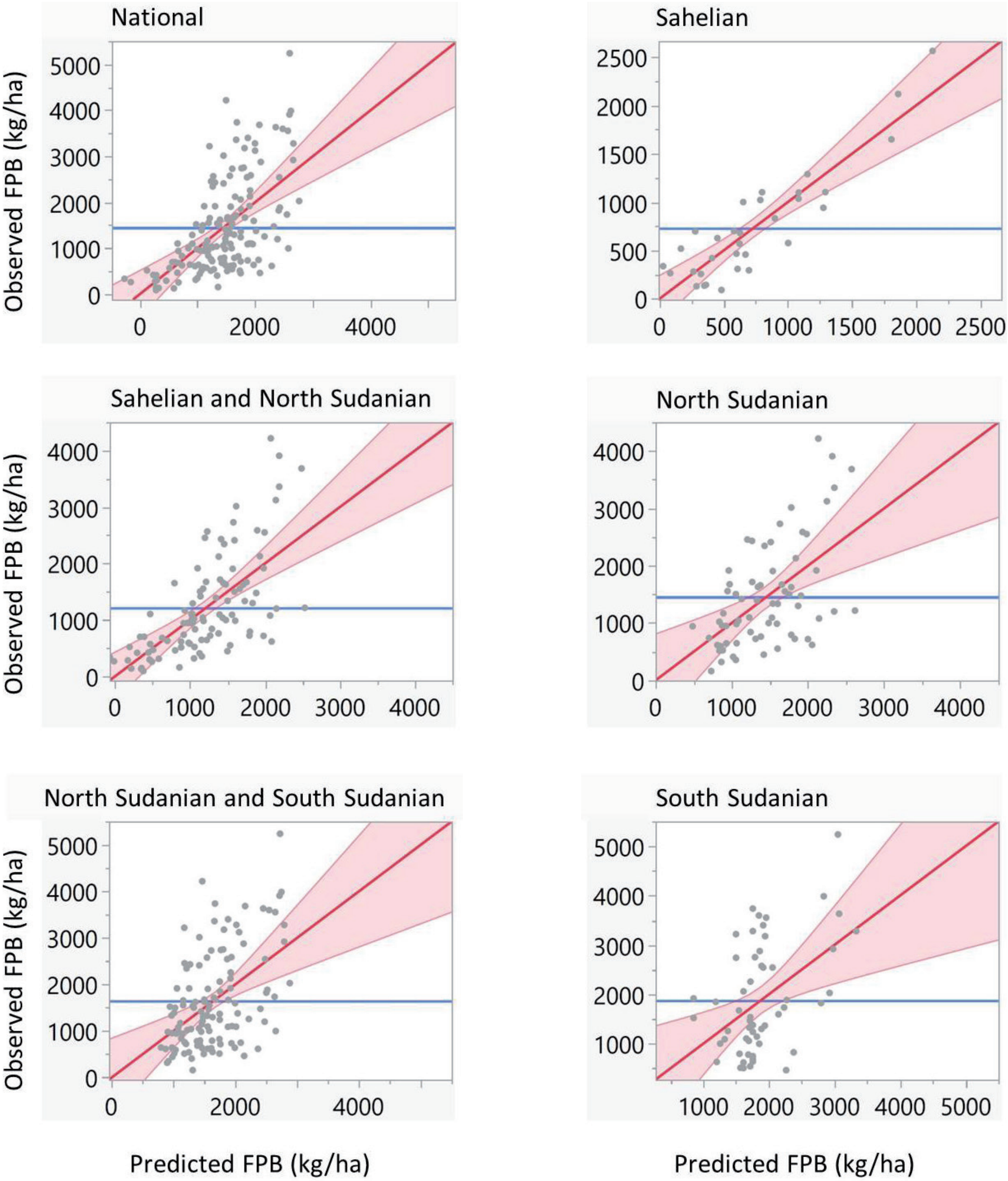


**Figure 9:** *Forage plant biomass (FPB) values observed and predicted by the best model* for each climatic zone in Burkina Faso /// Valeurs de biomasse végétale fourragère (BVF) observées et prédites par le meilleur modèle* pour chaque espace climatique du Burkina Faso*

* Best model: model minimizing the Bayesian Information Criterion (BIC) parameter in multivariate linear regression, allowing selection of 1 to 4 explanatory variables at most /// *Meilleur modèle : modèle minimisant le paramètre Bayesian Information Criterion (BIC) lors de la régression linéaire multivariée autorisant la sélection de 1 à 4 variables explicatives maximum*

**Legend:** Blue line: the average observed value. Red line: the theoretical perfect fit (x = y). Pink area: 95% confidence interval of the regression line, i.e., the range of values with a 95% probability of containing the regression line of the population corresponding to the data used, which form the sample. The sample regression line is not shown. The quality assessment parameters for these best models are shown in bold in Table III. The formulas for these best models are shown in Table IV /// *Droite bleue : la valeur observée moyenne. Droite rouge : la droite d'ajustement théorique parfait (x = y). Aire rose : intervalle de confiance à 95 % de la droite de régression, soit la plage de valeurs ayant une probabilité de 95 % de contenir la droite de régression de la population correspondante aux données utilisées qui, elles, forment l'échantillon. La droite de régression de l'échantillon n'est pas montrée. Les paramètres d'évaluation de la qualité de ces meilleurs modèles sont présentés dans le tableau III, en gras. Les formules de ces meilleurs modèles sont présentées dans le tableau IV*

## ■ DISCUSSION

### *Variation in model performance according to climatic zones*

The low overall performance of the models produced in this study (49% ≤ RRMSE press ≤ 61% for univariate models) is similar to that found in studies conducted in Niger by Garba *et al*. (2015) (RRMSE of univariate models of 47% in the Saharan zone, 51% in the northern Sahelian zone, 57% in the Sahelian zone) and by Schucknecht *et al*. (2017) (cross-validation RRMSE of the best univariate model of 54%). These results led these authors to acknowledge the need to improve these models.

The decrease, observed in this study, along the north-south gradient, in the performance of models estimating herbaceous biomass, and in the correlation of explanatory variables with this biomass, was also observed in pasture modeling studies conducted in Senegal by Tian *et al*. (2016).

This decrease in model performance along the north-south gradient in this region of the world can be explained in part by increasing cloud cover towards southern latitudes—cloud cover which directly impacts the quality of satellite products (NDVI, FAPAR, etc.). Lambert *et al*. (2016) reported that the contamination of satellite images by clouds and their shadows in the Sahel (between 9° and 18° North latitude) increased towards southern latitudes. The degree of cloud pollution in images in the Sahel is closely linked to the extent of monsoon penetration during the rainy seasons, with rainy seasons being marked by significant cloud development. Nevertheless, according to Lambert *et al*. (2016), the probabilities of obtaining good-quality images at the end of the vegetation growth season are not negligible. Thus, the existence of variables strongly correlated with herbaceous biomass offers opportunities to develop forage yield estimation models (Löw and Duveiller, 2014; Diouf *et al*., 2015; Lo *et al*., 2022).

Other factors may potentially explain the decrease in model performance towards southern latitudes: (i) a greater and more marked inter-seasonal variation in vegetation conditions in the northern zones relative to the southern ones, related to a drier climate and lower vegetation presence in the northern zones, allowing better sensitivity of satellite products to vegetation growth dynamics in the northern zones; (ii) greater spatial heterogeneity of pastures due to higher woody plant density in the Sudanian climatic zone (in the south), compared to the Sahelian zone (in the north); (iii) a difficulty in accurately assessing the foliar biomass of large woody plants in the field using the visual test-tree method, particularly in denser vegetation formations mainly found in the Sudanian zone (in the south).

This study showed a very slight improvement in the performance of models developed for the three smallest climatic zones (RRMSE press of four-variable models from 42% to 56%) compared to models for the three largest climatic zones (RRMSE press of four-variable models from 57% to 59%). This observation is similar to that already made in other pasture yield modeling studies in Senegal and Niger, which demonstrated accuracy gains for forage yield estimation in more homogeneous vegetation zones, namely the ecoregions in Senegal and the bioclimatic zones in Niger (Diouf *et al*., 2015; Garba *et al*., 2017; Schucknecht *et al*., 2017).

### *Recommendations for field data collection*

Modeling the relationship between ground data and remote sensing data, which are pixel-based by nature, requires, in order to improve model performance, the minimization of factors that disrupt this relationship, particularly at the level of the studied surface. Regarding the modeling of herbaceous biomass, care must therefore be taken to select sites whose size and location minimize the main sources of disturbance which, in the context of this study, are the presence of land cover other than grazing areas (croplands) and the presence of large woody plants. These aspects have already been highlighted by a series of authors (Woodcock and Strahler, 1987; Hoefsloot *et al*., 2012; Löw and Duveiller, 2014; Durgun *et al*., 2020).

Furthermore, in most studies assessing the pastoral value of Sahelian pastures, which aim to evaluate both the quantity of biomass and its quality (measured by the diversity of plant species), and which are based on field analysis of a transect using the point quadrat method, the size of observation sites is generally 1 km$^2$ in order to ensure proper representativeness of the ecological facies present in the field (Levang and Grouzis, 1980). According to Diouf *et al*. (2015), when these studies integrate satellite imagery, the images are of low resolution (1 km × 1 km).

While it is possible to find pure (homogeneous) pixels at low resolution in the United States and Russia, these are almost nonexistent in Africa and Europe (Hoefsloot *et al*., 2012), which leads to modeling difficulties using low resolution in these geographic contexts. In this regard, Durgun *et al*. (2020) demonstrated the continuous decrease in wheat yield prediction performance in Europe using satellite images of decreasing spatial resolution (100 m, 300 m, and 1 km).

In the context of this study, satellite data with a spatial resolution of 1 km were used. Given the specific characteristics of Burkinabe landscapes, particularly in the south, which present relatively high spatial heterogeneity with a mix of croplands and grazing areas and the presence of large woody plants, this spatial resolution makes it difficult to identify "pure" pixels composed only of pasture. During the field data collection, many sites were located near cultivated fields. Moreover, it was observed, during the variable extraction phase from satellite imagery, that some biomass collection sites intersected several pixels, thereby effectively enlarging the area considered for this extraction and increasing the risk of including land cover types other than the one of interest. These elements thus contribute to the extraction of a composite remote sensing signal (pasture, cropland, large woody plants), and ultimately to the disruption of herbaceous biomass modeling from remote sensing data, as also mentioned by Chen *et al*. (2016) and Durgun *et al*. (2020).

With a view to reducing errors in herbaceous biomass estimation models, it appears necessary to improve the coupling between field-collected herbaceous biomass data and the variables extracted from satellite images. To this end, the following recommendations are proposed: (a) ensure that each sampling site is included within a single pixel and is therefore not spread over several pixels; (b) ensure that each sampling site contains only land cover corresponding to the grazing areas to be evaluated, and does not include other land cover types not relevant to the evaluation (croplands, settlements, etc.). If this is not possible, it is necessary to seek to minimize the presence of these other land cover types in the evaluated pixel; (c) ensure that each sampling site does not present a very high density of large woody plants that could significantly impact the signal recorded by satellite products; (d) use a precise and recent land cover map and/or recent high or very high spatial resolution satellite imagery (Google Satellite, Planet) to identify and locate sampling sites meeting the aforementioned criteria; (e) use satellite data with a finer resolution than 1 km, for example 300 m (PROBA-V, Sentinel-3 OLCI) or 250 m (MODIS), which would allow a reduction in the size of field sampling sites and thus facilitate the identification of sites with only the land cover corresponding to the grazing areas to be evaluated; (f) complement field data collection with an estimation of herbaceous and woody biomass from drone imagery. This technique may provide more representative estimates of the sampled sites through a more systematic analysis of a larger area of these sites. This method, if effective and sufficiently calibrated, could potentially replace manual collection and visual estimation in the long term. Finally, note that another avenue for improving forage yield estimation is to identify other modeling techniques (non-linear modeling, for example) and/or other explanatory variables that would produce better results than those obtained in the context of this study.

## ■ CONCLUSION

This study evaluated, for the first time, the feasibility of estimating pasture forage yields in the climatic zones of Burkina Faso using univariate and multivariate linear statistical models built from field-collected forage plant biomass data and phenological and agroclimatic satellite variables. As such, it constitutes an original and innovative approach aimed at improving the assessment of forage resources in Burkina Faso, which is a key element in the governance of livestock food crises.

However, the performance of all the models obtained was relatively low, with press RRMSE values ranging between 55% and 61% (press $R^2$ between 0.07 and 0.36) across all climatic zones except the Sahelian zone, where press RRMSE values ranged between 42% and 49% (press $R^2$ between 0.59 and 0.69).

In order to improve model performance, a series of recommendations was identified, in particular to enhance the coupling between field-collected forage plant biomass data and variables extracted from satellite imagery.

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### Conflicts of interest

The study was conducted without any conflicts of interest.

### Author contributions statement

WS, AD, BHN, AGMB, and BT contributed to the design or planning of the study. WS participated in the field data collection. WS built the database containing all the studied variables. WS and AD participated in the analysis and interpretation of the data. WS, AD, and BT contributed to the writing of the first version of the manuscript. WS, AD, ALK, BD, BHN, AGMB, and BT participated in the critical revision of the manuscript.

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## *Résumé*

**Some W., Denis A., Kouadio A.L., Djaby B., Nacro H.B., Belem A.M.G., Tychon B.** Estimation des rendements fourragers des pâturages dans les espaces climatiques du Burkina Faso à partir de données satellitaires

L'évaluation des ressources fourragères est un élément clé de la gouvernance des crises alimentaires du bétail au Burkina Faso. Cette étude visait l'évaluation, pour la première fois, de la possibilité d'estimer les rendements fourragers des pâturages dans les espaces climatiques du Burkina Faso via l'utilisation de modèles statistiques linéaires uni et multivariés construits à partir de données de biomasse végétale fourragère collectées sur le terrain en 2017, 2018 et 2019, de variables satellitaires phénologiques (indice de végétation de la différence normalisée [NDVI] et fraction de rayonnement photosynthétiquement actif absorbé [FAPAR]) et agroclimatiques (précipitations, humidité du sol, évapotranspiration, température de surface). Une recherche exhaustive des meilleurs modèles statistiques linéaires comportant une à quatre variables a été réalisée et les meilleurs modèles selon le critère d'information bayésien (BIC) identifiés. La performance des modèles uni à quadrivariés obtenus s'est avérée assez faible avec, pour l'ensemble des espaces climatiques excepté l'espace sahélien, des RRMSEpress variant de 55% à 61% ($R^2$press de 0,07 à 0,36), et pour l'espace climatique sahélien des RRMSEpress variant de 42% à 49% ($R^2$ press de 0,59 à 0,69). La baisse de corrélation de la majorité des variables avec la biomasse végétale fourragère selon le gradient nord-sud résulte en une baisse de performance des modèles selon ce gradient. Les variables agroclimatiques se sont révélées inutiles, et celles issues du FAPAR sont globalement plus performantes que celles issues du NDVI. Une très faible plus-value des modèles multivariés comparés aux modèles univariés a été observée, excepté pour l'espace sahélien. Les modèles développés sur des espaces climatiques plus homogènes se sont montrés plus performants. Une série de recommandations a été identifiée pour améliorer le couplage entre données de biomasse végétale fourragère collectées sur le terrain et variables extraites des images satellitaires, et ainsi améliorer la performance des modèles.

***Mots-clés*** : Pâturages, rendement fourrager, biomasse aérienne, zone agroclimatique, imagerie par satellite, modèle linéaire, Burkina Faso

## *Resumen*

**Some W., Denis A., Kouadio A.L., Djaby B., Nacro H.B., Belem A.M.G., Tychon B.** Estimación del rendimiento forrajero de los pastos en las zonas climáticas de Burkina Faso mediante datos satelitales

La evaluación de los recursos forrajeros es un elemento clave en la gobernanza de las crisis alimentarias del ganado en Burkina Faso. Este estudio tenía como objetivo la evaluación, por primera vez, de la posibilidad de estimar los rendimientos forrajeros de los pastos en los espacios climáticos de Burkina Faso vía la utilización de modelos estadísticos lineales univariados y multivariados construidos a partir de datos de biomasa vegetal forrajera recopilados sobre el terreno en 2017, 2018 y 2019; de variables fenológicas de satélite (índice de vegetación de la diferencia normalizada [NDVI] y fracción de radiación fotosintéticamente activa absorbida [FAPAR]), y agroclimáticas (precipitaciones, humedad del suelo, evapotranspiración, temperatura de superficie...). Se realizó una investigación exhaustiva de los mejores modelos estadísticos lineales que comportan de una a cuatro variables y los mejores modelos según el criterio de información bayesiano (BIC) identificados. El rendimiento de los modelos de univariados a cuadrivariados obtenidos resultó bastante débil con, para el conjunto de los espacios climáticos excepto el espacio saheliano, RRMSE PRESS variando del 55 % al 61 % ($R^2$ PRESS de 0,07 a 0,36), y, para el espacio climático saheliano, RRMSE PRESS variando entre el 42 % y el49 % ($R^2$ PRESS de 0,59 a 0,69). La baja correlación de la mayoría de las variables con la biomasa vegetal forrajera según el gradiente norte-sur causa una baja de rendimiento de los modelos según este gradiente. Las variables agroclimáticas no resultaron útiles, y las provenientes del FAPAR proporcionan globalmente un mejor rendimiento que las provenientes del NDVI. Se observó una plusvalía muy débil de los modelos multivariados comparados con modelos univariados, excepto para el espacio saheliano, y un mejor rendimiento de los modelos desarrollados en espacios climáticos más homogéneos. Se identificaron una serie de recomendaciones para mejorar el acoplamiento entre datos de biomasa vegetal forrajera recopilados sobre el terreno y variables extraídas de las imágenes de satélite, y así acrecentar el rendimiento de los modelos.

***Palabras clave***: Pastizales, rendimiento del forraje, biomasa sobre el suelo, zonas agroclimáticas, imágenes por satélites, modelos lineales, Burkina Faso