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ESTIMATION OF THE HERBACEOUS AND WOODY PLANT BIOMASS FROM METEOROLOGICAL AND CLIMATIC DATA IN BURKINA FASO

Abstract: Estimating plant biomass in areas with highly contrasting vegetation using satellite indices remains a technological challenge. This study aims to develop models for estimating forage yields based on meteorological data in Burkina Faso. A database was created through spatial interpolation of weather station observations, covering 159 biomass collection points in the field between 2017 and 2019. The multiple regression method, combined with the BIC (Bayesian information criterion), was used to select the most effective models for estimating woody, herbaceous, and total biomass according to climatic domains. The most robust results were obtained in the Sahelian domain, with high explainability (adjusted R^2 from 0.69 to 0.85) and errors stabilized at around 29%. In contrast, in the Sudanese domain, characterized by highly heterogeneous vegetation, the explainability of the models decreased (adjusted R^2 from 0.15 to 0.48), although errors remained relatively low (15%). The most relevant climate variables for model development are temperature, number of rainy days, wind speed, and atmospheric pressure. These factors are essential indicators for projecting plant biomass at the national level.

Keywords: RRMSE, RMSE, estimation model, climate zone, Burkina Faso

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Introduction

Vegetation plays a fundamental role in maintaining ecological balance and regulating climate (Knauer et al., 2023). In tropical and Sahelian areas, it is a determining factor for soil stability, the availability of natural resources and, consequently, the food security of populations (PARM, 2021). However, the combination of climate variability and anthropogenic pressures intensifies the degradation of plant resources, thereby compromising the resilience and stability of ecosystems (Azuara, 2017; Diallo et al., 2011). This vulnerability particularly affects low-income populations that are heavily dependent on agricultural, pastoral, forestry, and wildlife ecosystems. In this context, monitoring these ecosystems is a priority for policymakers and the scientific community. On a technical level, several institutions have developed digital platforms (Agrhymet, Fewsnets) for remote monitoring of agro-meteorological conditions for vegetation growth. This monitoring is based mainly on the use of free, low-resolution satellite data, thus offering a low-cost surveillance solution. However, this approach remains limited, as it relies solely on vegetation indices that do not fully reflect the reality of highly fragmented ecological areas, due to a lack of coupling with field data. Indeed, vegetation indices according to Camaret et al. (2000) struggle to capture vegetation contrasts in large-scale heterogeneous areas. The objective constraints on their use are related to the saturation of indices in areas of dense vegetation, sensitivity to bare soil, atmospheric influence, and mixed pixels recognized as blurred photos of a heterogeneous landscape (El Kharki et al., 2015).

The collection of field data on plant biomass and the development of estimation models are now major challenges for national food security monitoring systems. Several initiatives are working to strengthen these two dimensions by improving the quality and reliability of field observations while refining estimation models. Optimizing field data collection relies in particular on the use of drones, which offer innovative prospects for acquiring accurate, high-resolution data (Barnetson et al., 2020; Gebremedhin et al., 2025; Lussem et al., 2020; Nungi-Pambu et al., 2024; Taugourdeau et al., 2022, 2023; Zhang et al., 2021).

Although drones have significantly improved field data collection, their capacity remains limited when it comes to covering large areas at the national level. To address this challenge, two main approaches are being used. The first involves developing models based on plant biomass data from field surveys, combined with vegetation indices extracted from satellite images, in order to estimate plant biomass on a large scale (Balaghi et al., 2008; Diouf et al., 2014, 2015; Gang et al., 2017; Garba, 2015; Garba et al., 2023; Peng et al., 2019; Some et al., 2024). The second approach is based on building models by coupling field data on plant biomass with meteorological data from plant biomass collection sites, then estimating plant biomass (Sanou et al., 2023). However, the use of vegetation indices is the most popular but has certain limitations in areas of highly fragmented vegetation due to the mosaic landscape. In the Sudanian climate zone of Burkina Faso, which is characterized by the development of agricultural activities, it is very difficult to obtain models that are well explained by vegetation indices with reduced estimation errors (Some et al., 2024). In most studies devoted to estimating pasture forage yields, methodological improvements are generally limited to reducing estimation errors through the use of vegetation indices extracted from satellite images. Given the margins of error inherent in satellite data, it is still possible to reduce them by relying on climate data from weather stations. In Burkina

Faso, a recent study based on synoptic station data highlighted contrasting rainfall trends between the southern Sahelian and southern sudanian climatic zones between 1990 and 2020, with an increase in extreme rainfall events in the Sahelian zone and a grater temporal spread of precipitation in the sudanian zone (Yanogo et Yaméogo, 2023). These contrasting dynamics underscore the added value of integrating meteorological data from stations into plant biomass estimation models.

The estimation of pasture plant biomass from climate data at the level of plant biomass collection sites remains largely unexplored at the local level. Climatic variables determine the development of forage plants and are closely linked to plant biomass production. The use of these climate data in estimating plant biomass can help to significantly reduce estimation errors in areas of dense vegetation. With this in mind, the present research aims to estimate woody and herbaceous biomass in Burkina Faso using meteorological climate data. Specifically, it involves: i) interpolating and spatializing meteorological data at the scale of plant biomass collection sites; ii) developing woody and herbaceous biomass models by coupling field data on plant biomass with climate data.

Materials and methods

Presentation of the study area

Climatic characteristics

Burkina Faso is a landlocked country in the West African Shield, located between the 9th and 15th parallels north and between the 2nd meridian west and the 5th meridian east (Albergel et al., 1984). Its climate is characterized by two distinct seasons: the rainy season (May to October) and the dry season (November to April). Its geographical location and climate give it a tropical character, typically Sudano-Sahelian. Climatic variables influence the availability of water and plant biomass, which are key determinants of the agricultural sector. Climatic variables have ranges of values that are useful for plant development. These variables are very useful in monitoring agricultural and environmental risk. There are many such variables, and those targeted in this study are: cumulative rainfall (Cumul), number of rainy days (NJP), evapotranspiration (ETP), temperatures (average (Tm), maximum (Tx) and minimum (Tn)), relative humidity (average (Rh moy), maximum (Rh max), minimum (Rh min)), insolation (Inso), atmospheric pressure, and wind. Because Burkina Faso is crossed by three climate zones, there is significant variation in certain climate parameters along the NW-SE gradient. Cumulative rainfall, number of rainy days, humidity, and pressure increase from northeast to southwest. These factors are linked to monsoon activity during the rainy season. In contrast, temperature, evapotranspiration, and insolation decrease from northeast to southwest. The values of these variables are presented in Table 1.

Table 1. Average values of climate variables in different climate domains and at the national level

Annual parameters	Sahelian zone	Sudano-Sahelian zone	Sudanese zone	National level
Cumulative rainfall (total)	450 mm	869 mm	1057.4 mm	906.90 mm
Number of rainy days (NJP)	38 days	63 days	105 days	80.94 days
Maximum temperature (Tx)	36.34 °C	35 °C	34.5 °C	34.96°C
Minimum temperature (Tn)	23,23 °C	23 °C	22.4 °C	24.46°C
Average temperature (Tm)	29.79°C	29 °C	28.4 °C	28.89°C
Wind	2.24 m/s	2 m/s	1.9 m/s	2 m/s
Pressure	18.62 hPa	20 hPa	19.3 hPa	19.14 hPa
Evapotranspiration (ETP)	2135 mm	2117 mm	2067. 4mm	2015.39 mm
Insolation (Inso)	3142.66 hours	3011 hours	2901.2hours	3010.01 hours
Maximum relative humidity (Rhmax)	60.17%	68 %	73.8%	66.83%
Minimum relative humidity (Rhmin)	26.86%	33%	37%	32.24%
Average relative humidity (Rh moy)	43.40%	50 %	55.60%	49.57%

Source: Weather data, 2017-2019

Vegetation

Based on climate, plant formations, and flora, Guinko and Fontès (1995) identified two major phytogeographic regions in Burkina Faso. The first, of the Sudanese type, covers the southern and central parts of the country and occupies 71.2% of its surface area. The second, of the Sahelian type, covers the northern part, accounting for 28.8% of the country's surface area. Each domain is also subdivided into two phytogeographic sectors. In the Sahelian domain, the vegetation is dominated by steppes of thorny shrubs and annual grasses. The Sudanese domain is dominated by savannas and open forests.

The northern Sahelian sector is located north of the 14th parallel and consists mainly of steppes. The southern Sahelian sector, located between the 13th and 14th parallels, is characterized by shrubby steppes that give way to wooded steppes further south.

The northern Sudanese sector, located between latitudes 13°N and 11°30'N, has an agroforestry park dominated by protected woody species. The southern Sudanese sector, located between the 5th and 11th parallels, is the transition zone with the Guinean climate. It is home to vegetation consisting mainly of wooded savannas and open forests.

The vegetation of Burkina Faso is varied and strongly influenced by land degradation. It remains highly sensitive to climate variability, leading to significant fluctuations in plant biomass. The vegetation map of Burkina Faso is shown in Figure 1.

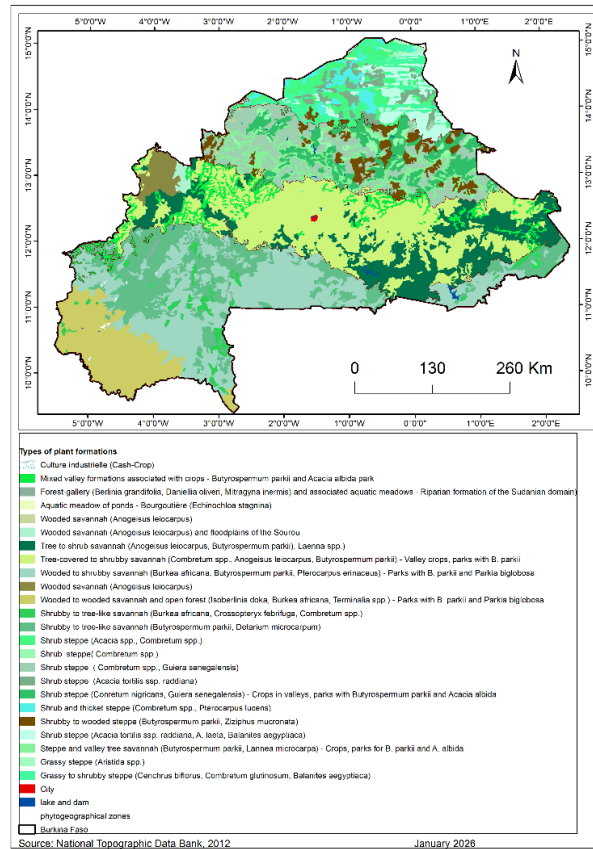


Fig 1. Vegetation map of Burkina Faso

Materials

Climate data from weather stations

The climate data used comes from rainfall and synoptic stations located throughout Burkina Faso. It was collected from the National Meteorological Agency (ANAM) of Burkina Faso, following an institutional request. The data obtained includes daily measurements: rainfall, evapotranspiration, humidity (maximum and minimum), temperatures (minimum and maximum); monthly measurements (wind pressure and speed) and annual measurements (number of rainy days). The coverage period extends from 1991 to 2023. For the purposes of the study, daily and monthly data were aggregated for the period from May to October between 2017 and 2019, corresponding to the forage production season. Some series had missing daily values. These were estimated from daily averages to ensure the consistency and continuity of the time series. Apart from rainfall, which was collected at 171 rain gauge stations, the other variables were collected at 10 synoptic stations (Figure 2).

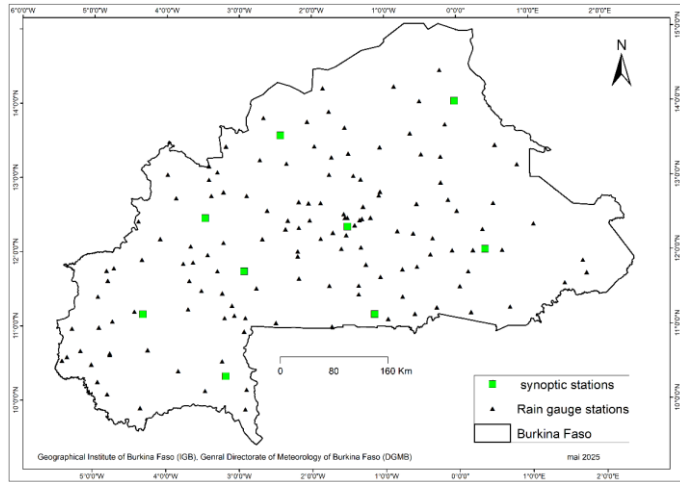


Fig. 2. Spatial distribution of weather stations in Burkina Faso

Field data on plant biomass collected

The plant biomass data used in this study come from the national pasture assessment system. This system is overseen by the National Scientific Committee for the Monitoring and Evaluation of Pastoral Resources (COSSERP), which is responsible for validating the methodology and ensuring the quality of the data collected in the field. The data collected concern woody and herbaceous biomass. Herbaceous biomass was collected using the quadrat method (Daget and Poissonnet, 1971; Boudet, 1984). Woody biomass was collected using the test tree method. The collection sites were established taking into account ecoregions, FAO soil layers, and the land use map. At the national level, 159 sites (Figure 3) were sampled over the period 2017 to 2019. The collection period was from mid-September to the end of October, corresponding to the peak vegetation period in the different climate zones.

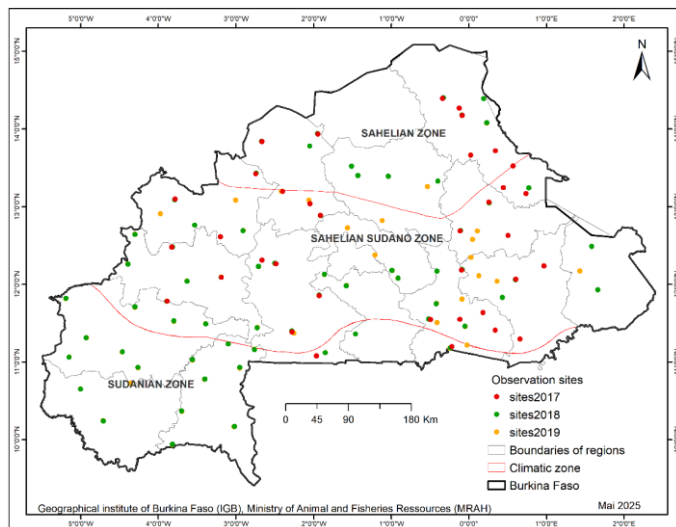


Fig. 3. Location of plant biomass collection sites between 2017 and 2019 in Burkina Faso

Methods

General approach to climate data processing and analysis

Figure 4 shows the general methodological framework used to develop plant biomass prediction models in the climatic regions of Burkina Faso. Overall, weather station climate data were interpolated across 159 biomass collection sites to create a database that included field data on plant biomass. The field plant biomass collected consisted of herbaceous plants, woody plants, and total biomass, including both woody and herbaceous plants. This database was used to perform multiple linear regression with the selection of the best models. The explainability of the model is indicated by the R^2 or adjusted R^2 criteria, and the errors or accuracy by the MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and RRMSE (Relative Root Mean Square Error) metrics.

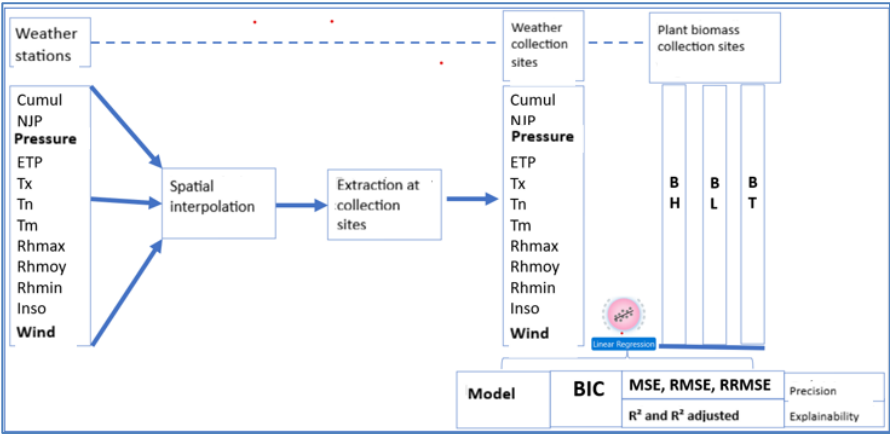


Fig. 4. Methodological diagram for the development of climate models

Spatialization of climate data from weather stations

Most plant biomass collection sites do not have climate measurement instruments. This limitation means that data from weather stations must be interpolated. Interpolation makes it possible to estimate, with acceptable accuracy, the local climate values corresponding to the collection sites. There are several methods for interpolating data (Baillargeon, 2005; Drouin and Saint-Laurent, 2010; Dubreuil et al., 2017; Joly et al., 2008; Lombardi et al., 2013; Rebai et al., 2007). Among these methods, kriging is the most frequently used (Gratton, 2002) because it is a better estimator and minimizes bias (Lozzo, 2017). This method was used to interpolate cumulative rainfall, number of rainy days, temperatures (minimum, average, and maximum), relative humidity (minimum, average, maximum), insolation, and potential evapotranspiration. Pressure and wind interpolation were performed using the Global Polynomial Interpolation method and the Radial Basis Functions method, respectively (Somé, 2010). GPI is used for phenomena that vary regularly, while radial basis functions produce good results for slowly varying surfaces (ESRI). The interpolation maps for the different parameters are shown in Figure 5. ArcGIS 10.8 was used for spatial interpolation and map production.

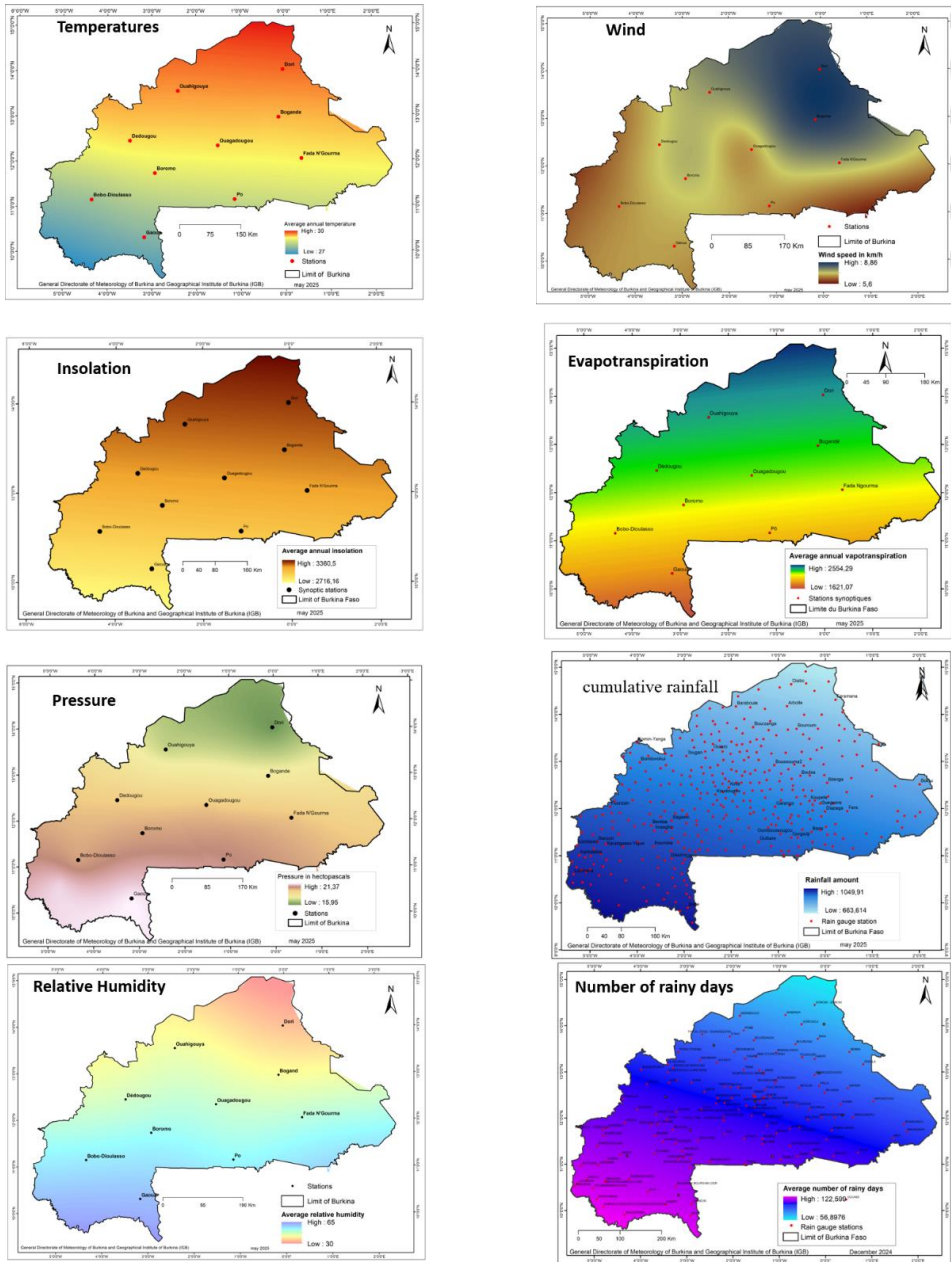


Fig. 5. Maps of interpolated climate variables for Burkina Faso

Extraction of climate data from plant biomass collection sites

The collection sites cover an area of 1 km*1 km for the Sahelian zone and 500 m*500 m for the Sudanian zone. This variability is linked to the availability of assessment areas in each zone. All sites have been digitized, allowing average climate values to be extracted from

maps based on meteorological data interpolation. This step ensures a precise correspondence between plant biomass observations and local climate conditions.

Multiple linear regression

The statistical method adopted is multiple linear regression, inspired by the work of Garba et al., (2023) on estimating pasture forage yields. The selection of variables is an essential step in the development of linear models. It was carried out using the Stepwise method, which allows variables to be added or removed successively according to their statistical significance (Lazraq & Cl  roux, 1988). The most relevant variables are introduced into the model based on their p-value. Non-significant variables are removed to improve the robustness of the model.

The best models were selected based on the following criteria:

The Bayesian Information Criterion (BIC), is a model selection tool that penalizes model complexity, thereby favoring more parsimonious models (Neath & Cavanaugh, 2012).

MSE is a cost function that evaluates the overall performance of the model across the entire dataset. It is measured by the mean square error or deviation between the estimator and the estimated value. It emphasizes the most significant errors.

The RMSE (Root Mean Square Error) is the square root of MSE, which allows the error to be converted to the same units as the response variable. It makes it easy to understand the average error in terms of actual values. The RMSE is widely used in model evaluation studies as an indicator of average model performance (Chai & Draxler, 2014). In modeling, the coefficient of variation of the RMSE, whose CV(RMSE) is calculated as the ratio of the root mean square error (RMSE) to the mean of the dependent variable, is expressed as a percentage (RRMSE). If the mean is close to zero, then the coefficient of variation can be misleading (Hodson, 2022). The closer the value of the RMSE or MSE criteria is to zero, the better the model is evaluated in terms of accuracy, which measures the precision of estimates by minimizing the difference between observed and predicted values.

R-squared or the coefficient of determination is the proportion of variance explained. It quantifies the proportion of variance in the dependent variable that is predictable from the independent variables. The closer R² is to 1, the better the prediction. It tends to increase when the number of explanatory variables is added. R-squared is not affected by the data scale and makes it easier to compare models at different scales.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2} \quad (\text{Chicco et al., 2021; Hodson, 2022}) \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (3)$$

Where n: number of observations, Y_i: value of observation i; $\hat{Y}_i$ value of the prediction of observation i; $\bar{Y}$: mean of observations

Results

Correlation between explanatory climate variables

Figure 6 shows the heat map of correlations between climate variables. Several climate variables appear to be significantly correlated with each other. Precipitation, humidity, and atmospheric pressure are strongly correlated. These conditions are accompanied by lower temperatures, less sunshine and wind, and reduced evapotranspiration. They describe an environment favorable to soil water recharge, but limit the energy available for plant growth. Conversely, temperatures, insolation, and evapotranspiration are positively correlated with each other and oppose humidity and precipitation. These conditions promote evaporation and increase water stress, while stimulating photosynthesis when water is available.

These climatic variables can therefore be grouped into two contrasting sets: those that characterize humid and cool conditions, and those that reflect dry and hot conditions. This diversity of relationships provides a solid basis for the development of estimation models.

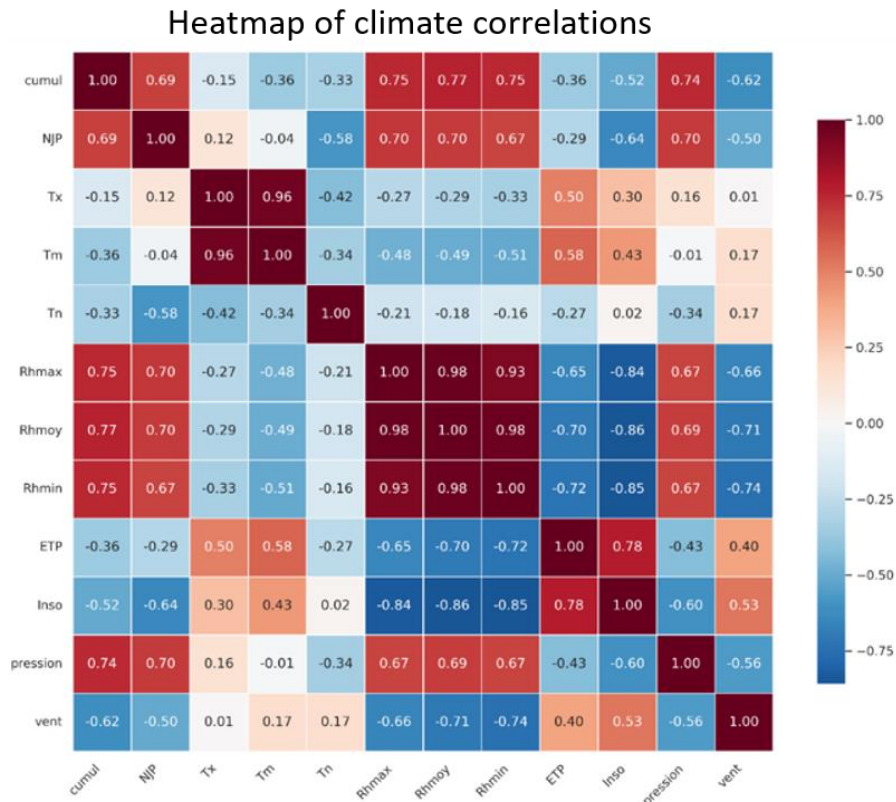


Fig. 6. Heat map showing the correlation between explanatory climate variables

Cumulative rainfall; NJP: number of rainy days; Rhmin: minimum relative humidity; Rhmax: maximum relative humidity; Rhmoy: average relative humidity; Tx: maximum temperature; Tn: minimum temperature; Tm: average temperature; ETP: evapotranspiration; Inso: insolation; pressure: atmospheric pressure; wind: wind speed.

Correlation between types of plant biomass and explanatory climate variables

Figure 7 shows the heatmap graph of the correlation between the climate variables studied and the types of plant biomass in the different climate domains of Burkina Faso. The types of biomass are herbaceous plant biomass, woody biomass, and total plant biomass (woody and herbaceous). The climatic domains are the Sahelian zone (SAH), the Sudano-Sahelian zone (NS), the Sudanese zone (SS), and the national level (Nat). Herbaceous biomass is very sensitive to thermal and atmospheric stress, but benefits from humid and cool conditions. Woody biomass is favored by humidity and rainfall, but is vulnerable to wind and atmospheric pressure. Total plant biomass is generally stimulated by humidity, but inhibited by hot and dry conditions. The Sahelian zones show the strongest negative correlations (thermal stress and pressure). Sudanian areas show positive correlations with humidity and rainfall, reflecting an environment more favorable to plant growth.

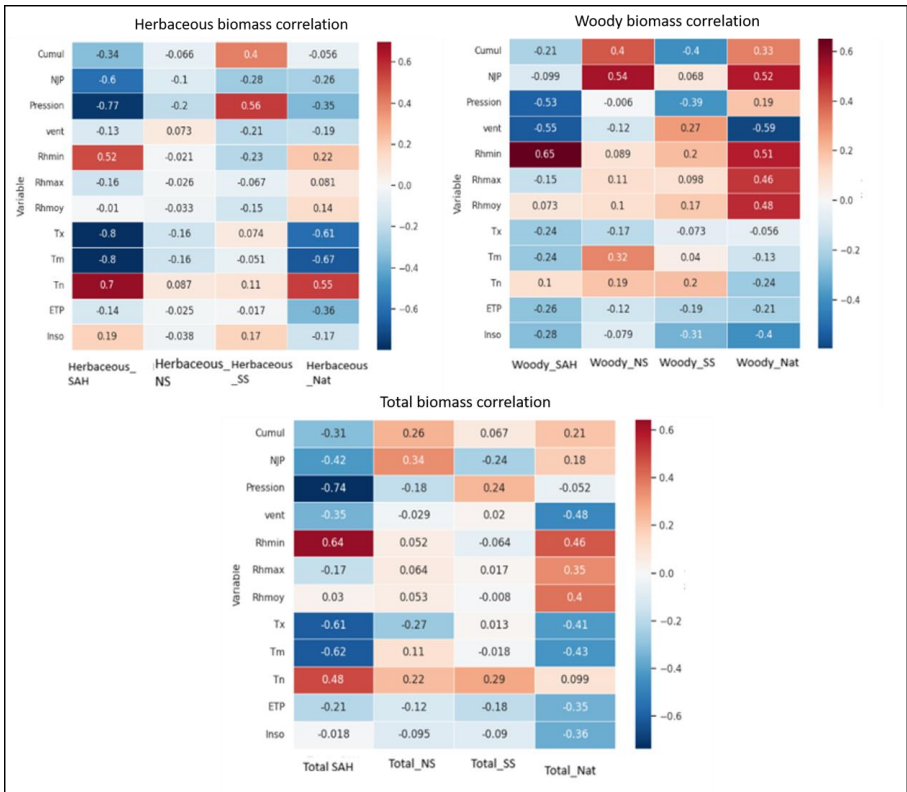


Fig.7. Heat map of correlation values between plant biomass types and variables in different climate domains in Burkina Faso

Cumul: cumulative rainfall; NJP: number of rainy days; Rhmin: minimum relative humidity; Rhmax: maximum relative humidity; Rhmoy: average relative humidity; Tx: maximum temperature; Tn: minimum temperature; Tm: average temperature; ETP: evapotranspiration; Inso: insolation; pressure: atmospheric pressure; wind: wind speed.

Variables selected for the development of estimation models

For herbaceous biomass, the variables selected for model development were average temperature, number of rainy days, pressure, and evapotranspiration. Herbaceous biomass is very sensitive to thermal and atmospheric stress. These variables are linked to the decrease in plant biomass. They are negatively correlated with herbaceous biomass.

For woody biomass, the variables selected for model development were average temperature, number of rainy days, humidity, and pressure. Woody biomass increases with humidity and rainfall, but remains vulnerable to wind and atmospheric pressure. Pressure and wind have a negative influence on woody biomass in the Sahelian region. In contrast, in the Sudanian region, humidity and temperature are climatic parameters that are very favorable to the growth of woody plant biomass.

Performance of models for estimating herbaceous and woody plant biomass

Table 2 presents the results of the performance of the models for estimating woody and herbaceous plant biomass. The performance of the estimation models differs according to the latitude gradient, the type of biomass considered, and climatic conditions.

Latitude gradient

Considering the latitude gradient, we observe a gradual decrease in the adjusted R^2 from northeast to southwest, reflecting a reduction in the explanatory power of the models along the climate gradient. Conversely, estimation errors increase from southwest to northeast, with higher values in the Sahelian domain than in the Sudanian domain. This reflects the greater variability and complexity of Sahelian climatic conditions, which make estimation more uncertain despite a higher proportion of explained variance.

Comparison of herbaceous versus woody estimates

The models for estimating herbaceous biomass have higher adjusted R^2 values on average than those for woody biomass. However, the relative errors (RRMSE) are greater for herbaceous biomass, reflecting better explanatory power but lower accuracy. Woody biomass models are less explanatory (lower adjusted R^2), but produce more stable estimates that are less prone to large errors. This suggests that herbaceous biomass is more directly influenced by climatic variables, but also more sensitive to fluctuations, while woody biomass responds in a more dampened manner to climatic conditions.

Performance according to climate zones and types of plant biomass

The models show contrasting effectiveness depending on the zone: more explanatory but less accurate in the north (Sahel), less explanatory but more stable in the south (Sudan). Herbaceous biomass is better explained but more difficult to estimate accurately. Woody biomass is less well explained but provides more robust estimates. These results highlight the importance of adapting models to specific regional characteristics and the type of biomass targeted.

Table 2. Best plant biomass estimation models in the climatic domains of Burkina Faso, including 1 to 4 explanatory variables

	Nb.of variables	Variables	MCE	RMSE	RRMSE (%)	R ²	R ² adjusted	BIC
Sahelian zone								
Herbaceous biomass	1	Pressure	125253,605	353,911	48,442	0,612	0,591	250,487
	2	Cumul / pressure	100090,092	316,370	43,304	0,706	0,673	247,687
	3	Pressure / Tn / Tx	69914,723	264,413	36,192	0,806	0,772	241,996
	4	NJP / pressure / ETP / Tx	45784,002	213,971	29,288	0,880	0,851	234,877
Woody biomass	1	Rhmin	136837,990	369,916	40,707	0,433	0,404	252,345
	2	Pressure / vent	70967,726	266,397	29,315	0,722	0,691	240,466
	3	Pressure / wind / NJP	68594,689	261,905	28,821	0,746	0,701	241,596
	4	Cumulative / Rhmax / Pressure / NJP	66142,676	257,1821	28,301	0,769	0,712	242,603
Sudano-sahelian zone								
Herbaceous biomass	1	Tm	76080,729	275,827	27,437	0,398	0,389	860,841
	2	NJP / Tm	65268,587	255,477	25,413	0,490	0,476	852,488
	3	NJP / Tm / Tn	52868,850	229,932	22,872	0,593	0,576	839,757
	4	NJP / Tm / Tn / Inso	47306,989	217,501	21,635	0,641	0,620	834,577
Woody biomass	1	Tn	58169,864	241,184	18,863	0,285	0,276	840,440
	2	NJP / Tn	42179,512	205,376	16,062	0,489	0,475	819,308
	3	NJP / Tn / Tm	39622,153	199,053	15,568	0,526	0,507	817,837
	4	NJP / Tn / Tx / Tm	38799,960	196,977	15,406	0,543	0,517	819,511
Sudanian zone								
Herbaceous biomass	1	Pressure	64065,496	253,111	19,29	0,289	0,266	370,163
	2	Tx/Tm	55791,613	236,202	18,008	0,401	0,361	368,014
	3	Tx/Tm/Tn	45601,025	213,543	16,281	0,526	0,477	363,736
	4	NJP / Tx / Tm / ETP	45135,393	212,450	16,197	0,547	0,483	365,735
Woody biomass	1	Cumulative	56242,832	237,155	16,806	0,189	0,163	365,865
	2	Tx/Tm	48302,577	219,778	15,575	0,326	0,281	363,257
	3	Inso/ Tx/Tm	45544,656	213,411	15,124	0,385	0,322	363,695
	4	wind / Rhmoy / Tx / Tm	43868,933	209,449	14,843	0,428	0,347	364,796

Source: Weather data and plant biomass data, 2017-2019

Performance of total plant biomass estimation models

Table 3 shows the performance of models for estimating total plant biomass (woody and herbaceous) in different climate zones: Sahelian, Sudano-Sahelian, Sudanese, and national. Figure 8, a heat map of adjusted R² values and RRMSE (%), provides a summary and facilitates interpretation of the results.

Overall, the adjusted R² increases with the number of variables included, reflecting an improvement in the explanatory power of the models. However, a marked decrease in the adjusted R² is observed when moving from the Sahelian zone to the Sudanian zone, indicating a decline in the explanatory power of the models in this climate zone. On the other hand, estimation errors (RMSE and RRMSE) tend to decrease in the Sudanese domain, suggesting a certain robustness of the models despite their low explanatory power. In the Sahelian domain, the models appear to be more sensitive to estimation errors, but their performance improves significantly with the addition of explanatory variables. Finally, in the Sudanese and national domains, increasing the number of climate variables does not significantly reduce estimation errors. This limitation could be explained by the high ecological heterogeneity and the impact of anthropogenic activities, which complicate the relationship between plant biomass and climate variables.

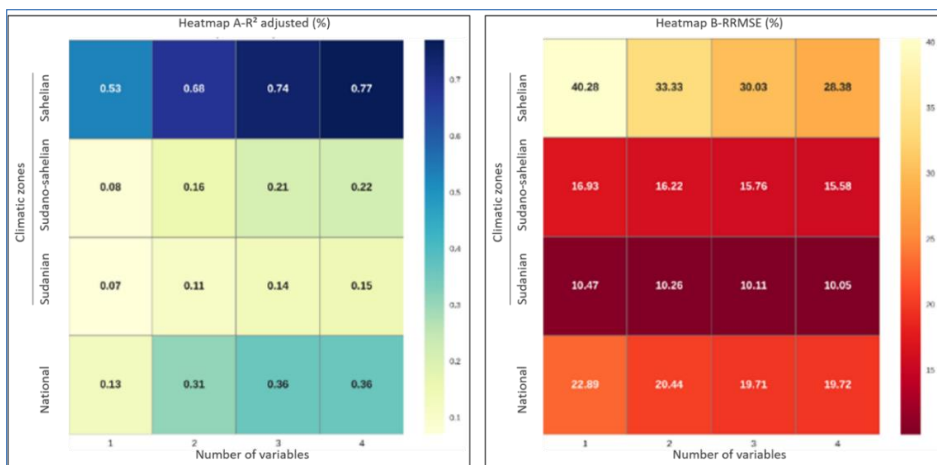


Fig. 8. Heatmap of adjusted R^2 values and RRMSE of the model for estimating total plant biomass in the climatic domains of Burkina Faso

Table 3. Model for estimating total plant biomass in the climatic domains of Burkina Faso

Nb. of variables	Variables	MCE	RMSE	RRMSE (%)	R^2	R^2 adjusted	BIC
Sahelian zone							
1	Pressure	435969,27	660,28	40,28	0,55	0,53	276,68
2	Pressure / wind	298491,21	546,34	33,33	0,71	0,68	270,63
3	Cumulative / Rhmax / pressure	242289,30	492,23	30,03	0,78	0,74	268,10
4	Cumulative / NJP / Rhmax / Pression	216405,91	465,19	28,38	0,81	0,77	267,50
Sudano-sahelian zone							
1	Tn	149432,45	386,56	16,93	0,10	0,08	912,14
2	NJP / Tn	137145,19	370,33	16,22	0,18	0,16	908,92
3	NJP / Inso / pressure	129480,95	359,83	15,76	0,24	0,21	907,83
4	NJP / Tm / Inso / pressure	126539,01	355,72	15,58	0,27	0,22	909,35
Sudanian zone							
1	Tn	81244,82	285,03	10,47	0,10	0,07	378,00
2	Tn / pressure	77986,92	279,26	10,26	0,17	0,11	379,07
3	Tn / Inso / pressure	75728,49	275,19	10,11	0,22	0,14	380,47
4	NJP / Inso / pressure / wind	74854,30	273,60	10,05	0,25	0,15	382,43
National							
1	wind	251553,95	501,55	22,89	0,14	0,13	1599,42
2	Rhmin / pressure	200571,75	447,85	20,44	0,32	0,31	1574,26
3	Rhmin / pressure / wind	186476,26	431,83	19,71	0,37	0,36	1568,76
4	Rhmax / Rhmoy / pressure / wind	186660,41	432,04	19,72	0,38	0,36	1572,70

Source: Weather data and plant biomass data, 2017-2019

Although several high-performance models were selected, their results differ in terms of predicting total plant biomass. Overall, Figure 9 shows that the adjusted R^2 values of the best models gradually decrease along the latitudinal gradient. At the same time, errors stabilize in the Sudanian domain but tend to increase in the Sahel. This decline in explanatory power in the Sudanian zone and the increase in model sensitivity in the Sahelian zone reflect the difficulty of capturing ecological contrasts based solely on climatic variables.

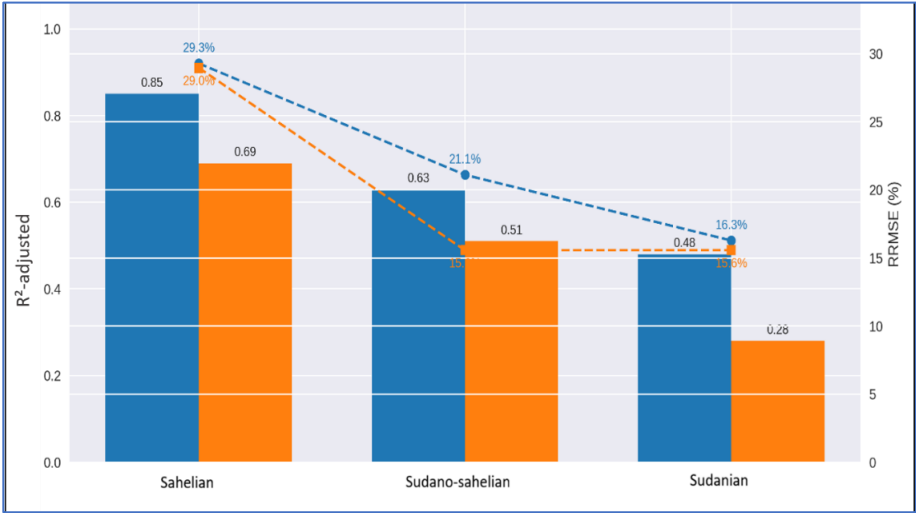


Fig. 9. Heatmap of adjusted R^2 values and RRMSE of the best estimation models

Equations of the best models for estimating different types of plant biomass

The most robust models for estimating plant biomass are based on a common core of explanatory variables: atmospheric pressure, number of rainy days (NJP), wind, and temperatures (Tx, Tm, Tn). These variables are said to be structuring because they appear in most of the equations and explain a significant portion of the variance in the models (adjusted R^2). They form the basis of statistical robustness, particularly in the Sahelian zones and at the national level.

Other variables such as insolation (Inso), relative humidity

(Rhmin/Rhmax), potential evapotranspiration (ETP), and cumulative rainfall play a complementary role. They are used in certain climatic zones to refine the accuracy of the models, but are not central to the overall explanation. Temperature variables, more specifically minimum temperature (Tn), contribute significantly to reducing prediction errors (RRMSE). Their impact is particularly marked in Sudanian zones, where they enable more accurate models to be obtained despite more modest adjusted R^2 values. Table 4 presents the equations of these best models for estimating plant biomass in the climatic domains of Burkina Faso.

Table 4. Equations of the best models for estimating plant biomass
BH: Herbaceous biomass; BL: Woody biomass; BT: Total biomass

Equation of the best models selected	MCE	RMSE (kg/ha)	RRMSE (%)	R ²	Ad- justed R ²
Sahelian zone					
BH = 217,237+24,156*NJP-436,057*pressure+8,094*ETP-283,800*T _x	45784,002	213,97	29,28	0,88	0,85
BL = 8514,653-239,874*pressure-1436,585*wind	69287,763	266,397	28,96	0,72	0,69
BT=26347,508+5,508*cumulative+22,376*NJP-135,406*R _{hmax} -1221,191*pressure	216405,905	465,194	28,377	0,813	0,766
Sudano-sahelian zone					
BH = 7581,147-10,479*NJP-328,548*T _m -328,161*wind+34,443*T _n +1,179*Inso	45007,587	212,149	21,1	0,66	0,63
BL = -4470,762+7,448*NJP+42,034*T _n +141,784*T _m	39622,153	199,05	15,56	0,526	0,507
BT = 12434,217+10,327*NJP-1,925*Inso-271,305*pressure	126539,015	355,723	15,575	0,265	0,2240
Sudanian zone					
BH = 16900,913+1795*T _x -2756,630*T _m +39,868*T _n	45601,025	213,54	16,28	0,526	0,477
BL = -8829,687-1195,696*T _x +1809,597*T _m	48302,577	219,77	15,57	0,326	0,281
BT = 1940,563+33,837*T _n	74854,301	273,595	10,048	0,253	0,147
National					
BH= 7560,688-190,689*pressure-115,496*T _x -458,612*wind+32,152*R _{hmin} +38,840*T _n	65954,721	256,816	26,96	0,577	0,563
BL = 4831,821-179,879*pressure-845,351*wind+8,574*NJP	80075,637	282,976	22,84	0,441	0,422
BT = 8041,402+74,397*R _{hmin} -334,516*pressure-932,334*wind	186476,26	431,83	19,71	0,37	0,36

Source: Weather data and plant biomass data, 2017-2019

Visualization of residuals from the national model for predicting total plant biomass

Figure 10 assesses the quality of the national model's predictions for the total plant biomass variable by visualizing the residuals, i.e., the differences between the observed values and the predicted values (Residuals = BT_{Nat} – Pred (BT)_{Nat}). The residuals appear to be broadly dispersed around the zero line, suggesting an absence of systematic bias in the predictions. The dispersion of the residuals remains relatively constant across all observed values, suggesting good homogeneity. Some points deviate further from the zero line, reflecting special cases or atypical values, but they do not call into question the overall performance. The regression line shows a general trend, but the dispersion of points around this line is significant. It does not generate systematic errors (balanced residuals), but its ability to accurately reproduce the observed values is limited. However, the Breusch-Pagan test indicates that there is no detected heteroscedasticity (statistical test value = 0.2729 and p-value = 0.6014), which confirms a constant variance of the residuals. The model complies

with the assumption of constant variance of errors. This reinforces the reliability of the confidence intervals and associated statistical tests.

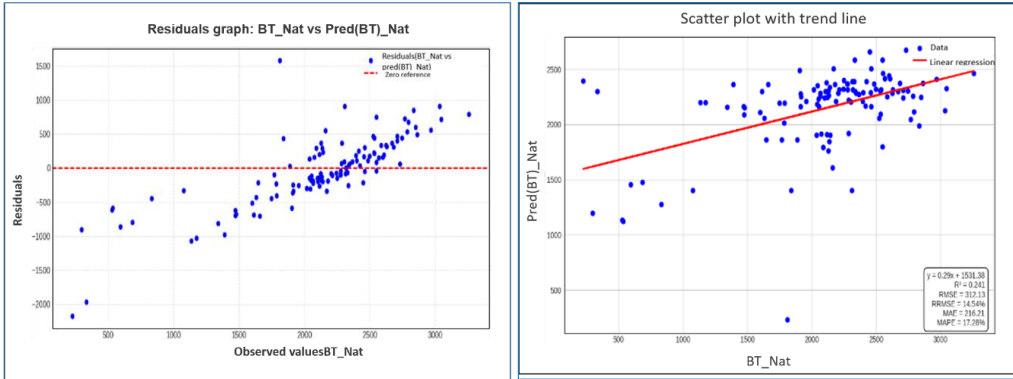


Fig. 10. Relationships between observations and residuals and prediction values

Discussion

The performance of plant biomass estimation models developed on the basis of meteorological data is broadly similar to that of models developed using vegetation indices in the Sahel region (Diouf et al., 2015; Lo et al., 2022; Garba et al., 2023; Some et al., 2024). The models offer a good compromise in the Sahel region, where vegetation is more or less homogeneous. They have good explanatory power (R^2 ranging from 0.68 to 0.81) and lower errors (RMSE between 250 and 282 kg/ha). Models developed on the basis of vegetation indices at the national level and in the Sudanese zone generally perform poorly. Explainability (R^2 varies between 0.15 and 0.35) drops dramatically with changes in climate zone. Errors become very significant with vegetation heterogeneity (RMSE varies between 427 and 1013 kg/ha) (Diouf et al., 2015; Some et al., 2024). The models developed in this study using climate data follow the same pattern of declining performance along the latitude gradient as those based on vegetation indices. In general, the models developed showed poor ability to capture the contrast between vegetation shaped by humans and climate (Fournier & Millogo-Rasolodimby, 2007). Spatialized climate data at the collection site level may contain interpolation biases (Chakri et al., 2025; Colston et al., 2018). Nevertheless, in the Sahelian region, where vegetation is more homogeneous, the models performed well.

The use of meteorological data allows us to reject the idea of Lambert et al., (2016), which suggests that image quality is a factor limiting the development of estimation models. According to Camaret et al., (2000), vegetation indices struggle to capture vegetation contrasts in large-scale heterogeneous areas due to objective limitations (saturation in dense vegetation areas, sensitivity to bare soil, atmospheric influence, pixel mixing, etc.). According to Delavaud et al., (2025), vegetation density and structure, soil type, and land degradation are factors closely linked to ecosystem functioning. Certain ecological or contextual limiting variables have been explored very little in forage biomass modeling. Furthermore, soil fertility and land degradation are not yet variables that are integrated into national plant biomass estimation models. Fournier (1990) reports that the limiting factor for plant growth in the Sudanian zone is soil nutrients. Thus, several factors threaten soil health and

contribute to increasing the spatial heterogeneity of vegetation (FAO: ITPS, 2015). However, data on soil quality at detailed spatial scales are very scarce to support forage production estimation models (FAO: ITPS, 2015). In the Sudanian zone, the contrast is marked by a densification of woody vegetation (Bognounou et al., 2009). The conversion of natural vegetation areas into cultivated land contributes to increasing the contrast in vegetation by fragmenting ecosystems, replacing homogeneous cover with a heterogeneous landscape mosaic (Traore et al., 2022). Assessing woody plant biomass without destroying it poses technological challenges (Bossoukpe et al., 2021). Improvements have been achieved through the use of drones (Taugourdeau et al., 2022). However, these drones cannot be used to cover the entire country (UA and NEPAD, 2019). Assessing plant biomass over large areas will always require the use of satellite Earth observation (EO) data.

Meteorological climate variables are not variables that measure the physiological processes of plants, but they do influence the environment in which vegetation develops (Scaetta, 1935). Thus, the relationships between these climatic variables and plant biomass are not linear, as they have thresholds and ranges of influence on vegetation (Zeng et al., 2024). In this study, specifically in the Sudanian zone, the best estimation models were obtained using temperature. In this climate zone, vegetation is dense, diverse, and competitive (trees, shrubs, and herbaceous plants), and plant development is linked to the speed of physiological processes. Thus, temperature and nutrients are essential elements in this modulation of vegetation during the rainy season. In contrast, in the Sahelian and Sudano-Sahelian regions, the number of rainy days, pressure, wind, and humidity were found to be the relevant variables for developing estimation models. Furthermore, the work of Piao et al., (2020) and Tagessons et al., (2021) has reported that air temperature, solar radiation, and vapor pressure deficit play a major role in influencing the spatial heterogeneity of vegetation dynamics. This information allows us to state that the modulation of vegetation by climatic variables depends on the type of climate zone. In the Sahelian zone Casenave & Valentin, (1989) report that rainfall is the major limiting factor for the development of annual herbaceous plants. Furthermore, the work of Somé et al., (2023) showed that in the Sudanian zone, climatic variables do not have a significant influence on vegetation production. This idea is corroborated by the results of the explanatory model for predicting total plant biomass at the national level. Temperature, wind, and atmospheric pressure are factors associated with a decrease in plant biomass due to their impact on water stress, erosion, and unfavorable climatic conditions. Conversely, humidity appears to be a determining variable in the increase in plant biomass.

In general, much scientific research has focused solely on the performance of plant biomass estimation models without giving sufficient consideration to the usefulness of these models for operational applications. The purpose of these operational estimation models is to quantify and map available plant biomass in order to identify environmental risks related to food security and the economy. The debate on performance should also focus on the usefulness of these forage yield estimation models for operational aspects, while updating their performance in line with technological developments. This research indicates that temperature, number of rainy days, wind, and atmospheric pressure are relevant variables for understanding the climate vulnerability of pastures in Burkina Faso.

Conclusion

In summary, this study was initiated to examine the contribution of meteorological climate variables to improving estimates of plant biomass yields in Burkina Faso. Spatialized meteorological data enable the development of models that perform well in estimating plant biomass in the Sahelian zone. The models showed good explanatory power (adjusted R^2 ranging from 0.85 to 0.69) and lower errors (RRMSE = 29.28%) in areas with more homogeneous vegetation. However, their explanatory power decreases with latitude due to the high spatial heterogeneity of vegetation from north to south. The models performed less well in the Sudanese zone, where vegetation was very contrasting, with adjusted R^2 values ranging from 0.48 to 0.15 and RRMSE more stable at around 5%. Climatic variables such as temperature, number of rainy days, wind, and atmospheric pressure were the most useful in developing biomass estimation models in climatic domains. These models will be used to improve forage balance estimates and implement index-based livestock insurance products.

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