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Original Research

Remote Sensing-Based Assessment of Dry-Season Forage Quality for Improved Rangeland Management in Sahelian Ecosystems[☆]

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A B S T R A C T

Residents of the Sahel depend on livestock, but harsh environmental conditions during the dry season limit rangeland forage, which is the main source of livestock feed. Al-though operational tools exist for assessing and monitoring forage quantity during the dry season, assessments of forage quality are lacking. We addressed this gap by developing satellite-based monitoring of forage quality across Sahelian rangelands during the dry season. Acid detergent fiber (ADF), neutral detergent fiber (NDF), and crude protein (CP) content (%) were measured in forage samples collected from 11 sites across the Senegalese rangelands in 2021. Multilinear (MML) regression and support vector machine (SVM) models were calibrated with spectral indices to estimate these parameters of forage quality. The vegetation variables assessed were herbaceous mass (HQ), woody foliage mass (LQ), and total fo-rage mass (HLQ). The MML regression provided the most accurate estimates for CP (HQ: $R^2 = 0.81$, LQ: $R^2 = 0.72$, and HLQ: $R^2 = 0.70$), ADF (HQ: $R^2 = 0.70$, LQ: $R^2 = 0.77$, and HLQ: $R^2 = 0.61$), and NDF (HQ: $R^2 = 0.47$, LQ: $R^2 = 0.83$, and HLQ: $R^2 = 0.60$). Temporal analysis revealed a slight decrease in CP and an increase in fiber during the dry season. Spatial analysis indicated that CP was higher in the steppe zone than in the savanna zone, and a decrease correlated with the rainfall gradient. The HQ alone was insufficient to meet livestock needs during the dry season, highlighting the importance of woody plants as an additional forage source. These findings will improve feed balance calculations in Sahelian countries, enable more sustainable use of rangelands, and contribute to the resilience of Sahelian communities to climate change.

Introduction

Rangelands cover approximately 26% of the global terrestrial land surface (FAOSTAT 2023). By supporting the livelihoods of at least 800 million people worldwide (Godde et al. 2020), rangelands contribute to the economy and resilience of many local communities (Coppock et al. 2017) and provide important ecosystem services such as carbon sequestration (Garnett et al. 2017). However, rangelands are threatened by the effects of climate change (Godde et al. 2020), and high interannual climate variability causes fluctuations in forage production (Giridhar & Samireddypalle 2015). The Sahel region has experienced discernible climate impacts that are characterized by temporally fluctuating and insufficient rainfall (Biasutti 2019), more erratic but intense rainfall events (Taylor et al. 2017), and a reduction in pastoral resources (Godde et al. 2020) with adverse impacts on food security (Moussa et al. 2022). A reduction in forage (herbaceous and woody plant mass) threat-

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ens livestock production, which constitutes the main income-generating activity for local populations in the Sahel (Assouma et al. 2019).

The sustainable use of rangeland resources is critical and requires near real-time monitoring of the quantity and quality of the forage, which determines livestock allocation (Mottet & Assouma 2024). Earth observation-based operational tools currently exist for monitoring forage quantity in the western Sahel at the end of the rainy season (Diouf et al. 2016) and during the dry season (Lo et al. 2022). However, no tools exist for estimating the forage quality (i.e., nutritional value). Such tools are particularly needed during the dry season, which lasts for almost 9 months and represents the period during which forage becomes increasingly limited. Monitoring forage quality during this period is therefore essential for managing forage resources and a healthy livestock population.

Multiple parameters have been identified for monitoring forage quality. Crude protein (CP), neutral detergent fiber (NDF), and acid detergent fiber (ADF) provide an indication of forage quality (Poppi et al. 2018; Wijesingha et al. 2020; Basbag et al. 2021), and several methods of measurement exist (Wachendorf 2018). However, to bypass costly and time-consuming chemical analyses, a faster method was developed. Near-infrared spectroscopy (NIRS) uses spectral absorption information to predict forage quality (Barotin et al. 2021).

Advancements in remote sensing technology now provide rapid and cost-effective means to monitor forage quality in near-real time. Different sources of remote sensing images, such as hyperspectral (Singh et al. 2017; Munyati et al. 2022) and very high-resolution (VHR) satellite data (Akumu et al. 2021; Naicker et al. 2023), are currently used for vegetation quality monitoring. However, even if these systems can be used for forage quality monitoring, the associated data are expensive and do not include short-wave infrared (SWIR) bands, which are important for detecting the biochemical content of dry plants in the senescent phase. The use of alternative multispectral data of coarser spatial resolution, yet still considered high resolution (e.g., the Copernicus Sentinel-2 satellite system), has therefore become attractive because these data are freely available and include measurements from the SWIR domain. Such data may provide reliable estimates of forage quality (Ramoelo et al. 2015).

In this context, how can satellite data be utilized to develop a semi-real-time monitoring tool for assessing forage quality in Sahelian rangelands during the dry season? Our goal is to use Sentinel-2 remote sensing data to estimate forage quality during the dry season by assessing CP, NDF, and ADF. The developed models were used to address the following questions:

1. Is it possible to model forage quality during the dry season across Senegalese rangelands?
2. How does the quality of the forage vary spatially and temporally?
3. Are there discernible patterns of change in forage quality during the course of the dry season?

Materials and Methods

Study area

The study was performed in the silvopastoral zone in northern and eastern Senegal (12.9 °N–16.8 °N; 12.3 °W–16.5 °W). The silvopastoral zone covers 52% of the country and is divided into five main ecoregions that are distinguished by soil type, climate, vegetation, fauna, and flora: the agricultural expansion zone, the eastern transition zone, the ferruginous pastoral zone, the northern sandy zone, and the southern sandy zone (Tappan et al. 2004) (Fig. 1A). The study area in Senegal (like other Sahelian countries) is characterized by a distinct bimodal seasonal rainfall distribution that includes a short (~3 months) rainy season and a long dry season (~9 months). During the dry season (which is slightly longer in the northern Sahel than in the southern Sahel), livestock range in search of forage.

Field data acquisition and preprocessing

Field measurements

The forage mass was collected at 11 sites throughout the study area (Fig. 1A) at three occasions during the dry season 2021 (January 31 to February 10, March 25 to April 04, and May 15 to May 25) (Lo et al. 2022).

Collection of herbaceous forage mass. At each site, standing herbaceous forage was collected along a 500 m transect (Kergoat et al. 2015; Lo et al. 2022). Plots (1 m^2) along this transect were categorized based on four different levels of production: (1) no production (bare soil), (2) low production, (3) medium production, or (4) high production. Of these 500 plots, 12 plots were selected using a stratified random method to include six plots at a medium level (the dominant stratum), three plots at a low level, and three plots at a high level (Kergoat et al. 2015). In each plot, percentage cover for different herbaceous species was recorded. Next, the standing mass in each of the 12 sample plots was harvested, weighed to obtain the fresh weight, and dried at 80°C for 48 h to obtain the dry weight. Then, the vegetation component corresponding to the standing herbaceous mass (HQ) was analyzed for quality.

Collection of woody foliage mass. Woody foliage was collected along the same 500 m transect at the same time as standing herbaceous mass. An inventory of the dominant tree/shrub species was made in two circular plots with centers located 200 m and 400 m from the beginning of the transect. Circular plots at the four northernmost sites had a radius of 28 m, while circular plots at the remaining sites had a radius of 20 m due to a higher vegetation density in the southernmost sites. For each dominant woody species, five branches of approximately 0.02 m in circumference were cut and defoliated, and the leaves were weighed in the field to obtain the fresh weight. Leaves were then dried for 48 h at 80°C to obtain the dry weight. Woody foliage mass (LQ) was then analyzed for quality.

Analysis of forage quality

Herbaceous and woody foliage samples were prepared for analysis of forage quality by first crushing the samples until all particles had a maximum diameter of 1 mm. Near-infrared spectroscopy (NIRS) was done using a Bruker TANGO Fourier-transform NIR spectrometer (Bruker Optik GmbH, Ettlingen, Germany), which captures spectra between 11,536–3,952 cm-1 with a step of 8 cm-1, for a total of 949 points. The NIRS models were based on the CIRAD Selmet calibration database, which comprises more than 2,000 forage samples available for the prediction of CP (CP = nitrogen × 6.25), NDF, and ADF. Calibrations were developed using Bruker's Opus software version 8.5 Copyright ® Bruker Optik GmbH 2020. The calibrations are shown in Table S1. The reliability of the prediction information was measured by using the Mahalanobis distance between the spectra of the samples and those of the NIRS calibration database. The smaller the distance is, the better the predictions are.

The average quality variables for HQ and LQ were used to produce a new dataset for total forage mass (HLQ); average herbaceous quality and average woody foliage quality were used to obtain a single percentage that represents the overall quality of the pixel and accounts for both vegetation components.

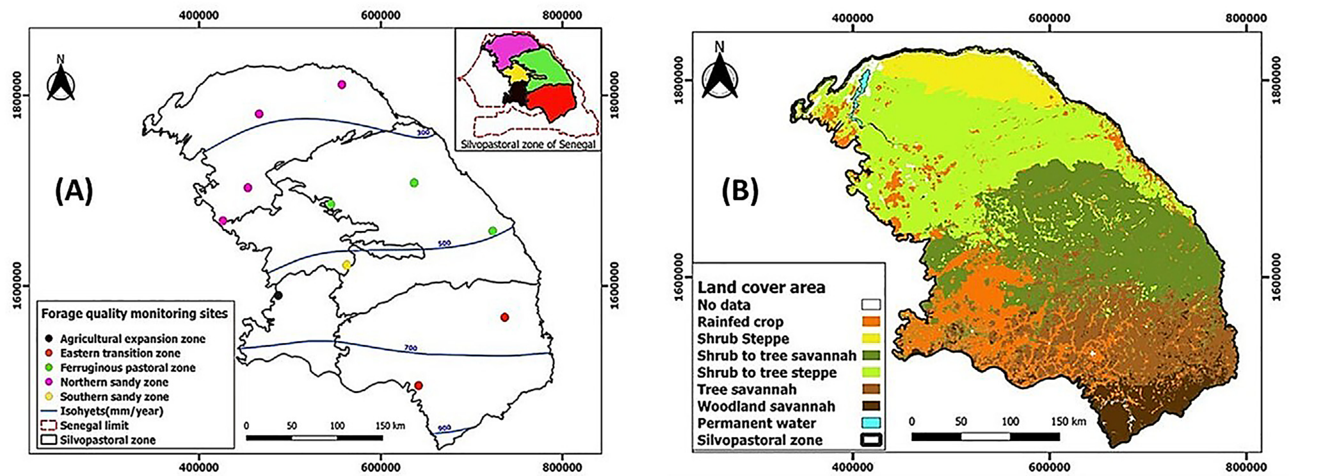

Figure 1. Map of the study area. (A) Locations of the 11 vegetation monitoring sites in the five ecoregions. (B) Land cover classes for the silvopastoral zone in Senegal.

Satellite image acquisition

Collection of satellite data

Data from the Multispectral Instrument (MSI) onboard Sentinel-2, which was launched in 2015 by the European Space Agency (ESA), were downloaded via the Earth Observation (EO) Browser platform (https://www.sentinel-hub.com/explore/eobrowser/). The MSI collects data at 13 spectral bands: four at 10 m, six at 20 m, and three at 60 m spatial resolution (Table 1). We downloaded atmospherically corrected Sentinel-2 L2A images (Drusch et al. 2012) with less than 5% cloud cover. Resampling was performed on the B11 and B12 spectral bands to achieve a spatial resolution of 10 m (nearest neighbor approach) using the Sentinel Application Platform (SNAP) to match the 10 m spatial resolution of the remaining bands. The main spectral bands used in this study were B2, B3, B4, B8, B11, and B12. QGIS software was used for visualization, and the Google Earth Engine and R software (R Core Team 2021) were used for spatial analysis.

Tree and land cover maps

We used a tree cover map (tree cover rate (%) of trees above 5 m) for the study area that was produced from PlanetScope data at 3 m resolution (Reiner et al. 2023) to create a tree mask (a pixel with more than 50% tree cover). The tree mask was used in upscaling the forage quality model. A 2020 land cover map was acquired from the *Centre de Suivi Ecologique* (CSE) database that followed the approach of the *Observatoire du Sahara et du Sahel* (OSS 2015). This map divided land cover into six classes (shrub grassland, shrub to woody grassland, shrub to woody savanna, woody savanna, woodland savanna, and rainfed croplands) (Fig. 1B).

Table 1
Description of the sensor used in the study.

Sensor	Sentinel-2A/MSI Central Wavelengths
Launch date	2015
Spatial resolution	10 m/20 m/60 m
Temporal resolution	5 to 10 days
Spectral bands and wavelengths (micrometer)	B1 Coastal aerosols 0.443
	B2 Blue 0.492
	B3 Green 0.560
	B4 Red 0.665
	B5 VRedEdge 0.704
	B6 VRedEdge 0.740
	B7 VRedEdge 0.783
	B8 NIR 0.833
	B8A Narrow NIR 0.865
	B9 Water vapor 0.945
	B10 SWIR Cirrus 1.373
	B11 SWIR 1 1.614
	B12 SWIR 2 2.202
Processing required	**-cloud processing**
	-resampling to 10 m
	-index calculation
	-modeling

Spectral bands and vegetation indices

Eight vegetation indices were used based on their ability to assess dry season forage mass using L2A Sentinel-2 images in the rangelands of Senegal (Lo et al. 2022). These indices were the normalized difference vegetation index 5 (NDI5), dead fuel index (DFI), transformed chlorophyll absorption in reflectance index (TACRI), green residue cover index (GRCI), simple ratio index (SRI), visible atmospherically resistant index (VARI), normalized difference vegetation index 7 (NDI7), and ratio vegetation index 3 (RVI3) (shown in Table S2). In addition to the indices, six bands were considered (B2: blue, B3: green, B4: red, B8: NIR, B11: SWIR1, and B12: SWIR2). The combination of these bands has been found to be suitable for monitoring forage availability during the dry season (Lo et al. 2022).

Pixelwise information on the vegetation indices and spectral bands was extracted within a 500 m buffer of each of the 11 field sampling sites. Two databases were created: One database contained only vegetation indices and the other database also included spectral bands. The same processing operations were carried out for each database.

Data analysis

Selection of explanatory variables

Explanatory variables were selected using the recursive feature elimination (RFE) method (Kuhn et al. 2021). For each quality variable, RFE was conducted for all explanatory variables (vegetation index and spectral band values), to analyze their performance in tracking the quality variables. Subsequently, a variance inflation factor (VIF) test was performed on the variables obtained from the RFE test to detect collinearity among the explanatory variables (Thompson et al. 2017). Explanatory variables with a VIF value exceeding the threshold of 10 were excluded. These two tests allowed us to select the final input data used for the modeling. Figure 2 displays the overall methodology.

Two types of machine learning models were tested. Multilinear (MML) regression was chosen because it appeared to be highly effective for monitoring forage mass during the dry season, while the

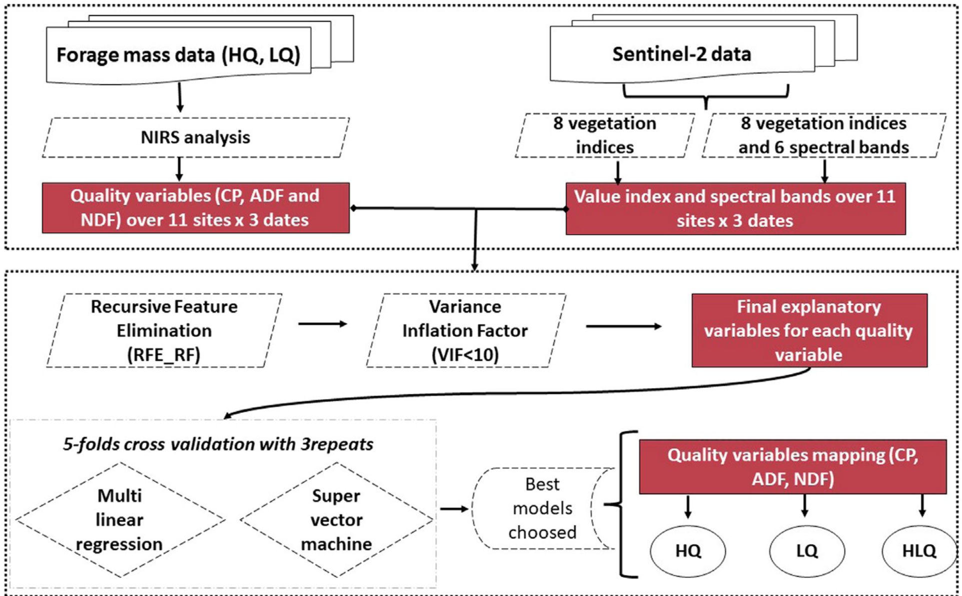

Figure 2. Methodology for assessing crude protein (CP), acid detergent fiber (ADF), and neutral detergent fiber (NDF) in each vegetation component corresponding to herbaceous mass (HQ), woody foliage mass (LQ), and total forage mass (HLQ).

support vector machine (SVM) model was selected because Zhou et al. (2019) found that it produced better estimates for the yield and forage quality of legume and grass mixtures. Variable selection and model development were performed using R software (R Core Team 2021). The final upscaling of the model was accomplished through the Google Earth Engine platform due to the processing requirements associated with the size of the Sentinel-2 images.

Modeling approaches

Support Vector Machine (SVM). Machine learning algorithms such as the SVM are often effective at predicting the quality of forage based on a small sample set (Baath et al. 2020). To run the model, combinations of explanatory variables, from three up to n, which was the maximum number of explanatory variables (HQ: $n = 8$ for CP, $n = 7$ for ADF, and $n = 6$ for NDF; LQ: $n = 8$ for CP, $n = 7$ for ADF, and $n = 7$ for NDF; HLQ: $n = 5$ for CP, $n = 5$ for ADF, and $n = 6$ for NDF), were used. The combination that produced the best prediction for each quality variable was subsequently selected. During model runtime in R, a grid search for the optimal values of the hyperparameters (C: cost parameter and γ: kernel parameter) was performed. The tested values of C varied from 0.25–2, and those of γ were between 10^{-1}–10^4.

Multilinear (MML) regression. Multilinear regression was shown to be effective for monitoring dry season forage mass with a small amount of training data (Lo et al. 2022). When running the models, combinations of explanatory variables, from 2 up to n, which was the maximum number of explanatory variables (HQ: $n = 8$ for CP, $n = 7$ for ADF, and $n = 6$ for NDF; LQ: $n = 8$ for CP, $n = 7$ for ADF, and $n = 7$ for NDF; HLQ: $n = 5$ for CP, $n = 5$ for ADF, and $n = 6$ for NDF), were tested. The combination that provided the best prediction for each quality variable was selected for the final application. The nonlinear mixed-effects models "nlme" package in R (Pinheiro et al. 2023) was used.

Model selection. Because of the limited dataset ($n = 33$, which corresponded to three sampling periods at 11 sites), it was not possible to separate the field samples into training and validation datasets. Therefore, for all models, 5-fold cross-validation was applied. The best model for each quality parameter (CP, ADF, and NDF), chosen by merging the performance of the resulting models from the two databases (Table S3 and Table S4), was selected and used for upscaling based on the coefficient of determination (R^2), the root-mean-square-error (RMSE), and the relative RMSE (RRMSE).

Assessing spatiotemporal variability in forage quality

Preprocessing of forage quality maps. The code used to produce forage quality maps was developed using the Google Earth Engine platform. The tree cover map was used to assign each pixel a value of woody (tree cover higher than 50%) or herbaceous (tree cover lower than 50%). The quality of each vegetation component (HQ or LQ) was then assigned to the herbaceous or woody pixels, respectively. No masking was applied to the HLQ maps.

Spatiotemporal variability in forage quality. To analyze the temporal dynamics of forage quality in each vegetation component (HQ, LQ, and HLQ) over the dry season, monthly maps of each quality variable (CP, ADF, NDF) were generated. The values of the 11 sites were extracted, and the median value was calculated to represent the monthly value for each quality variable.

For the analysis of spatial variation in CP, ADF, and NDF, land cover (Fig. 1B) and annual rainfall (based on average precipitation from 1981–2010) were used (Fig. S4).

Results

Field observations of forage quality

Analysis of the field observation data showed that fibers (ADF and NDF) were a significant part of forage mass (78% NDF versus 3.9% CP in the HQ and 44% NDF versus 12.7% CP in the LQ) during the dry season. In addition, the fiber content was greater in the HQ (ADF = 54%, NDF = 78%) than in the LQ (ADF = 30%, NDF = 44%) (Table 2).

The CP content decreased only marginally throughout the dry season, with values from January–May decreasing from 3.9% to 3.6% in HQ, 12.7% to 12.1% in LQ, and 10.2% to 10.1% in HLQ. Similarly, the fiber content increased slightly from January–May for the HQ (54.0% to 56.7% for ADF), whereas for the LQ and HLQ, the ADF

Table 2
Forage quality data (HQ = the vegetation component corresponding to herbaceous mass subsequently analyzed for quality, LQ = the vegetation component corresponding to woody foliage mass subsequently analyzed for quality, and HLQ = total forage mass subsequently analyzed for quality) for biomass collected in the field at three times during the dry season (CP, crude protein; NDF, neutral detergent fiber; and ADF, acid detergent fiber). Data are shown as means ± standard deviation.

	HQ			LQ			HLQ		
	CP %	ADF %	NDF %	CP %	ADF %	NDF %	CP %	ADF %	NDF %
Mean	3.89 ± 0.88	54.49 ± 3.63	78.11 ± 4.48	12.73 ± 2.46	29.71 ± 6.54	44.07 ± 8.07	9.95 ± 2.20	37.81 ± 0.13	55.10 ± 0.12
Max	5.47	60.44	88.17	18.41	41.12	56.19	15.00	49.67	72.18
Median	3.80	54.78	77.88	12.35	29.54	44.78	10.11	37.73	55.64
Min	2.41	48.67	70.25	8.86	18.54	27.42	5.98	30.54	42.25
CV %	23	7	6	19	22	18	22	13	12

Table 3
The best models obtained for crude protein (CP), acid detergent fiber (ADF), and neutral detergent fiber (NDF) contents with multilinear (MML) regression and the support vector machine (SVM) in each vegetation component corresponding to herbaceous mass (HQ), woody foliage mass (LQ), and total forage mass (HLQ).

			R^2	RMSE (% DM)	RRMSE (%)	Explanatory Variables
SVM	**HQ**	**CP**	0.73	0.58	15%	B12 + GRCI + VARI + B3
		ADF	0.55	2.81	5%	B2 + GRCI + RVI3
		NDF	0.46	3.71	5%	B12 + GRCI + B3 + TCARI + RVI3
	LQ	**CP**	0.67	1.79	14%	RVI3 + GRCI + VARI + TCARI + B2 + NDI5
		ADF	0.58	5.41	18%	B4 + GRCI + VARI + TCARI + RVI3 + NDI5
		NDF	0.5	6.58	15%	TCARI + RVI3 + VARI + NDI5
	HLQ	**CP**	0.74	1.04	13%	B12 + GRCI + B8 + VARI
		ADF	0.67	2.83	7%	B8 + GRCI + RVI3
		NDF	0.55	4.29	7%	RVI3 + GRCI + VARI + TCARI + NDI5
MML	**HQ**	**CP**	0.81	0.41	11%	GRCI + SRI + TCARI + RVI3 + NDI5 + NDI7
		ADF	0.70	2.30	4%	SRI + TCARI + RVI3 + NDI5
		NDF	0.47	3.44	4%	B12 + GRCI + TCARI
	LQ	**CP**	0.72	1.44	11%	B2 + NDI5 + TCARI + RVI3
		ADF	0.77	3.39	11%	VARI + GRCI + TCARI + SRI + RVI3 + NDI5 + DFI
		NDF	0.83	3.59	8%	GRCI + TCARI + NDI5 + DFI
	HLQ	**CP**	0.70	1.01	12%	B12 + GRCI + B8
		ADF	0.61	2.56	6%	B8 + VARI + RVI3
		NDF	0.6	3.53	6%	TCARI + NDI5

content decreased slightly, from 30.9% to 30.3% and from 37.7% to 37.3%, respectively.

Selection of input variables for forage quality modeling

The VIF values obtained for each explanatory variable that was ultimately retained in the study (Fig. S2), revealed information about the importance of each variable (a full list of variables is shown in Table S5 and Table S6). Upon observing repeated indices across different types of vegetation, it became evident that the GRCI and VARI indices were essential in detecting CP. Conversely, the TCARI, GRCI, RVI3, and VARI indices were more closely related to fiber content.

Model selection for the monitoring of dry season forage quality

Based on the R^2, RMSE, and RRMSE, the MML regression was better at predicting CP, ADF, and NDF regardless of the vegetation component. In the MML regression, CP was better predicted for HQ (RRMSE = 11%), while fiber was better predicted for LQ (ADF: RRMSE = 11% and NDF: RRMSE = 8%) (Table 3). The prediction equations from the most effective model for estimating each quality variable are provided in Table S7.

Model evaluation

Overall, the MML regression performed well according to the cross-validation (for CP: $R^2 = 0.85$ for HQ, $R^2 = 0.7$ for LQ, and $R^2 = 0.65$ for HLQ; for ADF: $R^2 = 0.71$ for HQ, $R^2 = 0.83$ for LQ, and $R^2 = 0.65$ for HLQ; for NDF: $R^2 = 0.41$ for HQ, $R^2 = 0.82$ for LQ, and $R^2 = 0.65$ for HLQ) (Fig. S3). The correlations between the predicted and observed data for ADF and NDF reached their highest values for the woody vegetation, with R^2 values exceeding 0.80. On the other hand, correlations with CP were highest for herbaceous vegetation, with an R^2 of 0.85. The weakest correlations were for the NDF variable for HQ ($R^2 = 0.41$).

Upscaling forage quality across the silvopastoral zone of Senegal

On the forage quality maps (Fig. 3), the same patterns in CP, ADF, and NDF occurred across the silvopastoral zone regardless of the vegetation component (HQ, LQ, or HLQ). These maps indicated lower CP values and higher fiber values in the HQ than in the LQ. The HLQ map showed that in the southernmost region, even in areas with more than 50% woody cover, the quality of herbaceous vegetation component dominated. Overall, this caused a low CP and a high fiber (ADF and NDF) content in forage from the southern region of the silvopastoral zone.

Spatiotemporal dynamics in forage quality

Dry season forage quality dynamics

The monthly data predicted a slight increase in fiber content over the 2021 dry season (NDF increased from 78.2% to 79.8%, and ADF increased from 53.5% to 58.4%) in the herbaceous layer (Fig. 4), which was supported by the field samples (Fig. S1). On the other hand, in the LQ, fiber content decreased from January–June (ADF decreased from 29.6% to 26.4%, and NDF decreased from 46.7% to 41.5%), with a small increase from January–March and then a decrease from April–June.

Minor variation in CP content occurred throughout the season. From January–June, the CP content increased marginally from 3.9%

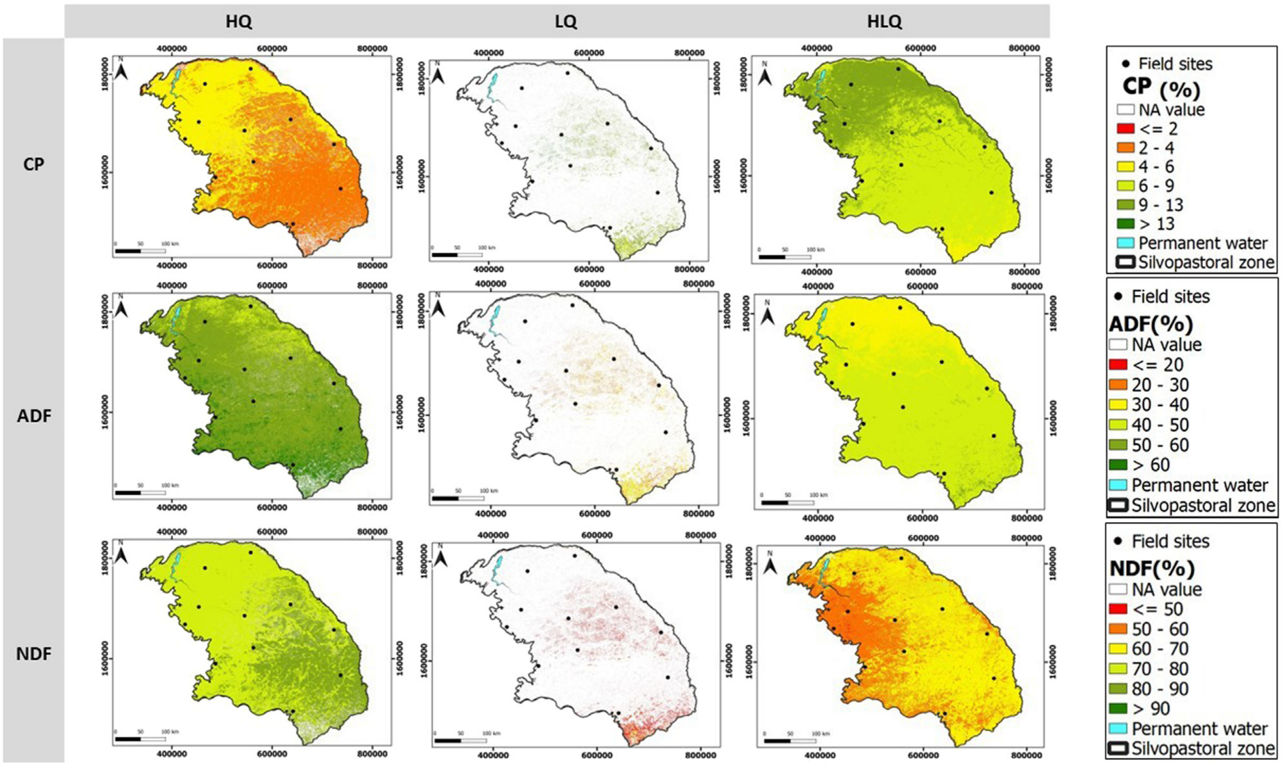

Figure 3. Maps of forage quality in the silvopastoral zone of Senegal. Only areas with more than 50% herbaceous mass and 50% woody mass are shown. The maps were calculated as dry season composites with the Google Earth Engine using the median value.

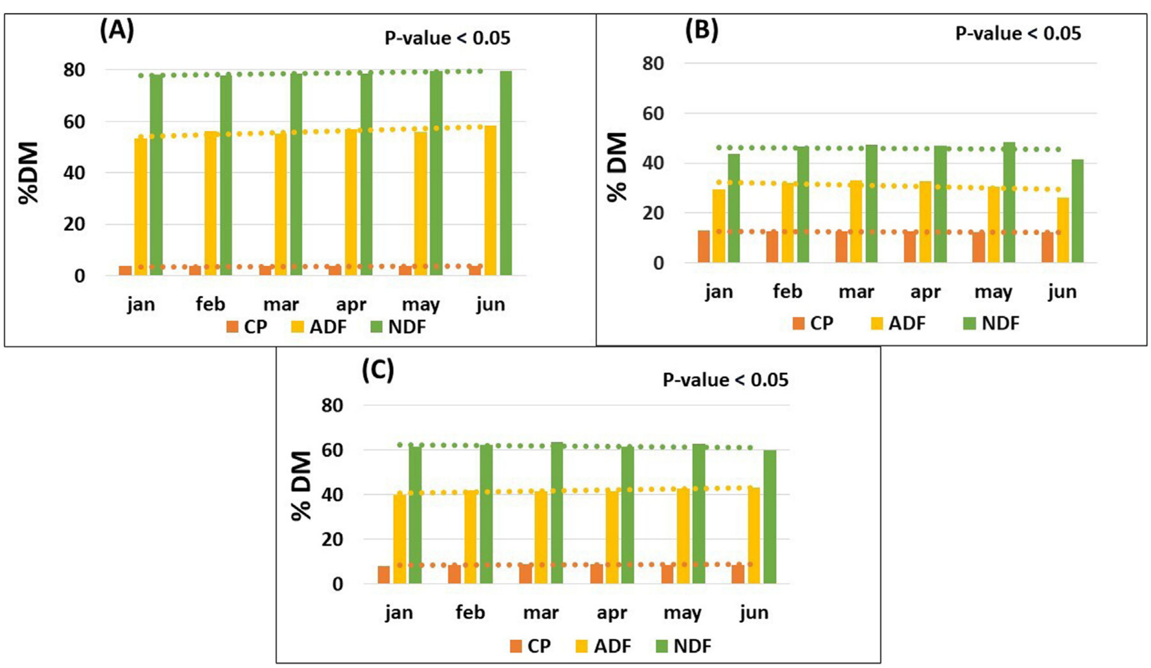

Figure 4. Monthly variation in forage quality prediction for crude protein (CP), acid detergent fiber (ADF), and neutral detergent fiber (NDF) in each vegetation component corresponding to (A) herbaceous mass (HQ), (B) woody foliage mass (LQ), and (C) total forage mass (HLQ).

to 4.0% in the HQ and decreased from 13.0% to 12.4% in the LQ (Fig. 4).

Spatial variation in forage quality across the silvopastoral zone of Senegal

Variation in forage quality was observed as a function of land cover type and rainfall. The CP content was greater in the steppe zone (shrub steppe and shrub to tree steppe) than in the savanna zone. In the steppe zone, the lowest fiber concentrations were observed (Fig. 5). On the other hand, more fiber (ADF and NDF) and less CP were found closer to the woodland savanna zones. Notably, high levels of CP were predominantly observed in the LQ, in contrast to the HQ, while higher levels of fiber were observed in the HQ.

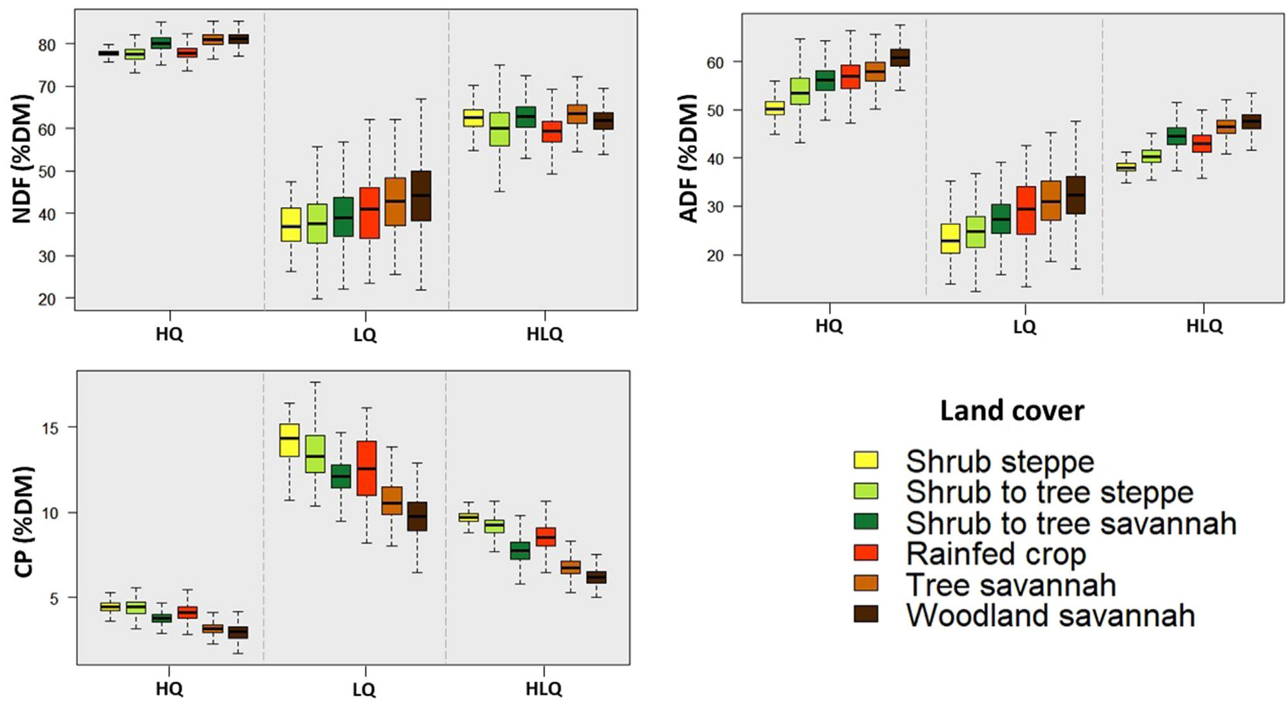

Figure 5. Variation in forage quality (CP: crude protein, ADF: acid detergent fiber, and NDF: neutral detergent fiber in each vegetation component) as a function of land cover type. The results are presented for each vegetation component corresponding to herbaceous mass (HQ), woody foliage mass (LQ), and total forage mass (HLQ).

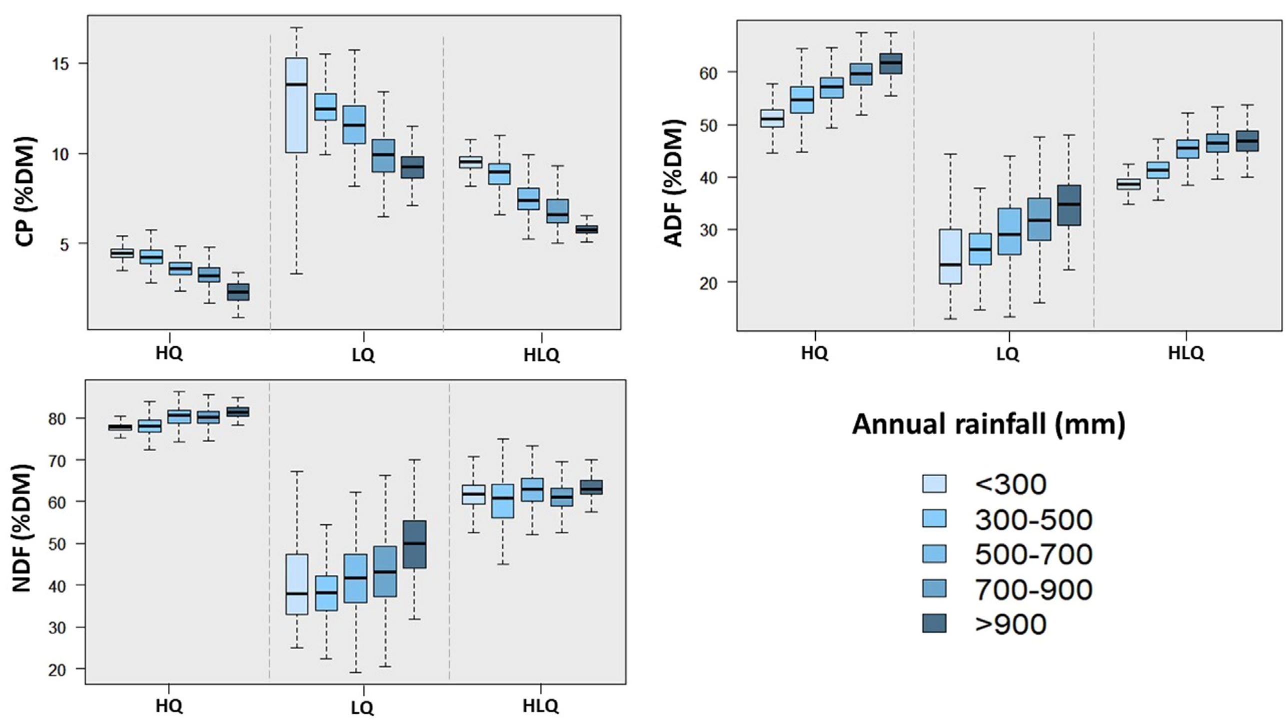

Figure 6. Variation in forage quality (CP: crude protein, ADF: acid detergent fiber, and NDF: neutral detergent fiber in each vegetation component) as a function of annual rainfall. The results are presented for each vegetation component corresponding to herbaceous mass (HQ), woody foliage mass (LQ), and total forage mass (HLQ).

Forage quality also changed as a function of annual rainfall (Fig. 6). As the area became wetter, CP levels decreased and fiber (ADF and NDF) levels increased. Areas with less rainfall contained forage with more CP, but the levels did not exceed 15%, regardless of the vegetation component considered. On the other hand, in areas with less than 300 mm rainfall, ADF and NDF contents reached 50% and 78%, respectively, in the HQ, 25% and 35%, respectively, in the LQ, and 35% and 60%, respectively, in the HLQ.

Discussion

Suitability of Sentinel-2 bands for monitoring the forage quality of rangelands

In this study, Sentinel-2 L2A data were used to map dry season forage quality in the rangelands of Senegal in 2021 (Table 3). With its high spectral, spatial, and temporal resolution, Sentinel-2 offers promising imagery for mapping the composition of vegetation at the landscape or regional scale, as previously shown by Aguirre Castro and Garbulsky (2018). Other studies have suggested that Sentinel-2 data could be used to predict forage quality (Gholizadeh et al. 2016; Raab et al. 2020). Our findings are consistent with several other studies, such as those of Ramoelo and Cho (2018) in South Africa and Chemura et al. (2018) in Zimbabwe. Finally, Ferner et al. (2021) showed that forage maps (quantity and quality) obtained with Sentinel-2 images in West Africa were more realistic than those obtained with Hyperion satellite images (Transon et al. 2018).

Vegetation indices that have been adapted for estimating CP, NDF, and ADF have the advantages of including the blue, red, green, NIR, SWIR1, and SWIR2 bands for monitoring forage characteristics. Knox et al. (2011) showed that when using only the visible and NIR spectral bands, less than 50% of the variation in the chemical composition of forage was retained. Indeed, as plants senesce in the dry season, photosynthetic pigments, which are more abundant in the visible spectrum, decrease. In contrast, the SWIR band becomes increasingly important as the water content decreases, and this spectral region has been shown to be important for discriminating protein levels in dry plants (Kokaly et al. 2009).

Compared with the SVM, MML regression was more effective at assessing dry-season forage quality in our study area. Zeng et al. (2018) also showed that the accuracy of a linear regression model built from spectral data provided more intuitive results in their study, which focused on the use of Earth observation data for estimating nutrient content at different growth stages.

Spatiotemporal variation in forage quality

Our results showed that forage quality in the HQ decreased in digestibility from January–June due to an increase in fiber (ADF and NDF) and a decrease in CP. These results align with observations of plant phenology (Ferner et al. 2018). During the dry season, herbaceous vegetation lignifies quickly at the expense of other plant constituents as part of the process of senescence.

A comparison of the CP and fiber (ADF and NDF) contents also revealed higher fiber values (generally higher than 60%) relative to CP values (less than 6%) in the HQ. Safari et al. (2016) found similar results when comparing ADF and protein contents seasonally, with an average ADF value of 32.7% versus an average protein value of 11.4%. Our results indicated that the HQ had less CP than the LQ from January–June. These results are consistent with the research of Chabala et al. (2020) in the Zemvelo Nature Reserve, Mpumalanga Province, South Africa, who found low concentrations of protein in areas covered by herbaceous vegetation relative to areas with woody vegetation. Babatounde et al. (2011) also reported that the protein content was greater in tree leaves than in herbaceous vegetation in a dry season experiment conducted in Burkina Faso. At advanced stages of senescence, the amount of fiber (such as lignin) increases, while the amount of chlorophyll decreases (Zeng & Chen 2018), and nitrogen (protein) levels have been shown to have an inverse relationship with fiber levels (Babatounde et al. 2011).

The observed and predicted data showed that the CP content in the HQ was generally lower than 6%, in contrast to the LQ (12–13%) in the dry season. The recommended level of CP in forage is 7% for beef cattle and 9% for small ruminants (Rad et al. 2015; Dalle 2020), which indicates that the amount of CP contained in herbaceous vegetation during the dry season is insufficient for the needs of the animals in the study area. A CP content below these thresholds reduces the activity of ruminal microbes, which leads to suboptimal livestock performance (Hassen et al. 2007). A supplementation program (İleri & Koç 2022) can be considered in such cases, and foliage is a reliable means of meeting the nitrogen requirements of animals (Dalle 2020). These results corroborate the traditional practices of herders in this study area who use woody vegetation as a food supplement during the dry season. Increasing the planting of trees, especially leguminous ones, and increasing their accessibility to livestock could compensate for the dry season food deficit. The use of maralfalfa (*Pennisetum* sp.), a fodder crop, is another option for satisfying the dietary needs of livestock. Its protein content, which varies from 10–20%, is well above the critical level of 8%.

Analysis of the land cover map and the soil map revealed variation in forage quality between the northern (steppe zone) and southern (savanna zone) areas. According to Maignien (1965), the soil in the savanna zone is less developed than that in the northern zone. In poorly developed soils (weakly evolved on lateritic cuirass), the decomposition of organic matter is limited, which results in low mineralization and a reduction in the nutrients available to plants. This may explain the low quality of herbaceous plants in the savanna zone.

In the LQ, better forage quality may be due to a greater proportion of legumes in the northern zone than in the southern zone. Our results support those of Grouzis and Diédhiou (1998), who showed that the proportion of legumes in the LQ of ecosystems in the Sahel increases in diversity from south (11%) to north (80%).

Our analysis of forage quality, which accounts for rainfall distribution, indicates that areas with low rainfall had higher CP concentrations than areas with higher rainfall. Previous studies also demonstrated a correlation between drier conditions and better forage quality, particularly in regard to nutrient content (Ferner et al. 2021). Nonetheless, it is crucial to emphasize that in the northern silvopastoral zone, annual plants that contribute to better forage quality are predominant. According to Hempson et al. (2015), arid zones are more favorable for the growth of annual plants, which often have high forage quality (Houerou 1980). However, forage quality does not depend solely on precipitation (Knox 2010). While forage production is strongly influenced by precipitation (Egeru et al. 2015), forage quality is more dependent on phenological stage and functional composition, as demonstrated by Ferner et al. (2018).

Forage quality differences in the northern region compared to the southern region may also be explained by the presence of woody species that are generally rich in CP. The northern zone of the study area is dominated by woody species such as *Acacia raddiana*, *Boscia senegalensis*, and *Balanites aegyptiaca*, which account for approximately 95% of the woody cover in the north (Akpo et al. 2003). NIRS analysis revealed that these species contributed 77% of the CP and 35% of the fiber (Table S8 and Table S9) to the total nutritional value of the forage.

In the Sahel, most countries carry out forage balances once per year and account only for the quantity of forage available after the rainy season. Forage availability during the dry season is considered, but despite this, forage balances remain unreliable and provide no indication of the quality of forage available to livestock during the dry season. Our study makes a significant contribution to understanding the seasonal feed balance, particularly in countries in the PRAPS 2 project (*Projet Régional d'Appui au Pastoralisme au Sahel*). In particular, our data on CP, one of the key driving factors of forage quality (Irisarri et al. 2022), are critical in assessing the metabolizable energy available to animals.

Forage quality monitoring during the dry season across the silvopastoral zones of the Sahel is crucial for achieving sustainable development objectives. The monitoring tool that we developed makes it possible to identify areas with better forage resources for livestock, which can have a positive impact on livestock productivity and on the economies of pastoral communities that depend heavily on livestock. We envision a reduction in poverty by ensuring food security for both Sahelian communities and livestock (SDG 1: No poverty and SDG 2: Zero hunger) while promoting better management of natural resources in Sahelian rangelands thanks to real-time monitoring of forage quality (SDG 15: Life on land).

Conclusion and Perspectives

This study focused on evaluating forage quality in Sahelian rangelands and revealed that Sentinel-2 is a promising data source for improving the mapping of forage quality parameters in the dry season. Using multilinear regression, we achieved good accuracy in predicting crude protein content in herbaceous ($R^2 = 0.81$), woody foliage ($R^2 = 0.72$), and total forage mass ($R^2 = 0.70$); in predicting acid detergent fiber in herbaceous ($R^2 = 0.70$), woody foliage ($R^2 = 0.77$), and total forage mass ($R^2 = 0.61$); and in predicting neutral detergent fiber in herbaceous ($R^2 = 0.47$), woody foliage ($R^2 = 0.83$), and total forage mass ($R^2 = 0.60$). The SWIR band carried by the Sentinel sensor system was essential for successfully modeling the chemical composition of forage quality. Land cover, annual rainfall, and soil type impacted the spatial distribution of forage quality during the dry season. The overall forage quality varied only slightly during the dry season (January–June) in the silvopastoral zone of Senegal. Finally, the crude protein content of herbaceous vegetation was insufficient to meet the livestock needs in this region, suggesting that trees are necessary as a forage supplement during the dry season.

Our results serve as a basis for developing a decision-support tool for land managers to predict forage quality, defined by protein (nitrogen content) and fiber (ADF and NDF) content, and for improved management of livestock resources in the silvopastoral zone of the Sahel.

Based on these results, we suggest the following: (1) Extend the study to incorporate multiyear field observations, which will enhance the robustness and generalizability of the findings. Using longitudinal data will provide a more comprehensive understanding of temporal forage quality trends and enable the assessment of interannual variability. (2) Investigate the influence of fires and other land management practices. Integrating these variables into the modeling framework will enable a more holistic assessment of the drivers of forage quality variation and inform targeted management interventions. (3) The study area should be enlarged to encompass a broader geographical region within the Sahel to capture spatial heterogeneity in forage quality. This expansion will facilitate the development of region-specific predictive models and enhance the transferability of findings across diverse ecological settings.

Declaration of Competing Interest

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

CRediT authorship contribution statement

Adama Lo: Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Abdoul Aziz Diouf:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Louise Leroux:** Conceptualization, Formal analysis, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Torbern Tagesson:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Rasmus Fensholt:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Anne Mottet:** Writing – original draft, Writing – review & editing. **Laurent Bonnal:** Writing – original draft, Writing – review & editing. **Ibrahima Diedhiou:** Methodology, Writing – original draft, Writing – review & editing.

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Data Availability

Codes and databases are available on GitHub https://github.com/adamalo/CaSSECS_FATIMA_files and source data are available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rama.2024.05.009.

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