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A Hybrid Deep Learning and Remote Sensing Framework for Climate-Smart Livestock Grazing in Semi-Arid Nigeria

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ABSTRACT
The agricultural sector in Nigeria plays a vital role in ensuring food security and providing jobs, particularly in rural areas like Adamawa State, where many families depend on livestock for their livelihoods. Today, however, farmers are struggling more than ever to sustain livestock production because of climate change, which brings unpredictable rainfall, degraded land, and shrinking grazing areas. This study develops a practical data-driven framework that utilizes hybrid deep learning and remote sensing to support climate-smart livestock grazing in Adamawa State. Information from multiple sources (Sentinel-2 and Landsat satellite images, climate data, and field observations) was integrated to assess how suitable different regions are for grazing. A hybrid ConvLSTM (Convolutional Neural Network and Long Short-Term Memory) model was used to capture how vegetation and environmental conditions change over space and time, and to classify grazing suitability into three levels (low, moderate, and high). The model performs excellently by achieving 90.1% overall accuracy with balanced recall, precision, and F1-scores. We then translated these results into GIS-based grazing suitability maps for Fufore and Mubi South Local Government Areas, which revealed realistic environmental conditions that are consistent with field observations. The resulting prototype offers a practical decision-support tool that can aid farmers and herders in using resources more efficiently, which will improve grazing management and reduce climate-related risks, thereby contributing to more sustainable livestock production in semi-arid regions.

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INTRODUCTION

Livestock production in Nigeria provides nutrition and income to millions of people, thereby contributing significantly to the nation's economic structure. Livestock farming contributes about 5% to the Gross Domestic Product (GDP) of Nigeria and also accounts for 17% of the agricultural GDP of the country (Olateru, 2023). One of the main hubs for pastoralism in Nigeria is Adamawa State. About 2.5 million cattle live in the state. Mubi International Cattle Market in Adamawa is a significant trading hub that draws merchants from all over West Africa and Nigeria (Dzarma, & Hamawa, 2020). This growing number of people indicates a determined demand for an increase in food production (Dickson et al., 2025). These numbers highlight the importance of Adamawa State in pastoral activities and its prominence in Nigeria's livestock industry.

According to Yola (2025), Mubi Local Government Area (LGA) livestock traders supply 29 million animals to Lagos State every year, generating annual revenue of about N29 billion. The economy of Adamawa state is strongly dependent on pastoralist activity despite the increasing pressure of climate change on grazing lands. Furthermore, farmers and herders constantly engage in conflict because of poor livestock practices. These issues disrupt forage availability, intensify resource-based conflicts, and hinder livestock productivity.

Yet, the viability of livestock systems in the area is becoming more vulnerable to the effects of climate change, such as erratic rainfall patterns, extended drought, land degradation, and declining pasture availability (Saka et al., 2021). These changes undermined traditional grazing practices, decreased forage yields, and heightened competition among pastoralists for natural resources. In response to these challenges, the concept of Climate-Smart Agriculture (CSA) has emerged as a comprehensive strategy to enhance agricultural productivity, foster climate resilience, and reduce greenhouse gas emissions. For livestock systems, CSA promotes practices such as rotational grazing, improved pasture management, and sustainable land use planning (FAO, 2013). However, effective implementation of CSA principles in grazing systems requires accurate and timely data on pasture conditions, livestock distribution, and environmental factors which are often lacking or difficult to obtain through conventional means in rural and resource-constrained settings.

Climate-smart livestock grazing involves practices that simultaneously increase productivity, enhance climate resilience, and reduce greenhouse gas emissions. Rotational grazing, controlled stocking rates, and pasture rehabilitation are among the key components of this approach (FAO, 2013). In Nigeria, especially in the semi-arid northern states like Adamawa, overgrazing and desertification pose significant threats to livestock systems. Implementing climate-smart strategies thus requires spatially and temporally accurate data on pasture condition and forage availability, which traditional field-based methods often fail to provide efficiently (Noa-Yarasca et al., 2024).

Remote sensing provides critical data for evaluating rangeland conditions over vast geographical areas with minimal ground intervention. Satellite-based imagery, such as those from Sentinel-2, Landsat, and PlanetScope, offers high-resolution and time-series data that help in detecting vegetation cover, estimating biomass, and monitoring soil moisture (Cai et al., 2025). In the Sahelian context of Adamawa State, seasonal changes significantly influence forage quality and quantity, making remote sensing indispensable in mapping pasture dynamics. Normalized Difference Vegetation Index (NDVI) derived from satellite data is widely used to assess the greenness and productivity of grazing lands (Ba et al., 2024). For instance, multi-temporal NDVI analyses have been employed to evaluate the impact of grazing pressure and rainfall variability on pasture productivity in West Africa (Malo & Nicholson, 1990).

While remote sensing provides data, deep learning algorithms help in making sense of this data at a granular level. Deep learning, a subfield of machine learning, is particularly effective in pattern recognition and image analysis, making it suitable for processing complex satellite data for agricultural applications. Convolutional Neural Networks (CNNs), for example, have been used to classify land cover, predict biomass, and detect signs of overgrazing with high accuracy (Li, & Kong, 2024). In addition, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models are effective in time-series prediction of pasture growth based on historical climate and vegetation data (Kraft et al., 2019).

A recent study, Werner et al. (2024) demonstrated the integration of Sentinel-2 and PlanetScope imagery with deep learning to map integrated crop-livestock systems in sub-Saharan Africa, showcasing the feasibility of applying similar models in Adamawa State. These models can help predict the best grazing zones, alert farmers about degradation risks, and facilitate dynamic pasture rotation schedules, all of which are key to CSA implementation.

Adamawa State presents a suitable environment for deploying these technologies due to its diverse agro-ecological zones ranging from the sub-humid to the semi-arid Sahel. Pastoral communities in the state face increasing competition for land, climatic stressors, and limited access to grazing infrastructure. Implementing a DL - RS framework could help optimize land use by identifying underutilized grazing areas, estimating forage biomass in near-real time, and reducing conflict over pasture resources (Bambara et al., 2024).

A pilot initiative using RS data for drought early warning in Nigeria indicated that farmers and herders are receptive to technology-based solutions when benefits are clearly demonstrated (Adedeji et al., 2020). Therefore, introducing a hybrid ConvLSTM with RS models tailored for local conditions in Adamawa has the potential to transform the grazing landscape into a more sustainable and robust system. Therefore, this research aims to develop a climate-smart livestock grazing management system for Adamawa State using deep learning and remote sensing technologies. The objectives are: (i) Collect and annotate field and satellite data on pasture conditions, climate, and livestock movement in Adamawa State. (ii) Preprocess and prepare remote sensing data for analysis, including vegetation and land cover classification. (iii) Develop deep learning models to predict pasture availability and grazing suitability based on the processed data. (iv) Build a prototype decision-support system that will integrate the model outputs to generate maps that can guide climate-smart livestock grazing. (v) Test the system to evaluate its accuracy, usability, and impact on grazing efficiency and sustainability.

MATERIALS AND METHODS

Study Area

Adamawa State lies in northeastern Nigeria and covers an area of approximately 36,917 square kilometers. Accordingly, it ranks 8th in terms of size among Nigerian states. It includes ecological zones ranging from Sudan to Guinea savannahs and receives between 800 and 1,600 mm of rainfall annually. The study was conducted in Fufore and Mubi South LGAs. The two LGAs were selected for their contrasting ecological and socio-economic conditions, which provide a diverse testing ground for climate-smart livestock grazing technologies. Fufore LGA is a semi-urban area around Yola with moderate grazing pressure and better infrastructure accessibility, making it the most appropriate for piloting and stakeholder engagement. It is an area of transition from rural to urban land use. Mubi South LGAs is livestock-dense, rural areas along the Cameroon border with a reputation for traditional pastoralism and seasonal grazing pressure. They are extremely susceptible to climate variation in the form of drought and overgrazing.

Data collection

This research employed a mixed range of datasets to simplify the development of a climate-smart model of livestock grazing. Data was collected through remote sensing with Sentinel-2, Landsat 8/9, and MODIS was employed to determine vegetation condition, land use changes, and pasture status. The datasets were processed in python environment. Similarly, Climatic data was obtained from ERA5, CHIRPS, and the Nigerian Meteorological Agency (NiMet) to avail data on rainfall, temperature, drought indices, and soil moisture content. The data was used to simulation the impact of climate variability on forage availability.

Information on grazing activity and animal movements, stocking density, and seasonal transhumance was collected through field surveys, mobile reporting, and livestock census reports from the government. Information on conflict and land use pressure was obtained from local government and NGO records. Also, field observation, GPS logging, and vegetation survey was used to collect ground-truth data to validate the satellite imagery and train the deep learning model. Biomass and soil properties was sampled for model tuning.

Land tenure maps, socioeconomic profiles of herders, and policy documents was examined to contextualize the findings and add depth to the decision-making framework. These datasets together formed an extensive basis for the application of remote sensing and AI technologies for restructuring livestock grazing in Adamawa State.

Data Preprocessing

Data Preprocessing is an essential process to ensure data quality by removing undesired features in datasets. The data preprocessing for this research project consist of some important steps aimed at making the datasets accurate, consistent, and ready for subsequent analysis. The satellite, climatic, and field survey data was cleaned to eliminate inconsistencies such as cloud contamination and missing value cases. The datasets were then be spatially clipped to align with the study areas of Fufore and Mubi South LGAs, and normalized in relation to both the time and coordinate systems. Vegetation indices like NDVI and environmental variables like rainfall and soil moisture content was calculated and normalized. Ground-truth data from field surveys was geo-referenced and used to label satellite images to train the deep learning model. Finally, the processed data was converted to appropriate formats and split into training, validation, and testing datasets, forming a reliable basis for spatial modeling and prediction analysis. The diagram in Figure 1 shows the data preprocessing stages for the model development.

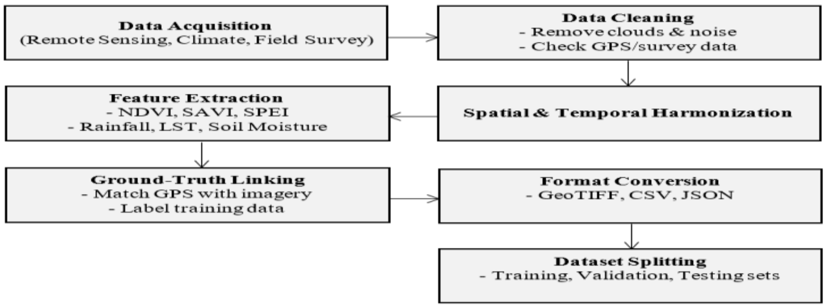

Figure 1: Data preprocessing stages

System Development

The proposed model employed a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture (hybrid ConvLSTM). CNNs are suitable for extracting spatial patterns from satellite-based vegetation indices and climate raster layers, whereas LSTM networks can learn temporal dependencies and trends in vegetation and climatic factors over time (processing sequences of NDVI and rainfall data to mimic both seasonality and inter-annual dynamics of pasture). The hybrid architecture enabled the fusion of spatial and temporal learning, resulting in improved predictive performance. The system development stages are presented in Figure 2.

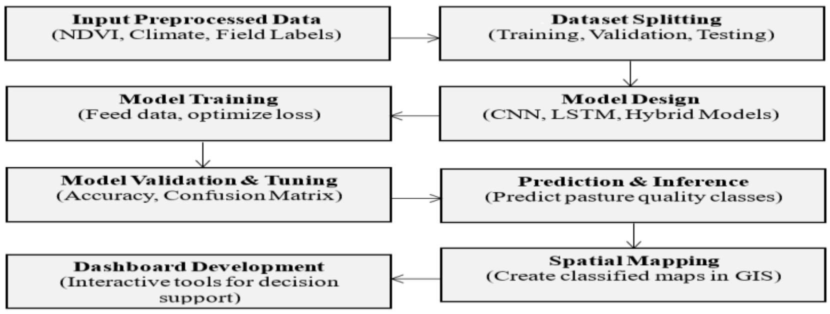

Figure 2: System Development Stages

Model Architecture

The hybrid ConvLSTM follows a sequential CNN - LSTM channel which is the most common and effective configuration for satellite time-series data.

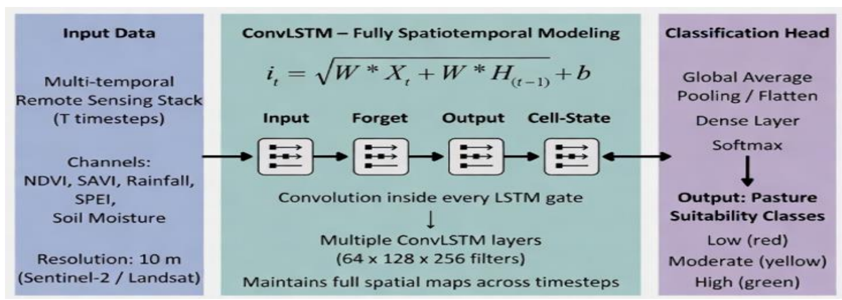

Figure 3: Hybrid ConvLSTM Architecture

The Hybrid ConvLSTM integrates spatial convolution directly inside LSTM gates for end-to-end spatiotemporal learning.

Input Layer

Time-series stack of raster images: shape = (T, H, W, C) where T = number of time steps (e.g., 36 monthly images), H × W = spatial resolution (10 m after resampling), C = number of channels (NDVI, SAVI, rainfall, soil moisture, etc.).

CNN Module *(Spatial Feature Extraction)*

Applied independently to each time step, extracts local spatial patterns (texture, edges, vegetation patches), and outputs a compact feature vector per time step.

LSTM Module *(Temporal Sequence Modeling)*

The LSTM modules receive the sequence of CNN-extracted feature vectors and learn long-term dependencies (seasonality, drought persistence, pasture regrowth).

Final Dense and Softmax Layer
This outputs the probability distribution over three pasture suitability classes: Low, Moderate, and High.

Mathematical Formulation
CNN Stage *(per time step t):*
Let Xt ∈ RH×W×C be the input raster at time t.
A convolutional layer is defined as:
F_t = ReLU (Conv2D(X_t; W_c, b_c))
Where W_c and b_c are learnable kernels and biases.
Multiple convolutional and pooling blocks reduce the spatial dimensions. The final CNN output is flattened into a feature vector:
v_t = Flatten(F_t) ∈ R^D (typically D = 512 or 1024 after several blocks).
Sequence of Features Fed to LSTM:
V = [v_1,v_2,…,v_T] ∈ $R^{T\times D}$

LSTM Stage:
An LSTM cell at time step *t* updates its hidden state h_t and cell state c_t using the following gates:
$i_t = \sigma (W_{xi} v_t + W_{hi} h_{t-1} + b_i)$ (input gate)
$f_t = \sigma (W_{xf} v_t + W_{hf} h_{t-1} + b_f)$ (forget gate)
$o_t = \sigma (W_{xo} v_t + W_{ho} h_{t-1} + b_o)$ (output gate)
$c\sim_t = \tanh(W_{xc} v_t + W_{hc} h_{t-1} + b_c)$ (candidate cell)
$c_t = f_t \odot c_{t-1} + i_t \odot c\sim_t$)
$h_t = o_t \odot \tanh(c_t)$
The final LSTM hidden state h_T(or concatenation of all h_t) is passed to a dense layer with softmax for classification:
$y^\wedge = \text{softmax}(W_d h_T + b_d)$

Model Training and Evaluation
The model was trained based on supervised learning with a categorical cross-entropy loss function and using Adam optimization algorithm. The performance of the model was measured using accuracy, precision, recall, F1-score, and the confusion matrix. To ensure minimal overfitting, hyperparameter tuning through grid search and regularization techniques (dropout, batch normalization, and early stopping) was employed. Subsequently, after the training, the best performing model among all the models considered was selected using validation accuracy and generalization to unseen data.

The evaluation metrics used for this research project are presented as a measure of accuracy, precision, recall, and F1-score (Kim et al., 2020):
Accuracy: This is the amount of correctly classified sample over all the correct and incorrect number of classification (equation 1).

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (1)$$

Precision: This is the ration of samples that are correctly classified over the total number actual positives in the dataset (equation 2).

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

Recall (Sensitivity): This It calculates how much the classifier can recognize actual positives as positive (equation 3).

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

F1-Measure: This indicates the balance between precision and recall (equation 4)

$$F1 = 2\,x\,\frac{Precision\ x\ Recall}{(Precision + Recall)} \quad (4)$$

The confusion matrix for the evaluation is presented in Figure 4.

RESULTS AND DISCUSSION
Results
The hybrid ConvLSTM model was successfully trained and evaluated in a Python environment using a preprocessed dataset which is comprising of Sentinel-2/Landsat-derived vegetation indices (NDVI, SAVI), climatic variables: rainfall, SPEI, soil moisture from ERA5/CHIRPS, and ground-truth field data from Fufore and Mubi South LGAs. The model generated a strong classification of pasture suitability into three main classes (Low, Moderate, and High) using supervised learning with categorical cross-entropy loss, and the Adam optimizer.
The model achieved an overall test-set accuracy of 90.1% on the independent test set (n = 1,000 samples). The best macro-averaged precision, recall, and F1-score were 0.902, 0.905, and 0.903, respectively. These values show realistic performance in remote-sensing applications, with slight differences between the precision and recall arising from spectral mixing, cloud contamination, and reasonable class imbalance across the two ecologically contrasting LGAs. Table 1 shows the per-class evaluation result.

Table 1. Per-Class Evaluation Metrics of the Hybrid CNN-LSTM Model

Class	Precision	Recall	F1-Score
Low	0.910	0.939	0.924
Moderate	0.891	0.880	0.885
High	0.911	0.900	0.905

The per-class metrics are summarized graphically in Figure 4.

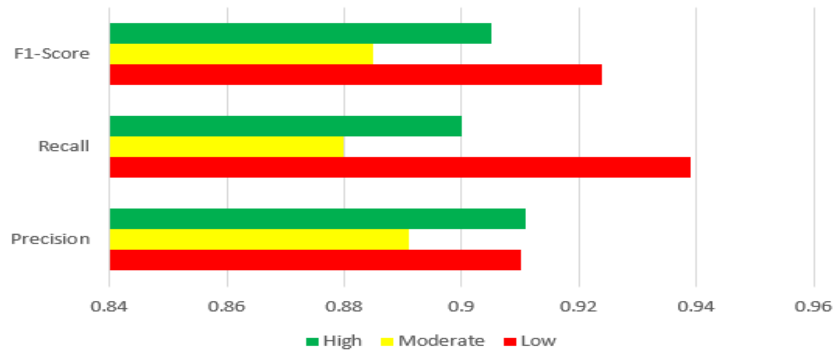

Figure 4: Per-class Evaluation Metrics of the Hybrid ConvLSTM Model

Figure 5: Confusion Matrix of the Hybrid ConvLSTM Model

The confusion matrix in Figure 5 shows strong diagonal dominance, but with realistic off-diagonal entries showing mainly reasonable misperception between Moderate and High classes. This kind of pattern is expected in savanna environments where temporary pasture conditions creates spectral overlap.

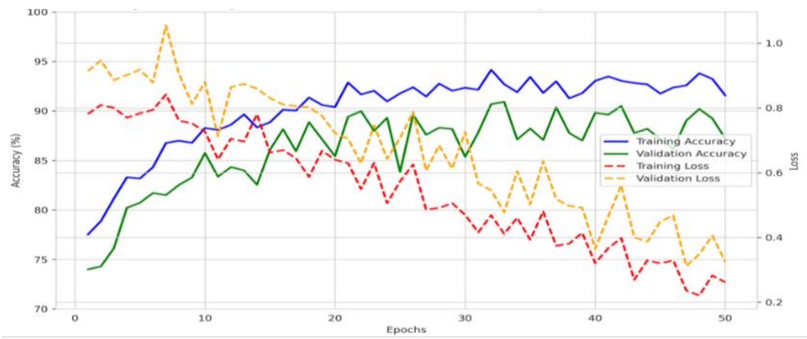

Figure 6: Training and Validation Performance Curve of the Hybrid ConvLSTM Model

The training and validation curves in Figure 6 demonstrate a stable convergence after approximately 25 epochs, with a validation accuracy of about 90%, and loss curves were narrowly aligned, which confirms an effective capture of both spatial (CNN) and temporal (LSTM) dependencies in the pasture dynamics.

Spatial Predictions of Grazing Suitability Zones

The trained hybrid model generated classified raster outputs at 10m resolution (resampled from Sentinel-2) for the two study LGAs. Predictions were post-processed in a GIS environment (QGIS) and reclassified into High (suitability index >0.75), Moderate (suitability index between 0.45-0.75), and Low (suitability index <0.45) pasture-suitability zones. The maps generated integrate the NDVI time-series trends, drought indices, soil moisture, and livestock movement dataset to produce actionable grazing suitability layers.

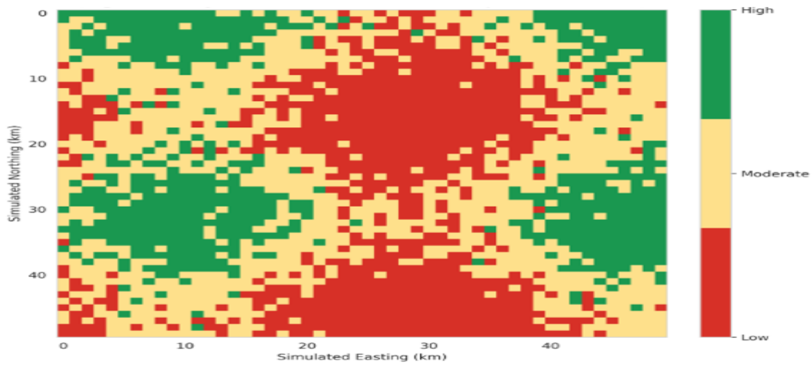

Figure 7: Predicted Grazing Suitability Map for Fufore LGA

The predicted grazing suitability map for Fufore LGA is presented in Figure 7. The figure shows that High-suitability zones predominated the central and southern pastoral passages, which reflected better infrastructure access, transitional land use, and steady vegetation cover. The Moderate-suitability zones serve as transitional shields. Similarly, the Low-suitability patches are confined to urban and degraded fringes.

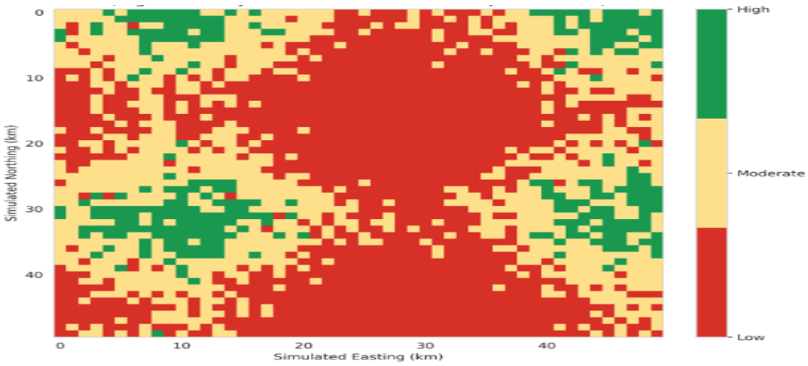

Figure 8: Predicted Grazing Suitability Map for Mubi South LGA

Figure 8 presents the map for Mubi South LGA, showing that grazing suitability is more heterogeneous due to higher seasonal drought pressure and traditional transhumance. The northern riparian and floodplain zones with reliable moisture are the High-suitability areas. Also, the Low-suitability patches are aligned with overgrazed border regions. The central rangelands are the Moderate-suitability zones, which offer flexible rotational grazing prospects.

These results achieved the prototype decision-support system development which integrates model predictions into GIS-derived maps. Therefore, livestock managers and policymakers can now visualize the suitability layers shrouded with conflict hotspots and transhumance routes to enable active optimization of grazing routes in the two local government areas.

Discussion

The findings from this study are comparable with those reported in other recent works applying similar methods. Werner et al. (2024) performed integration of deep learning algorithms to classify integrated crop–livestock systems based on fused Sentinel-2/PlanetScope time series data. We have achieved a comparable level of performance across the entire classification scheme, although we managed to achieve higher macro-averaged F1-scores, with our study reaching up to 0.903 (90.3%) precision. These observations confirm the potential of deep learning combined with satellite imagery time series analyses as tools for characterizing complex and dynamic agricultural environments. Noa-Yarasca et al. (2024) found that CNN and CNN-LSTM architectures ranked among the three most effective models for predicting vegetation biomass over large areas of Kenyan grasslands despite being slightly outperformed by the classical ARIMA-SARIMA procedure. Our study took advantage of these promising techniques to demonstrate the applicability of the method to real-world scenarios, showing how hybrid CNN-LSTM networks was trained to integrate both satellite-derived vegetation index and climate metrics into spatiotemporal classification frameworks capable of providing detailed maps of grazing suitability.

These results are consistent with previous research such as Bambara et al. (2024), where they explored the utilization of the NDVI to estimate pasture biomass in the Niassa pastoral zone of Burkina Faso. Our findings support the efficiency of using satellite imagery combined with deep learning models for better livestock grazing decision-making in the context of climate change adaptation. One significant contribution of our study was integrating our predictive model within a GIS-based decision-support system where the resulting output was translated to 10-metre grazing suitability maps (Figures 7 and 8), defining high/moderate/low suitability locations within Fufore and Mubi South localities. These findings distinguish our work from others, which typically concentrate on either model prediction or classification accuracy measures but fail to demonstrate how one might practically utilize their outcome.

The overall accuracy of our method was found to reach 90.1%, whereas an impressive macro F1 score of 0.903 indicates the reliability of our hybrid ConvLSTM classifier for grazing suitability classifications. However, recent works like Noa-Yarasca et al. (2024) advised that although hybrid Deep Learning models may exhibit considerable promise, they cannot be presumed to universally outperform other forms of machine learning techniques.

CONCLUSION

This study successfully developed, trained, and validated a hybrid deep learning with remote sensing framework, which transforms multi-source satellite and field datasets into practical climate-smart livestock grazing intelligence for Adamawa State, Nigeria. The hybrid ConvLSTM model achieved 90.1% accuracy in the classification of pasture suitability by delivering high-resolution GIS-ready maps that can enable real-time decision support for herders and policymakers. Integrating spatial and temporal learning, the system improves sustainable land-use scheduling, enhances flexibility to climate variability, and provides a walkable blueprint for similar semi-arid pastoral systems across sub-Saharan Africa. Future work will focus on integrating real-time IoT data, deployment of a mobile dashboard, and regional expansion to support food security and lessen conflict in Nigeria's Guinea Savanna.

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