A Deep Learning Model for Corn Yield Prediction Using Spatial and Temporal Features

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Abstract - Maize is a staple food crop in Zambia, making accurate yield prediction essential for food security and agricultural planning. This study presents an advanced deep learning approach for maize yield prediction that integrates Sentinel-2 satellite imagery with climate data. We develop a scalable and interpretable hybrid CNN-LSTM model to capture both spatial and temporal patterns of crop growth. The CNN component extracts spatial features from Sentinel-2 multispectral images (including vegetation indices such as NDVI and EVI), while the LSTM component learns temporal dynamics from time-series climate variables (rainfall, temperature, humidity). The model is trained and validated using historical yield records from major maize-growing regions in Zambia, demonstrating high predictive accuracy and outperforming traditional yield estimation methods. Accurate yield forecasts from this model enable early warnings of potential crop shortfalls, allowing farmers to take timely action to mitigate losses. Additionally, the predictions provide policymakers with insights for managing grain reserves, market supply, and food security strategies. By leveraging deep learning and remote sensing, this work offers a decision-support tool that contributes to sustainable agricultural practices and climate resilience in SSA, bridging the gap between academic and practical applications.

Keywords - *Maize yield prediction; CNN-LSTM; Sentinel-2; climate data; remote sensing; agricultural decision-making; Zambia.*

I. INTRODUCTION

Maize is a crucial staple food in Sub-Saharan Africa(SSA), providing over 50% of daily caloric intake and supporting food security, employment, and rural development[1][2]. The crop's significance is further emphasised by its contribution to the agricultural sector, which accounts for 20% of the country's GDP and employs over 71% of the population[3]. Maize production faces challenges like low productivity, climate change impacts, and market volatility, necessitating strategic interventions to improve its economic role[1][4]. Maize is a vital component of Zambia's agricultural economy, ensuring food security and reducing poverty[5]. Zambia's agriculture, predominantly rainfed, is facing significant challenges due to climate variability, which impacts food security and planning[3]. Predicting maize yield and food security is a complex challenge due to climate change, data limitations, and advanced modelling techniques[7][8]. Climate change affects temperature and precipitation patterns, leading to increased variability and frequency of extreme weather events, affecting yields by 5-14% in warm areas and 25-32% in precipitation reductions[8].

However, traditional maize yield prediction methods in Zambia rely on field-based assessments and farmer estimations, lacking precision and labour-intensiveness, while advanced techniques like crop simulation models are less common[9]. Zambia's Ministry of Agriculture conducts an annual Crop Forecast Survey(CFS) to estimate production before harvest, alerting policymakers to potential surpluses or deficits. The 2023/24 season projected maize production at 1.51 million tonnes, a 53.7% decline from the previous year[10]. The early warning of a poor harvest led to immediate policy responses. In 2024, the government declared a disaster due to a projected maize deficit, implementing relief measures such as importing over 600,000 tonnes of white maize, releasing stocks for community sales, and encouraging private grain imports to avert a deeper food crisis reported by [11]. Zambia faced a severe El Niño in 2023/2024, resulting in a 30-40% reduction in maize harvest due to drought, impacting more than 1 million hectares of cropland and creating a national disaster that affected food security and economic growth[11].

In recent years, advancements in remote sensing technologies, artificial intelligence, and deep learning have revolutionised the accurate and efficient monitoring and forecasting of crop yields[12]. The Sentinel-2 satellite from the European Space Agency(ESA) offers high-resolution multispectral imagery ideal for agricultural applications like vegetation health monitoring, land cover classification, and crop yield estimation[13]. Climate data, including rainfall, temperature, and humidity, has become more accessible and granular, providing data-driven insights into crop performance under various environmental conditions[14]. Global studies reveal that integrating deep learning models, Convolutional Neural Network (CNNs), and Long Short-Term Memory (LSTM) can significantly enhance crop yield predictions by capturing spatial and temporal patterns in large datasets[15].

Therefore, this study aims to develop a deep learning model using CNN and LSTM architectures, as shown in Figure 1, to predict corn yield in Zambia based on Sentinel-2 satellite imagery and climate data. Sentinel-2 imagery allows the extraction of essential crop health information, which can be combined with climate variables to enhance prediction models.[16]. The hybrid model, CNN+LSTM, has the potential to improve crop yield prediction in Zambia and the SSA region.

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The relevant studies pertaining to this area of study are discussed in Section II, which is expanded upon in this publication. In Section III, the design science research methodology (DSRM) that applies real-world experience to this research is described, along with the methodologies employed in the article. The evaluation techniques and metrics utilised to determine the yield tons per hectare are highlighted in Section IV. Finally, Section V discusses the paper's conclusion.

II. RELATED WORKS

The current crop yield prediction in Zambia and the SSA region has been utilising traditional mechanistic models and data-driven models, which struggle with scalability and adaptability, while CNN-LSTM hybrids leverage deep learning architectures for spatial-temporal data processing, outperforming models like Support Vector Regressors and Decision Trees in metrics [17]. The integration of attention layers and optimisation techniques further enhances accuracy and robustness in dynamic agricultural environments. Sentinel-2 imagery improves machine learning models' input quality, with CNNs outperforming traditional methods in spatial analysis. Additionally, climate variable integration enhances yield estimation [18].

Several studies highlight the effectiveness of these advanced approaches. For example, [17] developed a hybrid model using 1D CNN, LSTM, and an attention mechanism to predict rice and wheat yields in India, outperforming traditional models with an RMSE of 0.017 and an R^2 of 0.967. Similarly, [19] developed a deep CNN-LSTM model for predicting soybean yields at the county level in the US, integrating remote sensing data (MODIS Land Surface Temperature and Surface Reflectance) and weather variables, resulting in improved prediction accuracy compared to standalone CNN or LSTM models. In Northeast China, [20] evaluated a CNN-LSTM-Attention model for predicting maize, rice, and soybean yields from 2014 to 2020, showing improved accuracy over traditional models like random forest and XGBoost. Moreover, [21] developed a CNN-RNN framework to predict corn and soybean yields in the U.S. Corn Belt, achieving 9% and 8% RMSE, respectively. Lastly, [22] developed a hybrid deep learning framework using CNN, GAT, and LSTM modules to predict soybean yields across 1,115 counties in 13 U.S. states from 1980–2018, resulting in a 5% reduction in RMSE and a 6% improvement in R^2 compared to existing models.

Despite substantial advancements in crop yield prediction through machine learning and deep learning, several significant research gaps persist that this study aims to address. Firstly, many existing models are region-specific, having been developed and tested in areas such as Northeast China and India, and thus lack validation in diverse agro-ecological contexts [20]. This geographic bias limits the generalizability of current models to countries like Zambia, where climate conditions, soil types, and cropping systems differ considerably. Furthermore, the majority of models do not address climatic variability in Sub-Saharan Africa, despite its crucial influence on maize yield[23]. As such, there is a pressing need for yield prediction frameworks adapted to tropical environments and capable of handling spatial and temporal variability across seasons and regions.

Secondly, while numerous studies have successfully demonstrated the potential of hybrid deep learning architectures such as CNN-LSTM-Attention in integrating spatial and temporal data[24] integration of multi-source data-including remote sensing indices, climatic variables, and soil properties-remains underexplored in a unified framework. Most existing models utilise either remote sensing or climate data in isolation, resulting in limited predictive scope [25][26]. Moreover, the interpretability of these deep learning models remains a major concern, as they function largely as “black boxes” with limited insight into the agronomic factors influencing yield[27][28]. This lack of transparency hinders adoption among farmers and agricultural decision-makers who require actionable insights, not just predictions.

Lastly, there is limited progress in developing models that support real-time, in-season yield forecasting using dynamic data streams from satellites or weather stations. Many studies conduct retrospective analyses without extending their models to operational or real-time use[29][30]. Additionally, the computational complexity of deep learning models often renders them impractical for low-resource settings, which are common in developing countries[31]. Few studies have optimised their models for deployment in such environments or designed user-centric interfaces that enable farmers and policymakers to utilise the outputs effectively. These limitations collectively highlight the need for scalable, interpretable, and region-specific hybrid models, such as the CNN-LSTM framework proposed in this research, to enable accurate maize yield forecasting in Zambia using integrated satellite and climatic data.

The studies show that combining CNN and LSTM architectures with climate data for accurate crop yield prediction, along with attention mechanisms and spatial modelling techniques, enhances their ability to capture complex patterns.

A. Model Framework and Architecture

The model architecture uses CNN+LSTM networks to predict maize yields accurately. It uses Sentinel-2 imagery and climate data, extracting spatial features and modelling temporal evolution. The model is chosen for accurate crop yield prediction as shown in Figure 1 below:

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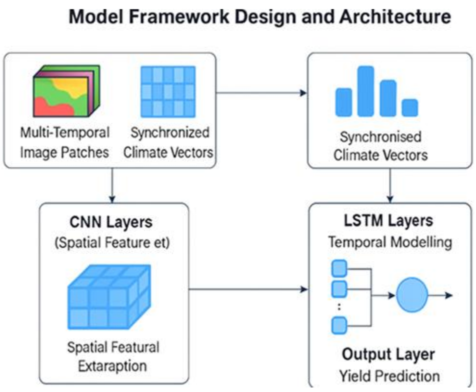

Figure 1: Model Architecture

The model inputs will be multi-temporal image patches (or features) and synchronised climate vectors. The input is a time sequence of multi-band Sentinel-2 data and associated weather values across the growing season.

CNN Layers (Spatial Feature Extraction)

A stack of 2D convolutional layers will process the multi-band imagery. Typical design: several conv layers (3×3 kernels, 32→64→128 filters) with ReLU activations, each followed by max-pooling to reduce spatial resolution[32]. Batch normalisation may be used to speed convergence. After the final conv layer, the output is a high-level spatial feature map (or vector). A dropout layer ($p \approx 0.2$) is inserted before passing features to the LSTM to mitigate overfitting.

LSTM Layers (Temporal Modelling)

The sequence of feature vectors (one per time step) is input to LSTM units. We may use one or more LSTM layers (64 or 128 hidden units, possibly bidirectional). These capture the temporal evolution of the extracted spatial features. In parallel, climate features for each time step can be concatenated with the CNN features before the LSTM or fed as a second input branch that merges later. This multi-source fusion has been effective in yield prediction[33][34], combining CNN-extracted features with climate variables in a Bi-LSTM to predict wheat yield, achieving $R^2 \approx 0.81$[33].

Output Layer

The final LSTM output (at season end) feeds a fully connected (dense) layer that produces the yield estimate. A linear activation can be used for regression; alternatively, a scaled tanh activation (with outputs re-scaled) may be used if yields are normalised, as some studies have done[32]. The network is trained to minimise the mean-squared error between predicted and observed yield.

Rationale

This CNN+LSTM architecture is chosen because "the CNN learns spatial features and the LSTM is used to learn the temporal features extracted by the CNN[35]. In other words, CNN layers will recognise spatial patterns (canopy structure, vigour) in each image, and LSTMs will model how these patterns change through time (reflecting phenology and weather effects). Such a hybrid model effectively integrates spatiotemporal data[35][32]. Prior studies confirm its suitability: for instance, a soybean yield model used CNN+LSTM to combine spectral and temporal data and achieved a greatly reduced RMSE[35]. Architecture details (number of layers, units) will be determined by experimentation and computational constraints.

B. *Proposed model*

The chapter presents a deep learning model for predicting maize yield using Sentinel-2 imagery and temporal climate variables. The model captures crop growth dynamics across Zambia, improving agricultural yield forecasting precision. It uses a CNN for spatial feature extraction and an LSTM network for temporal dependencies. Feature fusion is employed for joint learning as shown in Figure 2 below.

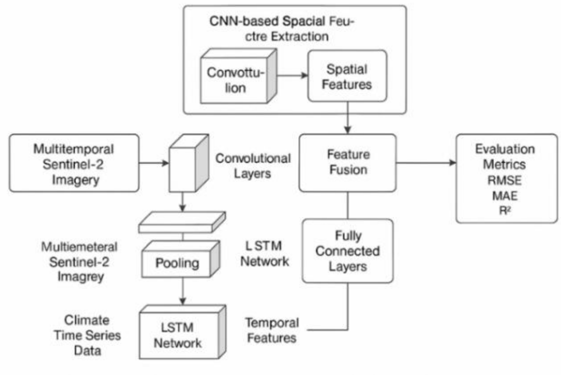

Figure 2: *Proposed model*

This study presents a deep learning model for maize yield prediction in Zambia, utilising multitemporal Sentinel-2 imagery and climate data. The model uses CNN to extract spatial features from satellite imagery, while LSTM learns long-term temporal relationships between climatic conditions and maize yield. The model uses feature fusion and fully connected layers to improve performance by integrating spatial-spectral information with climate trends. The output layer generates a continuous value representing predicted maize yield in tons per hectare, which can be aggregated and visualised at the district level for food security planning and early warning systems. The model's accuracy is assessed using metrics Root Mean Square Error(RMSE), Mean Absolute Error(MAE), and coefficient of determination(R^2).

III. RESEARCH DESIGN AND APPROACH

The research aims to create a predictive framework for maize yield in Zambia using the Design Science Research Methodology (DSRM). The model, a hybrid deep learning model, uses Sentinel-2 satellite imagery and climate data to enhance forecasting accuracy and reliability.

A. *Methodological framework*

The aim is to develop a CNN-LSTM architecture, combining Sentinel-2 satellite imagery and climatic variables, to predict maize yield at the district level in Zambia. The model extracts spatial features from Sentinel-2 imagery and captures temporal patterns in climate time series data. The model will be tested on real-world datasets and evaluated using metrics RMSE, MAE, and (R^2)[36][37]. The findings are then disseminated through academic publications and stakeholders in agriculture, emphasising the implications for precision farming and food security strategies.

B. Data Collection and Sources

The proposed methodological framework for predicting maize yield involves data integration, preprocessing, feature engineering, construction, training, optimisation, and evaluation. It begins with data alignment, preprocessing, feature engineering, and hybrid architecture design. The model is trained on historical data, optimised, and evaluated for accuracy using RMSE, R^2, and MAE metrics. The model architecture combines spatial and temporal information, with convolutional layers extracting spatial patterns and LSTM layers modelling temporal evolution. The final output layer produces a continuous yield estimate. The model is trained on historical data, with regular monitoring and evaluation using regression metrics. The study uses Sentinel-2 satellite imagery, climate data, and ground truth data to predict maize yield with key spectral bands at 10m resolution, employing climate data sourced from reliable providers CHIRPS and ERA5, as shown in Table 1 below.

Table 1: Spatial and Temporal Data Sources for Maize Yield Prediction

Data Type	Source	Resolution / Frequency	Key Variables / Bands	Usage
Spatial Data (Sentinel-2 Imagery)	Copernicus Open Access Hub, Google Earth Engine	10 m (B2, B3, B4, B8), 20 m (B5–B7, B11, B12) resampled to 10 m	Blue, Green, Red, NIR, Red-edge, SWIR; NDVI, red-edge indices	Covers maize season (Nov–Apr); used for spatial crop monitoring;
Temporal Data (Climate)	CHIRPS, ERA5	CHIRPS: ~5 km; ERA5: 0.25° (~28 km); daily or dekadal summaries	Precipitation, temperature (min/max), radiation, humidity	Aligned with imagery dates, downscaled to Sentinel-2 grid
Ground Truth Yield Data	Zambia Ministry of Agriculture, FAOSTAT and FRA	Region-level or aggregated national statistics	Observed maize yield (t/ha)	Used as a model target variable, spatially

The Sentinel-2 Imagery will use MultiSpectral Instrument data from the Copernicus Open Access Hub or Google Earth Engine to cover the maize growing season from November to April. The data will be preprocessed using a cloud and cirrus mask, atmospheric correction, spatial co-registration, and vegetation indices. Climate data will be acquired using CHIRPS and ERA5 reanalysis, with climate time series for the same dates as the imagery. This data will be used to improve maize yield forecasts, highlighting the importance of weather data in remote sensing.

IV. MODELLING FRAMEWORK

The proposed framework aims to accurately predict maize yield by combining multi-temporal Sentinel-2 imagery of each maize field with climate time-series (rainfall, temperature, and humidity) as inputs. This approach is motivated by prior findings that deep models extract rich representations from high-dimensional data and often surpass conventional machine learning methods in yield forecasting accuracy. The model comprises an encoder-decoder architecture, where each Sentinel-2 image is input into the CNN block, which applies convolution and pooling operations to extract high-level spatial features. The sequence of CNN feature vectors is fed into an LSTM layer to capture temporal dependencies, and climate inputs (rainfall, temperature, humidity) are integrated by concatenation with the CNN features before the LSTM or via a parallel branch merged in a fusion layer. The LSTM's output is then passed through one or more dense layers to produce the final yield estimate. The theoretical underpinnings of this approach are that CNNs are well-suited to processing spatial image data, while LSTMs are designed for sequential data. Hybrid CNN-LSTM models leverage both strengths, improving predictive power in crop yield modelling.

A. Components of the Framework

The CNN-LSTM model is a hybrid approach that uses convolutional layers, batch normalisation, ReLU activation, and Max Pooling layers to predict maize yield. It processes temporal sequences, leveraging memory capabilities and incorporates climate data fusion. The output layer produces yield predictions, with a loss function for accurate numerical estimation. The model is trained to minimise a regression loss, typically MSE, between predicted and observed yields. The model is optimised using stochastic gradient descent with an adaptive optimiser (Adam). The research introduces innovative crop yield prediction techniques, combining Sentinel-2 imagery with local climate time series for small-scale maize prediction in Zambia. The hybrid CNN-LSTM architecture is tailored for field-level resolution and climate seasonality, addressing gaps in existing remote sensing for smallholder farmers in SSA. The approach leverages the synergy of satellite and climatic inputs to improve yield accuracy, making it an innovation in this context. As shown in Figure 3, the components of the framework are used.

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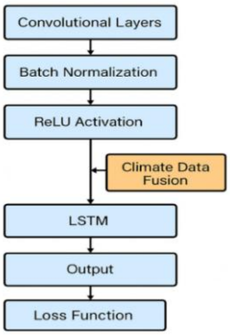

Figure 3: *Components of the framework*

B. Assumptions and constraints

The proposed methodology assumes cloud-free Sentinel-2 data during the maize growing season, accurate field delineation, data quality from historical yield records and climate data, crop consistency, significant computational resources for training, and transferability. It also assumes sufficient clear-sky images, accurate delineation of individual fields, accurate historical yield labels and climate records, uniform agronomic practices within the study region, and access to suitable GPUs or compute clusters. The model is assumed to generalise to future seasons, despite potential limitations due to climate or farming practices changes.

C. Evaluation methods and metrics

The proposed model will be evaluated using regression metrics and visual diagnostics, including R^2, RMSE and MAE. Cross-validation, statistical significance assessment, and visual evaluations will be employed to ensure robustness and validity. Benchmarking against simpler models will demonstrate the added value of the CNN-LSTM approach, as shown in Figure 3 below:

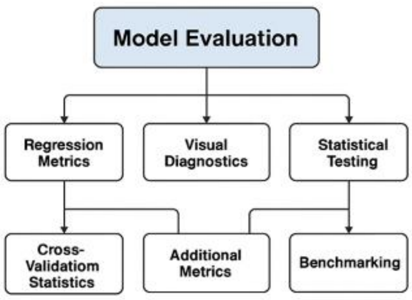

Figure 4: Model Evaluation

Primary Metrics: Model accuracy will be assessed using regression metrics. The Coefficient of Determination (R^2) indicates the proportion of variance explained, and the Root Mean Squared Error (RMSE) measures average prediction error magnitude[32]. We will also compute Mean Absolute Error (MAE) to complement RMSE[38]. Lower RMSE/MAE and higher R^2 indicate a better fit.

The metrics formulas to be used are:

Coefficient of Determination (R^2)

Where:

$$R^2 = 1 - \frac{ss_{res}}{ss_{tot}} \quad (1)$$

- SS_res = Residual Sum of Squares = $\Sigma(y_i - \hat{y}_i)^2$
- SS_tot = Total Sum of Squares = $\Sigma(y_i - \bar{y})^2$
- y_i = Actual observed value
- $\hat{y}_i$ = Predicted value by the model
- $\bar{y}$ = Mean of actual observed values
- n = Number of observations

Table 2: Interpretation of R^2

R^2 Value	Interpretation
1.0	Perfect prediction — all data points fall exactly on the regression line
0.9 – 1.0	Excellent fit — model explains most of the variance
0.5 – 0.9	Moderate fit — model explains some variance, but there's room for improvement
0.0 – 0.5	Poor fit — model explains little of the variance
< 0.0	Worse than a horizontal mean-line predictor — model introduces error

RMSE Formula

This is a commonly used metric in crop yield prediction for measuring the accuracy of a predictive model. It computes the square root of the average of the squared differences between observed and predicted values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

Where:

n = Number of observations (fields, districts, or periods)

y_i = Actual observed maize yield (in tons per hectare)

$\hat{y}_i$ = Predicted maize yield from the model

$(y_i - \hat{y}_i)^2$ = Squared difference between observed and predicted yields

Relevance in Maize Yield Prediction

Captures prediction accuracy and penalises large errors more heavily.

Results are interpretable in the same units as the output variable (tons/ha).

Facilitates comparison of various machine learning models, including CNN-LSTM, Random Forest, etc.

MAE Formula

The Mean Absolute Error (MAE) is a fundamental evaluation metric used in machine learning and crop yield prediction. It measures the average magnitude of the errors in a set of predictions, without considering their direction.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (3)$$

Where:

[1]. n = Total number of observations (fields, districts, or time periods)

[2]. y_i = Actual observed maize yield (in tons per hectare)

[3]. $\hat{y}_i$ = Predicted maize yield from the model

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[4]. $|y_i - \hat{y}_i|$ = Absolute error between observed and predicted yields

Relevance in Corn Yield Prediction

- Easy to interpret since it uses the same unit as the predicted variable (tons/ha).
- Less sensitive to large errors or outliers compared to RMSE.
- Complements RMSE by providing an additional perspective on model performance.

Cross-Validation Statistics - When using k-fold CV, report the mean and standard deviation of metrics across folds. For example, [39] computed R^2 and RMSE along with their standard deviations from repeated 10-fold cross-validation[40]. This quantifies confidence in the results.

Statistical Testing: If comparing two models, paired tests (paired t-test) on error metrics will check if differences are statistically significant.

Visual Diagnostics - Scatter plots of predicted vs. observed yield (with 1:1 line) will be used to visually assess performance. Residual plots (error vs. predicted) and maps of spatial error distribution will help identify systematic biases. Feature importance (via ablation or SHAP analysis) can reveal which inputs most influence predictions.

Benchmarking - Performance will be compared against simpler approaches. For instance, a multiple linear regression on NDVI and climate features or a Random Forest model will be trained as a benchmark. Demonstrating that CNN-LSTM outperforms these will justify its complexity.

V. CONCLUSION

This research proposes a novel deep learning framework that integrates Sentinel-2 satellite imagery and climate data using a hybrid CNN-LSTM model to predict maize yield in Zambia. The approach addresses limitations of traditional yield estimation methods by capturing both spatial and temporal patterns critical to crop development. The model leverages multispectral imagery and climatic variables to enable accurate, timely, and location-specific predictions that can inform early warning systems, agricultural planning, and food security interventions. By incorporating modern AI techniques into agricultural decision-making, the study contributes to precision agriculture, enhances climate resilience, and supports national efforts in achieving sustainable food systems.

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