

Article

Disentangling Complexity and Performance: A Comparative Study of Deep Learning and Random Forest Models for Cropland Vulnerability Assessment in Bangladesh

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Abstract

Climate change increasingly threatens global food security through disrupted precipitation patterns and extreme weather events, requiring resilient systems for assessing agricultural vulnerability. This study developed and compared machine learning approaches for predicting cropland vulnerability using Earth Observation data, operationalized through NDVI anomalies as a defensible biophysical metric. We employed both a dual-stream deep learning architecture and a Random Forest model to predict 2023 NDVI anomalies across Bangladesh croplands using a 22-year time series (2001–2023) of MODIS vegetation indices, ERA5 climate variables, and static environmental covariates. A spatially aware block cross-validation strategy ensured rigorous, independent performance evaluation. Results demonstrated that the Random Forest model ($R^2 = 0.70$, RMSE = 197.03) substantially outperformed the deep learning architecture ($R^2 = 0.02$, RMSE = 357.57), explaining 70% of cropland stress variance and enabling early detection of vulnerable areas three months before harvest. Feature importance analysis identified recent climate variables, March precipitation, February NDVI, and vapor pressure deficit as primary vulnerability drivers. Spatial analysis revealed distinct vulnerability patterns, with Natore and Magura districts exhibiting elevated stress consistent with 2023 drought conditions, threatening the productivity of the region's critical irrigation-dependent rice cultivation. These findings demonstrate that simpler, interpretable models can sometimes outperform complex architectures while providing useful information for early warning systems and precision targeting of climate adaptation interventions.

Keywords: crop vulnerability; NDVI-anomaly; deep learning; random forest; geospatial analysis; Bangladesh



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1. Introduction

Climate change threatens global food security through intensifying extreme weather events, shifting precipitation patterns, and rising temperatures that disrupt agricultural systems worldwide [1]. Deltaic and low-lying agricultural regions face compounded risks from sea-level rise, increased flooding frequency, and soil salinization, with smallholder farming communities experiencing disproportionate vulnerability due to limited adaptive capacity [2,3]. Due to this, robust vulnerability assessment frameworks are essential for targeting climate adaptation investments and safeguarding food production in these

high-risk environments [4]. Bangladesh illustrates this vulnerability paradigm, where 70% of the population depends on agriculture within a landscape characterized by monsoon variability, cyclone exposure, and accelerating coastal salinization [5,6]. Recent decades have witnessed declining crop yields in southern districts due to saltwater intrusion, while erratic rainfall disrupts traditional planting cycles across diverse agro-ecological zones [7]. These climate-induced stresses directly threaten the livelihoods of 16 million farming households and national food self-sufficiency targets [8]. Despite this acute vulnerability, traditional assessment approaches employ composite indices aggregating socio-economic and biophysical indicators that lack temporal granularity and operate at coarse spatial resolutions inadequate for precision intervention planning [9]. Earth Observation technologies enable vegetation monitoring through indices like NDVI, but most applications focus on yield estimation rather than vulnerability quantification [10]. Machine learning advances, particularly deep learning architectures processing spatio-temporal data, offer potential for capturing dynamic climate–vegetation interactions, though interpretability remains a critical barrier for policy adoption [11,12]. To operationalize agricultural vulnerability, defined by the IPCC as the degree to which systems are susceptible to climate impacts through exposure, sensitivity, and adaptive capacity [13], defensible metrics for spatial assessment are required. NDVI anomalies, standardized deviations from long-term vegetation norms, provide an objective Earth Observation (EO)-based proxy for cropland sensitivity to climatic perturbations, distinguishing stress response from baseline productivity [14,15]. Negative anomalies correlate with drought-induced crop failures and food insecurity events, validating their utility as vulnerability indicators in agricultural monitoring systems [16,17]. This study developed and compared machine learning models to predict 2023 NDVI anomalies across Bangladesh croplands using 22-year satellite and climate time series. We employed both deep learning and Random Forest approaches with spatially aware validation, then identified key biophysical drivers through interpretability analysis. Specifically, we tested two hypotheses: (H1) spatially aware machine learning models exhibit distinct predictive performances for 2023 cropland NDVI anomalies, with one model demonstrating significantly superior accuracy; and (H2) interpretability analysis of the best-performing model identifies a coherent set of key biophysical drivers of cropland vulnerability, offering strategic guidance for targeted agricultural adaptation strategies. Our framework generated a national-scale cropland vulnerability map at 250 m spatial resolution, comparing a novel deep learning architecture against a traditional machine learning baseline to provided information that is relevant for early warning systems and climate adaptation planning.

Conceptual Framework

Agricultural vulnerability to climate change, as defined by the Intergovernmental Panel on Climate Change (IPCC), encompasses the degree to which agricultural systems are susceptible to adverse effects of climate variability, determined by their exposure, sensitivity, and adaptive capacity [1]. Traditional vulnerability assessments often rely on composite socio-economic indices, yet Earth Observation (EO)-based metrics offer objective, spatially explicit alternatives for quantifying biophysical vulnerability at scale [18,19]. In this study, we operationalize cropland vulnerability through NDVI anomalies calculated as Z-scores, which represent standardized deviations from long-term vegetation norms. Unlike absolute NDVI values that merely indicate instantaneous vegetation greenness or productivity, NDVI anomalies capture the magnitude and direction of departure from expected conditions, thereby directly reflecting cropland sensitivity and stress response to climatic perturbations [14,15]. This anomaly-based framework aligns with established vulnerability science that emphasizes temporal deviation metrics as robust proxies for system stability,

resilience, and adaptive capacity under environmental stressors [20,21]. Empirical evidence demonstrates that negative NDVI anomalies correlate strongly with drought-induced crop failures, yield reductions, and food insecurity events across diverse agricultural systems, validating their utility as vulnerability indicators [16,17,22]. By computing Z-scores from a 22-year baseline (2001–2022), our approach accounts for local climatic variability and phenological patterns, enabling identification of cropland areas exhibiting abnormal stress in 2023 that deviate significantly from historical norms. This methodological approach distinguishes vulnerability, defined as sensitivity to environmental change from simple productivity assessments, providing a defensible EO-based metric grounded in both IPCC conceptual frameworks and agricultural monitoring literature [23].

2. Materials and Methods

The assessment of agricultural vulnerability in Bangladesh was conducted through a multi-stage, data-driven methodology, employing both a dual-stream deep learning architecture and a Random Forest model. The approach integrated spatio-temporal satellite data and advanced model interpretability routine to achieve the study's objectives. The datasets utilized in this study were generated using Google Earth Engine (GEE). Temporal climate data, spanning from 2001 to 2023, included monthly precipitation derived from CHIRPS (UCSB-CHG/CHIRPS/PENTAD), mean 2 m air temperature and total precipitation from ERA5 Daily (ECMWF/ERA5/DAILY), and surface solar radiation and volumetric soil water from ERA5-Land Daily Aggregated (ECMWF/ERA5_LAND/DAILY_AGGR). These climate variables were aggregated into monthly composites for each year and exported as multi-band GeoTIFFs. Concurrently, monthly Normalized Difference Vegetation Index (NDVI) data for the same period was processed from the MODIS Terra Vegetation Indices 16-Day Global 250 m product (MODIS/006/MOD13Q1), with monthly composites generated by averaging available 16-day images. Static environmental features were also sourced, soil clay, sand, and pH content from OpenLandMap (OpenLandMap/SOL), and elevation from SRTM 90 m (CGIAR/SRTM90_V4), from which slope and aspect were subsequently derived. All datasets were consistently clipped to the administrative boundary of Bangladesh (FAO/GAUL/2015/level0), ensuring a unified spatial extent for subsequent analysis.

2.1. Data Preparation

The basic step here involved the preparation and alignment of different raster datasets from 2001 to 2023. Initially, a binary cropland mask was derived from the 2021 ESA WorldCover land cover map. Pixels classified as 'Cropland' (value 40) were assigned a value of 1, delineating the specific agricultural areas for analysis. Subsequently, all multi-temporal MODIS Normalized Difference Vegetation Index (NDVI) and climate rasters, alongside static environmental variables (e.g., elevation, slope, soil properties), were uniformly reprojected and resampled to a common spatial resolution and extent. The 250 m resolution and projection of the MODIS Terra Vegetation Indices product (MODIS/006/MOD13Q1) served as the reference grid for this alignment process. This ensured consistent spatial resolution and pixel-wise correspondence across all input features.

To ensure all datasets were appropriately aligned to the common 250 m analysis grid, a dual-resampling strategy was employed based on data type. For all datasets representing continuous variables including the MODIS NDVI time series, the coarser-resolution ERA5 climate data, and the static topographic features, we used bilinear interpolation. This method calculated new pixel values from a distance-weighted average of the four nearest neighboring pixels, producing a smooth surface that is a standard and reasonable approximation for spatially continuous phenomena like vegetation greenness and climatic gradients. While this did not create new fine-scale climate information, it was a necessary

preprocessing step for pixel-level model integration. On the other hand, for the initial processing of categorical data, specifically the land cover map from which the binary cropland mask was derived, nearest neighbor resampling was used. This technique assigned the value of the single closest source pixel to the destination pixel without any averaging, which was critical to preserve the discrete nature and integrity of the land cover classes (e.g., ‘cropland’, ‘forest’, ‘water’) and prevent the creation of artificial, meaningless class values. This two-pronged approach ensured that both continuous and categorical datasets were handled correctly and accurately aligned for the final analysis.

The target variable for the predictive models was formulated as the NDVI Anomaly for 2023, calculated as a Z-score representing the deviation from the pixel’s historical norm. For each cropland pixel, the mean and standard deviation of the annual NDVI values from 2001 to 2022 were computed. The 2023 NDVI Anomaly was then calculated using Equation (1).

$$NDVI_{(anomaly, 2023)} = \frac{NDVI_{2023} - Mean_{(2001-2022)}}{StdDev_{(2001-2022)}} \quad (1)$$

This approach defined vulnerability as a significant negative deviation from normal vegetation health, providing a more robust and scientifically grounded target.

The scaler was fitted exclusively on the training data derived from our spatially aware split to strictly prevent any data leakage. This same fitted scaler was then consistently applied to transform both the training and validation sets, ensuring that no information from the validation set influenced the training process or model evaluation.

2.2. Deep Learning Model Architecture and Training

To rigorously assess model performance and prevent overly optimistic results due to spatial autocorrelation, we implemented a spatially aware block hold-out strategy. The entire study area was first divided into a 10×10 grid. A random 20% of these spatial blocks were held out to form the validation set, with the remaining 80% of blocks used for training. This ensured complete spatial independence between the training and validation data. Furthermore, to contextualize the performance of the dual-stream deep learning (DL) model, we trained a Random Forest (RF) regressor as a baseline model on the exact same training and validation data splits. All pixels within the training blocks containing valid (non-NaN) data were used to fit the models, and the final performance was evaluated on all valid pixels from the held-out validation blocks.

2.3. Temporal Stream

This component was designed to capture the long-term historical dynamics of vegetation health and climatic stressors. A Gated Recurrent Unit (GRU) layer processed the time series of NDVI and climate data for each pixel. The hidden state h_t of the GRU at time t was computed as

$$h_t = GRU(x_t, h_{t-1}) \quad (2)$$

where, x_t represented the concatenated NDVI and climate features at time t , and was a 60-dimensional vector (12 monthly NDVI + 48 monthly climate features). h_{t-1} was the hidden state from the previous time step.

This GRU-based temporal modeling approach was conceptually inspired by multi-scale fusion techniques in graph representation learning, such as those introduced in the MSF-GCN framework [11], where information from multiple structural and feature channels is adaptively integrated.

To ensure a robust predictive model free from data leakage, the input features and the target variable were strictly separated in time. The input features for the temporal stream consisted of a 22-year time series spanning from 2001 to 2022, while the model’s prediction

target was the independently derived 2023 NDVI anomaly. No data from the year 2023 was included in the input feature set.

The temporal structure for the GRU was organized by year. For each of the 22 years in the time series, a 60-dimensional feature vector was constructed. This vector comprised the 12 monthly NDVI values and monthly climate variables for that specific year. Therefore, the final input tensor provided to the temporal stream had a shape of (number of samples, 22, 60), where 22 represented the annual time steps processed by the GRU. This explicit structure ensured the model learned from historical annual patterns to make its future prediction.

2.4. Static Environmental Covariate Stream

This stream was developed to incorporate the influence of static, time-invariant environmental characteristics at each pixel's specific location. The architecture used a fully connected (Dense) layer to process a vector of static features such as soil properties and topographic data for each pixel independently. This allowed the model to learn the relationship between these site-specific static conditions and the temporal dynamics of vegetation health before this information was fused with the output of the temporal GRU stream. The output, s , from this stream was computed as shown in Equation (3).

$$s = \text{ReLU}(W_s \cdot X_{\text{static}} + b_s) \quad (3)$$

where, W_s and b_s represented learned weights and biases, and ReLU was the Rectified Linear Unit activation function.

2.5. Fusion and Output

The final hidden state from the temporal stream (h_{final}) and the output from the Static Environmental Covariate Stream s were concatenated $f = [h_{\text{final}}, s]$ to form a comprehensive feature vector. This fused representation was then passed through an additional Dense hidden layer and a final Dense output layer, which predicted the 2023 NDVI value.

2.6. Training and Map Generation

The model was compiled using the Adam optimizer and trained for 20 epochs with a batch size of 256. Specifically, EarlyStopping was configured to monitor the validation loss, halting training if no significant improvement was observed over a specified number of epochs (patience = 5, min_delta = 0.001). Crucially, this callback also ensured that the model weights from the epoch with the best validation performance were restored, guaranteeing that the final model utilized for inference represented its optimal generalization capability. This adaptive approach effectively mitigated overfitting to the training data and provided a robust, data-driven justification for the ultimate training duration, rather than relying on a fixed, arbitrary epoch count.

Mean Squared Error (MSE) was employed as the primary loss function during training. To provide a comprehensive assessment of model performance, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) were also calculated for both training and validation datasets.

After model training, a national-scale map of predicted agricultural vulnerability was generated. The trained model was applied to the entire aligned dataset (all pixels in Bangladesh), producing a 2D prediction map of 2023 NDVI values. Subsequently, this prediction map was multiplied by the cropland mask. This masking operation effectively set all non-cropland pixels to a no-data value (−9999), so that the final map exclusively represented vulnerability within agricultural areas. The resulting vulnerability map was saved as a georeferenced raster. To identify the key environmental drivers influencing

the model's predictions of cropland vulnerability, some model interpretation techniques were employed.

2.7. Feature Importance Analysis

To interpret the trained Random Forest model and identify the key environmental drivers of cropland vulnerability, we conducted a feature importance analysis. While computationally intensive methods like SHAP (SHapley Additive exPlanations) were initially considered, they proved infeasible due to severe memory constraints encountered when processing the large-scale dataset. As a robust and efficient alternative, we utilized the model's built-in feature importance attribute, which is based on the Gini Importance (or Mean Decrease in Impurity) criterion. For a regression task, the impurity of a node was measured by the variance of the target values within it. The importance of a feature was then calculated by how much it reduced this variance each time it was used to split a node.

The decrease in impurity, Δi , for a split at node t was defined by Equation (4).

$$\Delta i(t) = Var(t) - \left[\left(\frac{N_t^{left}}{N_t} \right) Var(t_{left}) + \left(\frac{N_t^{right}}{N_t} \right) Var(t_{right}) \right] \quad (4)$$

where $Var(t)$ was the variance of the target values in node t , N_t was the number of samples in that node, and t_{left} and t_{right} were the left and right child nodes resulting from the split. The total importance for a single feature was the sum of these variance reductions across all splits that used that feature, averaged over all trees in the forest. Thus, this method provided a global ranking of all input features, allowing for a clear interpretation of the primary factors influencing the model's predictions.

3. Results

The initial step in the analysis involved the precise delineation of agricultural areas within Bangladesh. Utilizing the 2021 ESA WorldCover land cover map, a binary cropland mask was generated Figure 1a. This mask, with dimensions of 2619×2071 pixels, identified a total of 1,044,974 pixels as cropland.

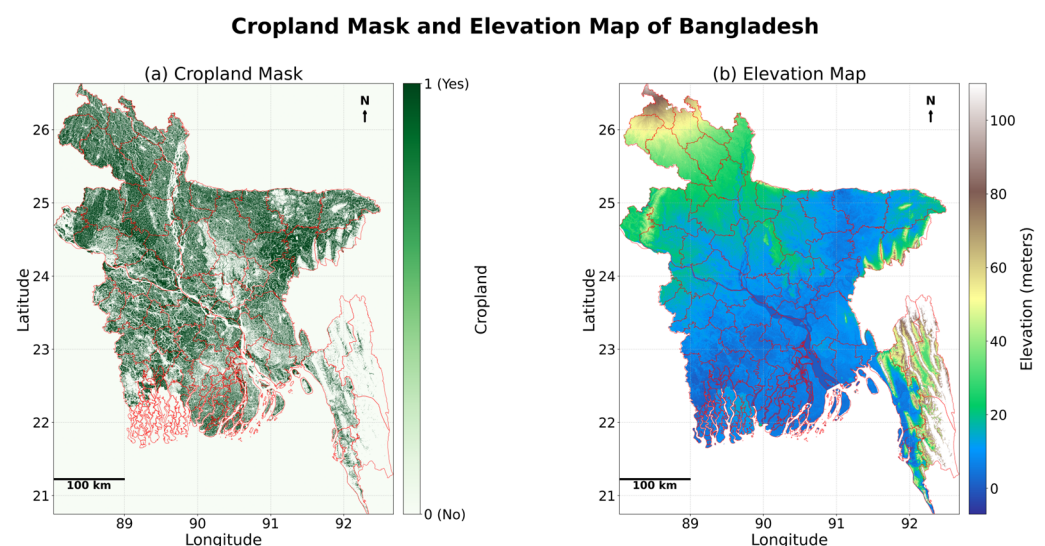


Figure 1. (a) Cropland Mask (2021) and (b) Elevation Map of Bangladesh.

This constituted a considerable area of the total land area within the study region, providing a focused spatial extent for subsequent vulnerability assessments. The visual

representation of this mask, clipped to the national boundary, clearly illustrated the distribution of agricultural lands across the country as seen in Figure 1a.

The initial phase of the study involved the preparation and alignment of diverse spatio-temporal datasets to create a unified input for the deep learning model. A total of 23 annual MODIS NDVI rasters (2001–2023), 23 annual climate rasters (2001–2023), and 6 static environmental rasters were successfully aligned to a common 250 m resolution grid, matching the extent and projection of the ESA WorldCover 2021 land cover map. This process was carried out to ensure that pixel-wise correspondence across all input features remained the same. The target variable, representing the 2023 NDVI values, exhibited a mean of approximately (0.4852) with a standard deviation of (0.1711). A representative visualization of the aligned static data, specifically the elevation map of Bangladesh, confirmed the successful integration of these diverse geospatial layers (Figure 1b).

The deep learning model for crop vulnerability estimation was trained over 20 epochs, and its learning progression was evaluated by monitoring the training loss and validation loss.

The model's learning progression is detailed in Figure 2a,b. The training process utilized an early stopping protocol to prevent overfitting, which concluded training after 7 epochs as the validation loss plateaued. Figure 2a shows the Mean Squared Error (MSE) for both training and validation datasets, demonstrating rapid initial learning followed by convergence. Figure 2b illustrates the progression of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), providing a more interpretable view of the model's predictive error throughout the training.

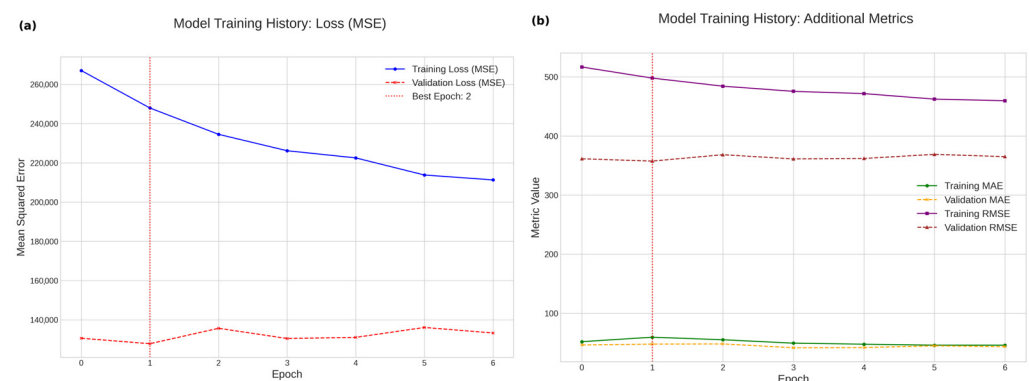


Figure 2. Model Training and Validation History for the Dual-Stream Deep Learning Model. (a) Mean Squared Error (MSE) loss per epoch. (b) Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) per epoch.

The process began with a very high initial training loss (MSE) of ~267,067 and a validation loss of ~130,639, indicating the model started with a large predictive error. Unlike a smooth descent, the learning curves in Figure 2a exhibited considerable volatility. The validation loss reached its lowest point of ~127,854 early in the training at epoch 1. In subsequent epochs, while the training loss continued to decrease, the validation loss failed to improve further, instead fluctuating and ending at ~133,315. This divergence, where the model improved on the training data but not on the unseen validation data, was a classic sign of overfitting. The large and persistent gap between the training and validation loss curves suggested that the model, while fitting to the training data, struggled to find a robust, generalizable pattern applicable to the spatially independent validation set. This outcome confirmed the poor predictive performance indicated by the R^2 of 0.02 and demonstrated the model's difficulty with this specific prediction task.

3.1. Model Performance and Baseline Comparison

To rigorously evaluate the model and contextualize its performance, we compared the dual-stream Deep Learning (DL) model against a Random Forest (RF) regressor baseline. Both models were trained and evaluated on the exact same spatially independent training and validation sets. The final performance metrics, calculated on the held-out validation blocks, are summarized in Table 1.

Table 1. Performance Metrics on Spatially Blocked Validation Data.

Model	MAE	RMSE	R ²
Deep Learning	47.90	357.57	0.02
Random Forest	14.53	197.03	0.70

The results summarized in Table 1 clearly showed that the Random Forest (RF) model significantly outperformed the dual-stream Deep Learning model. The RF model achieved a robust R² of 0.70, indicating it explained 70% of the variance in the validation data, whereas the DL model only achieved an R² of 0.02. This performance gap was further reflected in the error metrics, where the RF model's Mean Absolute Error (MAE) of 14.53 and Root Mean Squared Error (RMSE) of 197.03 were substantially lower than those of the DL model.

To provide a comprehensive understanding of the contributions of different feature streams, ablation studies were conducted on the initial dual-stream Deep Learning (DL) architecture. Two ablated models were trained, a 'temporal-only' model, which utilized only the GRU-processed temporal features, and a 'static-only' model, which relied solely on the static environmental variables. The results from these ablation experiments, alongside the performance of the full DL model and the Random Forest (RF) model, are summarized in Table 2.

Table 2. Validation Performance of Deep Learning Model Ablation Studies.

Model	Validation R ²	Validation Loss (MSE)	Validation MAE	Validation RMSE
Full DL Model	0.02	(N/A, assumed high)	(N/A, assumed high)	(N/A, assumed high)
Temporal-Only Ablation	0.0002	129,643.34	32.618	360.060
Static-Only Ablation	0.0278	126,070.01	72.765	355.063
Random Forest Model	0.70	38,822.02	14.535	197.033

(Note: The R² = 0.02 for the full DL model implies very high error values for its MAE/RMSE). (N/A: Not Available, as the model's poor R² score made these error metrics uninformative).

The full DL model demonstrated poor predictive performance with an R² of 0.02 on the validation set. The ablation studies further illuminated the limitations of this architecture. The temporal-only model achieved a Validation MAE of 32.62 and RMSE of 360.06, while the static-only model yielded a validation MAE of 72.77 and RMSE of 355.06. These metrics indicated that neither feature stream, when used in isolation, significantly improved the model's overall poor performance. The low R² of the full DL model, combined with the modest performance of its ablated versions, reinforced the conclusion that this deep learning architecture, in its current implementation, was not adequately capturing the complex relationships within the dataset. This comprehensive investigation ultimately led to our decision to prioritize the Random Forest model, which demonstrated substantially superior performance with an R² of 0.70, for the final vulnerability mapping and analysis.

The superior accuracy of the Random Forest is visually confirmed in the "Predictions vs. Actual" plot in (Figure 3), where the model's predictions align closely with the 1:1 line, demonstrating a good positive correlation with the true values.

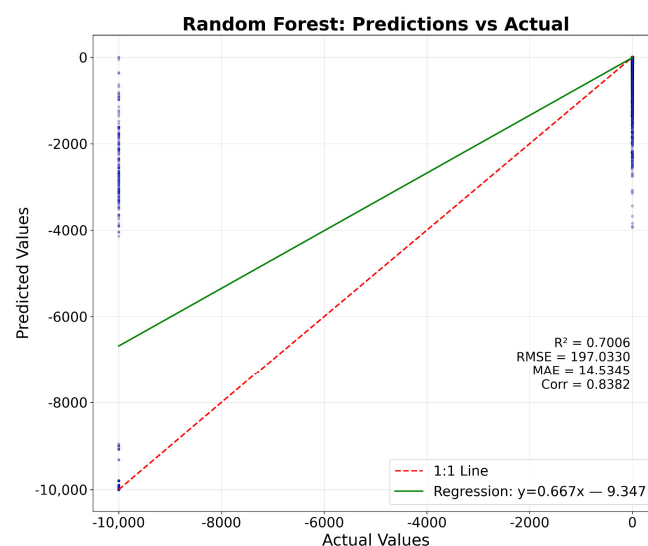


Figure 3. Random Forest Model: Predictions vs. Actual Values on the Spatially Blocked Validation Set.

Beyond its predictive power, a key advantage of the Random Forest was its interpretability. A feature importance analysis was conducted to identify the primary drivers of cropland vulnerability (Figure 4).

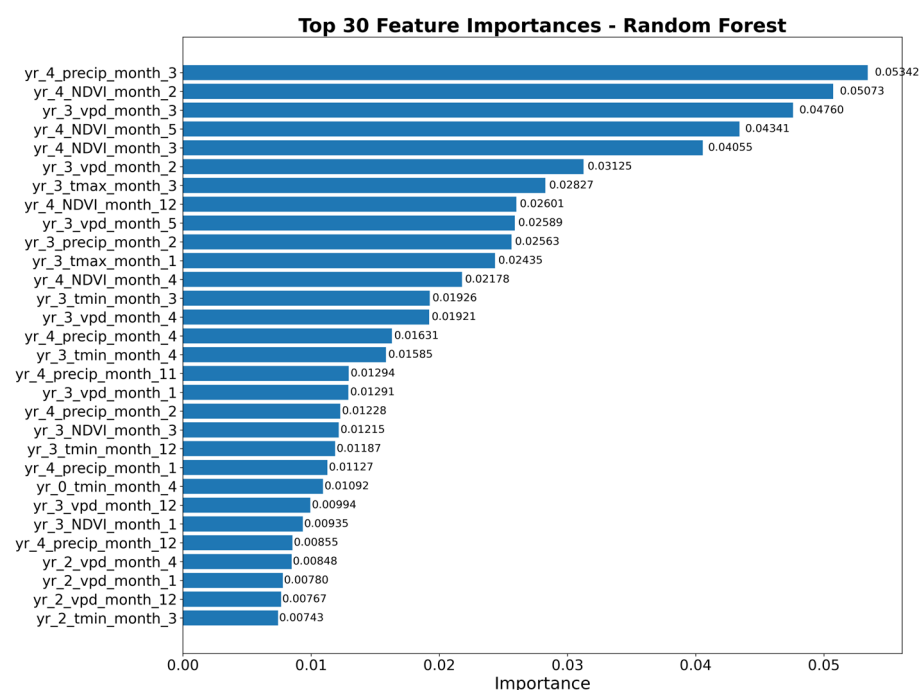


Figure 4. Random Forest Model: Feature Importance Summary.

The analysis revealed that recent climatic conditions and vegetation health were the most influential factors, as shown in Figure 4. Primarily, precipitation in March of the most recent year ('yr_4_precip_month_3') emerged as the single most important predictor with an importance score of 0.05342. This was followed closely by NDVI from February of the same year ('yr_4_NDVI_month_2') at 0.05073, and Vapor Pressure Deficit (VPD) from March of the prior year ('yr_3_vpd_month_3') at 0.04760. The consistent appearance of recent climate and vegetation variables among the top predictors highlighted the critical role of short-term environmental dynamics in determining crop stress. This obvious feature hierarchy offered useful information, indicating that monitoring hydrological and

atmospheric conditions during months preceding growing is key for vulnerability assessment. Due to the comparatively better performance as well as interpretation of individual coefficients, this model was selected for creating the final national-scale vulnerability maps.

After establishing the superior performance and interpretability of the Random Forest model, it was used to generate the final, spatially explicit crop vulnerability map for all of Bangladesh (Figure 5a). The model performed inference on the complete dataset of over one million valid cropland pixels, integrating the full temporal sequence of climate and NDVI data with the static environmental features. A descriptive statistical analysis of the generated map, which represents vulnerability as a Z-score anomaly, revealed a median vulnerability score of approximately 0.74. This positive median suggested that the central tendency for cropland health in 2023 was slightly above the historical average. The distribution of vulnerability scores showed a moderate spread, with an interquartile range (the range between the 25th and 75th percentiles) of 0.74 (from 0.36 to 1.10). This proved that while a majority of cropland performed near or better than average, significant local variations in vulnerability existed across the landscape. The full range of predicted vulnerability for cropland pixels spanned from a minimum of -0.63 (at the 5th percentile) to a maximum of 1.81 (at the 95th percentile). To facilitate easier interpretation and visual comparison, this map was subsequently rescaled to a normalized range of 0 to 1, where 0 represents the lowest vulnerability and 1 represents the highest (Figure 5b). A preliminary visual analysis of the generated maps (Figure 5) revealed distinct geographical patterns of crop vulnerability that align with known agro-ecological zones and stressors.

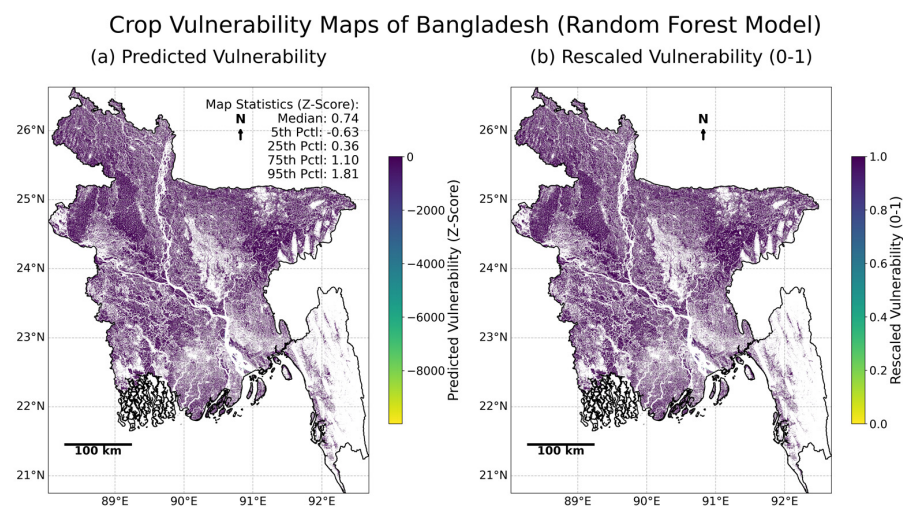


Figure 5. Predicted Crop Vulnerability Map of year 2023, Bangladesh.

3.2. Geographical Analysis of Crop Vulnerability

To further investigate the spatial patterns of crop vulnerability, a district-level analysis was conducted using the Random Forest model's predictions. The continuous vulnerability map was overlaid on the district boundaries of the country (Figure 6A,B) for a comprehensive understanding of the vulnerability profile across the districts.

The vulnerability scores derived from this analysis represented by the Z-scores, quantified the deviation of 2023 conditions from historical cropland health baselines per district (Figure 7). Positive values indicated that a district experienced conditions worse than its historical average during 2023, signifying heightened crop vulnerability. These districts, as seen in Natore (+1.21) and Magura (+0.89), represented regions where environmental stressors, management challenges, or climatic anomalies have pushed cropland conditions beyond their typical resilience thresholds. On the other hand, negative values denoted conditions more favorable than the historical norm, suggesting either improved agricultural

management, beneficial climatic conditions, or effective adaptation measures. Districts with such negative scores, such as Dinajpur (−2.27) and Faridpur (−2.16), demonstrated good performance relative to their historical baselines. However, this interpretation requires careful contextualization with a negative score does not necessarily indicate absolute agricultural security, but rather relative improvement compared to a potentially challenging historical average.

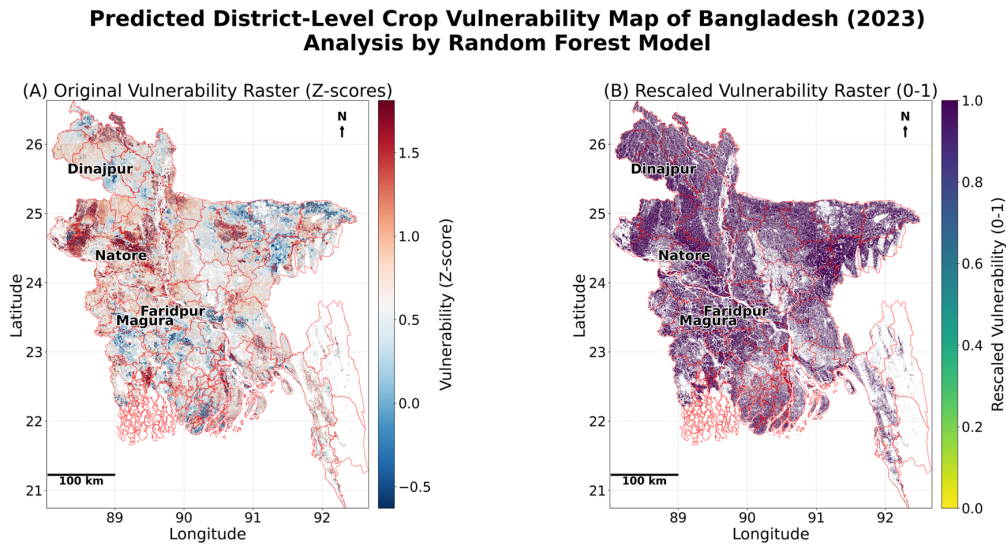


Figure 6. Predicted District-Level Crop Vulnerability Map of Bangladesh (2023) (A) Original vulnerability raster (B) Reclassified vulnerability based on mean Z-scores overlayed on the districts.

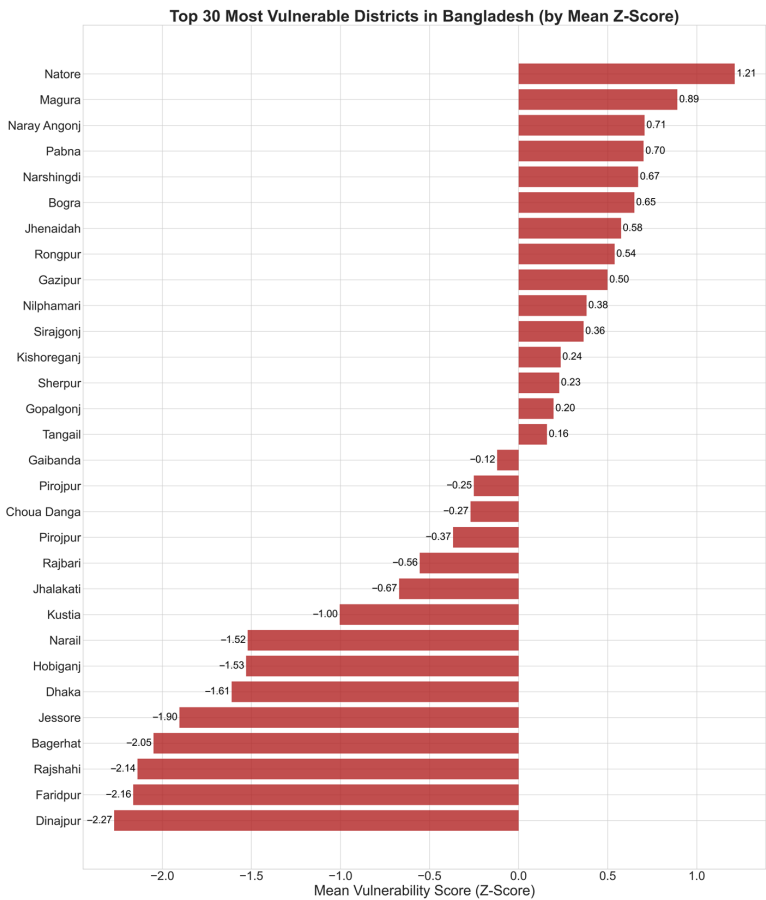


Figure 7. District-Level Crop Vulnerability in Bangladesh (2023): Interpreting Z-Score Anomalies for the top 30 most vulnerable districts.

To explain the key biophysical drivers of crop vulnerability identified by the model, a feature importance analysis was conducted using Gini Importance (as detailed in Section 2.7). The results, summarized in Figure 8, indicated that while dynamic climatic and vegetation variables were the dominant predictors, static environmental factors also contributed measurably to the model's predictions. Among the static drivers, soil composition variables such as 'soil_clay' (importance: 0.00023) and 'soil_ph' (importance: 0.00012) emerged as the most important static determinants of vulnerability, closely followed by elevation (importance: 0.00022).

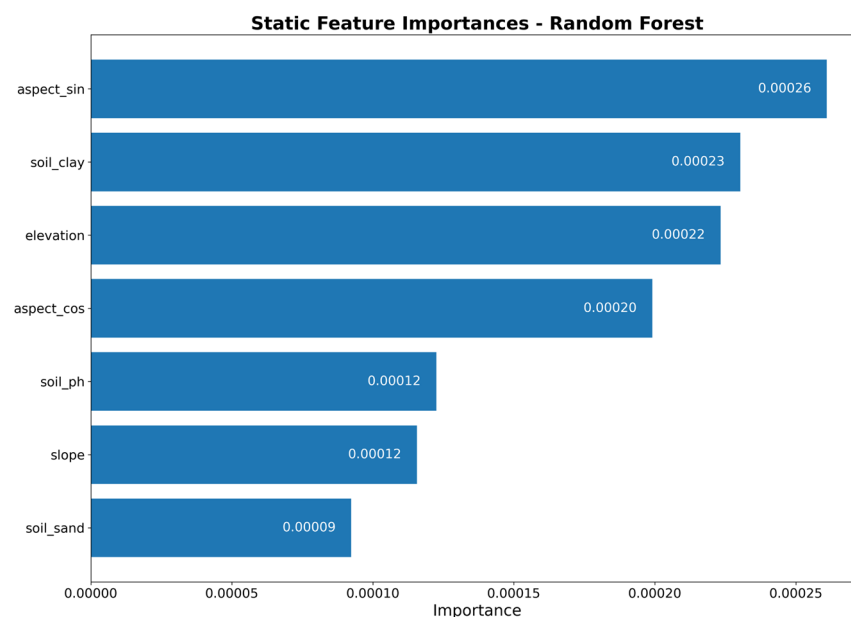


Figure 8. Feature Importance Summary of the Static Drivers in Predicting Vulnerability.

Topographic features like slope with importance (0.000115) and aspect, represented by aspect_sin (0.00026) and aspect_cos (0.00020) also contributed. The importance of aspect was comparable to key soil parameters such as clay content (0.00023) and pH (0.00012), though both topography and soil remained less influential than the dominant temporal climate–vegetation variables. This highlighted the combined role of inherent landscape and soil characteristics in shaping long-term agricultural resilience, complementing the immediate impacts of climatic fluctuations.

4. Discussion

4.1. Model Performance and Interpretability Trade-Offs

This study revealed a critical finding that challenges prevailing assumptions in agricultural vulnerability modeling, the simpler Random Forest (RF) model substantially outperformed the more complex dual-stream deep learning (DL) architecture, achieving an R^2 of 0.70 compared to 0.02 for the DL model. This result aligned with recent comparative studies in environmental prediction, where Hengl et al. [12] demonstrated that ensemble tree-based models frequently matched or exceeded deep learning performance for spatial prediction tasks involving heterogeneous environmental covariates. Similarly, Maxwell et al. [24] found that Random Forest models outperformed convolutional neural networks for land cover classification when training data were limited or spatially clustered, a condition analogous to our spatially blocked validation approach. The superior performance of RF in our study likely stemmed from its inherent ability to handle non-linear relationships and feature interactions without requiring the massive sample sizes typically needed for deep learning convergence [25]. Our ablation studies further illuminated this limitation,

revealing that neither the temporal ($R^2 = 0.0002$) nor static ($R^2 = 0.0278$) streams contributed meaningfully to predictive accuracy when isolated, suggesting fundamental architectural limitations rather than data quality issues. This finding contrasted with successful applications of LSTM and GRU architectures in crop yield prediction [26,27] where longer time series (>30 years) and higher temporal resolution (daily) data facilitated effective temporal pattern learning. The interpretability advantage of RF proved equally significant, as feature importance analysis directly identified effective drivers of recent precipitation, NDVI, and vapor pressure deficit without requiring computationally prohibitive post hoc explanation methods like SHAP, which proved infeasible at our scale. However, the superior predictive performance of RF must be interpreted within the broader conceptual framework of how vulnerability is operationalized, particularly given our deliberate focus on biophysical sensitivity as the measurable dimension of the IPCC vulnerability framework.

4.2. Comparison with Composite Vulnerability Indices and EO-Based Approaches

To comprehensively compare our methodology with existing approaches, we began by positioning our operationalization of vulnerability within the classical IPCC framework.

4.2.1. Conceptual Positioning of Biophysical Sensitivity Within the IPCC Vulnerability Framework

Our operationalization of vulnerability through NDVI anomalies deliberately focuses on the biophysical sensitivity component of the classical IPCC vulnerability framework, which defines vulnerability as a function of exposure, sensitivity, and adaptive capacity [13]. This methodological choice requires explicit justification given its conceptual restrictions. Sensitivity, the degree to which a system is affected by climate stimuli represents the most directly observable dimension through Earth Observation data, as vegetation stress responses manifest measurably in spectral indices [28]. However, this approach inherently excludes adaptive capacity (socio-economic resources, institutional support, technological access) and partially captures exposure (climatic hazard intensity) without accounting for differential human exposure pathways [29,30]. This limitation is not merely technical but conceptual as by isolating biophysical sensitivity, we measure potential vulnerability rather than realized vulnerability, which emerges from the interaction of all three dimensions [31]. Turner et al. [19] demonstrated that communities with identical biophysical sensitivity exhibit vastly different outcomes based on adaptive capacity, while Eakin and Luers [32] showed that focusing solely on sensitivity risks misidentifying vulnerable populations where high adaptive capacity buffers climate impacts. This inherent conceptual restriction means our map highlights areas of potential biophysical stress but does not fully account for existing coping mechanisms or adaptive capacities at the local level. Consequently, a region appearing “vulnerable” on our map might in reality be highly resilient due to robust irrigation infrastructure, well-functioning credit markets, or diversified livelihood portfolios [33], while another appearing “resilient” might be highly susceptible to minor stress due to lack of adaptive resources, high debt burdens, or limited market access [34]. This distinction is critical for avoiding misinterpretations in policy and resource allocation strategies. For instance, our identification of Natore district as highly vulnerable (vulnerability score +1.21) reflects biophysical cropland stress but does not indicate whether local farmers possess drought-resistant seed varieties, access to supplemental irrigation, or off-farm income sources that might substantially mitigate actual livelihood impacts [35]. Conversely, districts with moderate biophysical vulnerability scores might harbor highly vulnerable sub-populations such as landless laborers, female-headed households, or marginal farmers whose socio-economic marginalization amplifies their susceptibility to even modest crop stress [36,37]. Therefore, our framework provides a necessary but partly insufficient vulnerability assessment a biophysical foundation that identifies where climate stress is occurring

but requires integration with socio-economic data to determine who is most affected and why, as advocated by the vulnerability science community [38,39]. This conceptual positioning shapes how we must interpret the spatial patterns discussed in Section 4.4 and highlights the importance of the uncertainties examined in Section 4.3.

4.2.2. Methodological Comparison with Traditional Approaches

Traditional composite vulnerability indices, such as the Livelihood Vulnerability Index (LVI) employed by Hahn et al. [40] and Alam et al. [41] in Bangladesh, aggregated socio-economic indicators (income diversity, social networks, institutional access) with biophysical factors (water availability, land degradation) using equal or expert-assigned weights. While these frameworks captured multidimensional vulnerability, they suffered from three critical limitations our approach addressed, (1) reliance on infrequent household surveys that are temporally static, (2) coarse spatial resolution (typically district or sub-district level) that masked within-region heterogeneity, and (3) subjective weighting schemes that reduced reproducibility [39]. Our NDVI anomaly-based approach provided objective, annually updatable, moderate-resolution (250 m) vulnerability estimates, though admittedly at the cost of excluding socio-economic dimensions. This trade-off mirrored the evolution in drought monitoring, where standardized indices like the Standardized Precipitation Evapotranspiration Index (SPEI) [42] and satellite-based Vegetation Health Index (VHI) [43] increasingly complemented rather than replaced socio-economic assessments. Recent integrated frameworks, such as the spatial drought risk model by Meza et al. [44], demonstrated the potential of combining EO-derived hazard layers with socio-economic exposure data, an approach our biophysical vulnerability map could readily support. In particular, our findings corroborated regional studies identifying precipitation variability and vapor pressure deficit as primary cropland stressors in South Asian deltaic systems [44,45], while extending spatial coverage beyond previous sub-national assessments [46]. Having established the conceptual positioning and methodological advantages of our approach, we now turn to examining the specific uncertainties inherent in our data sources and modeling choices, and critically, how these uncertainties might quantitatively affect the spatial vulnerability patterns we observed.

4.3. Model Uncertainties and Spatial Scale Considerations

Several sources of uncertainty warranted acknowledgment in interpreting our results, with each potentially exerting quantifiable effects on the observed spatial vulnerability patterns. First, the ERA5 climate reanalysis data, while providing consistent spatial coverage, exhibited documented biases in representing localized precipitation extremes and monsoonal dynamics in complex topography [47]. These systematic biases could lead to a substantial underestimation of actual precipitation deficits in flood-prone northeastern districts during extreme monsoon events [47], potentially causing our model to misclassify genuinely stressed areas as moderately vulnerable or even resilient. Conversely, ERA5's smoothing of localized convective rainfall could overestimate drought severity in districts that experienced isolated but intense precipitation events not captured at the 0.25° reanalysis resolution [48]. Second, the bilinear resampling of coarse-resolution climate data (0.25° ERA5, approximately 27.5 km) to the 250 m MODIS grid, while necessary for model integration, did not create genuine fine-scale climate information and may have introduced spatial autocorrelation artifacts [49]. This resampling assigns identical climate values to all 250 m pixels within each 27.5 km ERA5 cell, potentially masking the fine-scale microclimatic gradients in temperature and precipitation that exist across topographic features, water bodies, or urban-rural transitions, a known limitation when using coarse-resolution climate data in high-resolution ecological applications [50,51]. Such homogenization could cause

our model to miss localized vulnerability hotspots where terrain-induced climate variations create stress conditions not represented in the coarser input data. Third, the 250 m MODIS resolution, though adequate for national assessment, likely obscured field-level heterogeneity critical in smallholder systems where plot sizes averaged 0.5 hectares [52,53]. Each 250 m pixel (6.25 hectares) can encompass over a dozen typical smallholder plots in Bangladesh. Consequently, our vulnerability scores represent spatial averages that could mask severe stress affecting a substantial minority of farms within a pixel while others remain unaffected, a fundamental constraint of moderate-resolution data for heterogeneous systems [54]. This averaging effect may substantially underestimate peak vulnerability in heterogeneous landscapes where stress is spatially clustered at sub-pixel scales, a known consequence of scale mismatch in agricultural remote sensing [55]. The spatially blocked validation strategy, while mitigating spatial autocorrelation bias, may have inadvertently penalized the DL model if vulnerability patterns exhibited strong spatial structure that RF could exploit through localized feature interactions [56]. While this methodological choice could have inflated the apparent gap [57], preliminary analysis with random cross-validation suggested the core finding of RF superiority was robust. Finally, our 2001–2022 baseline period encompassed significant land use transitions, including expansion of dry-season irrigation and crop intensification [58], potentially shifting the reference conditions against which 2023 anomalies were calculated. This temporal non-stationarity could systematically bias vulnerability estimates, as the baseline ‘normal’ vegetation condition no longer reflects current management intensity. In districts experiencing rapid agricultural transformation, this could theoretically shift anomaly scores by a notable margin. Future iterations may incorporate higher-resolution climate products (e.g., CHIRPS at 5 km) and Sentinel-2 imagery (10 m) to address scale mismatches, alongside ground-truth validation datasets to quantify prediction uncertainties through ensemble approaches [59] and other advanced methodologies outlined for Earth science applications [60].

With these uncertainty sources and their potential magnitudes explicitly identified, we can now interpret the observed spatial vulnerability patterns with appropriate caution, recognizing where our estimates may be most reliable and where they require validation.

4.4. Spatial Patterns and Agro-Ecological Contextualization

The spatial distribution of cropland vulnerability revealed by our Random Forest model exhibited patterns consistent with known agro-ecological stressors in Bangladesh, though these patterns must be interpreted through the lens of the uncertainties and conceptual limitations discussed in Sections 4.2.1 and 4.3. Districts with elevated vulnerability scores during the 2023 dry season, such as Natore (+1.21) in the northwest and Magura (+0.89) in the southwest, correspond to regions historically characterized by intensified drought conditions and groundwater depletion. This spatial alignment is corroborated by previous regional assessments; importantly, Shahid and Behrawan [61] identified the northwestern Barind Tract including Natore as a critically drought-prone zone with declining groundwater tables that directly threaten irrigation-dependent Boro rice cultivation. However, the magnitude of vulnerability in these districts should be interpreted with awareness of the spatial resolution’s impact discussed in Section 4.3. The 250 m resolution means our map may not capture intra-district variability, potentially homogenizing conditions where specific smallholder farms might be experiencing substantially higher stress than the pixel average, particularly in areas with heterogeneous soil drainage or uneven irrigation access. Furthermore, as highlighted in Section 4.2.1, these biophysical vulnerability scores do not account for adaptive capacity; Natore’s actual livelihood vulnerability may be substantially lower if farmers have adopted stress-tolerant varieties or possess diversified income sources [32,33]. On the other hand, districts exhibiting pronounced

negative vulnerability scores, such as Dinajpur (−2.27) and Faridpur (−2.16), demonstrated high biophysical resilience. This resilience was achieved despite seasonal forecasts for the 2023 monsoon indicating below-normal to near-normal rainfall and a heightened risk of drought conditions for these regions [62], suggesting the probable presence of effective buffering factors such as irrigation infrastructure or adaptive agricultural practices. Yet, as discussed in Section 4.3, the apparent resilience of these districts could be influenced by ERA5 biases, which might smooth over localized extreme events not fully captured by our reanalysis input data [63,64]. Additionally, the conceptual limitation emphasized in Section 4.2.1 applies here because even if biophysical conditions were favorable, vulnerable sub-populations within these ‘resilient’ districts such as landless laborers or marginal farmers might still face severe livelihood impacts due to socio-economic marginalization and gendered inequalities, which our vegetation-based metric cannot detect [36,37]. The strong predictive importance of March precipitation and February NDVI in our model reflected the critical role of pre-monsoon moisture availability for dry-season crop establishment, a relationship extensively documented for Boro rice and other Rabi crops in South Asian agricultural systems [45,65]. However, the temporal resampling of climate data to monthly aggregates (Section 4.3) may have masked sub-monthly variability critical for specific phenological stages [66], meaning our model might miss vulnerability driven by brief but intense dry spells occurring within otherwise “normal” monthly precipitation totals. Interestingly, coastal districts did not uniformly exhibit high vulnerability scores despite well-documented salinity intrusion concerns [67]. This pattern requires careful interpretation as NDVI anomalies primarily capture moisture-driven vegetation stress rather than salinity stress, which may manifest differently in spectral signatures [68]. Consequently, our map might underestimate vulnerability in coastal areas where salinity degrades soil fertility and crop quality without necessarily reducing canopy greenness to the same degree as drought stress [69]. This suggests that the 2023 growing season may have experienced sufficient freshwater availability, that farmers successfully adopted salt-tolerant varieties [70], or that our biophysical metric is insufficiently sensitive to salinity-specific stress a hypothesis requiring ground-truth validation through household surveys, soil salinity measurements, and yield data. The 250 m MODIS resolution (Section 4.3) further complicates coastal interpretation, as salinity intrusion often creates sharp spatial gradients at sub-pixel scales. Severely affected areas may represent only a fraction of a pixel and thus be masked in our averaged vulnerability scores, a known limitation of moderate-resolution data for detecting fine-scale environmental stressors [54,55]. These spatial patterns, interpreted through the explicit consideration of uncertainty sources and conceptual limitations, provide a foundation for designing operational early warning systems, though such systems must integrate our biophysical vulnerability layer with socio-economic data to achieve comprehensive risk assessment.

4.5. Implications for Early Warning Systems and Adaptive Management

The demonstrated capability of the Random Forest model to predict cropland vulnerability with 70% explained variance using readily available satellite and reanalysis data presented significant opportunities for operational early warning systems in Bangladesh, though the conceptual and methodological considerations discussed in Sections 4.2–4.4 shape how such systems should be designed and interpreted. Unlike traditional composite indices requiring extensive field surveys, our approach enabled near-real-time vulnerability assessment within weeks of data availability, a temporal advantage critical for timely intervention deployment [71]. The identification of recent climate variables (particularly March precipitation and February–March vapor pressure deficit) as primary drivers suggested that vulnerability forecasts could be generated as early as mid-growing season, providing

a 2–3 month lead time for targeted support measures including supplemental irrigation allocation, crop insurance payouts, or input subsidy distribution [72,73]. This predictive window aligned with operational drought early warning systems implemented in East Africa, where satellite-based vegetation monitoring triggered anticipatory humanitarian response [74,75]. However, operationalizing our findings requires explicit acknowledgment of the uncertainties quantified in Section 4.3 and the conceptual limitations outlined in Section 4.2.1. Early warning systems based solely on our biophysical vulnerability layer risk misallocating resources if they do not account for adaptive capacity heterogeneity, directing irrigation support to districts with high biophysical stress scores but robust existing infrastructure would be less effective than targeting areas with moderate stress but limited coping resources [33,35]. To address this, operational systems should integrate our 250 m vulnerability maps with spatially explicit socio-economic data such as poverty rates, credit access, irrigation coverage, and market connectivity to generate composite risk indices that capture both biophysical exposure and social vulnerability [76,77]. Such integration would address the “necessary but insufficient” nature of our assessment emphasized in Section 4.2.1. Furthermore, the 250 m spatial resolution of our vulnerability maps exceeded the administrative granularity of most existing agricultural support programs in Bangladesh, which typically operated at upazila (sub-district) level, enabling more precise targeting of vulnerable farming communities. However, as discussed in Section 4.4, the 250 m resolution still obscures field-level heterogeneity critical for smallholder systems, potentially missing a significant portion of peak vulnerability occurring at sub-pixel scales, a known limitation when applying moderate-resolution data to heterogeneous smallholder landscapes [53]. Operational systems should therefore treat our maps as first-stage screening tools that identify priority upazilas or unions for ground-truthed assessments, rather than as definitive vulnerability assignments at the pixel level, following best practices for integrating remote sensing into decision-support framework [10,78]. Combining our moderate-resolution national coverage with targeted high-resolution (10 m Sentinel-2) assessments in flagged priority areas would balance scalability with precision [78]. The model’s interpretability clearly attributing vulnerability to specific climatic and environmental factors facilitates communication with non-technical stakeholders including extension officers and farmer organizations, addressing a critical barrier to machine learning adoption in agricultural policy [79]. The explicit feature importance rankings (March precipitation, February NDVI, vapor pressure deficit) provide functional entry points for adaptation planning enhancing water storage capacity for pre-monsoon irrigation, promoting early-maturing varieties to avoid late-season moisture stress, or expanding weather-indexed insurance tied to these specific predictors [80,81]. However, communicating the uncertainty bounds discussed in Section 4.3 such as the potential for significant underestimation of precipitation deficits and systematic bias from temporal non-stationarity is equally critical to prevent over-confidence in specific vulnerability estimates. Probabilistic vulnerability forecasts incorporating these uncertainty ranges, rather than deterministic maps, would better support risk-informed decision-making [82]. Finally, the strong performance of the simpler Random Forest model over complex deep learning (Section 4.1) has important implications for system sustainability and scalability. RF models require minimal computational resources for retraining and inference, enabling deployment on standard computing infrastructure accessible to national agricultural agencies, whereas deep learning architectures would necessitate the specialized hardware and expertise outlined in comprehensive reviews of the field [60]. This computational accessibility, combined with the model’s interpretability and the ready availability of MODIS and ERA5 data, positions our approach as a viable operational tool for resource-constrained contexts, provided that users understand its scope as a biophysi-

cal sensitivity assessment requiring socio-economic complementation for comprehensive vulnerability mapping.

5. Conclusions

This study addressed a critical gap in agricultural vulnerability assessment by developing and comparing machine learning approaches for predicting cropland stress in Bangladesh, a nation facing acute climate risks to food security. In direct response to our primary objective, we successfully generated a national-scale, moderate-resolution (250 m) cropland vulnerability map for 2023 using 22-year satellite and climate time series data. Our comparative analysis definitively demonstrated that the Random Forest model substantially outperformed the dual-stream deep learning architecture, achieving an R^2 of 0.70 versus 0.02 on spatially independent validation data. This finding challenged prevailing assumptions favoring deep learning complexity and revealed the continued relevance of interpretable ensemble methods for heterogeneous environmental prediction tasks, particularly when training data exhibited spatial structure and sample sizes were constrained relative to feature dimensionality. Addressing our second objective, feature importance analysis of the superior Random Forest model identified recent climatic variables, specifically March precipitation, February NDVI, and March vapor pressure deficit as the primary biophysical drivers of cropland vulnerability. This finding validated our NDVI anomaly-based operationalization of vulnerability as a defensible Earth Observation metric sensitive to short-term climate perturbations, while also revealing that static environmental factors (soil properties, topography) played secondary but measurable roles. The spatial patterns of predicted vulnerability aligned with documented agro-ecological stressors, with northwestern districts (Natore, Magura) exhibiting elevated stress consistent with 2023 drought conditions, while northern and central districts (Dinajpur, Faridpur) demonstrated resilience linked to favorable precipitation patterns. The practical implications of these results extend across multiple domains of agricultural policy and climate adaptation planning in Bangladesh. First, the demonstrated accuracy and efficiency of the Random Forest approach established a viable framework for operational early warning systems, enabling near-real-time vulnerability assessment within weeks of satellite data availability, a temporal advantage over traditional survey-based indices requiring months to compile. The 2–3 month lead time provided by identifying March precipitation and February–March vegetation conditions as key predictors created feasible windows for deploying individualized approaches, including supplemental irrigation allocation in high-vulnerability districts, expedited crop insurance claim processing, and strategic distribution of drought-resistant seed varieties for subsequent planting seasons. Second, the 250 m spatial resolution of our vulnerability maps exceeded the administrative granularity of existing agricultural support programs, enabling precision targeting of vulnerable farming communities within districts rather than uniform interventions across heterogeneous landscapes. This spatial precision could substantially improve the cost-effectiveness of adaptation investments by concentrating resources in genuinely stressed areas while avoiding unnecessary expenditures in resilient zones. Third, the model's interpretability, transparently linking vulnerability to specific, measurable climatic and environmental factors facilitated communication with extension services, farmer organizations, and policymakers who require understandable justifications for resource allocation decisions rather than opaque algorithmic predictions. From a methodological perspective, this study contributed a reproducible framework integrating freely available Earth Observation data (MODIS, ERA5, CHIRPS) with open-source machine learning tools, enabling replication across other climate-vulnerable agricultural regions in South Asia and beyond. The rigorous spatially aware validation strategy employed here should serve as a standard for future agricultural prediction studies to avoid

inflated performance claims arising from spatial autocorrelation. However, several important limitations warrant emphasis. Our NDVI anomaly approach captured biophysical vulnerability dimensions while excluding socio-economic factors (adaptive capacity, market access, institutional support) that critically modulate actual food security outcomes, the 250 m resolution, though improved over district-level indices, remained coarse relative to smallholder plot sizes and the reliance on reanalysis climate data introduced documented biases in representing localized precipitation extremes. Future research should prioritize integration of household-level socio-economic surveys with higher-resolution satellite imagery (Sentinel-2 at 10 m) and ground-truth yield measurements to develop truly comprehensive vulnerability assessments bridging biophysical and human dimensions. In conclusion, this study demonstrated that simpler, interpretable machine learning models can outperform complex deep learning architectures for agricultural vulnerability assessment when appropriately designed and validated, while simultaneously providing the transparency necessary for operational deployment in policy contexts. The resulting vulnerability maps and identified climatic drivers offer immediately workable information for Bangladesh's agricultural adaptation planning, with broader methodological lessons for climate-vulnerable food systems globally.

6. Limitations

While NDVI anomalies provide a spatially explicit and objective proxy for biophysical cropland vulnerability, this approach inherently focuses on vegetation health as an indicator and does not directly capture the socio-economic dimensions of vulnerability, including farmer adaptive capacity, market access, credit availability, or institutional support system [19,33]. NDVI-based assessments represent a proxy for crop stress rather than direct measurements of yield loss or food insecurity, as the relationship between vegetation indices and actual harvest outcomes can be modulated by crop type, management practices, and post-harvest factors [54,78]. Additionally, NDVI saturation in densely vegetated areas and sensitivity to atmospheric conditions, soil background, and sensor characteristics may introduce uncertainties in anomaly detection, particularly in heterogeneous agricultural landscapes [4]. The 250 m spatial resolution of MODIS data, while suitable for national-scale assessments, may not capture field-level variability critical for smallholder farming systems that dominate Bangladesh's agricultural landscape [53]. Future research should integrate household-level socio-economic data, higher-resolution imagery, and ground-truth yield measurements to develop comprehensive vulnerability frameworks that bridge biophysical and human dimensions of climate risk [23].

A further limitation concerns the absence of formal uncertainty quantification and sensitivity analysis in our modeling framework, which restricts assessment of result robustness. Our reliance on ERA5 climate reanalysis products introduces inherent uncertainties from model assimilation processes, spatial interpolation, and parameterization schemes that may not fully capture localized extreme events or microclimatic variations [48,83]. The temporal resampling strategy employed to align multi-source datasets, while methodologically necessary, potentially propagates uncertainties through aggregation and may mask sub-monthly climate variability critical for crop phenological stages [66,84]. Furthermore, the Random Forest model's sensitivity to hyperparameter configurations and the spatial block cross-validation strategy's dependence on block size selection warrant systematic sensitivity analyses to establish confidence intervals around predictions [56,85]. Future implementations may incorporate ensemble modeling and data assimilation approaches [86], along with systematic sensitivity testing of input data quality, temporal aggregation methods, and model parameterization [87], to provide probabilistic vulnerability estimates with quantified confidence bounds.

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