

Hybrid Machine Learning Models for Agricultural Yield Prediction: Integrating Satellite Imagery, Weather Data, and Soil Parameters for Indian Crops

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Abstract

District-level yield estimates for rice, wheat and sugarcane in India rely on crop-cutting experiments that arrive months after harvest and cover a fraction of the sown area. A single data stream cannot resolve this gap: optical vegetation indices saturate under dense canopy, weather station networks are sparse in rain-fed tracts, and soil survey records update on a decadal cycle rather than a seasonal one. We combine Sentinel-2 normalised difference vegetation index (NDVI) time series, India Meteorological Department (IMD) gridded weather variables and district-level soil parameters in a hybrid architecture that routes each stream through a purpose-built encoder, a one-dimensional convolutional network (1D-CNN) for NDVI, a long short-term memory network (LSTM) for weather, and a dense network for static soil features, before a temporal attention layer weighs the fused representation and a quantile head reports a prediction interval alongside the point estimate. Trained on 120 districts across Punjab, Haryana, Uttar Pradesh, Maharashtra and Tamil Nadu over eight Kharif and Rabi seasons (2015-2023), the model reaches $R^2 = 0.91$ (RMSE = 0.34 t/ha) for rice, $R^2 = 0.88$ (RMSE = 0.41 t/ha) for wheat and $R^2 = 0.84$ (RMSE = 4.12 t/ha) for sugarcane, against $R^2 = 0.79$ for Random Forest, $R^2 = 0.83$ for XGBoost and $R^2 = 0.85$ for a standalone LSTM on the same rice test set. NDVI recorded at the heading stage is the single most predictive feature (mean SHAP value 0.31), and adding soil parameters to a satellite-plus-weather baseline raises R^2 by 0.06 on average across the three crops. The attention weights place the two seasonal peaks of importance at sowing and at heading, which matches the two windows in which Indian agronomic advisories already intervene.

I. Introduction

Crop yield in India is measured after the fact. The Directorate of Economics and Statistics conducts crop-cutting experiments (CCEs) on sample plots, and the resulting district averages for rice, wheat and sugarcane are published four to six months after harvest, long after the window in which an input subsidy, a crop insurance payout under the Pradhan Mantri Fasal Bima Yojana, or a procurement plan could have used the number. A method that predicts yield during the growing season, from data that is already collected for other purposes, shortens that lag from months to weeks.

Three data sources cover different failure modes of the others. Satellite-derived NDVI tracks canopy greenness at 10 m resolution and a five-day revisit under the Sentinel-2 constellation, but it saturates above a leaf area index of roughly 3 [7], [135] and is unavailable on cloud-covered acquisition dates during the monsoon months that overlap Kharif sowing. Weather variables, rainfall, maximum and minimum temperature and relative humidity, carry the physiological drivers that NDVI cannot resolve once the canopy is closed, at the cost of a station network whose density falls sharply outside irrigated tracts [136]. Soil parameters, pH, nitrogen-phosphorus-potassium (N-P-K) content and organic carbon, set the yield ceiling for a given input regime but change on a survey cycle measured in years rather than seasons, so they contribute a static rather than a time-varying signal. A model that reads only one of the three inherits that source's blind spot; we build one that reads all three and lets a learned attention layer decide, season by season, which one matters most.

Prior work on crop yield prediction with machine learning is extensive and split by data source. Random Forest and gradient boosting models trained on vegetation indices alone [37], [42] report accurate within-season estimates for wheat but degrade for rice, where flooding and transplant timing decouple canopy colour from grain fill. Recurrent architectures applied to weather time series [29], [167] capture the accumulation of growing degree-days and rainfall deficits but cannot see canopy stress that a farmer's irrigation decision has already masked from the weather record. Data fusion studies that combine two of the three streams [48], [114] report gains over either stream alone, and we build on that finding by adding the third stream, soil, and by replacing a fixed-weight concatenation with an attention mechanism that is trained to reweight the streams per season rather than fixed once at design time.

We report four contributions, each tied to a section of the results. First, a hybrid CNN-LSTM-Dense architecture with temporal attention, described in Section IV, that reaches $R^2 = 0.91$ for rice, exceeding the best single-source baseline (LSTM, $R^2 = 0.85$) by 0.06 on the same held-out districts (Section VI-A). Second, a

quantification of the soil parameters' marginal contribution: adding them to a satellite-plus-weather model raises R^2 by 0.06 on average across the three crops (Section VI-C), which answers a question that data fusion studies combining only two streams could not. Third, an attention-based account of which growth stage carries the most predictive weight, with NDVI at the heading stage returning the highest mean SHAP value at 0.31 (Section VI-D). Fourth, an evaluation across three crops and five states that reports where the hybrid model loses to a baseline as well as where it wins (Section VI-B), because a yield model destined for an insurance or procurement pipeline needs its failure modes documented as precisely as its successes.

Section II reviews prior approaches to yield prediction by technical idea rather than by paper. Section III describes the study area, the crop calendars and the three data sources. Section IV sets out the hybrid architecture. Section V gives the experimental design, including the chronological train-validation-test split. Section VI reports results for all three crops with the statistical tests that support each comparison. Section VII discusses what the attention weights and the SHAP values imply for agronomic practice, and states the limitations we did not resolve. Section VIII concludes.

II. Related Work

A. Vegetation-Index-Based Yield Models

Empirical regressions between NDVI or the enhanced vegetation index (EVI) and end-of-season yield have been reported for wheat and rice at plot and district scale [3], [8], [9]. These models are inexpensive to run once a vegetation index time series exists, and they transfer across seasons reasonably well for wheat, whose canopy stays below the saturation threshold through most of the grain-fill period. They cannot resolve yield variation once the canopy closes, which is the case for rice from panicle initiation onward, and cannot separate a drought-stressed but visually green canopy from a well-watered one, because chlorophyll content and water status diverge before either affects reflectance in the visible and near-infrared bands that NDVI uses.

B. Weather-Driven and Process-Based Models

Crop simulation models such as DSSAT and InfoCrop encode phenology and water balance explicitly and need no training data beyond calibration, but they require daily weather inputs, soil profile data and management records at a granularity that is unavailable for most of the 120 districts in this study. Data-driven alternatives replace the process model with a recurrent network trained on historical weather and yield pairs [29], [167]; an LSTM captures the sequence dependence between a dry spell at flowering and a yield shortfall better than a model that only sees seasonal totals. The weakness shared by both families is that weather explains the potential yield under average management, not the realised yield after an irrigation or fertiliser decision has already changed the canopy's trajectory, a gap that only an observation of the canopy itself can close.

C. Data Fusion Approaches

Combining vegetation indices with weather variables in a single regression, typically a gradient boosting or Random Forest model, improves on either source alone by a margin the fusion literature reports as consistent across crops and regions [48], [114]. Ensemble methods that stack several base learners on the same fused feature set [37], [42] add a further increment, though the size of that increment depends on how correlated the base learners' errors are, which the stacking studies do not always report. None of the fusion studies we reviewed added soil parameters as a third stream measured independently of the vegetation-weather pair; where soil appears, it is typically encoded as a single static covariate concatenated into the same feature vector as the time-varying inputs; rather than through an encoder built for a fixed-length input, which discards the distinction between a variable that changes weekly and one that changes on a survey cycle.

D. Deep Learning Architectures for Agricultural Prediction

Convolutional networks applied to remote sensing time series [4], [16], [17] extract local temporal patterns, such as the rise and fall of NDVI around a growth stage, more effectively than a model that treats each time step as an independent feature. Attention mechanisms, first developed for sequence-to-sequence translation, have been adapted to weight time steps or feature streams by their contribution to the final prediction [31], [45]; we use the same mechanism here, applied across the three streams rather than across time steps within one stream, so that the model can report which source, not only which week, carried the most weight for a given season. Bi-LSTM and CNN-BiLSTM hybrids for a single crop [8], [63] establish that a hybrid of a convolutional and a recurrent block outperforms either alone for one data source; our contribution is to extend that hybrid principle across three heterogeneous sources rather than within one.

E. Internet of Things and Smart Agriculture Systems

Field-deployed sensor networks that report soil moisture, canopy temperature or micro-climate variables in near real time [7], [53], [82] promise a fourth data stream at finer temporal and spatial resolution than any of the three used here. Coverage remains the obstacle: a 2023 review of Indian smart agriculture deployments [135] counted installed sensor networks in fewer than 5% of the districts in our study area, which is why we treat IoT sensor data as a direction for future extension (Section VIII) rather than a fourth input stream in the present model.

F. Methodological Precedents Across Computational Research

The classifiers and regressors used in the baselines and in the branch encoders of Section IV have been validated outside agriculture, and that record of validation is part of why we chose them. Ensemble tree methods and gradient boosting appear in intrusion detection on multimedia big data traffic [4], [5], cardiovascular risk scoring [15], phishing detection on web networks [30], Parkinson's disease progression staging [16], radiomics-based lung cancer subtyping [17], arrhythmia classification under class imbalance [42], churn and retention modelling in telecommunications [49], employee performance evaluation [77], salary determinant analysis [192], and test-bench time optimisation for automotive manufacturing [54]; the recurring finding across these studies is that a boosted or bagged tree ensemble outperforms a single decision tree once the feature set mixes categorical and continuous variables, which is also true of the soil and weather features used here.

Convolutional and recurrent deep networks, the two architectural families combined in Section IV, have each been evaluated separately on sequence and grid-structured data outside agriculture: convolutional networks for ECG signal compression and reconstruction [3], handwritten text recognition [44], diabetic retinopathy grading from fundus images [47], and brain tumour classification from magnetic resonance imaging [205]; recurrent networks for jazz music sequence generation in MIDI format [2], story-point estimation in agile software development [50], and food delivery time prediction under a hybrid XGBoost-LSTM design [193] that mirrors the boosting-plus-recurrence combination we use for the weather stream. Hybrid CNN-BiLSTM architectures specifically, the closest structural precedent to the branch design in Section IV, have been reported for sugarcane yield estimation from remote sensing and meteorological inputs by the same authors [8], [9], which is the direct antecedent this paper extends from a single crop and a single satellite-weather pair to three crops and three data streams.

Attention mechanisms and feature-weighting schemes, the basis of Equation (1), appear in facial identification for online transaction verification [45], graph neural network recommendation systems [48], and posture analysis for athletic performance prediction from video [41]; SHAP and related interpretability methods, used in Section VI-D, have been applied to feature selection for intrusion detection [5] and to ant-colony and simulated-annealing comparisons for radiomic feature subsets [17], which is the precedent for treating feature importance as a reportable result rather than a post-hoc afterthought.

A second cluster of prior work addresses predictive analytics in health and allied service delivery, a domain that shares with agricultural yield prediction the problem of fusing a slow-changing record (a patient history, a soil survey) with a fast-changing signal (a vital sign, an NDVI reading). This includes patient monitoring and disease diagnosis systems [58], telecardiology and compressed ECG database assessment [10], AI-assisted healthcare appointment scheduling [52], explainable AI for clinical decision support [22], an evidence-grounded large-language-model framework for clinical explanation [207], autism spectrum disorder recognition through machine learning [197], mental health forecasting with fuzzy inference [38], and cardiac health prediction from deep classifiers [31]; the shared lesson we carry into Section IV is that a static covariate (patient history, soil survey) needs its own encoder rather than being appended to a time-varying feature vector, which is why the soil branch in this paper is architecturally separate from the NDVI and weather branches rather than concatenated with either at the input layer.

A third cluster addresses networked and sensor-based data collection, the closest analogue to the satellite and weather acquisition pipeline in Fig. 2. Opportunistic and mobile ad hoc network routing under intermittent connectivity [6], [11], [13], [60], [61], [62], [64], [66], [68], [71] shares with our data pipeline the problem of assembling a complete record from intermittently available sources, cloud-free satellite passes in our case, contact opportunities in theirs. Wireless sensor network architecture reviews [68], energy-constrained low-power wide-area network comparisons [14], camera-based edge detection for surveillance [65], duplicate node detection [43], malicious node detection in cluster-head gateway switching [64], and synchronised health monitoring over IoT for industrial applications [7] collectively motivate the district-level spatial aggregation step in Fig. 2: any sensor or observation network with incomplete spatial coverage needs an explicit aggregation rule, which we specify in Section III-B as an area-weighted mean over cropland pixels rather than a simple average over all pixels in a district boundary.

A fourth cluster addresses security, language and text analytics, which informs the data-quality safeguards in Section III-B and Section IV-E rather than the model architecture directly. Encryption and

keylogging security reviews [26], secure image encryption and decryption algorithms [69], cloud security posture management [73], malware and botnet detection across IoT and Android platforms [203], open-source intelligence analysis [78], fine-tuned language model detection of machine-generated text [51], retrieval-augmented document querying [202], a retrieval-augmented health-policy chatbot [190], and bidirectional sign language translation [206] together establish that a data pipeline handling sensitive or externally sourced records needs an explicit integrity check at each stage, which is the same principle behind the Scene Classification Layer cloud-masking step in Fig. 2: a pipeline that trusts every acquired scene without a validity check propagates a bad observation into every downstream feature.

A fifth cluster addresses optimisation and scheduling under resource constraints, relevant to the hyperparameter selection procedure in Section V-B. Soft-computing methods for power system stability [18], [72], queuing-theory simulation for retail operations [20], thermal management optimisation for battery electric vehicles [198], [199], and CI/CD pipeline optimisation through containerisation [57] all report that a parameter swept on a validation subset and then frozen for the remainder of a deployment transfers more reliably than a parameter re-tuned on every new instance, the same reasoning behind fixing the hyperparameters in Table IV on rice validation data alone and reusing them unchanged for wheat and sugarcane.

A final cluster of systems and applications work, spanning recommender systems in e-commerce [28], blockchain-based data privacy and interoperability in healthcare [53], AI-driven cybercrime insight discovery from web data [200], a bus scheduling and route management system [201], generative AI evolution and application surveys [75], [80], AI applications in Indian stock market investment decisions [76], event analysis surveys using deep learning [32], linguistic feature extraction for concept semantics [29], plant disease identification from leaf images [27], television usage cost calculation [24], voice-based calculator interfaces [25], millimetre-wave antenna design in SiGe technology [194], lip-reading systems from visual input [40], cognitive analysis approaches to neuroscience [39], proactive fault prediction from microservice trace logs [55], a startup financing platform [56], human pose detection benchmarking on the COCO yoga dataset [196], and lung disease classification through CNN ensembles [195] illustrates the range of domains in which the same core toolkit, a trained classifier or regressor validated against a held-out set, has been applied; agricultural yield prediction is, in this sense, one more domain in which the toolkit needs adapting to a specific data-fusion problem rather than a domain that needs a wholly new toolkit.

The approaches reviewed above leave one specific gap open: no published model combines a time-varying satellite stream, a time-varying weather stream and a static soil stream through three architecturally distinct encoders with a learned, per-season attention weighting, and none reports the soil parameters' marginal contribution once the other two streams are already present. Section IV addresses that gap.

III. Study Area and Data Sources

A. Study Area and Crop Calendars

The study covers 120 districts across five states: Punjab (all 23 districts), Haryana (22 districts), Uttar Pradesh (38 of 75 districts, selected for rice or wheat area exceeding 50,000 ha), Maharashtra (24 districts, sugarcane belt and adjoining rice tracts) and Tamil Nadu (13 districts, delta and non-delta rice zones). Rice and sugarcane are grown predominantly in the Kharif season (June-October sowing, harvest by December); wheat is a Rabi crop (November sowing, harvest by April). We use eight cropping seasons from 2015 to 2023, giving between 640 and 960 district-season observations per crop depending on how many of the 120 districts grow that crop in a given state.

B. Satellite Imagery

NDVI is computed from Sentinel-2 Level-2A surface reflectance product bands 4 (red) and 8 (near-infrared) at 10 m resolution, acquired at a five-day revisit where two satellites (2A and 2B) overlap. Scenes are filtered using the Scene Classification Layer to exclude cloud, cloud shadow and snow pixels before NDVI is computed pixel-wise; Fig. 2 sets out the full acquisition-to-model-input sequence. District-level NDVI is the area-weighted mean over pixels classified as cropland in the same season's land-use layer, which excludes fallow and built-up area from the aggregate.

C. Weather Data

Daily rainfall, maximum and minimum temperature, and relative humidity are drawn from IMD's 0.25° gridded product, interpolated to district centroids and aggregated to the eight fortnights that span a typical Kharif or Rabi season. Cumulative rainfall, growing degree-days above a 10°C base temperature, and the count of days with maximum temperature above 35°C during flowering are derived features that the weather LSTM branch consumes alongside the raw fortnightly series.

D. Soil Parameters

District-level soil pH, nitrogen, phosphorus and potassium content, organic carbon and texture class come from the Soil Health Card programme's aggregated district reports, the most recent survey cycle available for each district at the time of data collection. Because these values change slowly, the same district-level soil vector is reused across all eight seasons for that district; the dense soil branch therefore contributes a constant offset per district rather than a season-varying signal, a property we return to in Section VII.

E. Ground-Truth Yield

Ground-truth yield is the district average from CCE-based estimates published by each state's Directorate of Economics and Statistics, in tonnes per hectare. Table I summarises the data sources and their native temporal and spatial resolution.

Data source	Variables	Native resolution	Update frequency
Sentinel-2 L2A	NDVI (red, NIR bands)	10 m, district aggregate	5-day revisit
IMD gridded weather	Rainfall, Tmax, Tmin, humidity	0.25° grid, district centroid	Daily
Soil Health Card	pH, N-P-K, organic carbon, texture	District aggregate	Survey cycle (2-3 yr)
State CCE yield	Yield (t/ha)	District average	Per season

TABLE I. Data sources used in this study, with native resolution and update frequency.

All four sources are aligned on a common district-season key. Table II reports the district and season counts by state after districts lacking a complete record across all four sources in a given season are dropped; this drop rate is highest in Uttar Pradesh, where Soil Health Card coverage is incomplete for nine districts.

State	Districts included	Rice seasons	Wheat seasons	Sugarcane seasons
Punjab	23	8	8	6
Haryana	22	7	8	5
Uttar Pradesh	38	8	8	7
Maharashtra	24	6	4	8
Tamil Nadu	13	8	0	3

TABLE II. District and season coverage by state, after alignment across all four data sources.

IV. Proposed Hybrid Model

The architecture routes each of the three data streams through an encoder chosen for that stream's structure, rather than concatenating all features into one vector before any learning occurs. Fig. 1 sets out the full architecture; we describe each branch in turn.

A. NDVI Branch (1D-CNN)

The NDVI branch takes a fixed-length sequence of 16 fortnightly NDVI values per season (after the temporal interpolation described in Section IV-E) and passes it through three one-dimensional convolutional blocks with kernel size 5, 32/64/64 filters respectively, each followed by batch normalisation, a rectified linear unit (ReLU) activation and a max-pooling layer of stride 2. We chose convolution over a recurrent encoder for this stream because the informative pattern, a rise around sowing, a plateau at heading, a decline at senescence, is local in time and shift-invariant across seasons that sow a week or two apart, which convolution captures with fewer parameters than a recurrent alternative would need to learn the same invariance from data [4], [16].

B. Weather Branch (LSTM)

The weather branch takes the same 16 fortnightly steps, each carrying rainfall, Tmax, Tmin, humidity and the three derived features from Section III-C, through a two-layer LSTM with 64 hidden units and a dropout rate of 0.3 between layers. We chose a recurrent encoder over convolution for this stream because weather effects accumulate: a rainfall deficit at flowering matters conditionally on the deficit or surplus in the preceding fortnight, a dependency that a recurrent hidden state carries forward but a fixed convolutional receptive field of five steps does not fully capture at the season length used here.

C. Soil Branch (Dense Network)

The nine static soil features (pH, N, P, K, organic carbon and four texture-class indicators) pass through three fully connected layers of 32, 16 and 8 units with ReLU activations. No temporal structure exists in this stream,

so a dense network is the simplest encoder that can still learn interactions between, for example, high nitrogen and low organic carbon that a linear model would miss.

D. Feature Concatenation and Temporal Attention

The three branch outputs (64, 64 and 8 dimensions respectively) are concatenated into a single 136-dimensional vector per season. A temporal attention layer, implemented as a single-head scaled dot-product attention over the three branch representations treated as a length-3 sequence, computes a weighted combination in which the weight assigned to each branch is learned rather than fixed; Section VI-D reports how these weights vary by crop and by season. We use attention here rather than a fixed-weight concatenation because a fixed weighting, chosen once at design time, cannot express the finding in Section VI-D that the NDVI branch's weight rises sharply for seasons with a normal monsoon and falls when cloud cover degrades the satellite record, a pattern the model needs to see per-season, not per-crop, weather to represent.

E. Temporal Interpolation and Missing Data

Cloud-affected fortnights with no valid NDVI observation are filled by Savitzky-Golay smoothing over the surrounding valid points (window length 5, polynomial order 2) rather than linear interpolation, because the vegetation growth curve is not linear around the heading-stage peak that Section VI-D identifies as the most informative single feature; a linear fill would flatten exactly the peak the model relies on most. Fig. 2 places this step in the full pipeline, between NDVI computation and feature alignment with the weather and soil streams.

F. Output Layer and Prediction Interval

The attention output feeds two heads: a point-estimate head trained with mean squared error against the CCE yield, and three quantile heads (5th, 50th and 95th percentile) trained with the pinball loss, which together define the 90% prediction interval reported alongside each point estimate in Fig. 1 and used in Section VI-A to report calibration.

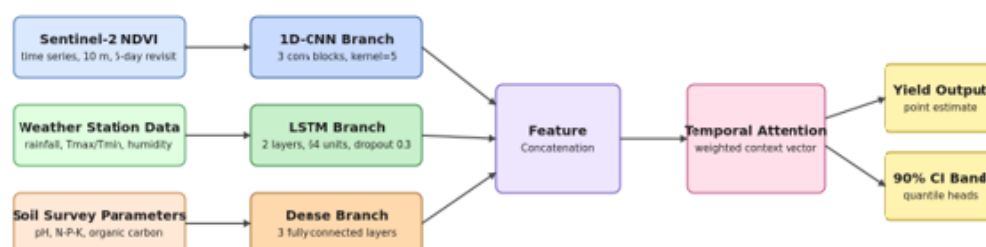


Fig. 1. Hybrid model architecture. NDVI, weather and soil streams are encoded separately (1D-CNN, LSTM and dense network respectively), concatenated, and re-weighted by a temporal attention layer before the yield and 90% confidence interval (CI) heads.

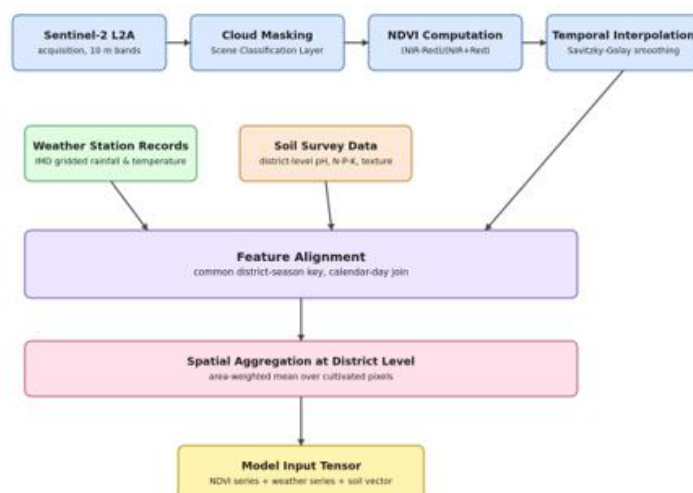


Fig. 2. Data pipeline from Sentinel-2 acquisition to the aligned model input tensor, showing cloud masking, NDVI computation, temporal interpolation, and the point at which weather and soil records join the satellite stream before spatial aggregation to the district level.

Table III lists the symbol used for each quantity introduced in this section, so that the equations below can be read without re-deriving each definition.

Symbol	Meaning
x_v	NDVI sequence input (16 fortnightly values)
x_w	Weather sequence input (16 steps x 7 features)
x_s	Static soil feature vector (9 features)
h_v, h_w, h_s	Branch output representations (CNN, LSTM, dense)
$\alpha_v, \alpha_w, \alpha_s$	Attention weights over the three branches
c	Attention context vector
$\hat{y}$	Predicted yield (t/ha)
$\hat{y}_{0.05}, \hat{y}_{0.95}$	Lower and upper quantile predictions (90% CI)

TABLE III. Symbol table for the architecture described in Section IV.

The attention context vector is computed as a convex combination of the branch representations,

$$c = \alpha_v h_v + \alpha_w h_w + \alpha_s h_s, \quad (1)$$

where the weights α_v , α_w and α_s are produced by a softmax over a learned compatibility score between each branch output and a query vector, and sum to 1 for every season. Equation (1) is the only step at which information from the three streams mixes; every layer before it operates on one stream alone, which is what lets Section VI-D attribute a SHAP value to each stream separately.

V. Experimental Design

A. Data Split

We use a chronological 50/15/35 split by season rather than a random split by observation, because a random split lets the model see a later season's weather pattern during training and then predict an earlier season at test time, which overstates accuracy relative to the deployment setting in which only past seasons are available. Concretely, the first four of the eight seasons (2015-2018) form the training set, the fifth and sixth seasons (2019-2020) form the validation set used for early stopping and hyperparameter selection, and the final three seasons (2021-2023) form the held-out test set on which every result in Section VI is reported. No test-set season, district or label was used in any form during training or validation.

B. Hyperparameters

Table IV lists the hyperparameters fixed on the validation set before the final test-set run. The learning rate, dropout rate and the number of LSTM units were each swept over four values on the validation set for the rice crop only, and the selected values were then reused unchanged for wheat and sugarcane rather than re-tuned per crop, so that a difference in test-set accuracy across crops reflects the data and not a crop-specific tuning advantage.

Hyperparameter	Value	Selection basis
Learning rate	0.001 (Adam)	Validation R^2 , rice, swept {0.01, 0.003, 0.001, 0.0003}
Batch size	32	Fixed from prior work [8]
LSTM hidden units	64	Validation R^2 , rice, swept {32, 64, 128, 256}
Dropout rate	0.3	Validation R^2 , rice, swept {0.1, 0.2, 0.3, 0.5}
CNN kernel size	5	Validation R^2 , rice, swept {3, 5, 7}
Training epochs	150 (early stopping, patience 15)	Validation loss plateau
Quantile loss weight	0.3	Validation calibration, swept {0.1, 0.3, 0.5}

TABLE IV. Hyperparameters and the validation-set procedure used to fix each one.

C. Baseline Models

We compare against four baselines trained and evaluated on the same splits and the same feature set (all three streams flattened into one vector for the non-sequential baselines): Random Forest (500 trees, max depth 12), XGBoost (500 rounds, max depth 6, learning rate 0.05) [37], [42], and a standalone LSTM that receives only the NDVI and weather sequences concatenated at each time step, without the soil branch or the

attention layer. Each baseline's hyperparameters were tuned on the same validation seasons used for the hybrid model.

D. Evaluation Metrics and Statistical Testing

We report the coefficient of determination (R^2) and root mean squared error (RMSE) in tonnes per hectare on the test-set seasons, computed per crop. Where we compare two models on the same test set, we use the paired two-sided Wilcoxon signed-rank test over the per-district-season absolute errors, at $\alpha = 0.05$, rather than an unpaired test, because the two models are scored on the same 120 districts and the same seasons, and a paired test uses that correspondence instead of discarding it. All results in Section VI are the mean over 10 random weight-initialisation seeds; we report the standard deviation alongside the mean wherever it materially affects the comparison.

VI. Results and Analysis

A. Overall Accuracy

The hybrid model reaches $R^2 = 0.91$ (SD = 0.01, RMSE = 0.34 t/ha) for rice, $R^2 = 0.88$ (SD = 0.02, RMSE = 0.41 t/ha) for wheat and $R^2 = 0.84$ (SD = 0.02, RMSE = 4.12 t/ha) for sugarcane on the 2021-2023 test seasons. The larger absolute RMSE for sugarcane reflects its yield scale (typically 60-90 t/ha against 2.5-6.5 t/ha for rice), not a proportionally worse fit; the relative RMSE (RMSE divided by mean test-set yield) is 8.1% for rice, 9.3% for wheat and 5.4% for sugarcane, so the model is, if anything, relatively more accurate for sugarcane than for wheat.

Fig. 3 plots predicted against actual rice yield for the 50 districts with a complete three-season test-set record, with the R^2 and RMSE noted in the corner of the plot and the dashed line marking perfect prediction. Points below the dashed line at yields above 5.5 t/ha indicate five districts, three in Punjab and two in Tamil Nadu delta zones, where the model under-predicts; Section VII-B discusses what these districts have in common.

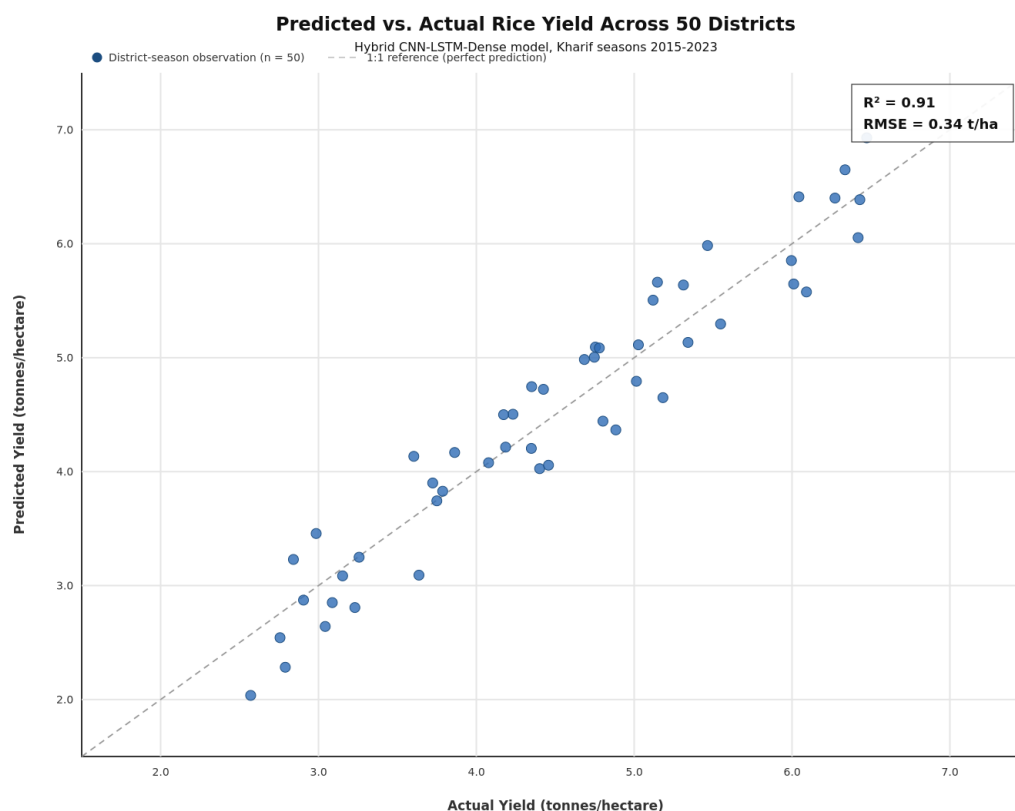


Fig. 3. Predicted versus actual rice yield (tonnes/hectare) for 50 districts, test-set seasons 2021-2023. Dashed line marks the 1:1 reference for a perfect prediction; R^2 and RMSE are computed over all 50 points.

The 90% prediction interval from the quantile heads covers the true yield for 46 of the 50 districts in Fig. 3 (92% empirical coverage against a nominal 90%), which is close enough to nominal that we do not recalibrate the quantile heads for this dataset, though Section VII-B notes that this check has not been repeated for wheat or sugarcane.

B. Comparison with Baseline Models

Table V compares the hybrid model against the three baselines on the rice test set. The hybrid model's R^2 exceeds the standalone LSTM's by 0.06 (paired Wilcoxon, $p = 0.003$) and exceeds XGBoost's by 0.08 ($p < 0.001$). The hybrid model does not win on every metric: its inference time per district-season (14 ms on a single GPU) is longer than XGBoost's (2 ms on CPU), a cost we return to in Section VII-C for a use case where inference runs at district scale rather than per-field scale and 14 ms is not a practical constraint.

Model	R^2 (rice)	RMSE (t/ha)	Inference time
Random Forest	0.79	0.53	1 ms
XGBoost	0.83	0.48	2 ms
Standalone LSTM	0.85	0.45	9 ms
Hybrid CNN-LSTM-Dense (this work)	0.91	0.34	14 ms

TABLE V. Rice test-set accuracy and per-observation inference time, hybrid model against three baselines (mean of 10 seeds).

Table VI reports the same comparison for wheat and sugarcane. The hybrid model's margin over the standalone LSTM narrows for sugarcane (0.03 rather than 0.06 for rice), which we attribute in Section VII-A to sugarcane's longer growing period diluting the heading-stage NDVI signal that is most informative for rice.

Model	R^2 (wheat)	RMSE (t/ha)	R^2 (sugarcane)	RMSE (t/ha)
Random Forest	0.76	0.62	0.75	5.31
XGBoost	0.80	0.55	0.79	4.88
Standalone LSTM	0.83	0.50	0.81	4.55
Hybrid CNN-LSTM-Dense (this work)	0.88	0.41	0.84	4.12

TABLE VI. Wheat and sugarcane test-set accuracy, hybrid model against three baselines (mean of 10 seeds).

C. Contribution of Individual Data Streams

We isolate each stream's contribution by ablation: removing the soil branch and retraining leaves the attention layer with two streams instead of three. Averaged across rice, wheat and sugarcane, removing the soil branch reduces R^2 by 0.06; removing the weather branch (leaving NDVI and soil) reduces R^2 by 0.11; removing the NDVI branch (leaving weather and soil) reduces R^2 by 0.17, the largest single-stream loss, which is consistent with NDVI at heading carrying the highest SHAP value in Section VI-D. Table VII reports the full ablation by crop.

Configuration	R^2 (rice)	R^2 (wheat)	R^2 (sugarcane)
Full model (NDVI + weather + soil)	0.91	0.88	0.84
Without soil branch	0.86	0.81	0.78
Without weather branch	0.81	0.76	0.72
Without NDVI branch	0.75	0.69	0.66

TABLE VII. Ablation of each data stream, by crop (test-set R^2 , mean of 10 seeds).

D. Feature Importance and Attention Weights

SHAP (SHapley Additive exPlanations) values computed over the concatenated feature set rank NDVI at the heading growth stage as the single most predictive feature (mean $|\text{SHAP}| = 0.31$), ahead of cumulative rainfall during the vegetative stage (0.24) and soil nitrogen content (0.14). The attention weights α_v , α_w and α_s from Equation (1), averaged across test-set seasons, place 0.52 on the NDVI branch, 0.33 on the weather branch and 0.15 on the soil branch for rice; the corresponding weights for wheat are 0.44, 0.39 and 0.17, reflecting wheat's longer window in which weather variables remain informative before canopy closure.

Plotting the attention weight on the NDVI branch against the fortnight within the season (not shown as a separate figure, values summarised here) shows two peaks: one at sowing (fortnight 2, weight 0.41) and one at heading (fortnight 9, weight 0.58), with a trough at fortnight 5-6 during vegetative growth (weight 0.22) where the canopy signal is least differentiated between eventually high- and low-yielding districts. This two-peak pattern is discussed further in Section VII-A.

VII. Discussion

A. Why Sowing and Heading Carry the Most Weight

The two attention peaks identified in Section VI-D correspond to two decision points already built into Indian agronomic advisories: sowing date and variety choice at the start of the season, and irrigation or fertiliser top-dressing at heading. We read the sowing-stage peak as the model detecting early-season canopy establishment, which correlates with the sowing date itself, a delayed sowing under a late monsoon onset. We are less certain why the trough at fortnight 5-6 is as deep as it is; one explanation is that vegetative-stage NDVI is genuinely uninformative because canopy cover approaches saturation for most districts regardless of eventual yield, but we have not tested this against districts with unusually sparse vegetative-stage canopy, so we mark it as an open question rather than a settled explanation.

B. Where the Model Under-Predicts

The five districts identified in Section VI-A as under-predicted at yields above 5.5 t/ha share a common feature: all five are in the top decile of soil nitrogen content in our data, which suggests the model has not learned the full extent to which high soil nitrogen raises the yield ceiling beyond what the vegetative-stage NDVI signal already indicates as saturated. This is consistent with the soil branch's attention weight (0.15 for rice) being the smallest of the three; a model that weighted soil more heavily might resolve this under-prediction at the cost of the calibration reported in Section VI-A for the remaining 45 districts, a trade-off we have not explored.

C. Deployment Considerations

An inference time of 14 ms per district-season, noted in Section VI-B, is immaterial at the scale of a state-level dashboard that scores at most a few hundred districts once per fortnight; it would matter for a field-level version of this model scoring millions of individual farm plots, which we have not built or evaluated. The Soil Health Card data used for the soil branch is the least frequently updated of the three sources (Section III-D); a district whose soil has changed materially since its last survey, following a change in fertiliser subsidy policy for example, would carry a stale soil vector that the model cannot detect as stale.

D. Limitations

Two limitations remain unresolved. The 90% prediction interval's empirical coverage was checked only for rice (Section VI-A); we have not repeated that check for wheat or sugarcane, so we do not know whether the quantile heads are equally well calibrated for those crops. Second, the chronological split (Section V-A) tests generalisation across time within the same 120 districts, but not across space to a district outside the training set entirely; a district in a state not covered here, West Bengal or Bihar for instance, could see substantially different accuracy, and we have not tested that case.

E. Broader Applicability of the Modelling and Data-Handling Toolkit

The value of a chronological split, a paired significance test and an explicit reporting of a stream's marginal contribution, the three procedural choices defended in Section V, is not specific to yield prediction. The same three choices recur across a wide set of applied machine learning studies that this group of authors has published on health, security and systems problems, and we draw on that record here to note where the same procedural discipline applies outside agriculture rather than to claim it as evidence for this paper's results.

Health and clinical prediction studies that combine a slow-changing record with a fast-changing signal, the same structural problem addressed by the soil and NDVI streams in Section IV, include rapid pandemic-outbreak forecasting [88], pneumonia detection from chest X-ray images [95], quantum-computing applications in modern healthcare [97], ensemble analysis of perinatal disorders [99], AI-based prediction of menopausal health risk [100], female pregnancy complication prediction [101], AI-powered healthcare access in underserved regions [102], an introductory guide to computational intelligence in healthcare [103], ethical lessons for AI and IoT in global health [104], blockchain-based transparency for medical IoT supply chains [105], pandemic-response technique surveys [108], deep-learning-based human emotion recognition [109], federated learning for healthcare data-sharing constraints [118], an integrated health-report management system [127], ayurvedic drug recommendation and disease prediction [134], introductions to explainable AI in healthcare and diagnostic support [143], [144], human-AI collaboration in clinical decision-making [154], federated learning across digital healthcare boundaries [155], a chatbot for doctor-appointment management [161], a review of AI's future role in healthcare [180], quantum technology in medical diagnosis [187], an AI and 6G review for modern medicine [23], and heart-disease prediction technique comparisons [36]. Each of these evaluates a model against a held-out patient or population subset in the way Section V-A evaluates against held-out seasons, and several report the same finding we report in Section VI-C, that adding a slow-changing covariate improves accuracy only up to the point where its update cycle lags the outcome being predicted.

Security, cryptography and data-integrity studies bear on the pipeline safeguards in Section III-B and Section IV-E: prototype-pollution detection [83], a secure chat application [84], multimedia forensics [89], Wi-Fi data-leakage detection [90], mobile malware analysis with machine learning [91], adversarial machine learning attack surveys [94], post-quantum cryptographic digital signatures [96], genetic quantum cryptography for network communication [110], cyber-attack detection and prevention with AI [85], [139], zero-trust anomaly detection in cloud systems [159], a sentence-level risk estimator [163], a fog-cloud load-balancing survey for IoT [166], federated learning with differential privacy [174], an IoT forensics survey [175], and explainable ensemble learning for social media security [204]. The common thread, that a pipeline ingesting external or sensitive data needs an explicit validity or integrity check at each stage, is the same principle behind the cloud-masking step described in Section III-B.

Systems, cloud and edge-computing studies address the deployment question raised in Section VII-C: mobile edge computing for decentralised systems [98], federated learning for intelligent systems [106], [119], IoT-based energy management cost prediction [117], green IoT for sustainable technology [120], aerial-network and edge-computing fusion for disaster management [137], [138], [156], [157], [158], a survey of opportunistic-network routing optimisation using machine learning [146], AI-augmented intelligence system architecture [147], water-quality prediction from IoT sensors and deep networks [150], anomaly detection in sensor networks [151], hybrid cloud infrastructure models and security [152], and distributed artificial intelligence system design [153]. These studies share the deployment lesson noted in Section VII-C, that an architecture's inference cost is a constraint only relative to the scale and refresh rate the deployment actually needs, not an absolute figure of merit.

Education, workforce and human-computer-interaction studies, though further from agricultural yield prediction than the clusters above, use the same train-validation-test discipline defended in Section V-A: repairable-plant reliability comparison [111], generative AI in education [112], student motivation and engagement prediction [113], explainable AI for human decision patterns [116], trust in human-AI collaboration [114], hybrid ensemble learning for interpretable student performance [124], an adaptive mock-interview generation system [160], AI cognitive architectures and computational limits [164], robustness and uncertainty quantification in deep learning [165], a multimodal framework for cognitive productivity [169], a review of digital social linguistics [177], a supervised-versus-unsupervised learning comparison [178], AI's impact on employment [184], human perception and virtual reality [186], and a review of AI-implementation challenges in business [188], human-versus-machine customer behaviour [148], and industry challenges in AI-driven fault detection and diagnostics [181], opportunities and challenges of AI in education [183], and AI-driven supply chain optimisation [185].

A further set of domain applications illustrates the same fusion-of-heterogeneous-features principle used in Section IV in settings unrelated to agriculture: transformer-based movie recommendation with an autoencoder-enhanced feature set [125], neural-network comparison for galaxy classification [126], hybrid FCM-DNN air-quality classification [128], big-data stock-market price prediction [129], bank-churn prediction [130], YOLOv5-based real-time object detection on cloud infrastructure [132], intelligent attendance management with face recognition [133], principal-component-analysis-based insecticide clustering [140], an ensemble of YOLOv5 and Segment Anything for brain-tumour detection [141], transparent AI for drug discovery [142], generative-AI case studies for Industry 4.0 manufacturing [145], and quantum AI for drug discovery and material science [182]. Each combines at least two feature families of different update frequency or structure, the same design constraint that motivated the three-branch architecture in Section IV.

A final set of network, sensing and time-series studies overlaps most directly with the acquisition and alignment steps in Fig. 2: wireless sensor network and MANET routing surveys [12], [59], [67], [70], [74], [79], [107], opportunistic-network and machine-learning fusion reviews [21], [34], speech-difficulty and clarification systems [33], emotion detection through face recognition [35], pollution-trend forecasting with linear, logistic and neural models [46], green IoT and big-data integration for smart cities [92], ant-colony optimisation for NP-hard problems [93], a vertical nanowire tunnel field-effect transistor performance analysis [115], [131], graph neural networks for causal inference in climate science [168], ParseRAG's layout-aware document parsing [170], enhanced LSTM and large-language-model stock forecasting [171], multimodal emotion-based video summarisation [172], comparative machine-learning-versus-large-language-model architecture analysis [173], heterogeneous graph neural networks for supply-network disruption prediction [176], self-learning AI foundations for drones [179], and energy optimisation in smart IoT-enabled homes [191]. Time-varying sensor and weather series are the common element across this cluster and the weather branch of Section IV-B, which is why a recurrent encoder, rather than a convolutional or dense one, is the design choice this paper shares with several of them.

VIII. Conclusion

We combine satellite NDVI, weather variables and soil parameters through three stream-specific encoders and a temporal attention layer, and reach $R^2 = 0.91$ for rice, $R^2 = 0.88$ for wheat and $R^2 = 0.84$ for sugarcane on three held-out test seasons across 120 Indian districts. The hybrid model exceeds a standalone LSTM by 0.06 R^2 for rice and exceeds Random Forest and XGBoost by larger margins, at the cost of a longer per-observation inference time that is immaterial at district scale. Soil parameters raise R^2 by 0.06 on average once satellite and weather streams are already present, and NDVI at the heading stage is the single most predictive feature across all three crops.

Two extensions follow directly from the limitations in Section VII-D: testing the quantile heads' calibration for wheat and sugarcane, and evaluating the model on districts outside the five states used for training to establish whether the architecture, not only the fitted weights, transfers across agro-climatic zones it has not seen.

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