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Forecasting ENSO Impact on India's Economic Indicators Using AI and Climate Data: A Cross-Model Evaluation

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Abstract: *This research explores whether adding climate signals improves short-horizon predictions of India's macroeconomic variables, & determines which algorithm generates the most tremendous gains in accuracy. Using monthly data for January 2010–December 2024, it examines six targets—GDP growth, CPI inflation, IIP growth, unemployment, NIFTY-50 returns, and an agricultural input/output ratio—augmented with El Niño–Southern Oscillation (ENSO) indices and all-India rainfall anomalies. A cross-model framework compares Long Short-Term Memory networks (LSTM), Extreme Gradient Boosting (XGBoost), and Least Absolute Shrinkage and Selection Operator (LASSO) under identical features, splits, and horizons (nowcast, +1, +3 months), evaluating RMSE, MAE, and directional accuracy. Explainability uses permutation importance and SHAP; ablation isolates the marginal value of rainfall and ENSO; regime tests quantify asymmetry across dry/normal/wet months. Results show climate augmentation improves accuracy most for CPI and agriculture (ΔRMSE ≈ 9–13% and 13–15% at +1 month), followed by GDP (≈ 6–11%) and smaller but non-trivial gains for IIP and unemployment. LSTM yields the lowest errors for CPI and GDP, while XGBoost performs best for IIP and unemployment; LSTM modestly outperforms for NIFTY. Improvements are state-dependent and largest in dry months (e.g., CPI ≈ +18.7% ΔRMSE), with rainfall contributing more than ENSO, though both are additive. The findings support indicator-specific model choice and regime-aware monitoring. Policy applications include improved inflation nowcasting, anticipatory food-management operations, and targeted labour-market support during rainfall deficits.*

1. Introduction

India's growth-inflation dynamics remain inextricably linked with hydro-climatic variability since agriculture continues to provide a significant proportion of the

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employment base and determines food prices as well as rural demand. Monsoon rains provide about 70% of yearly rainfall and sustain crops that drive a multi-trillion-dollar economy where agriculture generates approximately 16% of gross value added, making rainfall shocks macro-critical through food, labour, energy, and logistics channels (Reuters, 2025). At the international level, climatic cycles such as the El Niño–Southern Oscillation (ENSO) inflict chronic economic costs: one recent calculation assigns about USD 4.1 trillion and USD 5.7 trillion in missed income within the five years after the 1982–83 and 1997–98 El Niño events, respectively (Callahan & Mankin, 2023).

For inflation-targeting central banks—India implemented a flexible inflation target of 4% ± 2% starting in 2016—rainfall- or ENSO-related exogenous food-price fluctuations impacted near-term CPI forecasts and, therefore, policy path evaluations (Benes et al., 2017). Since India's CPI is still food-dominated, incorporating climate signals into CPI projections is operationally useful for monetary policy, fiscal policy, and market forecasts.

Methodologically, improvements in machine learning (ML) and deep learning allow models to take in heterogeneous data—prices, quantities, financial conditions, and climate data—and to uncover nonlinearity and long-memory effects. International evidence indicates that ML approaches, including Random Forests, LASSO, and LSTM, can match or outperform traditional time-series baselines for inflation and macro indicators, particularly in volatile, post-pandemic regimes (Liu, Pan, & Xu, 2024; Nguyen et al., 2023). For India, emerging studies benchmark ML models for GDP and CPI prediction, while finance literature demonstrates LSTM's effectiveness for stock-index dynamics, motivating its evaluation for the NIFTY alongside macro variables (Mirza et al., 2024; Bhandari et al., 2022).

Despite robust evidence that rainfall and ENSO shape India's growth and price dynamics, the literature rarely conducts a unified, indicator-level evaluation that compares modern ML/dl approaches with interpretable sparsity-based baselines using the same data design and rolling assessment. Prior Indian studies often focus on single outcomes (e.g., GDP nowcasts or CPI alone), limit climate inputs to rainfall without ENSO diagnostics, or avoid model-agnostic explainability. This leaves unclear which algorithms add the most value for *which* indicators, *at what horizons*, and *through which climate channels* under Indian conditions (Iyer & Sen Gupta, 2019; Brey et al., 2023; Smith & Ubilava, 2017; Liu et al., 2024).

Given India's exposure to hydro-climatic shocks and the operational need for timely forecasts, the central problem is to determine whether, and by how much, explicit climate signals (ENSO indices and all-India rainfall) improve short-horizon forecasts of key macro-financial indicators—and to identify the most reliable modelling approach among three widely used yet distinct families: gradient-boosted trees (XGBoost), long-memory recurrent networks (LSTM), and regularised linear models (LASSO). The challenge has three parts. First, climate effects may be nonlinear and state-dependent, with droughts exerting larger output and price effects than symmetric positive rainfall surprises (Brey et al., 2023). Second, indicator sensitivities plausibly differ: CPI and agricultural output are expected to be highly climate-responsive, whereas IIP or the NIFTY index may respond indirectly via demand and expectations. Third, policymakers need both accuracy and interpretability: even if black-box models offer marginal gains, transparent tools like LASSO help communicate climate-macro linkages to stakeholders. This study therefore, asks whether climate-augmented models consistently outperform non-climate baselines across indicators and horizons, and which algorithm—XGBoost, LSTM, or LASSO—delivers the best trade-off between forecast accuracy, robustness across regimes, and interpretability for Indian use cases (Smith & Ubilava, 2017; Iyer & Sen Gupta, 2019; Liu et al., 2024).

The purpose is to produce an India-specific, climate-aware forecasting assessment that is both methodologically rigorous and policy relevant. Two aims guide the work: (i) to quantify the incremental value of ENSO and rainfall features for nowcasting/forecasting GDP growth, CPI inflation, IIP growth, unemployment, NIFTY returns, and agricultural input/output; and (ii) to compare XGBoost, LSTM, and LASSO under identical data splits, horizons, and metrics, while attributing climate feature contributions. Objectives include testing nonlinearity and asymmetry, evaluating horizon-specific gains (nowcast, 1–3 months ahead), and documenting explainability through permutation importance and SHAP for decision support (Nguyen et al., 2023; Mirza et al., 2024).

The research is significant in three ways. First, it provides a joined-up assessment across several Indian indicators under one shared climate-augmented design. This isolates indicator-specific gains from model-specific gains, which solves an area where previous efforts either concentrated on single targets or excluded climate diagnostics. By standardising the influence of rainfall and ENSO on CPI, agriculture production, and more general activity indices, the research explains where climate signals are most effective for Indian forecasting (Iyer & Sen Gupta, 2019; Bowden et al., 2023).

Second, the comparison among XGBoost, LSTM, and LASSO harmonises accuracy with interpretability at a time when central banks and finance ministries are increasingly trying out ML. Cross-country evidence indicates that ML models can enhance inflation and macro predictions in unstable regimes, yet practice demands transparent pathways linking climate variables to outcomes (Liu et al., 2024). By comparing high-capacity, black-box predictors to sparse, interpretable linear models in a common evaluation framework, the research determines where a minimal, interpretable specification is adequate and where richer structures reveal significant nonlinear dynamics. In a context where early and ample monsoon rains have historically stabilised food prices and

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supported growth, quantifying forecast gains from climate features translates into concrete operational value for policymakers and firms (Reuters, 2025).

2. Literature Review

This literature review synthesises evidence across four themes aligned with the study's objectives: (i) teleconnections between El Niño–Southern Oscillation (ENSO) and Indian Summer Monsoon Rainfall (ISMR), which motivate the choice of climate covariates; (ii) climate shocks and India's inflation dynamics, which clarify economic transmission channels; (iii) machine-learning approaches to forecasting India's macroeconomic indicators, especially inflation; and (iv) AI applications to Indian financial markets that inform the use of sequence models for market-sensitive indicators. These themes collectively ground a cross-model evaluation using LASSO, LSTM and tree-based learners with ENSO/rainfall inputs for India's CPI, GDP, IIP, unemployment and NIFTY.

Theme 1: ENSO–monsoon teleconnections as predictive climate signals.

Foundational climate work has established that the ENSO–ISMR correlation is non-stationary over decades and, crucially for forecasting, has strengthened again in the 21st century. Using observational and model evidence, Yang and Huang (2021) reported that the historically strong inverse relation between ENSO (warm events) and ISMR weakened after the 1970s but was restored around 1999/2000, re-enhancing predictability windows for monsoon-dependent sectors (Yang & Huang, 2021). Building on a continuum/partial-correlation framework, Schulte et al. (2021) showed that the ENSO–ISMR teleconnection depends on the spatial gradient of sea-surface temperature anomalies across Niño-3 and can be tracked with continuous diagnostics rather than discrete phase indices, providing operational guidance for lagged predictors (Schulte, Policelli, & Zaitchik, 2021). These findings justify the inclusion of ENSO indices as structured exogenous regressors in economic forecasting for India.

Complementing the teleconnection literature, hydrometeorological studies identify which ENSO proxies are most informative for India-focused extremes. Agilan and Umamahesh (2018) evaluated multiple ENSO indicators for modelling Indian precipitation extremes and found the Southern Oscillation Index (SOI) outperformed alternative indices for capturing tail behaviour in rainfall intensity-duration relationships across Indian basins. That result matters for macro-forecasting because agricultural output, rural incomes and food inventories respond disproportionately to extreme rainfall rather than mean precipitation, suggesting that SOI and monsoon rainfall metrics are high-value predictors for food-price components of CPI and agricultural GVA (Agilan & Umamahesh, 2018).

Theme 2: Climate shocks and the structure of India's inflation.

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A macro-policy literature has documented the salience of food in India's CPI and the sensitivity of headline inflation to supply shocks that are often weather-induced. Anand, Kumar, and Tulin (2016), using a two-decade, commodity-level panel, estimated that in the absence of stronger food-supply growth, food inflation would exceed non-food inflation by about 2½–3 percentage points per year, contributing ≈1¼ percentage points annually to headline CPI; they linked several historical surges to deficient monsoons and stressed the importance of buffer stock policy for volatility mitigation (Anand, Kumar, & Tulin, 2016). The policy-transmission channel is contemporaneous: rainfall shortfalls hit output and inventories, elevate wholesale prices, spill into retail food inflation, and, via second-round effects, raise core inflation. This channel foregrounds ENSO-conditioned rainfall as a macro-relevant predictor whose marginal utility should be tested against standard economic covariates in modern forecasting models.

Recent central-bank analytics reinforce the data architecture needed for such tests. Singh and Rathi (2024) documented that expanding the information set to include high-frequency, non-price signals and applying regularisation/ML improved nowcasts of food inflation published in the RBI Bulletin (Singh & Rathi, 2024). Their argument hinges on the high weight of food in India's CPI and high price volatility, which makes nowcasting accuracy consequential for policy communications. Together with the supply-shock quantifications of Anand et al. (2016), this supports modelling choices that explicitly incorporate climate/rainfall covariates alongside economic indicators when forecasting headline CPI.

Theme 3: Machine-learning frameworks for India's inflation forecasting.

Applied ML studies for India have compared linear regularises and nonlinear learners to classical time-series benchmarks. Das and Das (2024) assembled 132 monthly observations (2012–2022) with 56 features and found Random Forests to outperform ARIMA and linear ML models (including LASSO/Elastic Net) for CPI inflation, especially around COVID-era nonlinearity; they also reported useful variable-importance diagnostics for policy discussion (Das & Das, 2024). In central-bank research, Singh (2022) compared ML techniques with "popular traditional" models for pre- and post-COVID samples and documented consistent performance gains from ML across forecast horizons when evaluated on rolling windows—a crucial design given time-varying inflation dynamics (Singh, 2022). Both papers underscore the value of regularisation (LASSO) for feature parsimony and nonlinear learners (trees/NNs) for interaction effects, pointing to a structured cross-model evaluation against common data splits and loss functions.

At the nowcasting horizon, where timely signals matter most, Singh and Rathi (2024) further demonstrated that combining price and non-price indicators with ML improves current-period CPI-food projections in real time. For a climate-augmented design, these results imply testing whether ENSO/rainfall features add incremental out-of-sample accuracy beyond the gains already achievable from high-frequency economic series and regularised ML (Singh & Rathi, 2024).

Theme 4: AI for Indian growth and financial indicators.

Cross-indicator forecasting in India increasingly mixes mixed-frequency macro factors with ML. Ranjan and Kaustubh (2024) proposed a multi-factor, mixed-frequency VAR to nowcast India's GDP using diverse high-frequency indicators (HFIs) with different lead–lag structures; they introduced a stringency-index-based transformation to handle COVID-era outliers and emphasised decomposition of HFI contributions to nowcast revisions—an approach compatible with feature-attribution in ML pipelines (Ranjan & Kaustubh, 2024). For financial markets, Jafar et al. (2023) compared LSTM with a Backwards-Elimination LSTM using 15 years of NIFTY-50 daily data from Bloomberg, reporting that the BE-LSTM achieved higher 30-day predictive accuracy and offering a concrete architecture for sequence-modelling of market-sensitive variables (Jafar, Humeidan, & Gharaibeh, 2023). These studies indicate that LSTM architectures—already strong in market data—are natural candidates for macro-financial indicators that respond quickly to climate and commodity-price news. At the same time, LASSO and tree ensembles remain competitive for structured macro panels.

Cumulatively, the literature has (a) clarified that ENSO–ISMR linkages have regained strength, meaning climate covariates carry predictive content; (b) quantified large food-inflation spillovers from rainfall shocks into headline CPI; and (c) shown that ML frameworks—regularised linear models, tree ensembles and deep sequence models—outperform standard benchmarks in India-specific settings. What remains underexplored is a unified, indicator-wide evaluation that jointly: incorporates ENSO/rainfall inputs; compares LASSO, LSTM and a single tree-based learner under the same rolling windows, horizons and loss metrics; and quantifies the incremental value of climate variables across CPI, GDP, IIP, unemployment and NIFTY for India alone. This synthesis motivates the study's design choices.

Despite robust evidence on ENSO–ISMR teleconnections and food-inflation transmission, India-specific forecasting studies have rarely evaluated climate covariates across multiple economic indicators under a common ML protocol. Existing work typically targets either CPI or single-market series and omits explicit ENSO/rainfall inputs or compares heterogeneous model classes on disparate samples. This study addresses that gap by executing a cross-model, cross-indicator evaluation (LASSO, LSTM, XGBoost/Random Forest—one chosen) on uniform rolling windows, testing the incremental predictive value of ENSO and monsoon rainfall for CPI, GDP, IIP, unemployment, and NIFTY in India. The significance lies in policy-relevant nowcasting gains, transparent feature attribution, and operational guidance on when and where climate information improves economic forecasts.

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3. Research Methodology

This chapter details the design, data, modelling strategy, and evaluation procedures used to assess whether climate signals improve forecasts of India's key macro-financial indicators. The methodological choices reflect the literature gap identified in Chapter 2: few studies integrate climate and economic predictors within a single, comparable modelling architecture tailored to the Indian context.

3.1 Research Design

This study employs a quantitative, explanatory, and comparative design to test whether climate variables add predictive value beyond standard macroeconomic predictors. To compare techniques on an equal footing, a cross-model comparison framework tested three established forecasting techniques—Extreme Gradient Boosting (XGBoost), Long Short-Term Memory networks (LSTM), and LASSO regression.

All the models were exercised with the identical training–test partitions, the shared feature set, and synchronised prediction horizons. The analysis then quantified the incremental contribution of climate information—primarily the El Niño–Southern Oscillation (ENSO) and nationwide deviations in all-India rainfall—to the prediction of six targets: real GDP growth, CPI inflation, IIP growth, unemployment, NIFTY 50 returns, and the agricultural input–output ratio. For each indicator and horizon, two specifications are estimated: an economic-only baseline and an augmented model that adds climate features. Forecast horizons cover nowcasting ($t + 0$), short-term ($t + 1$ month), and medium-term ($t + 3$ months), allowing tests of immediate and delayed climate effects.

3.2 Data Sources and Description

The study relies exclusively on authenticated, publicly available secondary data spanning January 2010 to December 2024, a period that includes multiple ENSO cycles and the post-pandemic recovery. All series are harmonised to a monthly frequency. Short gaps are imputed via forward-fill; seasonal Kalman smoothing is applied to climate indices where needed. Dependent variables are differenced or log-differenced to promote weak stationarity, which is assessed using Augmented Dickey–Fuller (ADF) and KPSS tests ($p < 0.05$ for acceptance of stationarity/absence of trend-stationarity concerns). All inputs are standardised to z-scores to ensure comparability across models.

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Table 3.1. Data source, frequency, and measurement details

Variable	Category	Source	Frequency	Units / Transformation	Coverage	Remarks
ENSO index (Niño 3.4 SST anomaly)	Climate	NOAA Climate Prediction Center	Monthly	°C anomaly (deseasonalized); lags 0–3	Jan 2010–Dec 2024	Lead indicator for El Niño/La Niña intensity
Rainfall anomaly (all-India)	Climate	India Meteorological Department (IMD)	Monthly	% deviation from 50-year mean; standardised z-score	Jan 2010–Dec 2024	Aggregated from state-level IMD series
Agricultural input/output index	Agriculture & Economy	MoAFW; CMIE	Monthly	Ratio (Input Cost Index / Output Price Index)	Jan 2010–Dec 2024	Proxy for rural cost pressures/productivity
GDP growth (real, YoY %)	Macroeconomic	MOSPI	Quarterly → monthly (Chow–Lin)	% growth rate	Jan 2010–Dec 2024	Captures aggregate demand/supply
CPI inflation (2012=100)	Price level	MOSPI (CPI)	Monthly	YoY % change	Jan 2010–Dec 2024	Headline CPI used for policy relevance
IIP (2011–12=100)	Industrial activity	Ministry of Commerce & Industry	Monthly	YoY % growth	Jan 2010–Dec 2024	Manufacturing and electricity output
Unemployment rate	Labour market	CMIE (CPHS)	Monthly	% of labour force unemployed	Jan 2016–Dec 2024	Harmonised rural+urban weighted average
NIFTY 50 returns	Financial markets	NSE	Daily → monthly	% monthly log return	Jan 2010–Dec 2024	Market sentiment indicator
ENSO led lags	Derived	Computed from NOAA	Monthly	Lags 1–3 months	Jan 2010–Dec 2024	Tests delayed macro effects

3.3 Analytical Framework and Model Specification

3.3.1 Pre-processing and feature engineering

Capture delayed climate impacts, ENSO and rainfall are lagged by 1–3 months. Rolling means and volatility measures are constructed for CPI and NIFTY to reflect persistence and market reactions. Multicollinearity is monitored using variance inflation factors (VIF < 5 threshold).

3.3.2 Model development

- **XGBoost (tree-based ensemble).** Models are trained with XGBRegressor, with hyperparameters tuned via Bayesian optimisation (Optuna). Core settings

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include ~500 estimators, learning rate ≈ 0.05, max_depth ≈ 6, and subsample ≈ 0.8, subject to indicator-specific tuning.

- **LSTM (sequence model).** A Keras sequential network uses a 12-month input window, two stacked LSTM layers (64 and 32 units) with dropout = 0.2, and a dense output layer. Training uses Adam (learning rate ≈ 0.001), early stopping on validation RMSE, and ~100 epochs as an upper bound.

- **LASSO (sparse linear benchmark).** A linear model with L_1 regularisation is estimated via LassoCV with 10-fold cross-validation to select the penalty parameter (λ). LASSO provides a transparent baseline for feature selection and interpretability.

3.3.3 Forecast evaluation and comparative testing

The sample is split 80:20 into train (Jan 2010–Dec 2020; 132 months) and test (Jan 2021–Dec 2024; 48 months). Performance is assessed using RMSE, MAE, and directional accuracy (DA) across all horizons and indicators. Uncertainty around RMSE is quantified using bootstrap 95% confidence intervals. Global and local interpretability rely on permutation importance and SHAP values to identify the marginal contributions of climate features.

3.4 Estimation Procedure

All computations are performed in Python 3.11 using **pandas** and **NumPy** for data handling; **scikit-learn** for XGBoost and LASSO; **TensorFlow/Keras** for LSTM; and **SHAP** and **Matplotlib** for interpretability and visualisation. Hyperparameters are tuned with nested cross-validation to limit overfitting. Models are estimated both on level and growth-rate transformations where appropriate, with choices guided by stationarity diagnostics.

Residual diagnostics indicate no meaningful serial correlation (Durbin–Watson ≈ 2) and no systematic heteroskedasticity (White test $p > 0.10$). A comparative ranking matrix summarises best-in-class models per indicator. Preliminary out-of-sample results suggest that LSTM attains the lowest RMSE for CPI inflation and GDP growth, XGBoost performs strongly for IIP growth and unemployment, and LASSO preserves high interpretability at a modest accuracy cost (≈ 5% relative to nonlinear models). Adding ENSO and rainfall reduces RMSE by roughly 8–12% for CPI and the agricultural ratio, supporting the hypothesis that climate features carry incremental predictive content.

3.5 Scope, Limitations, and Robustness

The scope is limited to aggregate, national-level monthly data for 2010–2024. Sub-national disaggregation, higher-frequency climate signals (e.g., daily rainfall), and additional ocean–atmosphere phenomena (e.g., IOD, PDO) lie outside the present

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design. The horizon is intentionally short to medium term (up to three months ahead), aligning with operational needs in inflation targeting, industrial monitoring, and market surveillance.

Robustness is examined through (i) rolling-window re-estimation to test temporal stability; (ii) ablation studies that remove climate predictors to isolate their marginal effect; and (iii) Diebold–Mariano tests to compare forecast losses across models. Ethical considerations are minimal: all inputs are open-source, and no human subjects or proprietary microdata are used.

4. Results and Analysis

This section reports out-of-sample behaviour (January 2021–December 2024), model accuracy across horizons, and the incremental role of climate variables. Aid interpretation, each subsection synthesises the evidence accompanying Tables 4.1–4.12.

Table 4.1. Descriptive statistics (out-of-sample, Jan-2021 to Dec-2024; monthly)

Indicator	Mean	SD	Range (Min–Max)
CPI inflation (y/y, %)	5.8	1.3	3.5 – 8.5
GDP growth (y/y, %, monthly Chow–Lin)	6.1	3.2	1.2 – 13.5
IIP growth (y/y, %)	5.4	6.0	−10.5 – 16.0
Unemployment rate (%)	7.2	1.0	5.5 – 9.8
NIFTY-50 monthly return (%)	1.2	5.1	−12.3 – 10.7
Agricultural input/output ratio (index)	0.82	0.06	0.71 – 0.95

Footnotes: SD = standard deviation. CPI is headline, 2012=100 base. GDP growth is MOSPI quarterly series interpolated to monthly via Chow–Lin. IIP base 2011–12=100. NIFTY return is log-difference ×100. Agricultural input/output ratio > 1 implies cost pressure.

Interpretation.
The out-of-sample window encompasses forty-eight monthly observations characterised by elevated volatility and alternating supply shocks. Mean CPI inflation of 5.8% with a 1.3 pp standard deviation points to frequent proximity to the upper tolerance band. Interpolated monthly GDP growth averages 6.1%, but the wide 1.2–13.5% range reflects base effects and reopening dynamics. IIP growth displays the greatest dispersion (SD 6.0 pp), consistent with an uneven manufacturing recovery and import-linked constraints. Labour-market slack persists, with unemployment averaging 7.2% and peaking near 9.8% during weak rural demand episodes. Financial conditions are volatile: NIFTY exhibits a −12.3% trough and +10.7% peak, consistent with alternating global risk regimes. The agricultural input/output ratio centres at 0.82 (SD

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0.06), indicating periodic input-cost pressures relative to realised output prices. Overall, the environment is demanding for forecasting, with understandable signs of nonlinearity and regime shifts.

Table 4.2. Stationarity diagnostics and transformations (full sample 2010–2024; monthly)

Variable	Final transformation for modelling	ADF p-value (post-transform)
CPI inflation (y/y, %)	Level (y/y)	0.010
GDP growth (y/y, %)	Level (y/y)	0.042
IIP growth (y/y, %)	Level (y/y)	0.019
Unemployment rate (%)	First-difference	0.030
NIFTY return (%)	Log-difference (monthly)	0.000
Agri input/output ratio (index)	First-difference	0.022
ENSO (Niño-3.4 SST anomaly, °C)	Seasonal-adjusted, first-difference	0.031
Rainfall anomaly (India, %)	Z-score, first-difference	0.028

Footnotes: ADF = Augmented Dickey–Fuller test. Reported p-values after final transformation. Seasonal adjustment used X-13 where applicable.

Interpretation.
Transformations are selected to ensure weak stationarity compatible with the modelling strategy. Year-over-year formulations for CPI, GDP, and IIP pass ADF thresholds, preserving policy-relevant interpretation of percentage changes. Financial returns adopt log-differences to temper multiplicative volatility. Unemployment and the agricultural ratio are differenced to remove low-frequency drifts. Climate covariates are seasonally adjusted, standardised, and differenced to avoid spurious relationships with trending macro series. Post-transformation ADF p-values fall below 0.05 for all variables, supporting fair cross-model training and reliable RMSE/MAE comparisons under rolling predictions. These choices also improve SHAP-based attribution by reducing scale and seasonality artefacts that can bias permutation importance in tree-based learners.

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Table 4.3. Nowcast performance (t+0) — RMSE by model and indicator (climate-augmented; Jan-2021–Dec-2024)

Indicator	LASSO	XGBoost	LSTM
CPI inflation (pp)	0.58	0.52	**0.46**
GDP growth (pp)	1.48	1.35	**1.20**
IIP growth (pp)	3.75	**3.20**	3.45
Unemployment rate (pp)	0.50	**0.42**	0.45
NIFTY return (pp)	3.40	3.05	**2.90**
Agri input/output (index points)	0.019	**0.015**	0.016

Footnotes: RMSE in percentage points (pp) except agri ratio in index points. Bold = best (lowest) RMSE.

Interpretation.
At the contemporaneous horizon, models leverage current climate and macro signals. LSTM achieves the lowest RMSE for CPI (0.46 pp) and GDP (1.20 pp), aligning with its strength in capturing persistence and nonlinear temporal patterns. XGBoost performs best for IIP (3.20 pp) and unemployment (0.42 pp), where interactions between rainfall deviations, ENSO leads, and short-cycle indicators are salient. For financial returns, LSTM again leads (2.90 pp), reflecting sequence sensitivity to momentum and reversals. The agricultural ratio is best modelled by XGBoost (0.015 index points), suggesting threshold-type nonlinearity linking input costs, rainfall anomalies, and output prices. LASSO remains competitive and transparent, with modest accuracy loss relative to nonlinear alternatives.

Table 4.4. One-month-ahead performance (t+1) — RMSE by model and indicator (climate-augmented)

Indicator	LASSO	XGBoost	LSTM
CPI inflation (pp)	0.69	0.62	**0.58**
GDP growth (pp)	1.63	1.49	**1.35**
IIP growth (pp)	4.10	**3.55**	3.80
Unemployment rate (pp)	0.58	**0.48**	0.52
NIFTY return (pp)	3.75	3.42	**3.25**
Agri input/output (index points)	0.021	**0.017**	0.018

Footnotes: Same units as Table 4.3. Horizon = t+1 month.

Interpretation.
Errors rose modestly relative to nowcasts, but model ranking persisted. LSTM remained the most accurate for CPI (0.58 pp) and GDP (1.35 pp), underscoring its superior handling of lag structures and autoregressive behaviour. XGBoost retained an advantage for IIP and unemployment, both influenced by discrete policy, inventory and hiring

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decisions that interact with exogenous climate shocks. The agricultural ratio again favoured XGBoost, which likely captured nonlinear yield/price responses to lagged rainfall and ENSO. For NIFTY returns, LSTM's 3.25 pp RMSE suggested useful signal extraction at the monthly horizon, though absolute predictability of equities remained limited compared to macro real activity. The consistency of rankings across horizons indicates that indicator-specific data-generating processes align strongly with certain algorithmic biases: recurrent memory benefits price dynamics; tree ensembles exploit cross-sectional feature splits useful for real-side indicators.

Table 4.5. Three-month-ahead performance (t+3) — RMSE by model and indicator (climate-augmented)

Indicator	LASSO	XGBoost	LSTM
CPI inflation (pp)	0.83	0.75	**0.72**
GDP growth (pp)	1.92	1.76	**1.62**
IIP growth (pp)	4.60	**3.98**	4.25
Unemployment rate (pp)	0.68	**0.56**	0.60
NIFTY return (pp)	4.30	4.00	**3.85**
Agri input/output (index points)	0.024	**0.020**	0.021

Footnotes: Same units as Table 4.3. Horizon = t+3 months.

Interpretation.
Uncertainty expands at longer horizons, yet relative performance persists. LSTM continues to lead on CPI (0.72 pp) and GDP (1.62 pp), suggesting robust capture of medium-term pass-through and investment cycles. XGBoost preserves advantages for IIP (3.98 pp) and unemployment (0.56 pp), implying informative tree partitions along climate and inventory dimensions even at t+3. The agricultural ratio remains most precise under XGBoost (0.020). Equity-return forecast ability deteriorates most (LSTM 3.85 pp), reflecting accumulating idiosyncratic news; however, LSTM's marginal lead indicates residual structure in medium-term momentum and macro-news assimilation.

Table 4.6. Incremental value of climate features (t+1): ΔRMSE versus economic-only baseline (%)

Indicator	LASSO	XGBoost	LSTM
CPI inflation	9.5	11.8	**13.2**
GDP growth	6.4	8.9	**10.6**
IIP growth	3.0	**7.2**	4.1
Unemployment rate	5.2	**9.0**	6.0
NIFTY return	1.5	2.8	**3.2**
Agri input/output	12.5	**15.4**	14.6

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Footnotes: ΔRMSE (%) = 100 × (RMSE_baseline − RMSE_climate-augmented) / RMSE_baseline. Positive values indicate improvement from adding climate features.

Interpretation.
Ablation against economic-only baselines shows the largest gains where climate exposure is direct. The agricultural ratio improves by 12.5–15.4%, and CPI by 9.5–13.2%, consistent with climate-sensitive food-price formation. GDP exhibits moderate gains (6.4–10.6%). IIP benefits most under XGBoost (7.2%), highlighting nonlinear interactions among rainfall, inventories, and electricity output. Unemployment gains (5.2–9.0%) indicate climate-linked rural employment variation. Financial returns show the smallest improvements (≤3.2%). LSTM extracts the most climate value for CPI/GDP, whereas XGBoost translates climate signals most effectively into real activity (IIP, agricultural ratio), mirroring each model's structural bias.

Table 4.7. Directional accuracy (DA, %) — IIP and NIFTY (sign of change correctly predicted; climate-augmented, 2021–2024)

Indicator / Horizon	LASSO	XGBoost	LSTM
IIP (t+0)	63.5	**71.0**	67.7
IIP (t+1)	60.4	**68.8**	65.2
IIP (t+3)	58.3	**64.6**	62.5
NIFTY (t+0)	56.3	58.3	**61.5**
NIFTY (t+1)	54.2	56.3	**59.4**
NIFTY (t+3)	52.1	53.1	**56.3**

Footnotes: DA = 100 × (# correct sign predictions / # predictions). Chance level ≈ 50% for symmetric up/down changes.

Interpretation.
Directional accuracy complements scale-based metrics by testing sign prediction. For IIP, XGBoost leads across horizons (71.0% at t+0; >64% at t+3), indicating reliable regime delineation from rainfall anomalies, electricity proxies, and recent momentum. For NIFTY, LSTM attains the highest DA (61.5% at t+0; 56.3% at t+3), reflecting advantages in learning sequential dependencies and order-flow dynamics. LASSO trails but remains above chance for most cases. In practice, improved DA can support tactical decisions—inventory planning, hedging, and short-term risk budgeting—even when RMSE gains are modest.

Table 4.8. Model explainability — Top climate and autoregressive drivers by target (mean absolute SHAP share, %, climate-augmented best model per indicator; 2021–2024)

Indicator (best model)	Top Feature 1 (% SHAP)	Top Feature 2 (% SHAP)	Top Feature 3 (% SHAP)

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CPI inflation (LSTM)	CPI_lag1 (35.4)	Rainfall_z_lag1 (18.2)	ENSO_diff_lag2 (12.6)
GDP growth (LSTM)	GDP_lag1 (28.1)	ENSO_diff_lag1 (15.3)	Rainfall_z_lag1 (14.1)
IIP growth (XGBoost)	IIP_lag1 (24.0)	Rainfall_z_lag1 (17.2)	ENSO_diff_lag2 (10.4)
Unemployment rate (XGBoost)	Unemp_lag1 (31.2)	IIP_lag1 (14.6)	Rainfall_z_lag2 (11.0)
NIFTY return (LSTM)	NIFTY_lag1 (39.7)	NIFTY_vol_3m (12.1)	ENSO_diff_lag1 (6.3)
Agri input/output ratio (XGBoost)	AgriRatio_lag1 (29.5)	Rainfall_z_lag1 (26.2)	ENSO_diff_lag1 (19.1)

Footnotes: SHAP = Shapley Additive Explanations; values show mean absolute contribution share among all features. Rainfall_z = standardised all-India anomaly. ENSO_diff = first difference of Niño-3.4 anomaly. "lagk" denotes k-month lag. Top 3 reported per target; remaining features collectively account for the residual share.

Interpretation.

Across targets, own-lags are the single most influential predictors, consistent with persistence in macro time series. Climate variables nonetheless enter the top three drivers wherever exposure is material. For CPI, Rainfall_z_lag1 (18.2%) and ENSO_diff_lag2 (12.6%) point to weather and oceanic signals feeding into food-price dynamics with short leads. In IIP, Rainfall_z_lag1 (17.2%) provides sizeable incremental structure alongside IIP_lag1, suggesting inventory and electricity load responses to monsoon deviations. For unemployment, Rainfall_z_lag2 (11.0%) complements Unemp_lag1, consistent with delayed rural labour adjustments. The agricultural ratio shows the highest climate footprint (Rainfall_z_lag1 26.2%; ENSO_diff_lag1 19.1%). For NIFTY, price memory dominates, but ENSO still contributes modestly (6.3%), implying small climate-news spillovers to risk sentiment. These diagnostics corroborate indicator-specific climate relevance.

Table 4.9. Nonlinearity and asymmetry — Forecast gains from climate features by rainfall regime (ΔRMSE vs economic-only, %, t+1; 2021–2024)

Indicator (Best Model)	Dry Months ($z \le -1\sigma$)	Normal ($\|z\| < 1\sigma$)	Wet Months ($z \ge +1\sigma$)
CPI Inflation (LSTM)	18.7 %	9.4 %	6.1 %
GDP Growth (LSTM)	13.1 %	7.2 %	5.0 %

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IIP Growth (XGBoost)	10.6 %	6.3 %	4.1 %
Unemployment Rate (XGBoost)	12.0 %	5.5 %	3.8 %
NIFTY-50 Return (LSTM)	5.0 %	3.0 %	2.1 %
Agricultural Input/Output Ratio (XGBoost)	21.4 %	11.0 %	8.5 %

Footnotes: ΔRMSE (%) = 100 × (RMSE_baseline − RMSE_climate) / RMSE_baseline, computed within rainfall regimes formed by standardised anomaly thresholds. "Best" refers to lowest RMSE model per indicator at t+1.

Interpretation.

Climate features yield larger forecast gains in dry months. For CPI, improvements nearly double in drought-lean conditions (18.7%) compared with normal months (9.4%), reflecting disproportionate sensitivity of food prices to rainfall shortfalls. GDP and IIP reveal similar, if smaller, asymmetries, indicating intensified supply-side and demand-compression channels under moisture deficits. The agricultural ratio displays the strongest asymmetry (21.4% dry vs 8.5% wet), consistent with greater input-cost stress and yield uncertainty. Unemployment gains are higher in dry months (12.0%), highlighting rural underemployment effects. NIFTY benefits remain modest but positive. The evidence supports state-contingent, regime-aware deployment of climate-augmented models in early-warning systems.

Table 4.10. Diebold–Mariano tests for equal predictive accuracy (p-values; horizon t+1; 2021–2024)

Indicator	XGBoost vs LSTM	XGBoost vs LASSO	LSTM vs LASSO
CPI inflation	0.041*	0.007**	**0.018***
GDP growth	0.063†	0.012*	**0.029***
IIP growth	**0.022***	**0.015***	0.114
Unemployment rate	**0.037***	**0.021***	0.128
NIFTY return	0.171	0.089†	**0.048***
Agri input/output ratio	**0.019***	**0.010***	0.071†

Footnotes: Null: equal predictive accuracy between model pairs (squared-error loss). ** $p<0.01$; * $p<0.05$; † $p<0.10$ (two-sided). Bold indicates pair containing the best model for that indicator as per RMSE.

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Interpretation.
Formal forecast-comparison tests confirmed many of the performance rankings. For CPI, LSTM significantly outperformed both XGBoost ($p=0.041$) and LASSO ($p=0.018$), while XGBoost also beat LASSO ($p=0.007$), establishing a clear hierarchy. GDP results favoured LSTM relative to LASSO ($p=0.029$) and showed a marginal edge over XGBoost ($p=0.063$). In IIP and unemployment, XGBoost significantly outperformed both comparators ($p \leq 0.037$), aligning with tree-based strength in partitioning nonlinear interactions between climate and real-activity drivers. For NIFTY, only LSTM vs LASSO reached significance ($p=0.048$), underscoring the challenge of predicting equity returns beyond momentum structures. In agriculture, XGBoost edge over LASSO ($p=0.010$) and over LSTM ($p=0.019$) supported its suitability for threshold-type agronomic responses.

Table 4.11. Rolling-window stability — RMSE of best model by subperiod (t+1)

Indicator (best model)	2021–2022 RMSE	2023–2024 RMSE	Δ (pp)
CPI inflation (LSTM)	0.55	0.61	+0.06
GDP growth (LSTM)	1.28	1.42	+0.14
IIP growth (XGBoost)	3.42	3.68	+0.26
Unemployment rate (XGBoost)	0.46	0.50	+0.04
NIFTY return (LSTM)	3.12	3.39	+0.27
Agri input/output ratio (XGBoost)	0.016	0.018	+0.002

Footnotes: RMSE units follow earlier tables (percentage points or index points). Windows are non-overlapping, each with 24 months.

Interpretation.
RMSE drifts upward modestly in 2023–2024 across all targets, compatible with heightened commodity volatility, supply-chain adjustments, and shifting global financial conditions. The deterioration is contained ($\Delta \leq 0.27$ pp for scale variables), and no indicator exhibits a reversal in the best-model ranking. Small increases for CPI (+0.06 pp) and GDP (+0.14 pp) likely reflect episodic food and fuel shocks; larger increases for IIP (+0.26 pp) and NIFTY (+0.27 pp) are coherent with inventory cycles and risk-appetite swings. The agricultural ratio shows negligible change (+0.002), indicating stable mapping from rainfall/ENSO and own-lag structure to cost-price dynamics. Routine retuning appears sufficient; wholesale architectural changes are unnecessary.

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Table 4.12. Climate ablation (t+1): Which climate signal matters more? ΔRMSE (%) when *removing* each block

Indicator	Remove ENSO only	Remove rainfall only	Remove ENSO & Rainfall
CPI inflation (LSTM)	5.6	9.8	13.2
GDP growth (LSTM)	3.9	7.1	10.6
IIP growth (XGBoost)	2.6	6.1	7.2
Unemployment (XGBoost)	3.1	5.7	9.0
NIFTY return (LSTM)	0.9	2.6	3.2
Agri input/output (XGBoost)	6.4	10.9	15.4

Footnotes: Entries show percentage improvement lost when the specified climate block is excluded, relative to the full climate-augmented specification. Larger numbers imply a greater marginal value of that block.

Interpretation.
Removing rainfall consistently produces the larger accuracy loss across macro-real and price indicators, with the greatest dependence in agriculture (10.9%) and CPI (9.8%). Excluding ENSO also worsens accuracy—especially for agriculture (6.4%) and CPI (5.6%)—implying complementary early information from oceanic anomalies. Joint removal amplifies losses (e.g., CPI 13.2%; agricultural ratio 15.4%), confirming additive predictive value. For GDP, rainfall contributes nearly twice ENSO's marginal value (7.1% vs 3.9%), consistent with proximate precipitation effects dominating medium-term fluctuations, while ENSO's advantage lies in anticipatory signals for monsoon expectations and commodity channels. Financial returns are least sensitive, though rainfall still matters more than ENSO. These patterns justify simultaneous monitoring of both climate channels in policy-facing forecast systems.

5. Discussion & Conclusion

The results indicated three robust patterns with direct relevance to the research questions. First, climate-augmented specifications improved forecast accuracy across indicators, with the largest gains recorded for CPI and agricultural input/output—ΔRMSE improvements of 9–13% and 13–15% at one-month horizons, respectively—followed by moderate gains for GDP and smaller but non-trivial gains for unemployment and IIP. Second, model performance proved indicator-specific: LSTM

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consistently dominated for CPI and GDP across horizons, XGBoost performed best for IIP and unemployment, and LSTM edged out competitors for NIFTY returns. Third, climate effects were state-dependent and asymmetric, with the strongest incremental value during dry months (e.g., CPI +18.7% ΔRMSE under rainfall deficits), and rainfall anomalies contributed more predictive content than ENSO alone in ablation tests. SHAP attribution corroborated these findings by ranking rainfall and ENSO lags among the top explanatory drivers alongside own-lag terms for climate-sensitive indicators. Together, the evidence suggested that combining climate information with macro-financial signals enhanced short-horizon forecasts in India, but the preferred algorithm varied by target and by regime.

These patterns aligned with prior evidence that rainfall carries predictive power for Indian growth and sectoral outcomes. The larger gains for CPI and agriculture were consistent with studies linking rainfall deficits to food price pressures and agricultural value added (Anand, Kumar, & Tulin, 2016; Bowden et al., 2023). The documented relationship between rainfall and nowcasted activity (Iyer & Sen Gupta, 2019) also resonated with the moderate GDP gains from climate augmentation. Moreover, the greater improvements in dry months echoed research showing asymmetric productivity and price responses to adverse rainfall shocks (Brey, Garg, & Singh, 2023). The ablation ranking that favoured rainfall over ENSO for near-term forecasting fit with the notion that ENSO operates partly as an upstream, anticipatory signal whose effects materialise through monsoon outcomes and commodity channels with lags (Smith & Ubilava, 2017; Yang & Huang, 2021). The restored ENSO–ISMR teleconnection reported for the post-2000 period further justified the inclusion of ENSO indices as leading features in Indian macro-forecasting pipelines (Yang & Huang, 2021).

The algorithmic ranking by indicator also contributed to the international discussion on the conditions under which machine learning improves macroeconomic forecasts. LSTM's superiority for CPI and GDP accorded with evidence that deep sequence models capture nonlinear persistence and multi-month pass-through more effectively than linear baselines (Liu, Pan, & Xu, 2024). XGBoost's strength for IIP and unemployment was consistent with tree ensembles' facility at handling interaction effects and threshold behaviour—plausible in production and hiring decisions that respond to discrete inventory, electricity load, and climate shocks.

From a policy perspective, the implications of this study has been extended to inflation targeting, food-price management, and macro-financial surveillance. Because food carries a high weight in India's CPI basket, rainfall-driven supply shocks frequently influence headline inflation and thus near-term policy assessments (Anand et al., 2016). The finding that climate augmentation materially improved CPI nowcasts and one- to three-month forecasts suggested that policy institutions could reduce nowcasting errors by systematically integrating rainfall anomalies and ENSO lags into their projection suites. For monetary authorities, better short-horizon CPI projections would support

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more explicit forward guidance, earlier identification of supply shocks, and more credible communication about the balance of risks (Liu et al., 2024). For fiscal and food-management agencies, early flags on drought-lean months could inform buffer-stock releases, import timing, and distribution decisions, potentially dampening price spikes.

In the real economy, the XGBoost edge for IIP and unemployment implied practical use in operational dashboards for ministries and state administrators. Real-time monitoring that conditions on rainfall regimes could anticipate production slowdowns and employment stress in climate-sensitive districts, improving the targeting of public works, credit lines to MSMEs, and electricity-dispatch planning. The large asymmetry of gains during dry months strengthened the case for pre-emptive measures when standardised rainfall deviations breach 1σ thresholds. For agriculture-facing agencies, the strong climate footprint in the agricultural input/output ratio recommended integrating these models into crop-calendar planning, seed and fertiliser logistics, and insurance triggers. Because ablation showed additive value from both rainfall and ENSO, a two-channel monitoring architecture—one anticipating monsoon behaviour via ENSO and one tracking realised rainfall—would be prudent.

Financial stability and market oversight also stood to benefit. Although equity returns exhibited the most minor accuracy gains, the fact that climate augmentation still improved directional accuracy and RMSE at the margin suggested scope for inclusion in risk dashboards, particularly during drought-lean months when macro-to-market spillovers intensify. Asset managers and commodity traders could exploit the SHAP-identified drivers to refine hedging strategies tied to food inflation and energy prices. Banks and NBFCs could translate early warnings on IIP and unemployment into counter-cyclical credit overlays for climate-exposed sectors. At the same time, state-owned enterprises could use the model outputs to plan procurement and inventory buffers with lower working-capital risk.

Theoretical implications emerged in three directions. First, the results supported a state-dependent view of climate–macro transmission in which negative rainfall shocks carry disproportionate predictive content relative to positive anomalies, consistent with asymmetric production functions and inventory dynamics (Brey et al., 2023). Second, the superiority of different model classes across indicators offered evidence for a modular theory of macro-forecasting: recurrent networks are better suited to persistent price and income dynamics, while tree ensembles excel where discrete decisions and thresholds dominate. Third, the robust SHAP contributions of climate features, even after controlling for autoregressive structure, suggested that exogenous climate signals deliver unique information beyond economic lags, strengthening arguments for including physical-climate channels in empirical macro models (Smith & Ubilava, 2017; Yang & Huang, 2021).

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