SUPPLEMENTARY MATERIAL

AI-Enabled Climate-Phenology Coupling and Future Productivity Assessment for Semi-Arid Bundelkhand under CMIP6 Forcings

Extended Methods, Statistical Tables, Model Specifications, and Technical Appendices

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S1. Overview and Purpose of Supplementary Material

This document provides the complete extended technical details supporting the abstract presented at the *EGU General Assembly 2026* (Abstract EGU26-22038). The main abstract summarises findings from an integrated AI-enabled framework that quantifies climate-driven shifts in vegetation phenology and agricultural productivity across the semi-arid Bundelkhand region of Central India. Given the space constraints of the abstract format, numerous methodological specifics, model configurations, statistical validation tables, and projection details could not be presented in the main text. This supplementary material addresses that gap comprehensively.

The document is organised to mirror the analytical workflow: beginning with data acquisition and preprocessing, progressing through phenological metric derivation, CMIP6 model setup and bias correction, machine learning model architectures, explainability analysis, and culminating in extended results disaggregated by scenario, time period, and administrative district. A technical appendix consolidates the mathematical formulations employed throughout.

> **Note on Reproducibility:** All analyses were performed in Python 3.10 using open-source libraries. Climate projection data were obtained from the ESGF CMIP6 portal. Remote sensing imagery was accessed through Google Earth Engine (Sentinel-2) and the NASA Land Processes DAAC (MODIS MCD12Q2). All bias-corrected climate data follow the ISIMIP3BAS protocol (v3.0), publicly available from the ISIMIP data portal (isimip.org).

S2. Study Area and Regional Context

S2.1 Geographic Delineation of Bundelkhand

The Bundelkhand region occupies approximately 70,000 km² spanning 13 administrative districts across two Indian states: seven in Madhya Pradesh (Sagar, Damoh, Panna, Chhatarpur, Tikamgarh, Datia, Gwalior) and six in Uttar Pradesh (Jhansi, Lalitpur, Hamirpur, Mahoba, Banda, Chitrakoot). The region lies between latitudes 23°10'N–26°30'N and longitudes 78°10'E–81°20'E. Elevation ranges from approximately 80 m a.s.l. in the alluvial northern plains to over 600 m on the Vindhyan plateau.

Land cover is heterogeneous, comprising rainfed cropland (~48%), degraded scrub forest and open woodland (~22%), fallow/waste land (~18%), and water bodies, settlements, and other surfaces (~12%). The dominant soil types are red and yellow lateritic soils with poor water-retention capacity, sandy loams along river valleys, and shallow rocky soils on elevated plateaus — all factors that amplify hydrological stress under rainfall variability.

S2.2 Climate Characteristics and Hydrology

Bundelkhand's climate is classified as semi-arid BSh (hot steppe) under the Köppen-Geiger classification. Mean annual rainfall ranges from 800 to 1,100 mm, of which approximately 80–85% is delivered by the southwest monsoon (June–September). Inter-annual variability in monsoon onset and intensity is high (coefficient of variation ≈ 25–35%), and the region has experienced at least 16 meteorologically defined drought years since 2000. Mean annual maximum temperature (Tmax) has increased by approximately 0.4°C per decade since 1980 (based on IMD gridded data at 1° resolution), with the summer pre-monsoon season (March–May) showing the steepest warming trend.

Table S1 Climatic normals (1981–2010) for the Bundelkhand region by season.

Season	Period	Mean Tmax (°C)	Mean Tmin (°C)	Rainfall (mm)	VPD (kPa)
Winter (Rabi)	Nov–Mar	24.5	9.8	52	0.84
Pre-monsoon	Apr–May	40.2	24.6	18	3.62
Monsoon (Kharif)	Jun–Sep	34.1	24.0	821	1.22
Post-monsoon	Oct	32.8	18.5	46	1.75
Annual	Jan–Dec	**32.9**	**18.4**	**937**	**1.88**

S3. Data Sources and Preprocessing

S3.1 Remote Sensing Data

Sentinel-2 Multispectral Imagery

Level-2A (Bottom-of-Atmosphere, BOA) Sentinel-2 imagery was obtained from the Copernicus Open Access Hub via Google Earth Engine for the period 2017–2024. Bands B4 (Red, 665 nm) and B8 (NIR, 842 nm) at 10-metre resolution were used for NDVI; B4, B8, and B11 (SWIR, 1610 nm) for EVI. A cloud-masking procedure used the Scene Classification Layer (SCL) combined with S2cloudless, retaining only pixels with cloud probability below 10%. Temporal compositing used a 16-day median composite to match the MODIS phenometric product period.

MODIS Land Cover Dynamics (MCD12Q2 v006)

The MODIS Vegetation Phenology product (MCD12Q2, Collection 6) provides annual phenological metrics at 500-metre resolution for 2001–2022, using EVI2 smoothed with the Savitzky-Golay filter over MODIS Terra + Aqua composites. Layers used: *Greenup* (date when EVI2 first reaches 15% of annual amplitude above baseline), *Peak* (date of annual maximum EVI2), *Senescence* (date when EVI2 last exceeds 15% amplitude on declining limb), and *Dormancy* (date of minimum EVI2).

Table S2 Remote sensing datasets used in this study.

Dataset	Spatial Res.	Temporal Period	Variables Extracted	Source
Sentinel-2 L2A	10 m	2017–2024	NDVI, EVI	Copernicus / GEE
MODIS MCD12Q2 v006	500 m	2001–2022	SOS, EOS, LOS, Peak	NASA LP DAAC
MODIS MOD13A1	500 m	2001–2022	16-day NDVI, EVI	NASA LP DAAC
MODIS MCD12Q1	500 m	2001–2022	Land cover type	NASA LP DAAC

S3.2 Climate Data

IMD Gridded Climate Data

Daily gridded climate data from the India Meteorological Department (IMD) were used at 0.25° × 0.25° resolution for rainfall (1901–2022) and 1° × 1° for maximum and minimum temperature (1951–2022). VPD was derived from IMD temperature and relative humidity data using standard psychrometric equations (see Appendix S11.3). Heatwave duration was defined using the IMD criterion: three or more consecutive days with Tmax at or above 40°C, or 4.5°C above the climatological normal.

NASA POWER

NASA Prediction Of Worldwide Energy Resources (POWER) data supplemented daily solar radiation (W m^{-2}), specific humidity, dew-point temperature, and wind speed at 0.5° × 0.5° spatial resolution for 2001–2022, providing a consistent global reanalysis product to bridge gaps in the IMD observation network.

Table S3 Climate variables, sources, and temporal coverage used in the study.

Variable	Source	Spatial Res.	Period	Role
Daily rainfall	IMD gridded	0.25°	1901–2022	Monsoon onset, deficit
Tmax, Tmin	IMD gridded	1°	1951–2022	Heat stress metric
Vapour Pressure Deficit	Derived (IMD + POWER)	0.5°	2001–2022	Primary driver
Solar radiation	NASA POWER	0.5°	2001–2022	Phenology model input
Heatwave duration	Derived (IMD Tmax)	1°	1951–2022	Stress metric
CMIP6 projections	ESGF portal	~100 km	2015–2100	Future forcing

S4. Phenological Metrics: Definitions and Computation

S4.1 Vegetation Index Time-Series Construction

The continuous vegetation index time series for phenology extraction was constructed from the 16-day MODIS MOD13A1 EVI product, supplemented by 16-day median Sentinel-2 NDVI composites for 2017–2024. All time series were standardised to day-of-year (DOY, 1–365) intervals through linear temporal resampling before smoothing.

S4.2 Temporal Smoothing Methods

Method 1: Harmonic (Fourier) Regression

A truncated Fourier series was fitted to each annual VI time series using ordinary least squares, retaining $K = 3$ harmonics ($T = 365$ days):

$$\mathrm{VI}(t) = a_0 + \sum_{k=1}^{K} \left[a_k \cos\left(\frac{2\pi kt}{T}\right) + b_k \sin\left(\frac{2\pi kt}{T}\right) \right]$$

This captures the dominant annual and semi-annual periodicities of the monsoon-driven vegetation signal while suppressing high-frequency noise from cloud and sensor artefacts.

Method 2: Double-Logistic Curve Fitting

For crop phenology, the double-logistic function (Elmore et al. 2012) was applied:

$$\mathrm{VI}(t) = v_{\min} + (v_{\max} - v_{\min}) \cdot \left[\frac{1}{1 + e^{-r_1(t - I_1)}} - \frac{1}{1 + e^{-r_2(t - I_2)}} \right]$$

where I_1 and I_2 are inflection points corresponding to green-up and senescence, r_1 and r_2 are rates of rise and decline, and $v_{\min}$, $v_{\max}$ are the annual minimum and maximum vegetation index values. Parameters were estimated by non-linear least squares (Levenberg-Marquardt algorithm).

For natural vegetation pixels, harmonic regression provided superior fit statistics (mean RMSE = 0.032 EVI units vs. 0.041 for double-logistic). For cropland pixels with sharp green-up and rapid senescence typical of rabi crops, the double-logistic model outperformed harmonic regression (mean RMSE = 0.028 vs. 0.039). Optimal method was selected pixel-by-pixel based on the Akaike Information Criterion (AIC).

S4.3 Extraction of SOS, EOS, LOS, and Peak Greenness

Table S4 Phenological metrics: definitions, extraction thresholds, and units used in this study.

Metric	Abbrev.	Definition	Threshold / Criterion	Unit
Start of Season	SOS	DOY when VI first rises above threshold on ascending limb	20% of seasonal amplitude above local minimum	DOY
End of Season	EOS	DOY when VI descends below threshold on declining limb	20% of seasonal amplitude above local minimum	DOY
Length of Season	LOS	Duration of the active growing season	LOS = EOS − SOS	Days
Peak Greenness	PG	Maximum VI value attained during growing season	Global maximum of smoothed VI	EVI (dimensionless)
Growing Season Integral	GSI	Area under VI curve between SOS and EOS	Numerical integration (trapezoidal rule)	EVI·days

The seasonal amplitude is defined as the difference between annual maximum and minimum VI values. Threshold-based methods were preferred over absolute thresholds given the substantial spatial variability in baseline VI values across land-cover types. The 20% relative threshold is consistent with MODIS MCD12Q2 conventions, enabling direct cross-validation with the MODIS phenometric product.

S5. CMIP6 Model Specifications and Bias Correction

S5.1 CMIP6 Model Descriptions

Five CMIP6 Global Climate Models (GCMs) were selected to span a representative range of climate sensitivities, atmospheric physics parameterisations, and modelling institutions. The ensemble was chosen to balance diversity of projected warming magnitude against computational feasibility for bias correction and downscaling.

Table S5 Specifications of the five CMIP6 GCMs used in this study.

Model	Institution	Country	Atmos. Res.	ECS (°C)	Ocean Component
ACCESS-CM2	CSIRO / Bureau of Meteorology	Australia	~1.25° × 1.875°	4.66	MOM5 (1° tripolar)
MPI-ESM1-2-HR	Max Planck Institut f. Meteorologie	Germany	~0.9° × 0.9°	2.98	MPIOM (0.4° tripolar)
MIROC6	AORI / NIES / JAMSTEC	Japan	~1.4° × 1.4°	2.61	COCO4.9 (tripolar)
NorESM2-LM	NorESM Climate Modelling Consortium	Norway	~1.9° × 2.5°	2.54	BLOM (tripolar)
FGOALS-g3	LASG / Institute of Atmospheric Physics, CAS	China	~2.0° × 2.0°	2.88	LICOM3.0 (tripolar)

ECS = Equilibrium Climate Sensitivity. All models provided daily Tmax, Tmin, precipitation, specific humidity, and surface downwelling shortwave radiation for historical (1850–2014) and SSP scenario (2015–2100) periods.

Rationale for Model Selection

The five models collectively span an ECS range of 2.54–4.66°C, encompassing the IPCC AR6 assessed likely range (2.5–4.0°C) with one high-sensitivity outlier (ACCESS-CM2) to bracket the upper uncertainty. MPI-ESM1-2-HR was selected for its high-resolution atmospheric component, which better resolves orographic precipitation over the Vindhyan plateau. MIROC6 and NorESM2-LM have demonstrated strong performance over the South Asian monsoon domain in independent multi-model evaluation studies.

S5.2 ISIMIP3BAS Bias-Correction Protocol

Raw CMIP6 outputs exhibit systematic biases relative to observations, including temperature offsets of 1–3°C and precipitation scaling errors of 20–50% over the South Asian domain. Before forcing the phenology models, all five GCMs were bias-corrected using the ISIMIP3BAS (Inter-Sectoral Impact Model Intercomparison Project Phase 3, Bias Adjustment Simplified) method (Lange 2019).

The method applies a trend-preserving quantile-delta mapping (QDM) algorithm that: (1) establishes empirical quantile-quantile mappings between the GCM historical simulation and the observational reference over the 1981–2014 calibration period; (2) applies mappings to the projected period (2015–2100) while preserving the model-projected long-term trend by scaling the transfer function relative to the historical GCM distribution; and (3) handles precipitation intermittency through a two-step approach adjusting first wet-day frequency, then wet-day amounts.

Table S6 Bias-correction performance (RMSE) before and after ISIMIP3BAS, averaged across five GCMs over the validation period (2000–2014).

Variable	Before BC (RMSE)	After BC (RMSE)	Improvement (%)
Tmax (°C)	2.18	0.48	78%
Tmin (°C)	1.96	0.41	79%
Precipitation (mm/day)	2.34	0.64	73%
VPD (kPa)	0.54	0.13	76%

S5.3 SSP Emission Scenarios

Two Shared Socioeconomic Pathway (SSP) scenarios were selected to bracket the plausible range of 21st-century climate forcing:

- **SSP2-4.5 ("Middle of the Road"):** Radiative forcing stabilises at 4.5 W m^{-2} by 2100, corresponding to a global mean warming of approximately 2.7°C above pre-industrial levels (IPCC AR6 median). Assumes moderate mitigation efforts and intermediate socioeconomic development.
- **SSP5-8.5 ("Fossil-Fuelled Development"):** Radiative forcing reaches 8.5 W m^{-2} by 2100, corresponding to approximately 4.4°C global warming. Represents the high-end emissions trajectory. Serves as the stress-test scenario for identifying worst-case agricultural impacts.

S6. Machine Learning Model Architectures and Hyperparameters

A multi-model ensemble of four ML algorithms was trained to map climate predictors to phenological response variables (SOS, EOS, LOS, Peak Greenness, GSI). All models were trained on the historical period (2001–2020) and cross-validated using a 5-fold blocked temporal cross-validation scheme to prevent data leakage from temporal autocorrelation.

S6.1 Generalized Additive Models (GAM)

GAMs extend ordinary regression by replacing linear terms with smooth nonparametric functions of the predictors, providing interpretability alongside flexibility for nonlinear response detection:

$$\mathrm{Phenometric}(t) = \beta_0 + \sum_{j=1}^{p} f_j(x_j(t)) + \varepsilon(t)$$

where f_j are penalised regression splines estimated using cubic B-splines with automatic smoothness selection via generalised cross-validation (GCV). Each smooth f_j was constrained to a maximum of 10 basis functions with an L_2 penalty on second derivatives. The `mgcv` package (v1.9-1) was used with Python integration via `pygam`.

Table S7 GAM configuration and hyperparameters.

Parameter	Value	Notes
Spline type	Cubic B-spline (cr)	Standard for continuous predictors
Max basis functions per term	10	k=10 in mgcv notation
Smoothness selection	REML	Preferred for mixed GAMs
Correlation structure	AR(1) residuals	Accounts for temporal autocorrelation
Link function	Identity (Gaussian)	DOY response is continuous
Interaction terms	Tensor product (te)	VPD × Tmax interaction included

S6.2 Random Forest

Random Forest (Breiman 2001) was applied as a non-parametric ensemble tree method, providing robustness to outliers and resistance to overfitting via bootstrap aggregation. Each tree was grown on a bootstrap subsample of 66% of training observations, with random feature subsets at each split.

Table S8 Random Forest hyperparameters (tuned via 5-fold grid search).

Hyperparameter	Tuning Range	Optimal Value
Number of trees (n_estimators)	100–1000	500
Max features	sqrt, log2, 0.5	sqrt
Max depth	5–30, None	None (fully grown)
Min samples per leaf	1–10	3
Bootstrap	True/False	True
OOB validation	—	Used for internal validation

S6.3 LightGBM

LightGBM (Ke et al. 2017) employs histogram-based leaf-wise tree growth, Gradient-based One-Side Sampling (GOSS), and Exclusive Feature Bundling (EFB), yielding fast training on the large spatially gridded feature matrices ($n \approx 14{,}000$ pixel-year observations) used in this study.

Table S9 LightGBM hyperparameters after Bayesian optimisation (Optuna, 100 trials).

Hyperparameter	Search Space	Optimal (SOS)	Optimal (LOS)
Learning rate	0.005–0.3 (log)	0.048	0.052
Num. leaves	16–256	63	55
Max depth	4–12	7	6
Min data in leaf	10–200	40	35
Feature fraction	0.5–1.0	0.82	0.78
Bagging fraction	0.5–1.0	0.88	0.84
Lambda L2 regularisation	0–10	1.4	1.8
Num. boosting rounds	100–3000 (early stop)	840	910

S6.4 Long Short-Term Memory (LSTM) Networks

LSTM networks (Hochreiter & Schmidhuber 1997) were chosen to model temporal dependencies and climate lag effects inherent in the phenology-climate relationship — specifically, the influence of antecedent moisture conditions in April–May on subsequent SOS in June. A 180-day lookback window of daily climate variables was used as input.

Table S10 LSTM network architecture and training configuration.

Component	Specification
Input sequence length	180 days (daily climate covariates)
Input features per timestep	7 (Tmax, Tmin, precipitation, VPD, radiation, wind, humidity)
LSTM hidden units	128 (Layer 1), 64 (Layer 2)
LSTM layers	2 stacked
Dropout rate	0.25 (between LSTM layers)
Fully connected layers	FC(64→32) → ReLU → FC(32→1)
Loss function	Huber loss (delta = 5.0 days)
Optimiser	AdamW (lr = 1e-3, weight decay = 1e-4)
LR scheduler	Cosine annealing (T_max = 50 epochs)
Batch size	128
Max epochs / early stopping	200 / patience = 20
Framework	PyTorch 2.0

Ensemble Integration: Final projections were obtained by averaging predictions from all four model types, weighted by each model's out-of-sample R^2 on the held-out test period (2019–2022). LightGBM and LSTM received highest ensemble weights for SOS and LOS, respectively. GAM received highest weight for interpretable climate sensitivity estimates used in SHAP analysis.

S7. SHAP Sensitivity Analysis Methodology

SHapley Additive exPlanations (SHAP; Lundberg & Lee 2017) were computed to attribute phenological model predictions to individual climate drivers in a theoretically grounded, model-agnostic manner. SHAP values satisfy the axioms of efficiency, symmetry, dummy, and additivity from cooperative game theory. For a model f and instance $\mathbf{x}$, the SHAP value ϕ_j for feature j is:

$$\phi_j(\mathbf{x}) = \sum_{S \subseteq \mathcal{F} \setminus \{j\}} \frac{|S|!\,(|\mathcal{F}| - |S| - 1)!}{|\mathcal{F}|!} \left[f(S \cup \{j\}) - f(S) \right]$$

The prediction decomposes additively as $f(\mathbf{x}) = \mathbb{E}[f(\mathbf{x})] + \sum_j \phi_j(\mathbf{x})$. For tree-ensemble models (Random Forest, LightGBM), exact TreeSHAP (polynomial-time) was computed via the `shap` library (v0.42). For LSTM, DeepSHAP (Gradient × Input approximation) was used with 200 background reference samples from the training set.

Table S11 Mean absolute SHAP values for each climate driver across phenological metrics, averaged over all pixels and years (2001–2020). Values are in units of the respective phenometric scale.

Climate Driver	SOS (days)	EOS (days)	LOS (days)	Peak Greenness (EVI)
VPD anomaly (Apr–May)	**4.82**	1.34	**5.41**	**0.038**
Tmax anomaly (Mar–May)	**3.97**	2.18	4.21	0.029
Pre-monsoon rainfall deficit	3.41	1.02	3.89	0.034
Monsoon onset date	2.88	0.85	3.12	0.021
Heatwave duration (days)	2.31	1.45	2.67	0.022
Solar radiation (Jun–Sep)	0.92	1.82	1.68	0.019
Post-monsoon Tmax	0.64	**3.44**	2.93	0.015
Monsoon rainfall total	0.58	0.91	1.44	0.026

Bold values indicate the top driver for each phenometric.

S8. Validation Protocols and Accuracy Metrics

Model accuracy was assessed using a strictly temporal held-out test set spanning 2019–2022 (not used in any model fitting or hyperparameter tuning). The following metrics were computed for each phenometric at each 500-m grid cell with valid MODIS MCD12Q2 observations: RMSE (Root Mean Square Error), MAE (Mean Absolute Error), Bias (mean signed error), R^2 (coefficient of determination), and IOA (Index of Agreement; Willmott 1981).

Table S12 Ensemble model validation against MODIS MCD12Q2 phenological observations (2019–2022). Statistics are spatial medians across all valid cropland pixels in Bundelkhand.

Phenometric	RMSE	MAE	Bias	R^2	IOA
SOS (DOY)	7.4 days	5.6 days	+0.8 days	0.78	0.91
EOS (DOY)	8.9 days	6.8 days	-1.2 days	0.72	0.88
LOS (days)	11.3 days	8.7 days	+2.1 days	0.69	0.85
Peak Greenness (EVI)	0.042	0.031	-0.004	0.81	0.93
GSI (EVI·days)	3.21	2.45	+0.18	0.76	0.90

The positive bias in LOS (+2.1 days) was examined by land-cover type and found to be concentrated in fallow/disturbed pixels where double-logistic curve fitting produced spurious multi-peak detections. Applying an additional quality filter (GSI > 3.5 EVI·days) reduced the LOS bias to +0.7 days at a cost of 8% pixel exclusion. All reported projection results use this quality-filtered dataset.

S9. Extended Results and Statistical Tables

S9.1 Phenological Shift Projections by Scenario and Period

Table S13 Projected shifts in Start-of-Season (SOS) relative to the 1981–2010 baseline. Negative values indicate advancement. Values are ensemble means with GCM spread in parentheses. Unit: days.

Period	SSP2-4.5 Mean	SSP2-4.5 Range	SSP5-8.5 Mean	SSP5-8.5 Range
2030s (2025–2044)	-7.4	-5.1 to -10.2	-9.8	-7.3 to -13.8
2050s (2045–2064)	-12.6	-9.4 to -17.3	-17.3	-13.1 to -22.4
2080s (2065–2100)	-14.9	-11.2 to -19.8	-24.7	-18.6 to -31.4

Table S14 Projected changes in Length-of-Season (LOS). Negative values indicate shortening. Unit: days.

Period	SSP2-4.5 Mean	SSP2-4.5 Range	SSP5-8.5 Mean	SSP5-8.5 Range
2030s	-5.2	-3.4 to -7.8	-7.1	-4.9 to -10.3
2050s	-10.4	-7.6 to -14.1	-14.8	-11.2 to -19.6
2080s	-12.8	-9.1 to -17.6	-20.3	-15.4 to -26.7

Table S15 Projected changes in Peak Greenness (EVI × 10^{-2}). Negative values indicate decline. Values are ensemble mean (± 1 SD).

Period	SSP2-4.5	SSP5-8.5
2030s	-2.8 (±1.4)	-4.1 (±1.8)
2050s	-5.3 (±2.1)	-8.2 (±3.0)
2080s	-7.1 (±2.6)	-13.4 (±4.3)

Table S16 Projected vegetation productivity decline (%) by land cover type under SSP5-8.5, relative to 1981–2010 baseline. Productivity index = Growing Season Integral (GSI).

Land Cover Type	2030s (%)	2050s (%)	2080s (%)
Wheat (rabi)	-8.4	-15.9	-26.3
Gram / Chickpea (rabi)	-9.1	-17.4	-28.8
Mustard (rabi)	-7.8	-14.2	-23.6
Rice (kharif)	-5.6	-10.8	-18.4
Pulses (mixed)	-10.2	-18.7	-30.1
Natural vegetation	-6.3	-12.6	-21.8
Region average	**-7.9**	**-14.9**	**-24.8**

S9.2 District-Wise Detailed Statistics

Table S17 District-wise baseline phenological characteristics (1981–2010 mean) and projected changes (SSP5-8.5, 2080s) with risk classification.

District	State	Baseline SOS (DOY)	Baseline LOS (days)	Baseline PG (EVI)	ΔSOS (days)	ΔLOS (days)	ΔPG (%)	Risk
Tikamgarh	MP	161	94	0.362	-24.8	-20.1	-31.4	Critical
Chhatarpur	MP	158	97	0.371	-23.6	-19.4	-29.8	Critical
Mahoba	UP	163	91	0.348	-22.4	-18.7	-28.9	Critical
Hamirpur	UP	166	89	0.341	-21.8	-17.9	-27.6	Critical
Panna	MP	155	102	0.389	-19.3	-15.8	-24.2	High
Banda	UP	164	93	0.355	-18.7	-15.2	-23.6	High
Lalitpur	UP	157	99	0.374	-17.9	-14.3	-22.1	High
Chitrakoot	UP	162	95	0.368	-17.1	-13.8	-21.4	High
Jhansi	UP	160	96	0.361	-16.2	-13.4	-20.7	High
Sagar	MP	153	108	0.412	-15.4	-12.1	-19.3	Moderate
Damoh	MP	151	111	0.421	-14.8	-11.6	-18.4	Moderate
Datia	MP	159	98	0.372	-15.9	-12.7	-19.8	Moderate
Gwalior	MP	157	101	0.381	-14.1	-11.3	-17.9	Moderate

MP = Madhya Pradesh; UP = Uttar Pradesh. Risk based on Phenological Stress Index (PSI); see Appendix S11.5.

S9.3 Climate Driver Attribution Results

Table S18 Projected changes in primary climate drivers under SSP5-8.5, Bundelkhand region, relative to 1981–2010 baseline. Values are five-GCM ensemble means (± 1 SD).

Climate Driver	2030s	2050s	2080s	Unit
Tmax anomaly (Apr–May)	+1.6 (±0.4)	+2.8 (±0.6)	+4.9 (±1.0)	°C
VPD anomaly (Apr–May)	+0.38 (±0.09)	+0.64 (±0.14)	+1.12 (±0.22)	kPa
Pre-monsoon rainfall deficit	-18 (±8)	-31 (±12)	-52 (±19)	mm
Heatwave duration (Apr–May)	+3.2 (±1.1)	+6.8 (±2.0)	+14.3 (±4.1)	days/season
Monsoon onset delay	+2.1 (±1.3)	+4.4 (±2.1)	+7.8 (±3.4)	days
Annual mean Tmax	+1.2 (±0.3)	+2.1 (±0.5)	+3.8 (±0.8)	°C

S10. Uncertainty Quantification

Total projection uncertainty was decomposed into three variance components following Hawkins & Sutton (2009): (1) Internal variability (U_I), (2) Model uncertainty (U_M), and (3) Scenario uncertainty (U_S):

$$U_{\text{total}}^2(t) \approx U_I^2 + U_M^2(t) + U_S^2(t)$$

Table S19 Fractional contributions (%) of three uncertainty components to total SOS projection uncertainty across time horizons.

Uncertainty Source	2030s (%)	2050s (%)	2080s (%)
Internal variability (U_I)	48%	27%	14%
Model (GCM) uncertainty (U_M)	38%	42%	36%
Scenario uncertainty (U_S)	14%	31%	50%

At the 2030s horizon, internal variability dominates (48%), meaning natural variability would blur the signal even with perfect emissions and model knowledge. By the 2080s, scenario uncertainty (50%) becomes the dominant term — the choice of emissions pathway is the primary determinant of projected phenological shifts. This underscores the policy relevance of aggressive mitigation: SSP2-4.5 delivers substantially smaller impacts than SSP5-8.5 at century-end. An additional source of uncertainty is the ML model structural error (estimated at 10–15% of the total phenological signal based on out-of-sample test RMSE), not formally partitioned above but quantified implicitly through the ensemble averaging of four model types.

S11. Technical Appendices — Equations and Formulas

S11.1 NDVI and EVI Formulas

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{Red}}}$$

$$\mathrm{EVI} = 2.5 \times \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{NIR}} + 6\,\rho_{\mathrm{Red}} - 7.5\,\rho_{\mathrm{Blue}} + 1}$$

where ρ denotes surface reflectance in the respective spectral band. EVI is preferred for high-biomass environments as it reduces canopy background noise and atmospheric contamination relative to NDVI.

S11.2 Growing Season Integral

$$\mathrm{GSI} = \int_{\mathrm{SOS}}^{\mathrm{EOS}} \left[\mathrm{VI}(t) - v_{\min}\right] dt \approx \sum_{i=\mathrm{SOS}}^{\mathrm{EOS}} \left[\mathrm{VI}(t_i) - v_{\min}\right] \cdot \Delta t$$

GSI serves as a proxy for integrated photosynthetic activity and net primary productivity during the growing season. The background baseline $v_{\min}$ is subtracted to isolate the phenologically active component from soil and structural reflectance contributions.

S11.3 Vapour Pressure Deficit

$$\mathrm{VPD} = e_s(T) - e_a \quad \text{where} \quad e_s(T) = 0.6108 \times \exp\left(\frac{17.27\,T}{T + 237.3}\right)$$

T is air temperature (°C), e_s is saturation vapour pressure (kPa), and e_a is actual vapour pressure from dew-point temperature T_d via the same formula. High VPD indicates atmospheric dryness and is a direct driver of plant transpiration stress and stomatal closure, which delays green-up and accelerates senescence in semi-arid environments.

S11.4 Quantile Delta Mapping (Bias Correction)

For temperature variables, the bias-corrected future value at model quantile τ is:

$$x_{\mathrm{BC}}^{\mathrm{fut}}(\tau) = F_{\mathrm{obs}}^{\mathrm{hist}\,-1}\big(F_{\mathrm{mod}}^{\mathrm{hist}}(\tau)\big) + \Delta(\tau)$$
$$\Delta(\tau) = x_{\mathrm{mod}}^{\mathrm{fut}}(\tau) - F_{\mathrm{mod}}^{\mathrm{hist}\,-1}\big(F_{\mathrm{mod}}^{\mathrm{hist}}(\tau)\big)$$

where F denotes empirical CDFs (subscripts: obs = observed, mod = model, hist = historical, fut = future). The Δ term preserves the model-projected change signal while applying the observational quantile mapping.

S11.5 Phenological Stress Index (PSI)

A composite PSI was developed for district-level risk ranking, combining normalised anomalies in SOS, LOS, and Peak Greenness weighted by their relative SHAP-derived importances:

$$\mathrm{PSI} = w_1 \cdot \left|\frac{\Delta\mathrm{SOS}}{\sigma_{\mathrm{SOS}}^{\mathrm{hist}}}\right| + w_2 \cdot \left|\frac{\Delta\mathrm{LOS}}{\sigma_{\mathrm{LOS}}^{\mathrm{hist}}}\right| + w_3 \cdot \left|\frac{\Delta\mathrm{PG}}{\mu_{\mathrm{PG}}^{\mathrm{hist}}}\right|$$

Weights: $w_1 = 0.35$ (SOS), $w_2 = 0.35$ (LOS), $w_3 = 0.30$ (PG). Risk thresholds: PSI > 2.0 = Critical; 1.5–2.0 = High; 1.0–1.5 = Moderate; <1.0 = Low.

S11.6 Index of Agreement (IOA)

$$\mathrm{IOA} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (|y_i - \bar{y}| + |\hat{y}_i - \bar{y}|)^2}$$

IOA ranges from 0 to 1, where 1 indicates perfect agreement. It is preferred over R^2 for validation of bounded-range variables because it penalises both systematic and unsystematic errors.

S12. References

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