

Rainfall Decline Explains About a Quarter of Falling River Water Levels in Northwest Bangladesh: Machine-Learning Attribution and Specific-Stage Evidence

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Abstract: River water levels in northwest Bangladesh have fallen over recent decades, and standardised water level indices are often used to describe hydrological drought where discharge records are scarce. Whether these declines reflect a rainfall deficit, a loss of river flow or a change in the channel itself has not been tested. We combined monthly rainfall from 44 Bangladesh Water Development Board (BWDB) gauges (35 retained after relative homogeneity testing), monthly water levels at 22 river gauges and 15, discharge gaugings for 1980-2022. Regional rainfall declined by 86 mm per decade ($p = 0.015$), and 2001-2022 was 11% drier than 1980-2000. Over the same period, dry-season (January-May) water levels fell significantly at 16 gauges and monsoon (July-October) levels at 19, by a median of 0.55 m and 0.60 m between the two periods. Water levels responded most strongly to rainfall accumulated over two to six months, but the association was moderate (median $r = 0.48$), and shared trends produced spuriously long propagation times at four gauges unless the series were detrended. Ridge regression, Random Forest and XGBoost models trained on 1980-2000 attributed a median of 24% of the later decline to lower rainfall (14% in the dry season and 39% in the monsoon), with an upper bound of 49% after allowing for underestimated rainfall sensitivity. The unexplained decline (median 0.43 m) was significantly negative at 18 of 22 gauges for all three models. Stage at a fixed discharge, derived from gaugings, fell at most gauged sites, and the unexplained decline was correlated with this specific-stage change ($r = 0.74$ in the dry season and 0.75 in the monsoon; 0.57 and 0.58 without one influential station). The non-rainfall decline is therefore consistent with channel-bed lowering. The share of months classed as hydrological drought by the raw water level index rose almost fivefold, compared with a less than two-fold rise for rainfall indices. Water level drought indices for alluvial rivers should be corrected for channel change before they are used for drought monitoring.

Keywords: Drought Propagation; SHAP; Specific Stage; Channel Change; Barind Tract; Bangladesh.

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I. INTRODUCTION

Northwest Bangladesh is the driest part of the country and the part most exposed to drought. The Barind Tract and the Teesta basin form the national hotspot of meteorological drought, with the highest drought frequency and intensity recorded over 1980-2018 (Kamruzzaman et al., 2022), and an early assessment already placed the western districts at high drought risk (Shahid and Behrawan, 2008). The region is also the centre of groundwater-fed dry-season rice cultivation. Pumping for irrigation captured an estimated 75-90 km³ of freshwater in Bangladesh between 1988 and 2018 (Shamsudduha et al., 2022), and groundwater storage in the

southern districts of the northwest, including Nawabganj, Naogaon and Rajshahi, is falling by 8.9 to 12.5 mm per year according to net-recharge estimates (Janardhanan et al., 2023). Groundwater levels in the Barind Tract have declined steadily with growing irrigation demand (Rasel et al., 2023). The rivers that cross this landscape, most of them transboundary tributaries of the Ganges and Jamuna, carry the combined signal of rainfall, groundwater exchange, upstream inflow and channel change.

A rainfall deficit (meteorological drought) propagates, with delay and attenuation, into deficits of soil moisture, groundwater and river flow (hydrological drought) (Van Loon,

2015). A common way to describe this propagation is to correlate a hydrological index with the Standardised Precipitation Index (SPI; McKee et al., 1993) computed over a range of accumulation periods, and to take the period with the highest correlation as the characteristic propagation time (Barker et al., 2016; Huang et al., 2017). Event-based approaches that match the onset of meteorological and hydrological droughts give complementary estimates (Wang et al., 2021). Propagation depends on climate and catchment storage (Apurv and Cai, 2020), and human activities change it: reservoirs, abstraction and irrigation can lengthen, shorten or break the link between rainfall and streamflow (Tijdeman et al., 2018; Zhang et al., 2023). A synthesis of 28 case studies found that water abstraction lengthened streamflow droughts by 20% to 305% (Van Loon et al., 2022), and the skill of forecasting hydrological drought from rainfall indices falls where discharge is regulated or aquifers are pumped (Sutanto et al., 2024).

Separating the rainfall-driven part of a hydrological change from the part caused by other factors requires a reference that describes how the system would have behaved under the observed rainfall. The observation-modelling framework does this by running a model calibrated on an earlier, less disturbed period through the later period and treating the difference from observations as the human influence (Van Loon and Van Lanen, 2013). Machine learning (ML) is well suited to building such references from long observational records, because it can represent non-linear responses to rainfall accumulated over several time scales without a process model. ML has been used for drought forecasting with explanation of the drivers through SHAP values (Dikshit and Pradhan, 2021; Lundberg et al., 2020). ML skill, however, has to be judged on data kept out of training and in time order (Kapoor and Narayanan, 2023), and a data-driven reference means little without physical reasoning behind it (Nearing et al., 2021).

A further problem is specific to water level records. In many data-scarce regions, including Bangladesh, long discharge series are derived from water levels through rating curves, and water level indices are therefore used directly as drought indicators. Yet the stage-discharge relation of an alluvial river is not fixed. Scour, deposition and sand extraction shift it over time (Mansanarez et al., 2019; Darienzo et al., 2021), and riverbed incision can lower water levels even when discharge rises; in the Mekong Delta, dry-season water levels fell although discharge increased, because the bed incised (Binh et al., 2021). A fall in water level can therefore be read as a hydrological drought when the river carries as much water as before. We found no study that tests how much of the fall in river levels in northwest Bangladesh is explained by rainfall, how much by channel change, and how much by other losses of flow.

This study uses 43 years of BWDB rainfall, water level and discharge measurements to address four objectives: (i) to quantify changes in rainfall and river water levels between 1980-2000 and 2001-2022; (ii) to identify the rainfall accumulation periods to which river levels respond and to test whether this link has changed; (iii) to estimate, with ML models trained on the earlier period, the part of the water level change expected from the observed rainfall; and (iv) to test whether the remaining non-rainfall change agrees with independent evidence of channel change from discharge gaugings.

II. STUDY AREA AND DATA

➤ Study Area

The study area covers about 23.9-25.2°N and 88.1-89.7°E in Rajshahi Division (Fig. 1). It includes the Barind Tract, an uplifted Pleistocene terrace, and the surrounding floodplains of the Ganges, Jamuna, Atrai, Little Jamuna, Karatoa, Bangali, Mahananda, Punarbhaba and their distributaries. Mean annual rainfall at the homogeneous gauges was 1,556 mm over 1963-2022, and 80% of it fell between June and October. River levels rise by several metres during the monsoon and fall to their lowest values in March and April, when irrigation demand is highest.

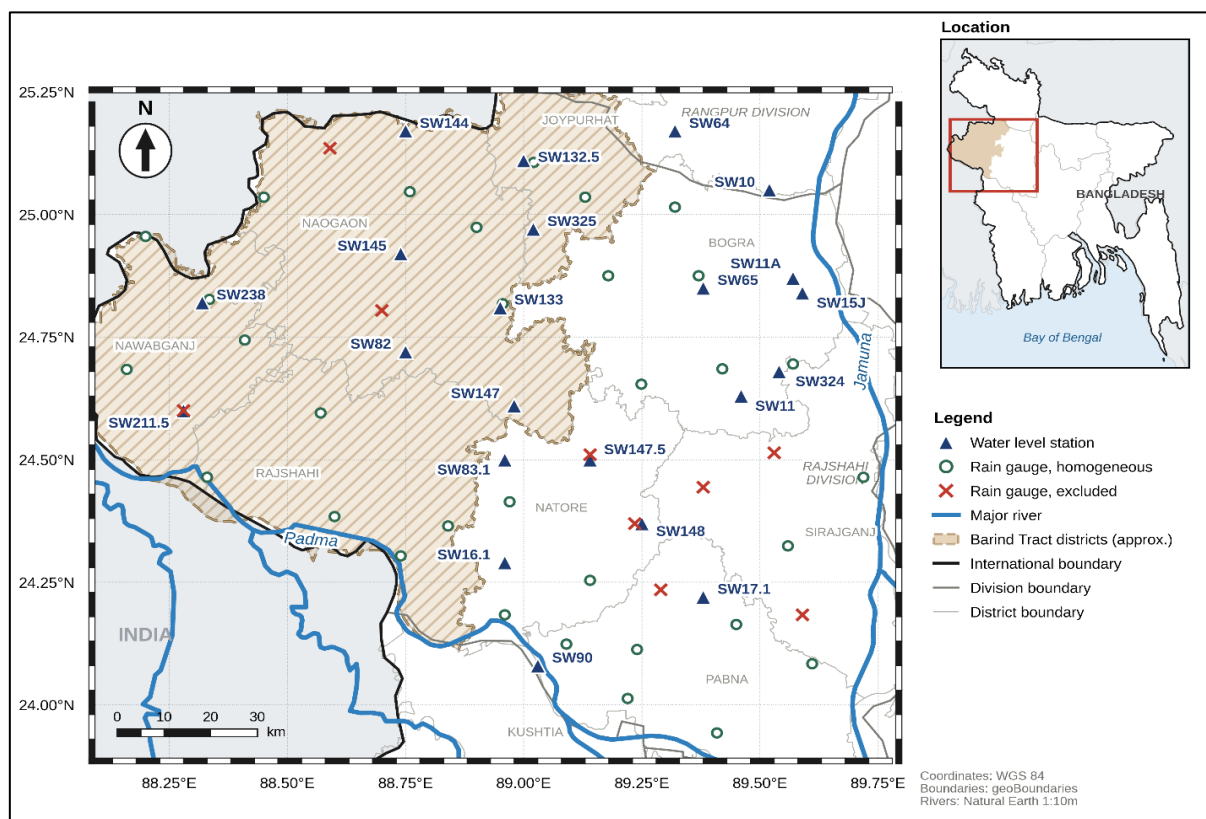


Fig 1 Study Area, Showing the 22 BWDB Water Level Stations and 44 Rain Gauges (35 Homogeneous; 9 Excluded, Shown as Crosses).

➤ Rainfall

Daily rainfall was available at 48 BWDB gauges. Four gauges with less than 40% completeness were removed, and nine daily values above 400 mm, which no neighbouring gauge confirmed, were set to missing. Monthly totals were computed where at least 25 days were available and scaled to the length of the month. Because gauge relocation or changes in observation practice can create artificial trends, each gauge's annual totals were divided by the mean of its neighbours within 50 km, and the resulting ratio series was tested with the Pettitt (1979) test and the standard normal homogeneity test (SNHT; Alexandersson, 1986). A gauge was flagged when the Pettitt *p*-value was below 0.01, the SNHT statistic exceeded 9.56 and the shift exceeded 15%. The test was repeated once with flagged gauges removed from the reference, and gauges flagged in either pass were excluded. Nine gauges were excluded (Chapai Nawabganj, Chatmohar, Gurudaspur, Manda, Raiganj, Sapahar, Shazadpur, Singra and Taras), with shifts between -45% and +65%, leaving 35 homogeneous

gauges. Rainfall for each river gauge was taken as the arithmetic mean of the homogeneous gauges within 40 km (five to eleven gauges; Table 1).

➤ Water Level and Discharge

Daily mean water levels were available for 30 BWDB stations. Values more than 2 m outside a station's 0.1 and 99.9 percentiles, and isolated jumps of more than 2 m followed by an equal return, were removed (21 values, including a run of a -0.92 m error code at Singra). Monthly means were computed where at least 20 days were available. Records after 31 October 2022 were excluded because BWDB changed its reference datum on 1 November 2022. Twenty-two stations with at least 35 years of data in 1980-2022 were retained (456-514 months each; Table 1). Field discharge gaugings (discharge, stage and date) were used for the specific-stage analysis (Section 3.6); after removing gaugings with stage more than 1 m outside the station's daily range, 15,625 gaugings at 25 stations remained for 1980-2022.

Table 1 River Gauges, Contributing Rain Gauges and Mean Annual Areal Rainfall, 1980-2021.

ID	Station	River	Lat, Lon (°)	Rain gauges	WL months	Rainfall (mm)
SW10	Simulbari	Bangali	25.05, 89.52	5	513	1731
SW11	Khanpur	Bangali	24.63, 89.46	7	501	1707
SW11A	Shariakandi	Bangali	24.87, 89.57	6	509	1709
SW132.5	Joypurhat	Little Jamuna	25.11, 89.00	9	493	1574
SW133	Naogaon	Little Jamuna	24.81, 88.95	9	488	1549
SW144	Chak Hariharpur	Atrai	25.17, 88.75	5	500	1495
SW145	Mohadebpur	Atrai	24.92, 88.74	7	506	1480
SW147	Atrai Rly. Bridge	Atrai	24.61, 88.98	6	497	1523
SW147.5	Singra	Atrai	24.50, 89.14	8	498	1519

SW148	Chanchkair	Atrai	24.37, 89.25	10	493	1574
SW15J	Mathurpara-Milanpur	Jamuna	24.84, 89.59	6	511	1716
SW16.1	Malanchi	Baral	24.29, 88.96	9	498	1484
SW17.1	Baral Rly Bridge	Baral	24.22, 89.38	8	506	1599
SW211.5	Chapai Nawabganj	Mahananda	24.60, 88.28	6	505	1419
SW238	Rohanpur	Punarbhaba	24.82, 88.32	6	507	1444
SW324	Dhunot	Old Bangali	24.68, 89.54	5	456	1732
SW325	Sonaimukhi	Tulshiganga	24.97, 89.02	11	479	1597
SW64	Shibganj	Karatoa	25.17, 89.32	6	501	1719
SW65	Bogra	Karatoa	24.85, 89.38	8	505	1712
SW82	Jote Bazar offtake	Atrai	24.72, 88.75	7	493	1464
SW83.1	Naldanga Rly. Crossing	Fakirni Barnai	24.50, 88.96	9	456	1480
SW90	Hardinge Bridge	Ganges	24.08, 89.03	8	514	1504

Rain Gauges = Number of Homogeneous Gauges within 40 km. WL Months = Months with at Least 20 Days of Water Level Data, 1980-2022.

III. METHODS

➤ Drought Indices

SPI was computed from the areal rainfall of each river gauge for accumulation periods of 1-12, 15, 18, 21 and 24 months. For each calendar month, a two-parameter gamma distribution was fitted to the non-zero accumulated totals over 1963-2022, the probability of zero rainfall was added as a point mass, and the cumulative probability was transformed to a standard normal variate (McKee et al., 1993; Stagge et al., 2015). Water levels do not follow a known distribution, so the Standardised Water Level Index (SWI) was computed non-parametrically. For each calendar month, the empirical cumulative probability of each monthly mean level was estimated with Gringorten plotting positions over 1980-2022 and transformed to a standard normal variate (Farahmand and AghaKouchak, 2015). A detrended SWI was also computed after removing a linear trend from each calendar month's series. Months with an index below -1 were classed as drought months.

➤ Trend Analysis

Trends in annual areal rainfall and in dry-season (January-May) and monsoon (July-October) mean water level were tested with the Mann-Kendall test (Mann, 1945; Kendall, 1975) and quantified with Sen's (1968) slope. Serial correlation was handled with the variance correction of Hamed and Rao (1998), applied only when it increased the variance, so that the test was never made more permissive. Changes were also expressed as the difference between the 2001-2022 and 1980-2000 means. The split at 2000 divides the record into two periods of similar length (21 and 22 years).

➤ Propagation Analysis

For each river gauge, the Pearson correlation between monthly SWI and SPI at each accumulation period was computed. The accumulation period with the highest correlation was taken as the propagation time and the correlation itself as the propagation strength (Barker et al., 2016; Huang et al., 2017). The analysis was done for all months, the dry season and the monsoon; for raw and detrended SWI; and separately for 1980-2000 and 2001-2022. Paired differences between periods across stations were tested with the Wilcoxon signed-rank test (Wilcoxon, 1945).

➤ Machine-Learning Attribution

The target variable was the monthly water level anomaly, defined as the difference between the monthly mean level and the 1980-2000 mean for the same calendar month. Inputs were SPI at 1, 2, 3, 4, 5, 6, 9, 12, 18 and 24 months and the sine and cosine of the calendar month, so the models could learn season-specific responses to rainfall accumulated over short and long periods. No lagged water levels were used, because they would carry non-rainfall changes into the predictions. Three models were fitted separately for each station: ridge regression (MLR) with the penalty chosen by internal cross-validation, Random Forest (RF; Breiman, 2001; 500 trees, minimum leaf size 5, half of the inputs per split) and XGBoost (XGB; Chen and Guestrin, 2016; 300 trees, learning rate 0.03, maximum depth 3, row and column subsampling 0.8, minimum child weight 10, L2 penalty 5). Hyperparameters were fixed in advance.

Skill was assessed on 1980-2000 with seven-fold cross-validation in which whole years were held out together, and summarised by the Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe, 1970) and the correlation of monthly, annual, dry-season and monsoon means. Each model was then refitted on all of 1980-2000 and applied to the observed SPI of 2001-2022. Its output is the rainfall-expected anomaly, and the residual (observed minus expected) is the change not explained by rainfall. Residuals were averaged by season and year, and 95% confidence intervals for the station mean were obtained by resampling years with replacement 1,000 times.

Models with modest skill tend to underestimate sensitivity, because weak predictors shrink predictions towards the mean. The expected change could therefore be too small and the residual too large. As an upper bound on the rainfall contribution, the expected change at each station was multiplied by the ratio of the standard deviations of observed and cross-validated predicted annual anomalies in 1980-2000, which assumes that all unexplained year-to-year variance in the reference period is rainfall-driven.

➤ Interpretation

SHAP values (Lundberg et al., 2020) were computed with the TreeExplainer algorithm for the RF models fitted on 1980-2000. Mean absolute SHAP values were calculated

separately for dry-season and monsoon months, normalised to sum to one at each station and summarised across stations.

➤ Specific-Stage Analysis and Decomposition

Channel change was estimated independently from the discharge gaugings. For each station with at least 30 gaugings in both 1980-2000 and 2001-2022 (18 stations), reference discharges were set at the 25th, 50th and 75th percentiles of all its gaugings (Q25, Q50 and Q75). In each period, stage was regressed linearly on the logarithm of discharge using gaugings within ± 0.5 log units of the reference, and the stage at the reference discharge was predicted. The difference between periods is the specific-stage change: a negative value means the river now flows at a lower level for the same discharge, which indicates bed lowering or channel enlargement. Confidence intervals were obtained by resampling gaugings 500 times. For the 15 stations with both water level and gauging records, the dry-season residual was compared with the change at Q25 and the monsoon residual with the change at Q75, and the remaining change (residual minus specific-stage change) was interpreted as change in flow not explained by local rainfall. Pearson and Spearman correlations were calculated with and without the most influential station.

All analyses used Python with pandas, SciPy, scikit-learn, XGBoost and SHAP. A significance level of 0.05 was used throughout.

IV. RESULTS

➤ Rainfall and Water Level Trends

Regional rainfall declined over 1980-2022 by 86 mm per decade, or 5.6% per decade (Mann-Kendall $p = 0.015$; Fig. 2a). Over the longer 1963-2022 record the decline was smaller and only marginally significant (38 mm per decade, $p = 0.057$), because 1980-2000 was wetter than the 1960s and 1970s. Mean annual rainfall fell from 1,634 mm in 1980-2000 to 1,454 mm in 2001-2022 (-11%), and the areal rainfall of 13 of the 22 river gauges showed a significant decline, with a median of -6.5% per decade (Table 2). The dry years of 2009-2014 stand out in the record.

Water levels fell more consistently than rainfall. Dry-season levels declined significantly at 16 gauges and monsoon levels at 19, with median Sen slopes of -0.29 and -0.27 m per decade, and no gauge showed a significant rise (Table 2). Between the two periods, the median change was -0.55 m in the dry season and -0.60 m in the monsoon. The largest falls were on the Little Jamuna at Joypurhat (-1.22 m dry, -1.82 m monsoon), the Atrai at Mohadebpur (-1.31 m monsoon) and Chak Hariharpur (-1.16 m monsoon), the Jamuna at Mathurpara (-1.11 m dry) and the Old Bangali at Dhunot (-1.20 m monsoon). Malanchi on the Baral was the only gauge whose level rose ($+1.02$ m dry, $+0.36$ m monsoon). The median anomaly across all gauges (Fig. 2b) shows that levels were close to their 1980-2000 mean until about 2004 and have stayed 0.3 - 1.0 m below it in most years since 2005.

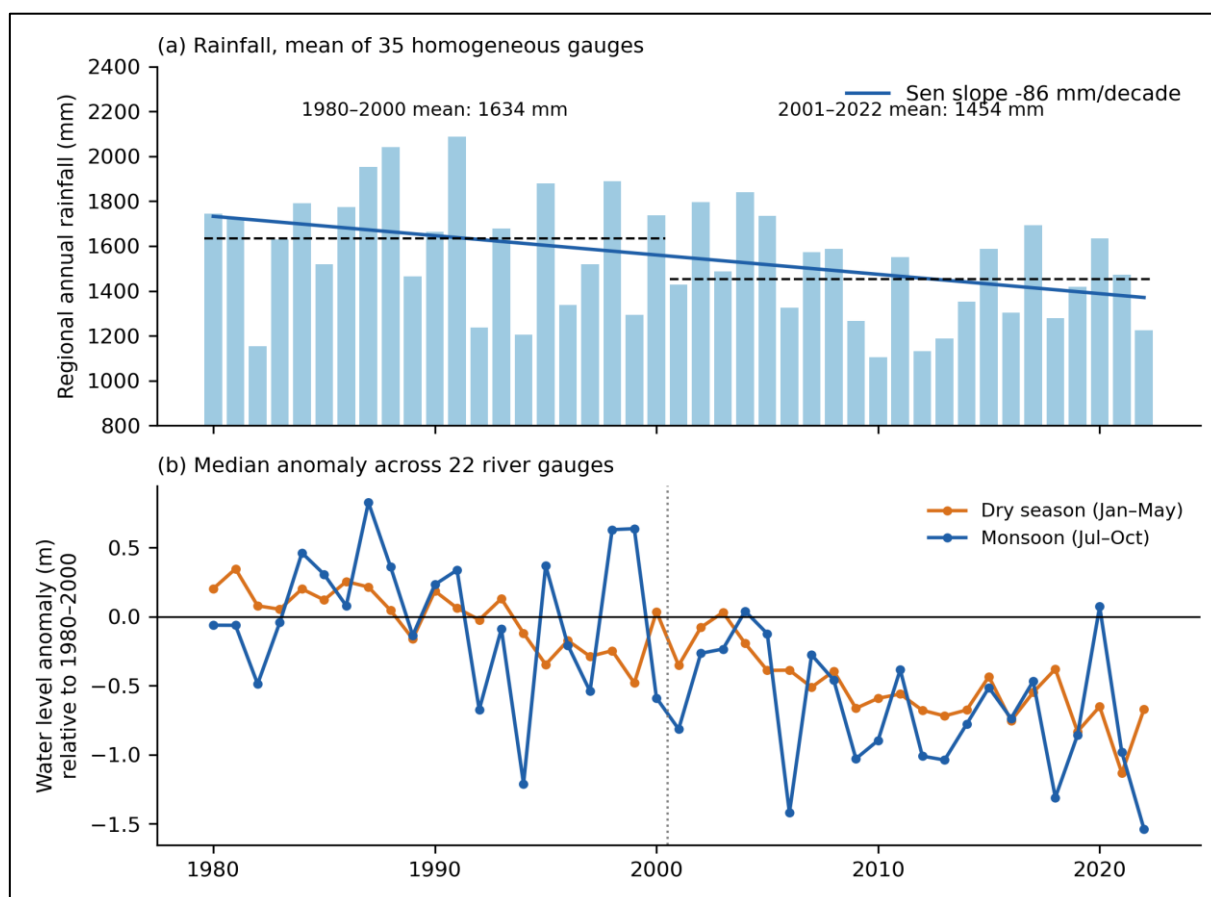


Fig 2 (a) Annual Areal Rainfall (Mean of 35 Gauges) with Sen's Slope and Period Means; (b) Median Water Level Anomaly of 22 Gauges Relative to 1980-2000.

Table 2 Trends in Areal Rainfall (1980-2021) and Seasonal Water Level (1980-2022), and Change from 1980-2000 to 2001-2022.

Station	Rainfall trend (% per decade)	Rainfall change (%)	Dry WL trend (m per decade)	Monsoon WL trend (m per decade)	Dry WL change (m)	Monsoon WL change (m)
SW10 Simulbari	-9.5*	-17.4	-0.10*	-0.21*	-0.15	-0.47
SW11 Khanpur	-6.8*	-12.4	-0.43*	-0.38*	-0.83	-0.91
SW11A Shariakandi	-8.8*	-15.7	-0.18*	-0.26*	-0.33	-0.56
SW132.5 Joypurhat	-8.5*	-15.4	-0.49*	-0.74*	-1.22	-1.82
SW133 Naogaon	-6.0*	-13.3	-0.43*	-0.36*	-1.26	-0.84
SW144 Chak Hariharpur	-7.4*	-12.7	-0.30*	-0.49*	-0.76	-1.12
SW145 Mohadebpur	-6.6*	-12.4	-0.31*	-0.55*	-0.74	-1.31
SW147 Atrai Rly. Bridge	-3.4	-9.0	-0.35*	-0.23*	-0.73	-0.54
SW147.5 Singra	-4.2	-9.7	-0.20*	-0.01	-0.34	-0.12
SW148 Chanchkair	-4.0	-8.6	-0.45*	-0.26*	-0.81	-0.53
SW15J Mathurpara- Milanpur	-8.0*	-14.7	-0.51*	-0.26*	-1.09	-0.53
SW16.1 Malanchi	-2.5	-6.4	0.19	0.04	1.09	0.34
SW17.1 Baral Rly Bridge	-4.5	-9.0	-0.06	-0.12*	-0.26	-0.38
SW211.5 Chapai Nawabganj	-3.6	-10.0	-0.19	-0.17	-0.19	-0.51
SW238 Rohanpur	-3.7	-7.9	-0.30*	-0.38*	-0.57	-1.00
SW324 Dhunot	-6.6*	-12.6	-0.11	-0.51*	-0.24	-1.18
SW325 Sonaimukhi	-7.1*	-14.6	-0.12	-0.51*	-0.27	-1.12
SW64 Shibganj	-8.3*	-15.3	-0.31*	-0.29*	-0.60	-0.66
SW65 Bogra	-8.8*	-15.5	-0.10	-0.23*	-0.20	-0.60
SW82 Jote Bazar offtake	-6.5*	-14.1	-0.31*	-0.27*	-0.53	-0.61
SW83.1 Naldanga Rly. Crossing	-2.9	-7.1	-0.29*	-0.32*	-0.64	-0.86
SW90 Hardinge Bridge	-2.5	-6.8	-0.16*	-0.23*	-0.29	-0.54

* Significant at $p < 0.05$ (Mann-Kendall Test with Hamed-Rao Correction).

Changes are 2001-2022 Means Minus 1980-2000 Means.

➤ *Propagation from Rainfall to River Level*

River levels correlated most strongly with rainfall accumulated over a few months (Fig. 3; Table 3). With raw SWI, the median propagation time was 5 months for all months, 6 months in the dry season and 4 months in the monsoon, and the median maximum correlation was 0.48, 0.39 and 0.55. The link was clearly stronger in the monsoon, when levels respond to current rain, than in the dry season, when they depend on baseflow and upstream inflow. Correlations were weakest on the large rivers fed from outside the region, the Ganges at Hardinge Bridge (0.22) and the Baral at Malanchi (0.15).

Shared trends distorted these estimates at four gauges (Joypurhat, Chak Hariharpur, Mohadebpur and Mathurpara), where the highest correlation with raw SWI occurred at 24 months, the longest scale tested. Long-scale SPI is dominated by the multi-decadal rainfall decline, which lines up with the declining water levels whether or not one causes the other. After detrending, no gauge had a propagation time of 12 months or more for all months (two did in the dry season alone); the median fell to 3 months (4 in the dry season and 2 in the monsoon), and the correlation curves peaked at 2-5 months and decayed at longer scales (Fig. 3b).

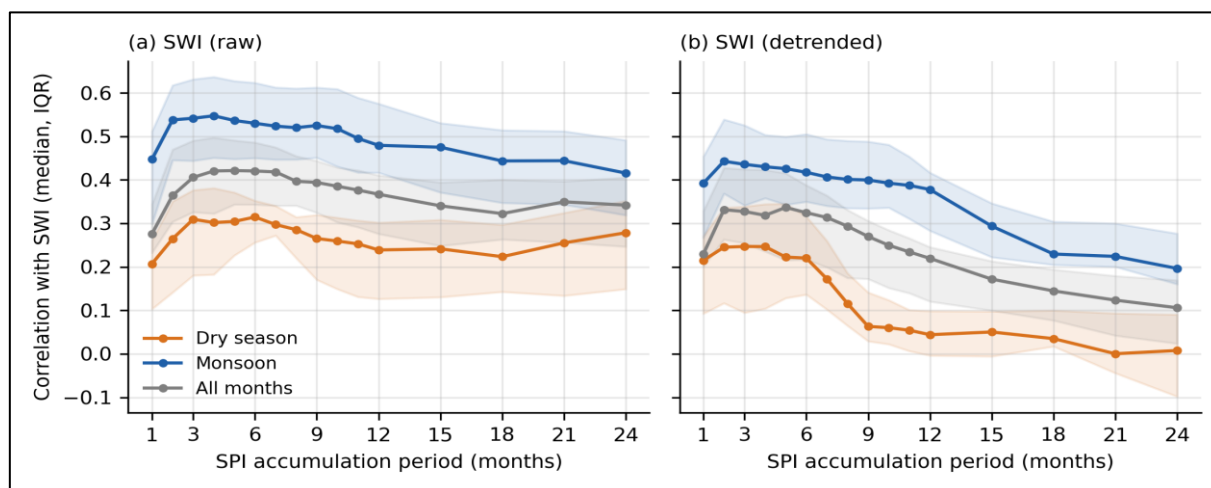


Fig 3 Median SWI-SPI Correlation of 22 Gauges by SPI Accumulation Period, 1980-2022: (a) Raw SWI; (b) Detrended SWI. Shading: Interquartile Range.

Table 3 Propagation Time and Strength at 22 Gauges, 1980-2022.

Index	Season	Propagation time, months: median (IQR)	Maximum r: median (range)	Gauges with time ≥ 12 months
Raw SWI	All months	5 (4-8)	0.48 (0.15-0.61)	4
Raw SWI	Dry season	6 (4-11)	0.39 (0.07-0.59)	6
Raw SWI	Monsoon	4 (2-5)	0.55 (0.25-0.72)	2
Detrended SWI	All months	3 (2-4)	0.36 (0.17-0.50)	0
Detrended SWI	Dry season	4 (3-6)	0.31 (0.09-0.43)	2
Detrended SWI	Monsoon	2 (2-2)	0.46 (0.21-0.63)	0

Propagation Time = SPI Accumulation Period with the Maximum Correlation; Propagation Strength = that Maximum Correlation.

The link between rainfall and river level weakened slightly after 2000. For all months, the median maximum correlation fell from 0.43 in 1980-2000 to 0.41 in 2001-2022 (both below the full-record median of 0.48, probably because the shared trend inflates correlations computed over 1980-2022) and decreased at 15 of 22 gauges (Wilcoxon $p = 0.036$), while the seasonal differences were not significant. The largest drops were at Chanchkair (0.56 to 0.24), Malanchi (0.41 to 0.06) and Hardinge Bridge (0.33 to 0.09). The Mahananda and Punarbhaba gauges moved the other way (0.27 to 0.51 and 0.25 to 0.53).

➤ Frequency of Drought Months

Meteorological drought became more frequent in 2001-2022. The median share of months with SPI-3 below -1 rose

from 11.7% to 21.4%, and with SPI-12 from 15.3% to 26.1% (both Wilcoxon $p < 0.001$). The share of months with raw SWI below -1 rose far more, from 5.4% to 25.2%, almost a five-fold increase ($p < 0.001$). With detrended SWI, the frequency did not change (15.5% and 16.0%, $p = 0.61$), as expected, because detrending removes any change in the mean by construction; the detrended index serves only as a reference from which all trends, including the rainfall-driven one, have been removed. The raw index therefore places a large part of the network in permanent drought in recent years: 44%, 42%, 23%, 53% and 46% of station-months in 2018-2022 were in hydrological drought, although fewer than 12% of station-months were in meteorological drought in 2018, 2020 and 2021 (Fig. 4).

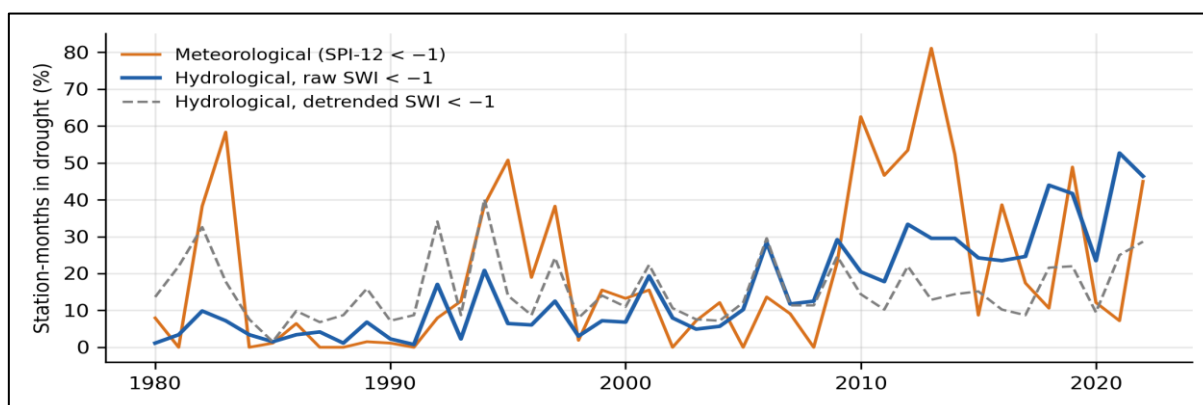


Fig 4 Annual Share of Station-Months in Drought (Index < -1) by SPI-12, Raw SWI and Detrended SWI.

➤ Skill of the Rainfall-Driven Models

In cross-validation on 1980-2000, rainfall explained a modest part of the month-to-month variation in water level anomalies (Table 4). Median monthly NSE was 0.17 for MLR and RF and 0.08 for XGB, and the median monthly correlation was 0.38-0.43. Monsoon means were reproduced better (median correlation 0.47-0.54) than dry-season means (0.23-

0.30). The linear model was as good as the tree models, which suggests that the response of seasonal mean levels to rainfall is close to linear at this scale and that the extra flexibility of the tree ensembles mainly fits noise. Skill was lowest (monthly NSE of 0.08 or less for MLR) on the Punarbhaba, Mahananda, upper Atrai, Baral, Ganges and Jamuna, rivers fed largely from outside the region or affected by regulation.

Table 4 Cross-Validated Skill of Rainfall-Driven Models, 1980-2000 (Median and Range, 22 Gauges).

Model	NSE (monthly)	r (monthly)	r (annual mean)	r (dry-season mean)	r (monsoon mean)
Ridge regression (MLR)	0.17 (0.03 to 0.34)	0.42 (0.18 to 0.59)	0.37 (−0.06 to 0.66)	0.30 (−0.16 to 0.65)	0.54 (0.26 to 0.72)
Random Forest (RF)	0.17 (−0.06 to 0.39)	0.43 (0.13 to 0.63)	0.39 (−0.32 to 0.74)	0.24 (−0.12 to 0.77)	0.53 (0.02 to 0.71)
XGBoost (XGB)	0.08 (−0.20 to 0.36)	0.38 (0.04 to 0.60)	0.39 (−0.33 to 0.75)	0.23 (−0.10 to 0.84)	0.47 (−0.11 to 0.73)

Seven-Fold Cross-Validation with whole Years held Out.

➤ Rainfall-Expected Versus Observed Change

Applied to the drier 2001-2022 rainfall, the models expected water levels to fall, but by much less than observed (Fig. 5). Averaged over the three models, the median observed annual change was -0.64 m, the rainfall-expected change -0.17 m and the residual -0.43 m. Rainfall accounted for a median of 24% (median of station-wise ratios) of the decline across the 21 gauges where levels fell, 14% in the dry season and 39% in the monsoon. The residual was significantly negative at 18 of 22 gauges in annual means for each of the three models (block bootstrap), at 15 gauges in the dry season, and at 16 to 19 gauges in the monsoon depending on the model. It was significantly positive only at Malanchi. The three models agreed closely: the range of residuals across models was below

0.1 m at 21 of 22 gauges for annual and dry-season means, and exceeded 0.2 m only in the monsoon at Khanpur and Naogaon. Within 2001-2022 the residual continued to grow, with a median trend of -0.22 to -0.25 m per decade.

Allowing for underestimated rainfall sensitivity raised the median rainfall share from 24% to 49%. Even under this upper bound, rainfall explained less than half of the decline at 11 of the 21 gauges, including Joypurhat (24%), Mohadebpur (28%), Naogaon (34%) and Hardinge Bridge (27%). At three gauges the decline was fully consistent with rainfall: Simulbari, Shariakandi and Bogra, all in the Bogura area, where rainfall declined most (-15% to -17%) and water levels fell relatively little.

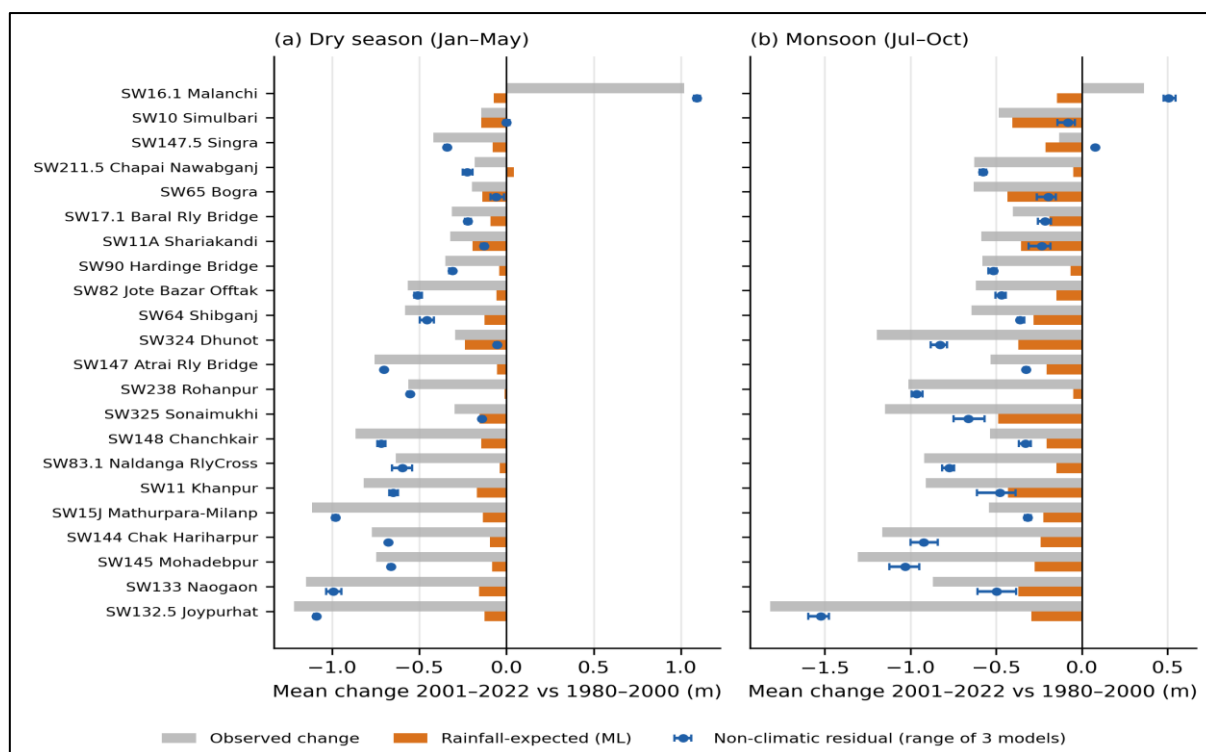


Fig 5 Observed, Rainfall-Expected (Mean of MLR, RF and XGB) and Residual Change in Water Level, 2001-2022 Minus 1980-2000: (a) Dry Season; (b) Monsoon. Bars Show the Range Across Models; Stations are Ordered by Annual Change.

➤ Channel Change from Discharge Gaugings

The gaugings show that the stage-discharge relation has shifted at most stations. At Q25, stage fell significantly at 10 of 18 stations and rose at 2; at Q75 it fell at 11 and rose at 4. On the Ganges at Hardinge Bridge, where more than 5,900 gaugings give tight intervals, the river now flows 0.47-0.56 m lower for the same discharge at all three reference flows. Large falls were also found on the Little Jamuna at Naogaon (−1.00 m at Q25), the Atrai at Mohadebpur (−0.56 to −0.63 m) and the Baral at Baral Railway Bridge (−0.71 to −0.96 m). Stage rose for the same discharge at Malanchi (+0.41 to +0.98 m) and at Ullapara (+1.08 to +2.14 m; a gauging station without a long water level record), indicating deposition.

The non-rainfall residual agreed with the specific-stage change (Table 5; Fig. 6). BWDB station histories for gauge relocations and datum or benchmark changes between 1980-2000 and 2001-2022, since these would shift the residual and the specific stage equally. In the dry season, the correlation between the residual and the change at Q25 was $r = 0.74$ ($p = 0.002$, $n = 14$; Spearman $\rho = 0.60$, $p = 0.023$); in the monsoon, the correlation with the change at Q75 was $r = 0.75$ ($p = 0.001$,

$n = 15$; $\rho = 0.59$, $p = 0.021$). Malanchi, where both quantities are strongly positive, is influential; without it the Pearson correlations were 0.57 ($p = 0.04$) and 0.58 ($p = 0.03$), and the Spearman correlations 0.50 ($p = 0.08$) and 0.50 ($p = 0.07$). Summed over the stations with gaugings and falling levels, the specific-stage change was 106% of the dry-season residual and 86% of the monsoon residual, and the median remaining change was +0.02 m in the dry season and −0.07 m in the monsoon. At several stations, however, water level fell by more than the channel change: Chak Hariharpur (−0.68 m remaining in the monsoon), Mohadebpur (−0.45 m, monsoon), Atrai Railway Bridge (−0.45 m, dry season), Chapai Nawabganj (−0.35 m, monsoon), Naldanga (−0.33 m, monsoon) and Khanpur (−0.31 m, dry season). At these stations, less water appears to reach the gauge than before, beyond what local rainfall explains. The opposite occurred at Baral Railway Bridge (+0.74 m in the dry season and +0.61 m in the monsoon), Rohanpur (+0.23 m and +0.30 m) and Sonaimukhi (+0.26 m, dry season), where the channel lowered more than the water level residual; this could indicate more water reaching these gauges or error in the specific-stage estimate, and the present data cannot separate the two.

Table 5 Decomposition of Water Level Change (m), 2001-2022 Minus 1980-2000, at 15 Gauged Stations.

Station	Dry: observed	Dry: rainfall-expected	Dry: residual	Specific stage at Q25	Monsoon: observed	Monsoon: rainfall-expected	Monsoon: residual	Specific stage at Q75
SW10 Simulbari	−0.15	−0.14	0.00	−0.05	−0.49	−0.40	−0.08	0.14
SW11 Khanpur	−0.82	−0.17	−0.65	−0.34	−0.91	−0.43	−0.48	−0.41
SW133 Naogaon	−1.15	−0.16	−0.99	−1.00	−0.87	−0.37	−0.50	−0.53
SW144 Chak Hariharpur	−0.77	−0.09	−0.68	−0.65	−1.16	−0.24	−0.92	−0.24
SW145 Mohadebpur	−0.75	−0.08	−0.66	−0.56	−1.31	−0.28	−1.03	−0.58
SW147 Atrai Rly. Bridge	−0.75	−0.05	−0.70	−0.25	−0.53	−0.21	−0.33	−0.37
SW147.5 Singra	−0.42	−0.08	−0.34	−0.37	−0.13	−0.21	0.08	0.29
SW16.1 Malanchi	1.02	−0.07	1.09	0.41	0.36	−0.14	0.51	0.76
SW17.1 Baral Rly Bridge	−0.31	−0.09	−0.22	−0.96	−0.40	−0.19	−0.21	−0.82
SW211.5 Chapai Nawabganj	−0.18	0.04	−0.23	−0.05	−0.63	−0.05	−0.58	−0.23
SW238 Rohanpur	−0.56	−0.01	−0.55	−0.78	−1.01	−0.05	−0.96	−1.26
SW325 Sonaimukhi	−0.30	−0.15	−0.14	−0.40	−1.15	−0.49	−0.66	−0.75
SW65 Bogra	−0.20	−0.14	−0.06	0.03	−0.63	−0.43	−0.20	−0.43
SW83.1 Naldanga Rly. Crossing	−0.63	−0.04	−0.60	-	−0.92	−0.15	−0.77	−0.44
SW90 Hardinge Bridge	−0.35	−0.04	−0.31	−0.47	−0.58	−0.06	−0.51	−0.51

Rainfall-Expected Change and Residual are Means of the MLR, RF and XGB Models. - = too Few Gaugings Near Q25.

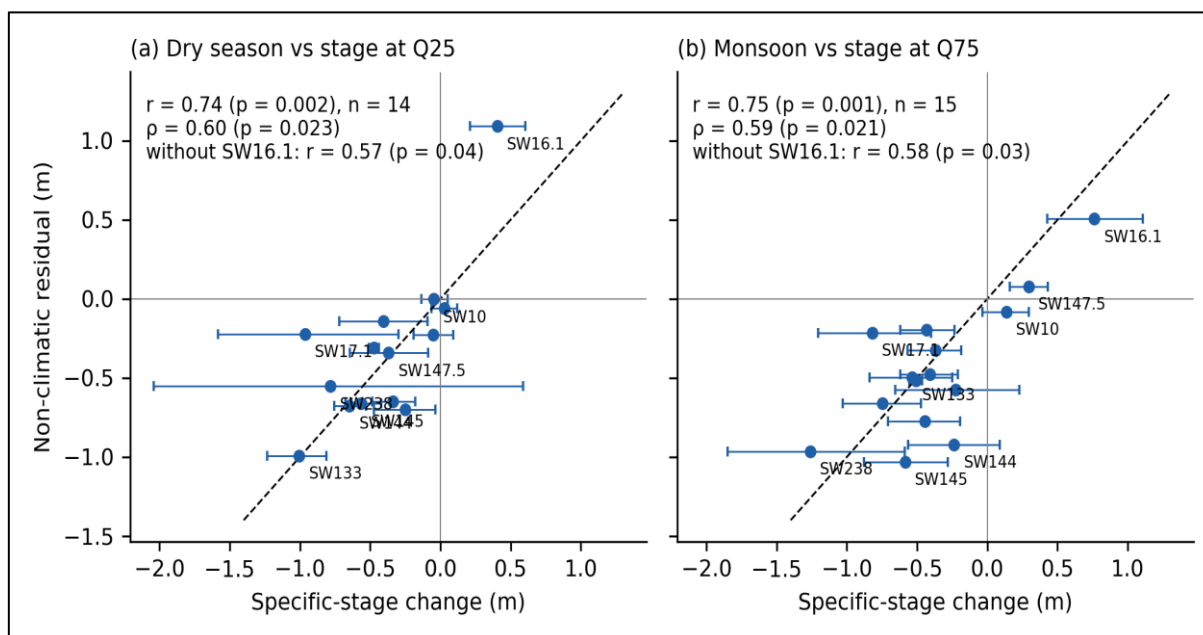


Fig 6 Non-Rainfall Residual Versus Specific-Stage Change: (a) Dry Season, Q25; (b) Monsoon, Q75. Bars: 95% Bootstrap Intervals; Dashed Line: 1:1.

➤ Rainfall Accumulation Scales Used by the Models

SHAP values showed that the RF models drew on rainfall accumulated over several time scales rather than one (Fig. 7). Short scales (SPI-1 to SPI-6) accounted for a median of 56% of mean absolute SHAP in the monsoon and 51% in the dry season, with SPI-2 and SPI-4 contributing most. Long scales (SPI-9 to SPI-24) contributed more in the dry season (29%) than in the monsoon (25%), mainly through SPI-12 (8.1%

against 6.0%) and SPI-24 (8.8% against 7.0%). The two seasonal terms accounted for the remaining 20% (dry season) and 19% (monsoon). This matches the longer propagation time in the dry season: low-season levels depend partly on the rainfall of the previous monsoon and on longer-term storage. The spread between stations was large (Fig. 7), so these patterns describe the network as a whole rather than every station.

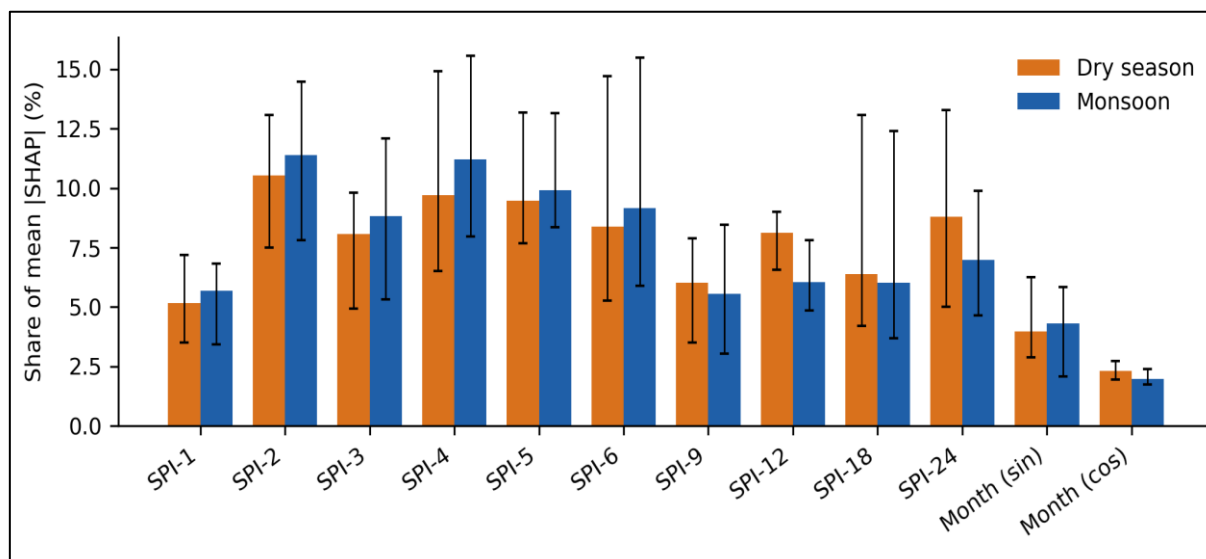


Fig 7 Share of Mean |SHAP| by Input for the RF Models, Dry Season and Monsoon (Median and IQR, 22 Gauges).

V. DISCUSSION

➤ Falling River Levels are Only Partly a Rainfall Drought

Rainfall in northwest Bangladesh did decline over 1980–2022, and meteorological drought months became almost twice as frequent after 2000, consistent with the persistence of the Barind drought hotspot reported by Kamruzzaman et al. (2022). The rainfall decline, however, explains only about a

quarter of the fall in river levels, and less than half even under a generous upper bound. The remaining fall is widespread, statistically clear at 18 of 22 gauges, consistent across three different model types, and still growing. The residual is unlikely to be a model artefact: the linear and tree-based models, which make very different assumptions, give almost the same residuals, and the discharge gaugings show a channel change of similar size at the same stations.

➤ *Channel Change as the Main Non-Rainfall Driver*

The agreement between the residual and the specific-stage change suggests that a large part of the fall in river level reflects a lower channel rather than less water. For the same discharge, the Ganges at Hardinge Bridge now flows about half a metre lower, and several Atrai and Little Jamuna stations flow 0.5-1.0 m lower. Bed lowering of this kind has several possible causes, including reduced sediment supply, sand extraction and channel straightening, and our data cannot separate them. The same mechanism, riverbed incision, explained falling dry-season water levels in the Mekong Delta despite rising discharge (Binh et al., 2021). Malanchi on the Baral, where the channel aggraded, supports this interpretation: here the channel has aggraded, the specific stage rose by 0.4-1.0 m and water levels rose, although rainfall declined. Shifts in the stage-discharge relation of this kind are well documented in hydrometry, and methods exist to detect and correct them (Mansanarez et al., 2019; Darienzo et al., 2021).

➤ *Remaining Losses of Flow*

At several stations, channel change explains only part of the residual. At Chak Hariharpur, Mohadebpur and Atrai Railway Bridge on the Atrai, at Chapai Nawabganj on the Mahananda and at Naldanga, water levels fell by 0.3-0.7 m more than both rainfall and channel change would suggest. The most plausible explanations are reduced inflow from upstream and reduced baseflow. Most of these rivers enter Bangladesh from India, and upstream abstraction and regulation affect transboundary flows; our data contain no upstream observations, so we cannot quantify this. Groundwater abstraction for dry-season irrigation has lowered groundwater levels in exactly this part of the region (Janardhanan et al., 2023; Rasel et al., 2023), which reduces groundwater discharge to rivers in the dry season. Globally, abstraction has been found to lengthen and deepen streamflow droughts in most studied cases (Van Loon et al., 2022). The slight weakening of the rainfall-river link after 2000, strongest on the Ganges, at Chanchkair and at Malanchi, is consistent with a growing influence of non-rainfall factors, as found for managed basins elsewhere (Tijdeman et al., 2018; Zhang et al., 2023; Sutanto et al., 2024).

➤ *Implications for Drought Monitoring*

Water level indices are attractive in Bangladesh because water level is measured daily at many stations while discharge is not. Our results show that, in alluvial rivers with changing beds, a raw water level index mixes water deficit with channel change. The share of months in hydrological drought rose almost five-fold under raw SWI, against a less than two-fold rise in meteorological drought, and several recent years with near-normal rainfall were classed as widespread hydrological drought. Without correction, such an index would overstate the frequency and extent of drought and could misdirect drought response. We recommend three practical steps: (i) compute indices on discharge derived from periodically updated rating curves, or correct water levels for the specific-stage change, since plain detrending also removes genuine drought trends; (ii) check stage at fixed discharge regularly, which BWDB's gauging programme already makes possible; and (iii) analyse propagation on detrended indices, because shared trends produce spurious long propagation times, as shown in Table 3.

Short-range drought forecasting based on SPI at 2-6 months is feasible in the monsoon, but the weak dry-season link means that rainfall indices alone will not forecast low-season river levels well.

VI. LIMITATIONS

The ML models explain only part of the month-to-month variation (median NSE 0.17), mainly because local rainfall does not represent upstream catchments in India. We addressed this with an upper bound on the rainfall share, but the attribution remains conditional on the local rainfall inputs. The reference period, 1980-2000, is not free of human influence; the results describe change relative to that period, not relative to natural conditions. Potential evapotranspiration could not be included because temperature data were not available, so SPEI could not be computed. The specific-stage analysis compares two periods and cannot resolve the timing of channel change. The comparison of residual and channel change rests on 14-15 stations, and the rank correlations were only marginally significant without Malanchi. Records after October 2022 were excluded because of the datum change. Finally, areal rainfall was taken from gauges within 40 km, and the homogeneity test, being relative, cannot detect a shift shared by all gauges in a cluster. Both the residual and the specific-stage change are derived from the same staff gauge, so an unrecorded datum change or gauge relocation between the two periods would affect both equally; station histories should be checked before the specific-stage change is read as bed lowering at individual stations.

VII. CONCLUSIONS

Using 43 years of BWDB rainfall, water level and discharge data for northwest Bangladesh, we examined how much of the fall in river levels can be explained by rainfall. The main conclusions are as follows.

- Rainfall declined by 5.6% per decade over 1980-2022, and 2001-2022 was 11% drier than 1980-2000.
- River levels fell significantly at 16-19 of 22 gauges, by a median of 0.55-0.60 m between the two periods.
- Levels respond most to rainfall accumulated over 2-6 months, more strongly in the monsoon than in the dry season; long propagation times obtained from raw indices were artefacts of shared trends.
- ML models trained on 1980-2000 attribute a median of 24% of the decline to lower rainfall (upper bound 49%); the remaining decline is significant at 18 of 22 gauges and is growing.
- The non-rainfall decline agrees with the fall in stage at fixed discharge obtained from gaugings, which is consistent with channel-bed lowering, while several Atrai and Mahananda stations show an additional loss of flow.
- Raw water level indices overstate hydrological drought in these rivers and should be corrected for channel change before use.

Future work should extend the analysis with upstream flow and groundwater level data, reconstruct discharge with time-varying rating curves, and test whether drought forecasts

based on corrected indices improve dry-season water management in the Barind region.

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DECLARATIONS

- Data availability. The discharge and water level data were obtained from the Bangladesh Water Development Board (BWDB) and are available from BWDB on request, subject to its data-sharing conditions. The analysis code is available from the corresponding author on reasonable request.
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- Author contributions: All authors read and approved the final manuscript.
- Declaration of generative AI use. During the preparation of this work, the authors used Claude (Anthropic) to assist with drafting and language editing, checking the consistency of reported values, verifying reference details and writing code for figures. The authors reviewed and edited all content and take full responsibility for the content of the publication. Every author has read, comprehended, and cooperated with the Instructions for Authors' "Ethical responsibilities of Authors" declaration.

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