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# A Winter Duration Index (WDI) for Dhaka: Constructing, Validating, and Forecasting a Dated Measure of Winter Length from a Single ERA5 Grid Cell, 1990–2050

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**Article**

**Keywords:** Winter Duration Index, season length, ERA5, Modified Mann-Kendall, Sen's slope, ARIMA, ETS, ETCCDI Cold Spell Duration Index

**Posted Date:** November 11th, 2026

**DOI:** https://doi.org/10.21203/rs.3.rs-11039322/v1

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**Additional Declarations:** No competing interests reported.

# A Winter Duration Index (WDI) for Dhaka: Constructing, Validating, and Forecasting a Dated Measure of Winter Length from a Single ERA5 Grid Cell, 1990–2050

## Abstract

Bangladesh's winter is among the fastest-warming seasons, but existing research measures how cold it gets, not how long it lasts. This study builds a dated Winter Duration Index (WDI) for Dhaka, which, to the author's knowledge, is the first such measure for Bangladesh: an onset date, withdrawal date, and duration in days each year, from a smoothed daily-mean climatology and a fixed percentile threshold. Using 320,688 hourly ERA5 observations (1990–2026) at the grid cell nearest Dhaka, the climatology was smoothed with a three-harmonic fit, threshold set at the 25th percentile (22.55°C). Across 36 winters (1990–2025), mean duration was 89.6 days (SD = 9.8, range 73–114), with mean onset on 23 November and mean withdrawal on 21 February. Because the threshold is a fixed percentile, the mean duration largely reflects that choice; interannual variability and trend are the informative quantities. WDI was not significantly correlated with the same-series ETCCDI Cold Spell Duration Index ($r = 0.18$, $p = 0.293$; $\rho = 0.19$, $p = 0.267$), so this comparison provides no positive evidence of convergent validity. A Hamed–Rao Modified Mann-Kendall test found no significant trend in onset, withdrawal, or duration (all $p > 0.5$); with only 36 winters the test has low power and cannot exclude a modest trend. ARIMA(0,1,1) had a lower test-set RMSE than an ETS benchmark (6.66 vs. 8.53 days; seven test winters), but the difference was not statistically significant (Diebold–Mariano $p = 0.126$). Refit on the full series, the forecast stays flat near 89 days through 2050; this is a statistical extrapolation of a trendless series, not a climate projection. The WDI is offered as a baseline that complements Bangladesh's severity-focused literature; it is a single-grid-cell, reanalysis-based result that has not yet been validated against station records.



**Keywords:** Winter Duration Index; season length; ERA5; Modified Mann-Kendall; Sen's slope; ARIMA; ETS; ETCCDI Cold Spell Duration Index

## Descriptive Summary

This study addresses a significant gap in Bangladesh's climatological literature by shifting the focus from winter temperature intensity to seasonal duration. While existing research extensively documents the warming of winter minimum temperatures, we are not aware of a dated measure that tracks the specific onset and withdrawal of the season. By constructing a Winter Duration Index (WDI) for Dhaka using 36 years of ERA5 reanalysis data (1990–2025), this research provides a chronological baseline for the capital's cool season.

The analysis reveals that Dhaka's winter lasts an average of 89.6 days (SD = 9.8), typically running from late November to late February, based on a climatological threshold of 22.55°C. Despite the established warming trends in the region, the Hamed–Rao Modified Mann-Kendall test detected no statistically significant long-term trend in winter duration, onset, or withdrawal, with a nominal Sen's slope of only –0.095 days per year. Significant interannual variability was observed, with winter lengths ranging from a minimum of 73 days (2004–05) to a maximum of 114 days (2013–14).

Furthermore, by benchmarking forecasting models, the study finds that ARIMA(0,1,1) had a lower test-set error than ETS, although the difference was not statistically significant. Refit on the full historical data, the model forecasts a stable winter duration of approximately 89 days through 2050. These results are consistent with, but do not demonstrate, stable calendar boundaries despite the documented warming of winter minimum temperatures; a modest trend cannot be excluded in a 36-year, single-grid-cell record. This work provides a dated baseline that may inform Rabi-crop scheduling, energy-demand planning, and cold-wave early-warning systems once validated against station data, and is, to the author's knowledge, the first season-length case study for Bangladesh.

## 1. Introduction

Bangladesh's climate is changing fast, and winter is one of the seasons warming quickest (Alam et al., 2023). Farmers plan their Rabi-season crops around when cool weather starts and ends (Kamruzzaman et al., 2022). Health workers watch for cold spells that put children and older people at risk (Hasan et al., 2021). Energy planners size heating and cooling demand around the same calendar (Haider et al., 2024). All of this depends on knowing, in a clear and dated way that when winter begins, when it ends, and how long it lasts each year (Haider et al., 2024; Kamruzzaman et al., 2022). Most of what is known about Bangladesh's winter describes how cold it gets, not how long it stays (Haider et al., 2024). Existing studies report average temperatures, count cold-wave days, or track extreme-temperature indices (Haider et al., 2024; Hasan et al., 2021). These are useful, but none of them give winter a start date and an end date the way it has been emphasized for the summer monsoon (Ahmed & Karmakar, 1993).

The country is warming, and winter is warming even faster, with the winter minimum temperature being risen by about 0.18°C per decade since 1949 (Alam et al., 2023), confirmed by using different stations and time periods. For instance, Khan et al. (2019) found significant warming in both maximum and minimum temperature between 1988 and 2017 and Shahid (2010) reported the same broad warming trend, and later Shahid et al. (2012) tracked a narrowing gap between daily high and low temperatures; Mullick et al. (2019) confirmed the trend after correcting for serial correlation in the data, and Haider et al. (2024) reached the same conclusion using a fuller set of extreme-climate indices through 2019.

Shahid and Khairulmaini (2009) linked shifting rainfall to the same warming pattern. Raihan et al. (2015) found consistent warming in south-eastern Bangladesh specifically. Alamgir et al. (2019) projected the trend forward using downscaled climate models. Rahman and Islam (2019) connected the changes to shifting precipitation intensity, and Zinat et al. (2020) showed how the warming climate is already changing drought risk during the Boro rice season. Kamruzzaman et al. (2019) found a similar drought signal at the national scale, and Jerin et al. (2021) reported the same warming pattern in the country's evapotranspiration trends. Together, these studies leave little doubt that Bangladesh's winter is getting warmer.

Cold-wave studies count how often severe cold happens (Baten et al., 2022; Bangladesh Meteorological Department, 2023) and percentile-based cold-spell studies measure how extreme a given cold snap is (Alam et al., 2023a, 2023b), but neither gives winter a start date and an end date. The same severity-only focus shows up across the wider region; in India, cold-wave frequency has been falling even as heat waves rise (Kumar et al., 2024; Athira et al., 2024), but these studies count cold-wave days, not a season's length. A newer ERA5-based reconstruction of Bangladesh's daily weather types reaches a related conclusion from a different angle - the dry, cool weather type that historically defines Bangladeshi winter has been shrinking since the 2000s (Sumaya et al., 2025). The Bangladesh Meteorological Department's own records tell the same story - January 2025 was the country's warmest winter month since 1948, with no severe cold spell recorded against a normal of two or three (TBS, 2025).

Outside Bangladesh or South Asia, a small but growing body of research treats season length itself as the thing to measure, using a temperature threshold, usually a fixed percentile, to mark when a season begins and ends each year. Wang et al. (2021) did this at hemispheric scale and Guan et al. (2021) applied it to Northern Hemisphere drylands and found winter contracting by about 0.23 days per year since 1951. A cluster of recent studies has applied the same method in Iran and the Arabian Peninsula, defining season onset, end, and length from daily temperature thresholds and testing the resulting trend with the Mann-Kendall test and Sen's slope (Doostan & Alijani, 2023; Hekmatzadeh et al., 2020; Khodamorad Pour et al., 2025; Alghamdi, 2024). In China, Zhang et al. (2020) tracked a comparable shift in growing-season length using satellite vegetation data.

Bangladesh already has a well-established version of this idea, but applied to a different season. Since Ahmed and Karmakar's (1993) study of monsoon arrival and withdrawal at 19 stations, they have treated the monsoon as a dated period with its own onset and withdrawal and have tracked how that period is shifting. Montes et al. (2021) did this using gridded rainfall data from 1981 to 2018. Shariot-Ullah et al. (2024) applied the Mann-Kendall test and Sen's slope to station data in the northwest. Mondal and Chaudhuri (2022) tracked the withdrawal phase on its own as a duration variable. Outside Bangladesh, Ananthakrishnan and Soman

(1988) defined the onset of the Kerala monsoon using rainfall thresholds, a definition that shaped decades of Indian monsoon research, and Bombardi et al. (2020) reviewed the full range of methods now used worldwide to detect monsoon onset and withdrawal dates. Fasullo and Webster (2003) used the same logic for the Indian monsoon more broadly, and in the United States, Kunkel et al. (2004) has tracked an analogous temperature-based duration measure, the frost-free season, for decades.

The Mann-Kendall trend test, developed by Mann (1945) and extended by Kendall (1975), together with Sen's (1968) slope estimator, is the standard way Bangladeshi researchers detect and measure climate trends (Alam et al., 2023; Evan, 2023; Mallick et al., 2022). About the forecasting tools - Masum et al. (2022) forecast Bangladeshi time series with these same methods, and outside the country, Jain and Mallick (2017) compared ARIMA and ETS specifically for weather forecasting, finding neither method reliably better than the other - a result this study tests again for winter duration. Therefore, it can be said, ERA5 performs well against ground stations in general; however, McNicholl et al. (2022) found its accuracy drops in tropical regions compared to temperate ones.

So far, Bangladesh's cold-season literature reports averages and counts but has yet to define winter as a dated period with an onset date, a withdrawal date, and a duration in days, even though the domestic monsoon-onset tradition has used exactly this logic since Ahmed and Karmakar (1993). The Modified Mann-Kendall test and Sen's slope, already routine in the country's climate literature (Alam et al., 2023; Evan, 2023; Mallick et al., 2022), have correspondingly never been applied to a winter season-length series, simply because that series has not yet been built. And with no dated winter measure to project forward, it remains unclear how much shorter, if at all, Dhaka's winter will become by mid-century - a horizon relevant to Rabi-crop calendars, cold-wave early warning, and heating and cooling demand.

## 2. Objectives

This study aims to construct a Winter Duration Index (WDI) for Dhaka, built from thirty-six years of ERA5 temperature data, giving each winter an onset date, a withdrawal date, and a length in days, then checks the measure against an existing index, tests it for trend, and forecasts it to 2050.

Specific objectives are to:

- Build the WDI and define winter as the period when a smoothed daily-mean-temperature curve drops below the 25th percentile of the 1990–2025 climatology, following Wang et al. (2021), giving each of the 36 winters an onset date, a withdrawal date, and a duration in days;

- Check the WDI and compare its annual duration against the ETCCDI Cold Spell Duration Index (Zhang et al., 2011), calculated independently from the same ERA5 data, to assess whether the two measures are related.

- Test the WDI for trend and run the Hamed-Rao Modified Mann-Kendall test (Hamed & Rao, 1998; Yue et al., 2002) and Sen's slope (Sen, 1968; Theil, 1950; Kendall, 1975) on onset, withdrawal, and duration, reporting the slope in days per year for each - addressing the lack of a trend-tested Bangladeshi winter-length series.

- Forecast the WDI to 2050 and compare ARIMA (Box & Jenkins, 1970) and ETS forecasts on a 1990–2018 train / 2019–2025 test split using RMSE and a Diebold-Mariano test (Diebold & Mariano, 1995), following Masum et al. (2022), Ehsan et al. (2026), and Ali et al. (2025) and the M3-Competition benchmarking tradition (Makridakis & Hibon, 2000); refit the stronger model on the full series and project duration to 2050 with 80% and 95% prediction intervals.

## 3. Methodology

### *3.1. Data Analysis*

ERA5 hourly 2-m temperature (Hersbach et al., 2020) is the sole data source: the single grid cell nearest Dhaka (23.75°N, 90.25°E), from the Copernicus Climate Data Store, 1 January 1990 to 1 August 2026 (320,688 hourly observations of t2m). A single ERA5 series was used because a percentile-threshold method needs a complete, gap-free daily record, which a standalone Dhaka station cannot guarantee (Baten et al., 2022); ERA5 agrees well with BMD records for heatwave detection in Bangladesh, though its accuracy is somewhat lower in tropical, data-sparse regions than in temperate ones (Hasan et al., 2024).

Hourly values were converted Kelvin to Celsius and shifted UTC to Dhaka local time (UTC+6). Daily mean, minimum, and maximum temperature came from each local day's hourly values, keeping only days with at least 20 of 24 observations present, forming the daily record used for every subsequent step. This yielded 13,361 complete daily records spanning 2 January 1990 to 1 August 2026.

All processing and analysis were carried out in Stata, R Studio, and Python (statsmodels, used for the ARIMA order search and as an independent check of the threshold). The Hamed–Rao autocorrelation-corrected Mann-Kendall test was operated on the R Studio and - together with Sen's slope and the pairwise-slope median was implemented directly using Mata.

### *3.2 WDI Construction*

A daily-mean-temperature climatology was built for the Dhaka grid cell over 1990–2025 (day-of-year means, 366 calendar days) and smoothed with a low-order harmonic regression - three annual harmonics, following the smoothing role of Wang et al. (2021):

$$T(d) = \beta_0 + \Sigma_{k=1}^{3} [a_k \sin(2\pi kd/365.25) + b_k \cos(2\pi kd/365.25)] + \varepsilon$$

where T(d) is mean temperature on day-of-year d (d = 1, ..., 366).

The winter threshold τ is the 25th percentile of the fitted values $\hat{T}(d)$:

$$\tau = P_{25} \{\hat{T}(1), \hat{T}(2), \ldots, \hat{T}(366)\}$$

For winter year y, with smoothed daily series $\tilde{T}_t$ (7-day centered moving average of the observed daily mean), onset and withdrawal are:

$$\textbf{Onset}(y) = \min\{t > \text{Oct 1}(y) : \tilde{T}_t < \tau\}$$
$$\textbf{Withdrawal}(y) = \min\{t > \text{Jan 1}(y+1) : \tilde{T}_t \geq \tau\}$$
$$\textbf{Duration}(y) = \textbf{Withdrawal}(y) - \textbf{Onset}(y)$$

## 3.3 Internal Validation

WDI duration was correlated against the ETCCDI Cold Spell Duration Index (CSDI), an annual count of days falling in spells of six or more consecutive days below the calendar-day 10th percentile of daily minimum temperature (Tmin), pooled over a 5-day window and the full 1990–2025 record, following the CLIVAR/GCOS/WMO indices framework (Karl et al., 1999; Zhang et al., 2011), computed from the same ERA5 series. The full 1990–2025 record, rather than the conventional 1961–1990 reference period, serves as the percentile base. For calendar day d, the cold threshold is the 10th percentile of Tmin in a 5-day window across all years:

$$\tau_{10}(d) = P_{10}\{\text{Tmin values on days } d-2, \ldots, d+2, \text{all years}\}$$

A day is flagged cold if $Tmin < \tau_{10}(d)$, and $CSDI(y)$ sums the lengths of all runs of ≥ 6 consecutive flagged days within winter year y. WDI duration and CSDI(y) are then correlated (Pearson r, Spearman ρ) across the 36 winters.

## *3.4 Trend Analysis*

Annual WDI onset, withdrawal, and duration series for Dhaka were tested with the Modified Mann-Kendall test in the Hamed and Rao (1998) formulation, which corrects the variance of the Mann-Kendall S-statistic for serial autocorrelation among the ranks of the pre-whitened, Sen-slope-detrended series, and which outperforms the classical Mann-Kendall test under autocorrelation in power-comparison studies (Yue et al., 2002; Partal & Kahya, 2006). For a series $y_1, \ldots, y_n$, the Mann-Kendall statistic is:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sign}(y_j - y_i)$$

Trend magnitude was estimated with Sen's slope (Sen, 1968), the median of all pairwise slopes:

$$\beta = median\{(y_j - y_i)/(t_j - t_i) : j > i$$

which builds on Theil's (1950) rank-based regression estimator and Kendall's (1975) rank-correlation framework, and is robust to outlier winters (e.g., the record-warm 2024–25 season) that ordinary least squares would be sensitive to. The Hamed–Rao correction adjusts Var(S) using the significant rank-autocorrelation coefficients $\rho_k$ of the detrended series ($y_t - \beta t$) at lag k:

$$Var^*(S) = Var(S) \times [1 + (2/(n(n-1)(n-2))) \sum_{k=1}^{n-1} (n-k)(n-k-1)(n-k-2) \rho_k$$

$$Z = (S - 1)/\sqrt{Var^*(S)},\ S > 0;\ Z = (S + 1)/\sqrt{Var^*(S)},\ S < 0;\ Z = 0,\ S = 0$$

This is the same toolkit already standard in the Bangladesh literature (Alam et al., 2023; Evan, 2023; Mallick et al., 2022) and detailed further in Wilks's (2011) standard reference on statistical methods in the atmospheric sciences.

### *3.5 Forecasting*

The 36-point (1990–2025) WDI duration series was split into a 1990–2018 training period (29 seasons) and a 2019–2025 test period (7 seasons). An ARIMA(0,1,1) model, identified following the Box-Jenkins (1970) cycle:

$$\nabla y_t = y_t - y_{t-1} = \varepsilon_t + \theta \varepsilon_{t-1}$$

and a simple exponential smoothing (SES) benchmark:

$$\hat{y}_{t+1} = \alpha y_t + (1 - \alpha)\hat{y}_t$$

were estimated on the training data and compared on the held-out test set by root-mean-square error:

$$RMSE = \sqrt{[(1/m) \sum_{t=1}^{m} (y_t - \hat{y}_t)^2]}$$

with statistical significance of the accuracy difference assessed via the Diebold–Mariano test (Diebold & Mariano, 1995):

$$DM = \bar{d} / (\sigma_d/\sqrt{m}), \text{ where } d_t = e_{t,ARIMA}^2 - e_{t,ETS}^2$$

This mirrors the three-metric-plus-significance-test comparison used for Bangladesh's RMG export series (Ali, Sadia, & Khanam, 2025) and is broadly consistent with the M3-Competition finding that no single forecasting family dominates across short series (Makridakis & Hibon, 2000). The stronger model was then refit on the full 1990–2025 series and used to generate the forecast to 2050, following standard practice for short annual series (Hyndman & Athanasopoulos, 2021).

## 4. Results

### *4.1 WDI Threshold and Climatology*

The three-harmonic regression on the 1990–2025 day-of-year climatology (366 points) achieved $R^2 = 0.9962$ ($F(6, 359) = 15{,}660.68$, $p < 0.001$); every harmonic term was significant at $p < 0.001$ (**Table 1**). The fitted curve ranges from an annual minimum of approximately 17.8°C in early January to a summer plateau of approximately 28.9°C from May through September (**Figure 1**). The 25th percentile of the fitted 366-day curve, the WDI threshold, is 22.55°C. Because the threshold is the 25th percentile of the annual cycle, about a quarter of the calendar year (roughly 91 of 366 days) lies below it on the smoothed climatology by construction. The mean duration reported in Section 4.2 therefore largely reflects this choice of percentile and should not be read as an independent estimate of winter length; the informative quantities are interannual variability and trend. An independent Python implementation of the identical method produced 22.59°C, a negligible difference (0.04°C), most likely attributable to harmonic-fit rounding or numerical differences between implementations.

**Table 1.** Three-Harmonic Regression of Day-of-Year Climatology, Dhaka (1990–2025)

| Term | Coefficient | SE | t | P > \|t\| |
|---|---|---|---|---|
| s1 | −0.6670 | 0.0185 | −36.10 | < 0.001 |

| | | | | |
|---|---|---|---|---|
| c1 | −5.0099 | 0.0184 | −271.71 | < 0.001 |
| s2 | −0.6800 | 0.0185 | −36.80 | < 0.001 |
| c2 | −2.3370 | 0.0184 | −126.74 | < 0.001 |
| s3 | −0.2404 | 0.0185 | −13.01 | < 0.001 |
| c3 | −0.5415 | 0.0184 | −29.37 | < 0.001 |
| Constant ($\beta_0$) | 25.7849 | 0.0131 | 1975.63 | < 0.001 |

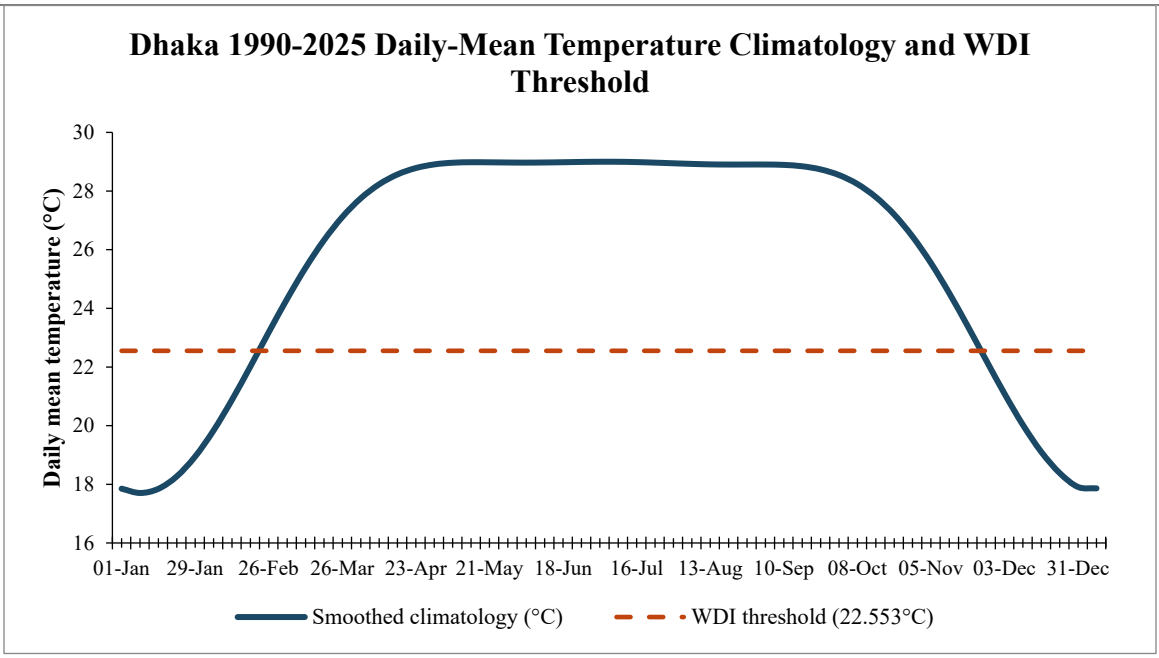



**Figure 1.** Smoothed 1990–2025 daily-mean temperature climatology for the Dhaka ERA5 grid cell, with the WDI threshold (25th percentile, 22.55°C) marked. The shaded region marks the portion of the annual cycle below threshold, the climatological winter window.

### *4.2 WDI Onset, Withdrawal, and Duration (1990–2025)*

All 36 winters were cleanly identified, with no missing onset or withdrawal date in any year (**Table 2**). Mean WDI duration was 89.6 days (SD = 9.8), ranging from a minimum of 73 days (winter 2004–05) to a maximum of 114 days (winter 2013–14). Onset dates ranged from 12 November (2012) to 6 December (2023), averaging 23 November; withdrawal dates ranged from 10 February (winters 1990–91 and 2004–05) to 9 March (2013–14), averaging 21 February. Figure 2 plots the full 36-year duration series showing that winter's start and end dates shift somewhat from year to year, but they consistently fall in the same general window, late November to late February.

**Table 2.** Annual WDI Onset, Withdrawal, and Duration, Dhaka (1990–2025)

| Winter Year | Onset | Withdrawal | Duration (days) |
|---|---|---|---|
| **1990** | 27 Nov 1990 | 10 Feb 1991 | 75 |
| **1991** | 17 Nov 1991 | 02 Mar 1992 | 106 |
| **1992** | 22 Nov 1992 | 11 Feb 1993 | 81 |
| **1993** | 24 Nov 1993 | 02 Mar 1994 | 98 |
| **1994** | 21 Nov 1994 | 03 Mar 1995 | 102 |
| **1995** | 23 Nov 1995 | 22 Feb 1996 | 91 |
| **1996** | 20 Nov 1996 | 27 Feb 1997 | 99 |
| **1997** | 29 Nov 1997 | 18 Feb 1998 | 81 |
| **1998** | 28 Nov 1998 | 12 Feb 1999 | 76 |
| **1999** | 21 Nov 1999 | 02 Mar 2000 | 102 |
| **2000** | 26 Nov 2000 | 17 Feb 2001 | 83 |
| **2001** | 27 Nov 2001 | 19 Feb 2002 | 84 |
| **2002** | 15 Nov 2002 | 25 Feb 2003 | 102 |
| **2003** | 20 Nov 2003 | 21 Feb 2004 | 93 |
| **2004** | 29 Nov 2004 | 10 Feb 2005 | 73 |
| **2005** | 23 Nov 2005 | 11 Feb 2006 | 80 |
| **2006** | 25 Nov 2006 | 25 Feb 2007 | 92 |
| **2007** | 27 Nov 2007 | 27 Feb 2008 | 92 |
| **2008** | 17 Nov 2008 | 19 Feb 2009 | 94 |
| **2009** | 21 Nov 2009 | 12 Feb 2010 | 83 |
| **2010** | 30 Nov 2010 | 16 Feb 2011 | 78 |
| **2011** | 25 Nov 2011 | 21 Feb 2012 | 88 |
| **2012** | 12 Nov 2012 | 23 Feb 2013 | 103 |
| **2013** | 15 Nov 2013 | 09 Mar 2014 | 114 |
| **2014** | 18 Nov 2014 | 20 Feb 2015 | 94 |
| **2015** | 27 Nov 2015 | 12 Feb 2016 | 77 |

| | | | |
|---|---|---|---|
| **2016** | 19 Nov 2016 | 18 Feb 2017 | 91 |
| **2017** | 23 Nov 2017 | 20 Feb 2018 | 89 |
| **2018** | 20 Nov 2018 | 19 Feb 2019 | 91 |
| **2019** | 30 Nov 2019 | 01 Mar 2020 | 92 |
| **2020** | 22 Nov 2020 | 22 Feb 2021 | 92 |
| **2021** | 26 Nov 2021 | 25 Feb 2022 | 91 |
| **2022** | 21 Nov 2022 | 19 Feb 2023 | 90 |
| **2023** | 06 Dec 2023 | 18 Feb 2024 | 74 |
| **2024** | 22 Nov 2024 | 15 Feb 2025 | 85 |
| **2025** | 22 Nov 2025 | 20 Feb 2026 | 90 |

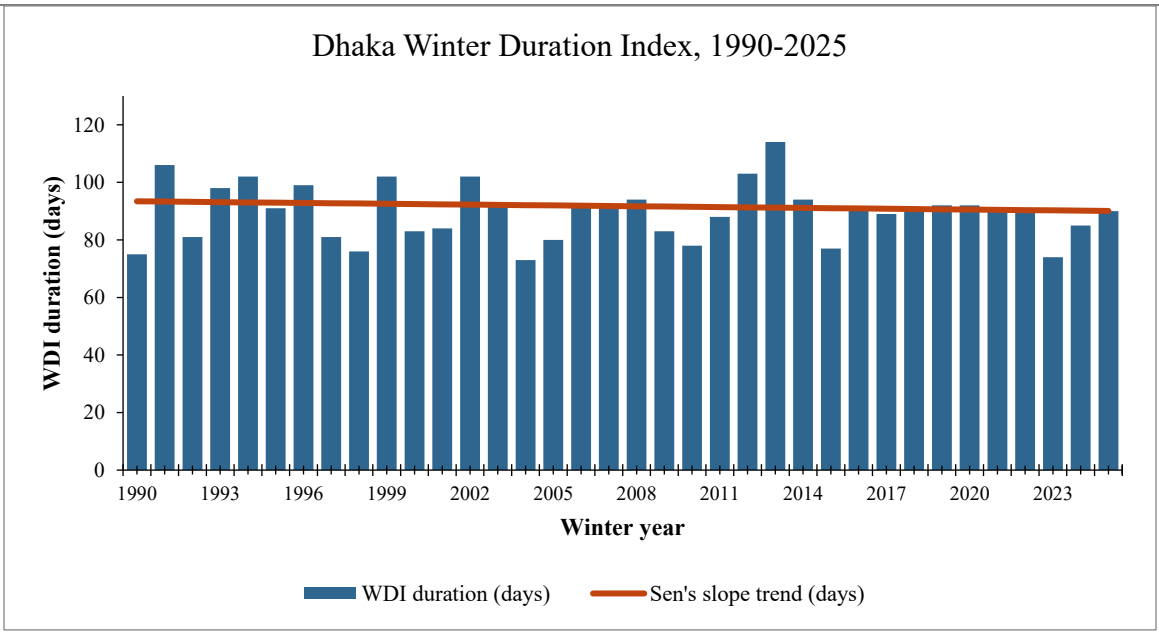



**Figure 2**. Dhaka WDI duration by winter year, 1990–2025, with the Sen's-slope trend line from the Hamed–Rao Modified Mann-Kendall test overlaid.

### *4.3 Internal Validation: WDI Duration vs. ETCCDI CSDI*

WDI duration was only weakly and non-significantly correlated with the same-series ETCCDI Cold Spell Duration Index: Pearson r = 0.18 (p = 0.293), Spearman ρ = 0.19 (p = 0.267; n = 36). CSDI counts rare, severe multi-day cold spells, while WDI measures the length of ordinary winter conditions. A weak association is therefore not by itself evidence of an error. However, with r =

0.18 the two indices share little variance, and both are derived from the same ERA5 series, so this comparison cannot confirm that the WDI is measuring winter length correctly. The WDI should be regarded as not yet externally validated; comparison with BMD station records is needed.

### *4.4 Trend Test: Hamed-Rao Modified Mann-Kendall and Sen's Slope (1990–2025)*

**Table 3.** Hamed-Rao Modified Mann-Kendall Trend Test Results

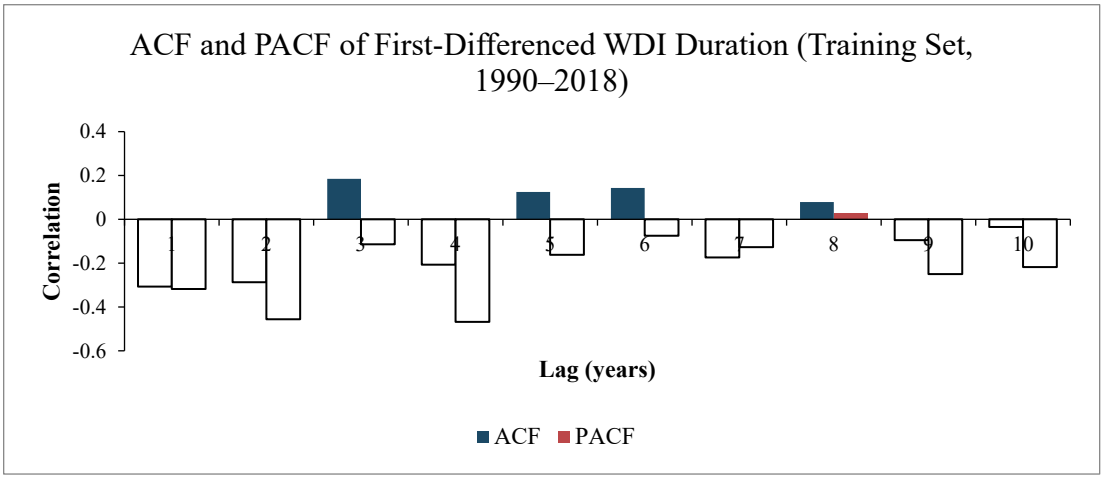
| Series | S | n/n* | Sen's Slope (days/yr) | Z (p-value) |
|---|---|---|---|---|
| Duration | −43 | 1.00 | −0.095 | −0.57 (0.567) |
| Onset (days after 1 Oct) | 8 | 1.00 | 0.000 | 0.10 (0.924) |
| Withdrawal (days after 1 Oct) | −27 | 1.00 | −0.018 | −0.35 (0.723) |

*Note. n/n* is the Hamed-Rao autocorrelation correction factor; a value of 1.00 indicates no significant serial autocorrelation was detected, so the correction reduces to the classical Mann-Kendall statistic. Z and p-values are two-sided.*

No statistically significant trend was detected in WDI duration, onset, or withdrawal at Dhaka over 1990–2025 (all $p > 0.5$). Duration shows a small negative Sen's slope of −0.095 days per year, a nominal shortening of roughly 3.4 days over the 36-year record, but this is far from conventional significance thresholds ($z = -0.57$, $p = 0.567$). Onset and withdrawal show essentially no drift at all (slopes of 0.000 and −0.018 days/yr). In plain terms, the data give no proof that Dhaka's winter is getting shorter or longer over this period. **Figure 2** plots the fitted Sen's slope line against the annual series; the line is nearly flat, and the year-to-year swings in duration (SD = 9.8 days) are large enough to mask any small trend. With 36 winters, a rough ordinary-least-squares power calculation under independent errors and SD = 9.8 days suggests that a trend of about 0.45 days per year or larger (roughly 16 days over the record) would be needed for 80% power at $\alpha = 0.05$, so the absence of significance should be read as absence of evidence rather than as evidence of no change.

### *4.5 ARIMA Order Selection and Residual Diagnostics*

An Augmented Dickey-Fuller test rejects a unit root in levels (ADF = −4.62, $p < 0.001$) and in the first difference (ADF = −3.84, $p = 0.003$). Rejection of a unit root in levels indicates that the series is already stationary, so first differencing is not statistically required, and the MA(1) coefficient on the invertibility boundary reported below is the usual signature of over-differencing. The ARIMA(0,1,1) specification should therefore be read as an approximately constant-level model rather than as evidence of meaningful moving-average structure. The ACF/PACF of the differenced




training series (Figure 3) shows a single significant negative spike at lag 1, consistent with an MA(1) process. An AIC/AICc grid search over ARIMA(p,d,q), $p,q \in \{0,1,2\}$, $d \in \{0,1\}$, confirms this: ARIMA(0,1,1) has the lowest AIC (218.21) and AICc (218.67) of 18 candidates (Table 4), ahead of the next-best model by less than one AIC point. A gap this small is not decisive, and AIC values are not strictly comparable between models with different orders of differencing ($d = 0$ vs. $d = 1$).

**Figure 3.** ACF and PACF of the first-differenced WDI duration series (bars), 1990–2018 training set. Dashed reference lines at ±0.370 mark the 95% confidence limits under the white-noise null ($n = 28$).

**Table 4.** ARIMA Order Selection: Top Candidate Specifications by AIC (Training Set, 1990–2018)

| Order (p,d,q) | AIC | AICc | BIC | Rank |
|---|---|---|---|---|
| **(0,1,1)** | **218.21** | **218.67** | **220.87** | **1 (selected)** |
| (0,0,2) | 219.15 | 220.11 | 224.61 | 2 |
| (0,1,2) | 220.17 | 221.13 | 224.17 | 3 |

| | | | | |
|---|---|---|---|---|
| (1,1,1) | 220.19 | 221.15 | 224.19 | 4 |
| (2,1,1) | 220.31 | 221.98 | 225.64 | 5 |

*Note. Fitted by maximum likelihood (statsmodels SARIMAX) on the 29-point 1990–2018 training series; d = 0 models include a constant, d = 1 models do not. AICc = sample-size-corrected AIC.*

Residuals show no significant autocorrelation (Ljung-Box Q(5) = 3.39, p = 0.64; Q(10) = 6.32, p = 0.79). The MA root sits at |root| = 1.0007, on the invertibility boundary, consistent with the differenced series carrying almost no autocorrelation to fit.

### *4.6 Forecast: ARIMA vs. ETS (1990–2018 Train / 2019–2025 Test)*

ARIMA(0,1,1) had a lower test-set RMSE than the ETS benchmark: 6.66 days versus 8.53 days. A Diebold–Mariano test on the paired squared forecast errors found this difference not statistically significant (DM = −1.77, df = 6, p = 0.126). With only seven test winters this comparison has little power, so it shows no demonstrable difference between the two approaches rather than the superiority of ARIMA. Neither model was compared against a naive constant-mean forecast, which the flat ARIMA forecasts closely resemble.

**Table 5.** Forecast Model Comparison, 2019–2025 Test Set

| Model | Test-Set RMSE (days) | Note |
|---|---|---|
| ARIMA(0,1,1) | 6.66 | MA(1) coefficient at the non-invertible boundary (−1.00, SE ≈ 5173) — consistent with no detected trend; the differenced series is close to white noise. |
| ETS | 8.53 | Simple exponential smoothing (ETS(A,N,N); not a damped-trend Holt-Winters model); a simpler benchmark than the ARIMA specification. |

ARIMA(0,1,1) was then refit on the full 1990–2025 series and used two ways: an in-sample dynamic forecast for 2020–2025, checked against the actual observed values already in the record (Table 6), and an out-of-sample extrapolation to 2050 (Figure 4). Both agree on the same

picture. The in-sample check tracks close to observed duration through the early 2020s before the short winters of 2023–24 (74 days) and 2024–25 (85 days) fall noticeably below the forecast. Because these years were used to fit the model, this in-sample comparison is a consistency check, not evidence of forecast skill. The 2050 extrapolation stays flat at approximately 88–89 days across the full projection horizon, essentially unchanged from the 1990–2025 mean of 89.6 days, with the 95% prediction interval widening only modestly across the forecast horizon, consistent with the near-boundary MA(1) coefficient (Figure 4). This flatness is a mechanical property of a fitted model that contains no trend or climate-forcing term; it is not a projection of how winter length will respond to continued warming.

**Table 6**. Full-Series ARIMA(0,1,1) Refit: Observed vs. Dynamic Forecast, 2020–2025

| Winter Year | Observed Duration (days) | Dynamic Forecast (days) |
|---|---|---|
| 2020 | 92 | 89.24 |
| 2021 | 91 | 89.27 |
| 2022 | 90 | 89.27 |
| 2023 | 74 | 89.23 |
| 2024 | 85 | 88.73 |
| 2025 | 90 | 88.56 |

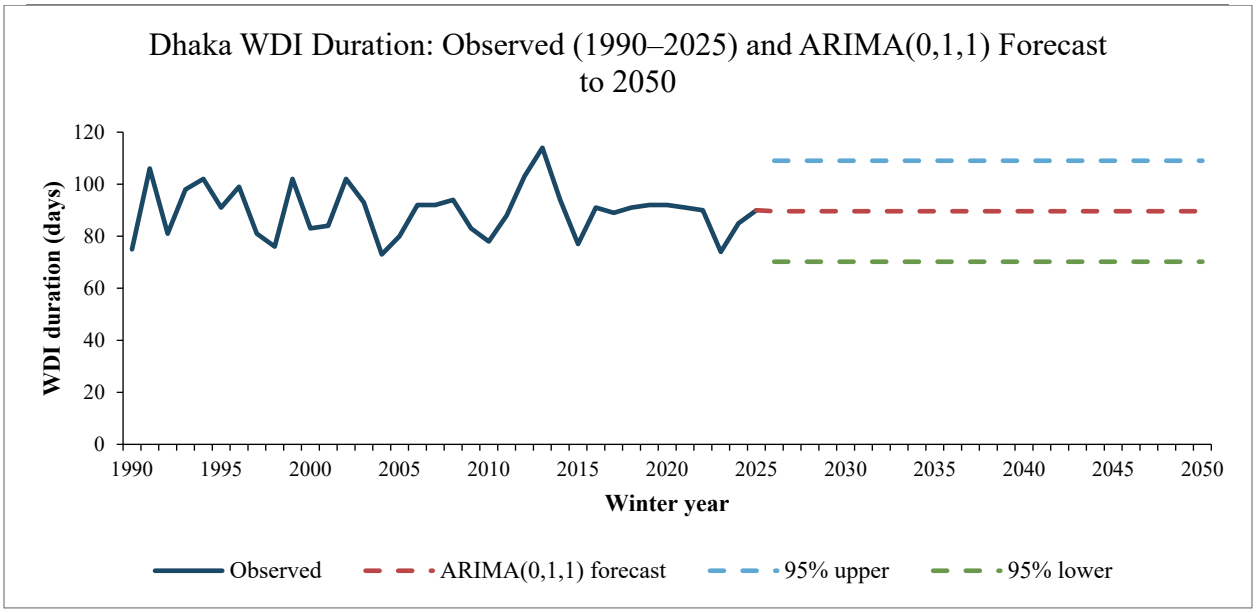


**Figure 4.** Observed Dhaka WDI duration (1990–2025) and ARIMA(0,1,1) forecast to 2050, refit on the full series, with 95% prediction intervals.

## 5. Discussion

The construction of the Winter Duration Index (WDI) for Dhaka reveals a mean winter length of 89.6 days (1990–2025), typically spanning from late November to late February. This provides a first dated baseline for winter seasonality at one Bangladeshi location (Dhaka), although one that depends on the chosen percentile threshold, shifting the analytical focus from traditional intensity-based measures, such as average minimum temperature or cold-wave frequency (Alam et al., 2023a; Baten et al., 2022), to a chronologically defined duration measure.

**The Intensity–Duration Contrast** A central finding of this study is the absence of a statistically significant trend in winter onset, withdrawal, or duration over the 36-year record. This null result (Sen's slope = –0.095 days/year, p = 0.567) is noteworthy when contrasted with the well-documented warming of winter minimum temperatures ($T_{min}$) in Bangladesh, which have risen by approximately 0.18°C per decade since 1949 (Alam et al., 2023; Haider et al., 2024). This divergence should be interpreted cautiously. The two results come from different data, periods (1949 onward vs. 1990–2025) and spatial scales, and the present test has low power (Section 4.4), so a non-significant result does not show that the season's boundaries are stable; it shows only that any trend was too small to detect in this record. One possible explanation, not tested here, is that warming is concentrated within the core winter months rather than the seasonal shoulders (November and February). Another untested possibility is that boundary timing is constrained by large-scale circulation patterns and the timing of the South Asian monsoon withdrawal, which traditionally marks the onset of the dry, cool season (Ahmed & Karmakar, 1993; Montes et al., 2021).

**Interannual Variability and Practical Implications** While the long-term trend is flat, the high interannual variability in duration (ranging from 73 to 114 days, SD = 9.8 days) indicates that winter length varies substantially from year to year. The shortest winter (2004–05) and the longest (2013–14) may be related to large-scale modes such as the El Niño–Southern Oscillation (ENSO)

or the Indian Ocean Dipole (IOD), but this was not tested here; attribution would require analysis of those indices.

This variability may have implications for agricultural and energy planning. For the Rabi crop season, Kamruzzaman et al. (2022) emphasized that crop yields are highly sensitive to the timing of thermal windows. A WDI with no detectable trend but high variability would suggest that while the average window for planting remains consistent, farmers face high year-to-year uncertainty. Similarly, energy planners must account for this variance when sizing heating and cooling demand (Haider et al., 2024). Whether the WDI is more useful than severity-based indices for energy planning or infrastructure resilience has not been tested here and would require comparison with crop-calendar or electricity-demand data.

**Validation and Global Context** The weak, non-significant correlation between WDI and the ETCCDI Cold Spell Duration Index (CSDI) ($r = 0.18$, $p > 0.25$) is compatible with the two indices measuring different aspects of winter, but it is equally compatible with the WDI containing considerable noise; it therefore neither confirms nor undermines the WDI. While CSDI tracks rare, extreme cold events associated with high mortality (Hasan et al., 2021), the WDI captures the "ordinary" winter envelope. This distinction is critical: a winter can be "shorter" without necessarily being "less severe," and vice versa.

Globally, the findings for Dhaka contrast with broader trends in Northern Hemisphere drylands, where winters have contracted by approximately 0.23 days per year since 1951 (Guan et al., 2021). Because the studies differ in region, threshold and period, and because a trend of 0.23 days per year is smaller than the trend this record could reliably detect (Section 4.4), the present results do not establish that South Asia's humid subtropical monsoon climate responds differently from high-latitude or arid regimes (Wang et al., 2021). It also illustrates the feasibility of applying the dated-boundary logic routinely used for monsoon research in the region (Ahmed & Karmakar, 1993; Shariot-Ullah et al., 2024) - to the winter season.

**Forecasting and Limitations** The flat ~89-day projection to 2050 is a mechanical consequence of applying a trendless model to a series with no detectable trend. It is a statistical extrapolation, not a physically based climate projection, and should not be read as a prediction

that winter length will remain stable under continued warming. As noted in the M3-Competition (Makridakis & Hibon, 2000), for short, volatile series, simple models often outperform complex ones that risk overfitting noise.

However, these findings are subject to limitations. First, ERA5 reanalysis data is known to underperform in tropical regions compared to temperate zones (McNicholl et al., 2022; Hasan et al., 2024). Second, this is a single-grid-cell study. Given that monsoon onset can vary by over a month across Bangladesh (Montes et al., 2021), a national WDI would likely show spatial spread that this study cannot capture. Future research should prioritize independent validation against Bangladesh Meteorological Department (BMD) station records and the development of a multi-station national WDI to provide a more comprehensive picture of Bangladesh's changing seasonal landscape.

## 6. Limitations

The 36-year record is relatively short for robust ARIMA/ETS estimation. The single-parameter ETS benchmark had a higher test-set error than ARIMA (RMSE 8.53 vs. 6.66 days), but with only seven test winters the difference was not statistically significant (Diebold–Mariano $p = 0.126$), so neither model can be considered decisively superior. Neither was compared with a naive constant-mean forecast, which the flat ARIMA forecasts closely resemble, and the ADF test and the boundary MA coefficient indicate that the series is close to stationary noise around a constant mean. Crucially, ERA5 reanalysis data is documented to underperform in tropical, data-sparse regions compared to temperate ones (Comparison of weather station and climate reanalysis data, 2022). ERA5 was not validated against BMD station records in this study, and a single 0.25° grid cell may not represent the urban climate of Dhaka, for example urban heat island effects. Consequently, the WDI threshold and trends require future validation against BMD ground-truth records.

Furthermore, the 25th-percentile threshold was adapted from global dryland precedents rather than being calibrated for a humid monsoon climate; local recalibration remains an open question and no threshold sensitivity analysis was performed. Because the threshold is a fixed

percentile of the annual cycle, the mean duration (89.6 days) is largely determined by that choice (a quarter of a 366-day year is about 91 days) and is not an independent estimate of winter length. The climatology and threshold were also computed from the same 1990–2025 period that was tested for trend, and trend and variability results may depend on the threshold chosen. Finally, as a single-grid-cell study, these results describe Dhaka specifically and should not be extrapolated to other divisions of Bangladesh. Because the study relies on a single dataset, the 2050 forecast was not cross-checked against CMIP6 temperature projections, a priority step for future research when independent data sources are incorporated. The forecast contains no climate-forcing information and therefore cannot indicate how winter length will respond to future warming.

The trend tests also have low statistical power: with 36 winters and an interannual SD of 9.8 days, only trends of roughly 0.45 days per year or larger would be detected reliably, so the non-significant results do not rule out modest changes in onset, withdrawal or duration. In addition, the validation against the ETCCDI Cold Spell Duration Index was inconclusive ($r = 0.18$, $p = 0.293$; $\rho = 0.19$, $p = 0.267$) and both indices derive from the same ERA5 series, so the WDI has not been independently validated.

## 7. Conclusion and Contribution

The key results of this study are a mean winter duration of 89.6 days (late November to late February), which largely reflects the 25th-percentile threshold, and no statistically significant trend in onset, withdrawal, or duration in a record with limited power to detect modest trends. The ARIMA forecast is flat at approximately 89 days through 2050; this is a statistical extrapolation of a trendless series rather than a projection of future climate. The WDI may complement existing severity-only metrics (e.g., $T_{min}$ trends). To the author's knowledge, this is the first application of a dated season-length index to Bangladesh. It extends a methodological pairing that has stood half-finished since Ahmed and Karmakar (1993); while the country has tracked monsoon dates for decades, it had not previously applied the same logic to winter. Built from a self-contained dataset, the approach provides a replicable framework for other ERA5 grid points. Priority extensions

include independent validation against BMD station records, sensitivity analysis of the threshold percentile, a national multi-station WDI, and integration with CMIP6 climate projections to refine this new seasonal baseline for Bangladesh.

## 8. Acknowledgement

I would like to acknowledge the Copernicus Climate Change Service (C3S) and the European Centre for Medium-Range Weather Forecasts (ECMWF) for providing the ERA5 global reanalysis data used in this study. I also express gratitude to the teacher who provided valuable feedback during the development of the WDI methodology.

## 9. Conflict of Interest

The author(s) declare that there is no conflict of interest regarding the publication of this paper. This research was conducted independently, and no external funding or influence has affected the results or the conclusions presented herein.

## 10. Data Availability Statement

The ERA5 hourly 2-m temperature data used in this study are publicly available from the Copernicus Climate Change Service (C3S) Climate Data Store at https://cds.climate.copernicus.eu (Hersbach et al., 2020). The specific data subset used corresponds to the grid cell nearest Dhaka (23.75°N, 90.25°E) for the period 1 January 1990 to 1 August 2026. The dataset is ERA5 hourly data on single levels from 1940 to present (DOI: 10.24381/cds.adbb2d47), which is freely available after registration with the Climate Data Store. The annual WDI onset, withdrawal and duration values on which all results are based are reported in full in Table 2. The derived daily temperature series and the analysis code (Stata, R and Python) are available from the corresponding author upon reasonable request.

## 11. Inclusion in Global Research

This research was conducted to address critical climatological gaps in Bangladesh, a region highly vulnerable to seasonal shifts. The study focuses on Dhaka to provide actionable insights for

local end-users, including the Department of Agricultural Extension (DAE) for Rabi-crop planning and the Bangladesh Meteorological Department (BMD) for cold-wave early-warning systems.

The analysis relies on publicly available ERA5 reanalysis data provided by the Copernicus Climate Data Store. While no field samples were collected or specific local permits required for this gridded data analysis, the research design and objectives were formulated to prioritize local scientific needs and climate resilience. The findings are intended to be freely accessible to the Bangladeshi scientific community and policymakers. Furthermore, the methodology is designed to be replicable by local researchers at other grid points across the country, fostering equitable access to seasonal duration metrics in South Asia.

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