

Predicting Monthly Heatwaves and Assessing their Impact on Summer Tomato Production

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ABSTRACT

Background and Objective: The global mean temperature is gradually increasing, which has become a serious environmental concern. Prolonged periods of high temperature often lead to heatwaves (HWs), causing substantial damage to agricultural production. This study aims to predict monthly heatwave occurrences and assess their impact on summer tomato production by examining the influence of key climatic factors on crop yield and overall performance. **Materials and Methods:** This study applied the Zero-Inflated Poisson (ZIP) model to predict the monthly Heat Wave Count (HWC). The impact of heatwaves on the yield of summer tomatoes cultivated in Gazipur district was examined using simple linear regression (LR). Agro-climatological gridded data (1982-2023) were obtained from the assimilation model (MERRA-2) of the NASA POWER Project, while summer tomato yield data (2004-2023) were collected from the Olericulture Division of the Horticulture Research Center (HRC), Bangladesh Agricultural Research Institute (BARI). **Results:** The findings revealed that heatwaves occurred in Gazipur district from March to May, with the highest frequency recorded in April. The number of heatwave days (HWDs) also peaked in April, and the duration of HWDs showed an increasing trend over the years. The ZIP model demonstrated reliable performance with low Mean Squared Error (MSE) and Mean Absolute Error (MAE) during the validation period (2022-2023). Moreover, a significant negative association was observed between heatwaves and summer tomato yield at the 5% significance level ($p = 0.029$). **Conclusion:** The results highlight the increasing occurrence of heatwaves and their adverse effects on summer tomato production in Gazipur district. The ZIP model showed strong potential for reliable heatwave prediction under changing climatic conditions, which could support climate-resilient agricultural planning and crop management strategies.

KEYWORDS

Heatwave forecasting, zero-inflated poisson model climate change, agroclimatology, summer tomato yield, temperature extremes, crop productivity, Bangladesh

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INTRODUCTION

Global average temperatures are rising, intensifying concerns about climate change and its effects on agricultural sustainability¹. Heatwaves (HWs) are becoming more frequent and severe, posing serious risks to crop yields due to increased heat stress^{2,3}. In Bangladesh, shorter winters and prolonged summers



further heighten the likelihood of extreme heat during critical crop growth stages^{4,5}. These conditions can significantly reduce agricultural productivity, making it essential to study heatwave patterns and their impacts to ensure food security and maintain farm profitability under changing climatic conditions.

In Bangladesh, tomato (*Lycopersicon esculentum* Mill.) is a widely cultivated and popular vegetable, traditionally grown in winter for optimal yield⁶. However, rising demand and profitability have expanded its cultivation into summer, supported by heat-tolerant hybrids developed by the Bangladesh Agricultural Research Institute (BARI), such as BARI Hybrid Tomato-3, -4, and -8, often grown under polytunnels⁶⁻⁸. Summer tomatoes are typically planted between April and July and harvested from August to October, but temperatures during this period frequently exceed the optimal range for fruit setting^{7,9-11}. Although these varieties show some heat tolerance, excessive temperatures can still reduce yield by affecting flowering and fruit development^{3,12}.

Many studies have examined heatwave (HW) prediction and summer tomato production separately. Hajong *et al.*⁷ and Karim *et al.*⁸ reported that BARI Hybrid-4 tomato farming is profitable, with high yields (50.41 t/ha), strong returns, and favorable benefit–cost ratios (2.64–3.04)^{7,8}. However, HWs, along with pests, diseases, limited seed and credit access, and high production costs, remain major constraints¹³. Various methods have been used to predict HWs: Nissan *et al.*¹⁴ applied generalized additive models (GAMs), Jacques-Dumas *et al.*¹⁵ used deep learning, and Ke *et al.*¹⁶ applied machine learning based hybrid time series approaches¹⁴⁻¹⁶. While GAMs perform well without excessive zeros and machine/deep learning require large datasets, the Zero-Inflated Poisson (ZIP) model is specifically suited for data with many zeros¹⁷⁻¹⁹. Therefore, this study uses the ZIP model to predict HWs. To date, no research has statistically examined HW frequency alongside its impact on summer tomato production in Bangladesh. Thus, by combining yield effect evaluation with heatwave forecast in the context of Bangladesh, this study contributes to new knowledge. Its specific objectives are to forecast monthly heatwave occurrences using a suitable statistical modeling framework and assess how heatwaves affect summer tomato yield. This study offers empirical evidence to enhance climate-resilient agricultural planning and decision-making by establishing a connection between crop performance and climate extremes.

MATERIALS AND METHODS

Study area: In this study, the primary purpose is to derive a statistical model to predict the monthly HW as accurately as possible and to find the relationship (if any) between HW and the yield of summer tomato. As the yield trial of summer tomato is going on in the Olericulture Division, HRC, BARI for past few years, we selected Gazipur district (Latitude 23.9999, Longitude 90.4203) for monthly HW prediction.

Data source

Agro-climatological data: To investigate the HW scenario in Gazipur district and develop a statistical model for monthly HW prediction the agro-climatological data were collected from the Prediction of Worldwide Energy Resources (POWER) project funded by the National Aeronautics and Space Administration (NASA) Earth Science Directorate Applied Science Program. The POWER project provides satellite and model-based, sufficiently accurate, reliable solar and meteorological resource data over regions where surface measurements are sparse or nonexistent²⁰. The meteorological data in POWER are based upon the Goddard's Global Modeling and Assimilation Office (GMAO) Modern Era Retrospective-Analysis for Research and Applications (MERRA-2) assimilation model and GEOS 5.12.4 FP-IT. The data in POWER are provided on a global grid with spatial resolutions equal to the input data. That resolution is $\frac{1}{2}^\circ$ latitude by $\frac{5}{8}^\circ$ longitude (About 50×62.5 km) for the meteorological data sets with the WGS84 (World Geodetic System 1984) grid reference system²⁰. The parameters, related to the HW, we collected from the POWER project data are daily maximum temperature, minimum temperature, specific humidity, relative humidity, wind speed at 2 m, wind speed at 10 meters, wind direction at 2 m and, precipitation, surface soil wetness, profile soil moisture, and surface pressure from 01/01/1982 to 12/31/2023. The worldwide daily temperature, obtained from the MERRA-2 assimilation model of the POWER project, is depicted in Fig. 1.

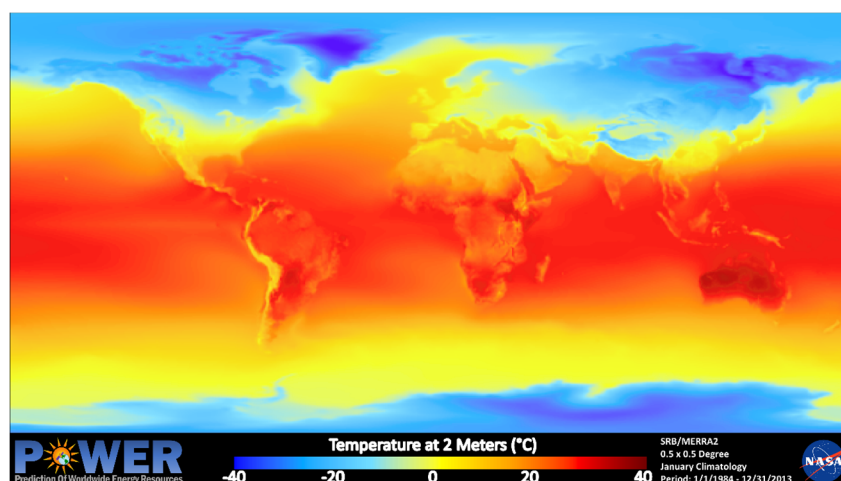


Fig. 1: Daily worldwide temperature obtained by POWER project using MERRA-2 assimilation model from 01/01/1984-12/31/2013

Table 1: Classification and threshold of maximum temperature as per BMD

Types	Heatwaves maximum temperature (°C)	For calculation HW
Mild	36-38	≥ 36
Moderate	38-40	≥ 40
Severe	40-42	≥ 42
Extreme	> 42	> 42

Summer tomato data: The Olericulture Division of HRC, BARI, has been conducting various experiments on two summer tomato varieties, BARI hybrid tomato-4 and BARI hybrid tomato-8, for a number of years to improve these varieties, as stated in their annual reports. These experiments include recording several parameters, such as the yield of these varieties. The annual yield (t/ha) data for summer tomatoes from 2004 to 2023 was obtained from the annual report of the Olericulture Division. The records for BARI hybrid tomato-4 cover the years 2004 to 2007, while the rest of the data is for BARI hybrid tomato-8²¹.

Data arrangement: We obtained daily meteorological data from the above source and checked for outliers, missing values, and other anomalies. Detected outliers were replaced by the missing values in the data. Then, we searched for the heat wave days (HWD) using the maximum daily temperature based on the definition of HWDs and count the number of monthly HWDs, HWs. Other parameters in the study were used as the monthly average.

Heatwave definition: The World Meteorological Organization (WMO) defines a heatwave (HW) as unusually hot weather persisting for at least two consecutive days during the hot season, with temperatures exceeding a set threshold²². This study adopts WMO's definition alongside the Bangladesh Meteorological Department's (BMD) maximum temperature thresholds (Table 1). Using these criteria, mild HW is defined as $\geq 36^{\circ}\text{C}$ for two or more consecutive days, with similar thresholds applied for moderate, severe, and extreme HWs²³.

Statistical analysis: In our investigation of the heat wave (HW) scenario and its impact on the yield of summer tomatoes, we utilized several statistical tools. We employed Spearman's rank correlation to determine the correlation between the number of heat waves and various climatological parameters due to the zero-inflated, over-dispersed, and right-skewed nature of the monthly HW data^{24,25}. Additionally, we used the Zero Inflated Poisson (ZIP) model, which is designed for count models with excessive zeros, to further our research objectives^{18,26}. To evaluate the predictive performance of the ZIP model, we employed Mean Squared Error (MSE)^{12,27} and Mean Absolute Error (MAE)²⁸. Furthermore, we utilized Linear Regression (LR) models to assess the impact of HWs on the yield of summer tomatoes^{29,30}. All analyses were conducted using R software.

Zero-inflated poisson (ZIP) regression: The ZIP regression is a model for count data with excess zeros^{18,26}.

Suppose a random variable, X follows the usual Poisson distribution with parameter λ , $Poi(\lambda)$, with the following probability mass function (Eq. 1).

$$P(X = k) = \exp(-\lambda) \frac{\lambda^k}{k!}, k = 0, 1, 2, 3, \dots \quad (1)$$

$(P(X = k))$ denotes the probability of observing (k) events. (π) is the Poisson rate parameter representing the average number of occurrences within a fixed interval. (k) is the count variable taking non-negative integer values.

Can be used to model many count data (for example: The number of yearly heatwaves). Note that X takes only nonnegative integer values. However, the $Poi(\lambda)$ distribution may not be useful (or it gives a bad fit) when X takes the value 0 with a high probability²⁰. In such a case a modified version of a regular $Poi(\lambda)$ distribution known as the zero-inflated Poisson (ZIP) distribution becomes useful^{19,26}. The ZIP distribution with parameters π and λ , denoted by ZIP (π, λ) , has the following probability mass function (Eq. 2).

$$P(X = k) = \begin{cases} \pi + (1 - \pi)e^{-\lambda} & \text{if } k = 0 \\ (1 - \pi)e^{-\lambda} \frac{\lambda^k}{k!} & \text{if } k \in \{1, 2, \dots\} \end{cases} \quad (2)$$

$(P(X = k))$ denotes the probability of observing (k) events under the zero-inflated Poisson (ZIP) model. (π) represents the probability of excess (structural) zeros, while $((1 - \pi))$ is the probability of counts arising from the standard Poisson process. (π) is the mean (rate parameter) of the Poisson component. (k) takes non-negative integer values, and (e) is the base of the natural logarithm.

where $0 \leq \pi \leq 1$ and $\lambda \geq 0$. The parameter π gives the extra probability thrust at the value 0; when it vanishes, ZIP (π, λ) reduces to $Poi(\lambda)$.

RESULTS AND DISCUSSION

Exploratory data analysis: The variables associated with the occurrences of HW are provided in Table 2 along with the descriptive analysis. Table 2 shows that the daily maximum temperature is 44.47°C, while the minimum temperature is 3.43°C. The maximum precipitation is 167.28 mm/day, and the average daily rainfall is 9.72 mm/day in Gazipur district. We found that the yearly maximum number of HW is 12, while no HW is also observed in a year with a standard deviation 2.91. The average relative humidity, surface pressure, wind speed at 2 m, and soil moisture is observed 70.56%, 100.67 Kpa, 2.04 m/sec, 0.58 (moderate saturated soil), respectively. The later section revealed more findings about climate parameters and HWs obtained in our research.

The graph in Fig. 2 illustrates the trend of the average daily maximum temperature in Gazipur district from 2017 to 2023. The data shows a consistent increase in the mean daily maximum temperature over the years. This increasing pattern is causing an alarming situation for the people of Gazipur district, and hence Bangladesh. This situation has led us to conduct this research.

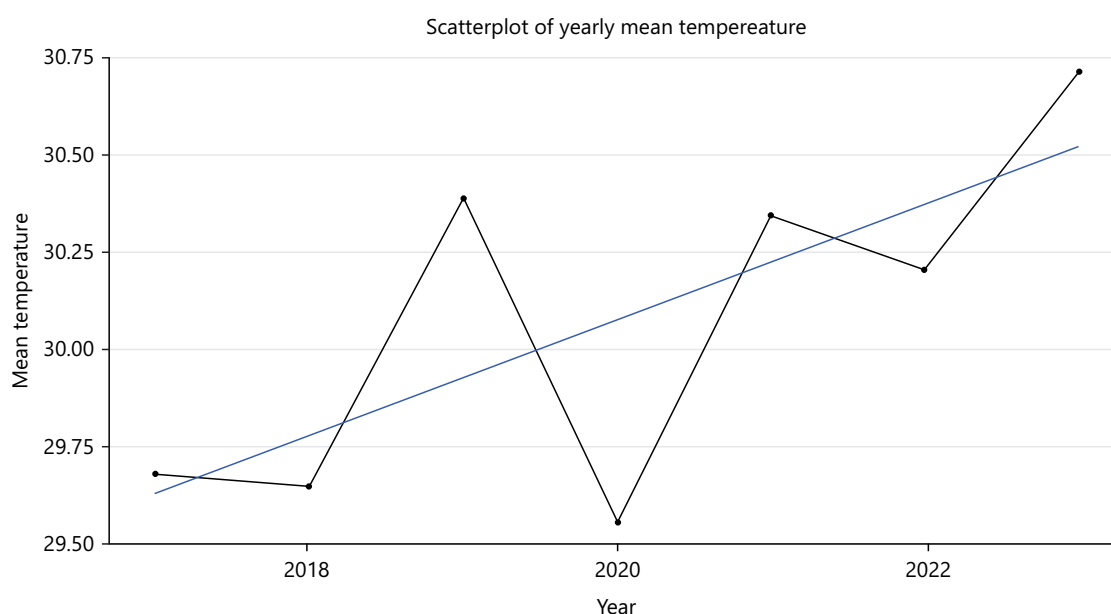


Fig. 2: Scatter plot of yearly mean temperature with trend line

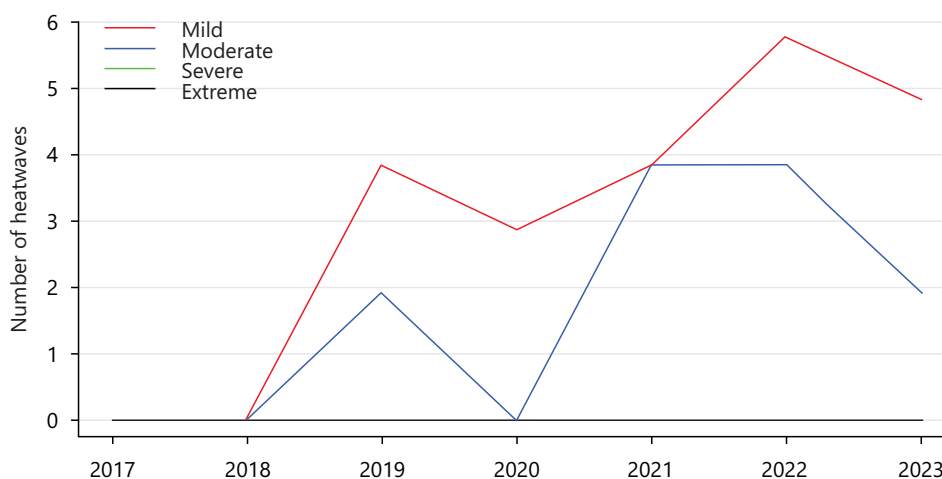


Fig. 3: Yearly frequency of heatwave (Temperature $\geq 38^{\circ}\text{C}$ for \geq two days)

Table 2: Descriptive statistics of climate parameters (measured daily): 1982-2023

Variables of the interest	Mean	Standard deviation	Minimum	Maximum
Heatwave (No./year)	6.38	2.91	0	12
Maximum temperature ($^{\circ}\text{C}$)	31.24	3.93	16.38	44.47
Minimum temperature ($^{\circ}\text{C}$)	21.21	5.43	3.43	29.42
Specific humidity (g/kg)	14.93	5.77	2.2	23.99
Relative humidity (%)	70.56	17.76	12.56	95.75
Precipitation (mm/day)	4.89	9.72	0	167.28
Surface pressure (Kpa)	100.67	0.55	98.94	101.98
Wind speed at 2 m (m/sec)	2.04	1.01	0.4	9.16
Wind speed at 10 m (m/sec)	3.01	1.37	0.58	12.95
Wind direction at 2-meter (degree)	188.83	58.31	17.06	348.62
Surface soil wetness (0-1: Index)	0.59	0.21	0.09	0.99
Profile soil moisture (0-1: Index)	0.58	0.17	0.34	0.98

Scenerarios of heatwaves

Yearly heatwave: According to the definition of heatwaves (HW) given above (Table 1), we have calculated the occurrences of mild, moderate, severe, and extreme HWs. The analysis of heatwave occurrences is presented in Fig. 3. The occurrences of mild and moderate heatwaves have increased over the years, but no severe and extreme heatwaves have been observed in Gazipur district

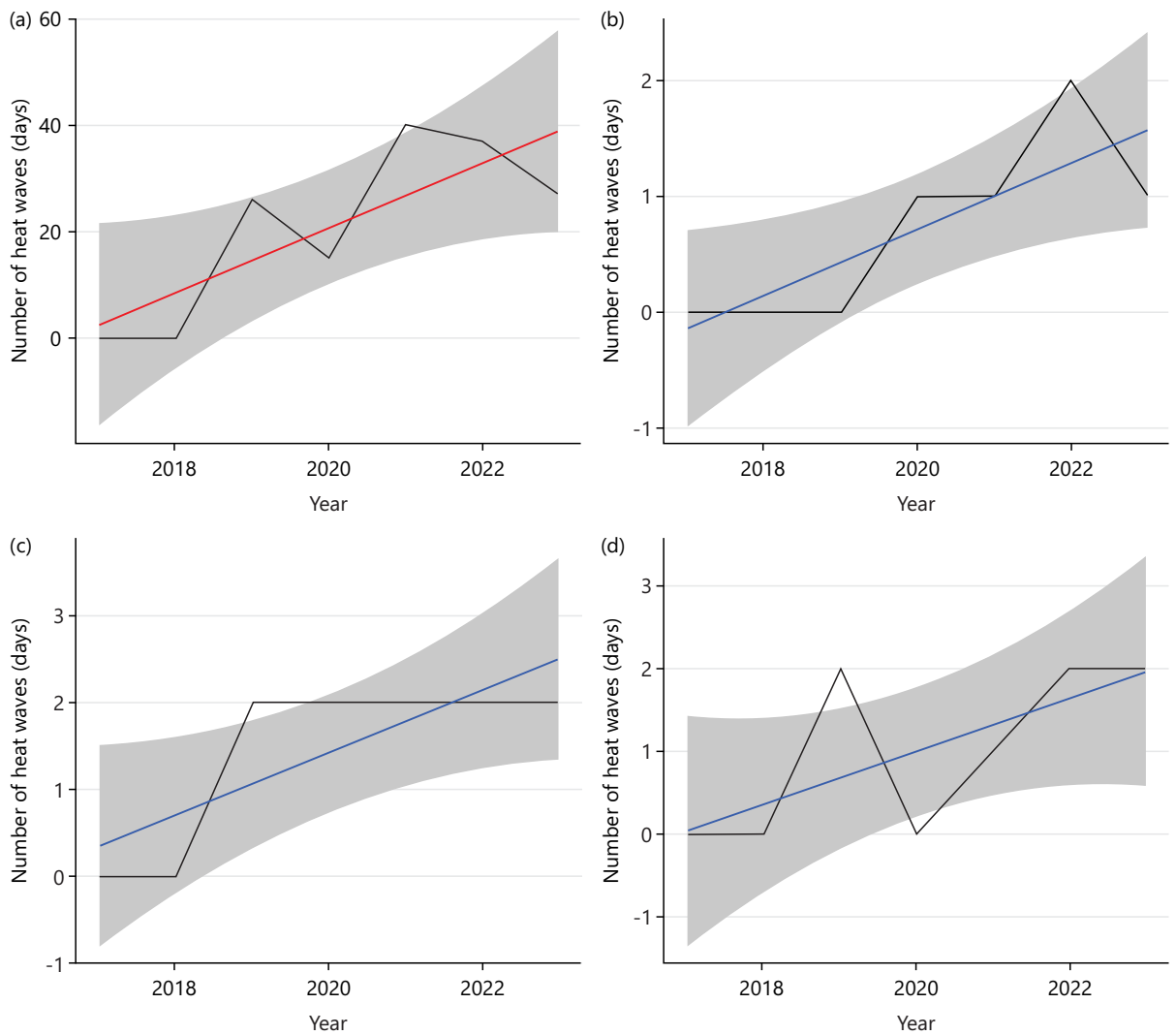


Fig. 4(a-d): Monthly heatwave illustration of Gazipur district, (a) Yearly mild Hws, (b) HWC in March, (c) HWC in April and (d) HWC in May
Heat Wave Count (HWC) and Heat Waves (HWS)

from 2017 to 2023. This means no two or more consecutive days have a temperature greater than 40 degrees. However, it is possible for the temperature to be below 40 degrees one day and above 40 degrees the next day. On those days, we may feel extremely hot, but we do not count them as severe or extreme HW days. The graph in Fig. 4a illustrates a gradual increase in the yearly count of mild heatwaves.

In our observations from Fig. 4a, we noted that there were no heatwave occurrences from 2017 to 2018, indicating that the temperature remained below the threshold of 36. However, in this study, we did not investigate the reasons behind this.

Monthly heatwave: In this research, one of our specific objectives was to explore the current scenario of HW in Bangladesh. The results for the HW scenarios in Gazipur district are presented in yearly and monthly heatwave paragraphs, based on the POWER project data from NASA. We specifically chose to focus on Gazipur district because the POWER project provides gridded (50×62.5 km) data²⁰.

Using data for the entire Bangladesh would not accurately represent the country. Figure 4(b-d) illustrates the monthly heatwave scenario in Gazipur district for March, April, and May. No heatwaves are observed other than in these months, and we found that the number of heatwaves is gradually increasing. Additionally, we observed no HW in March 2017-2019 and April-May 2017-2018 in the Fig. 4(b-d).

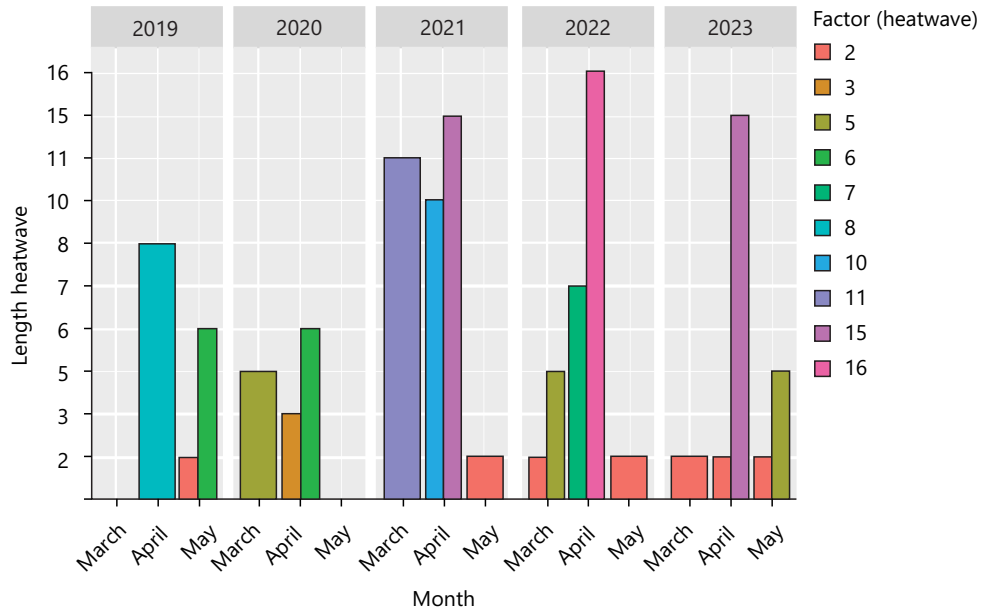


Fig. 5: Monthly length of heatwaves: Number of days having temperature greater than 36°C

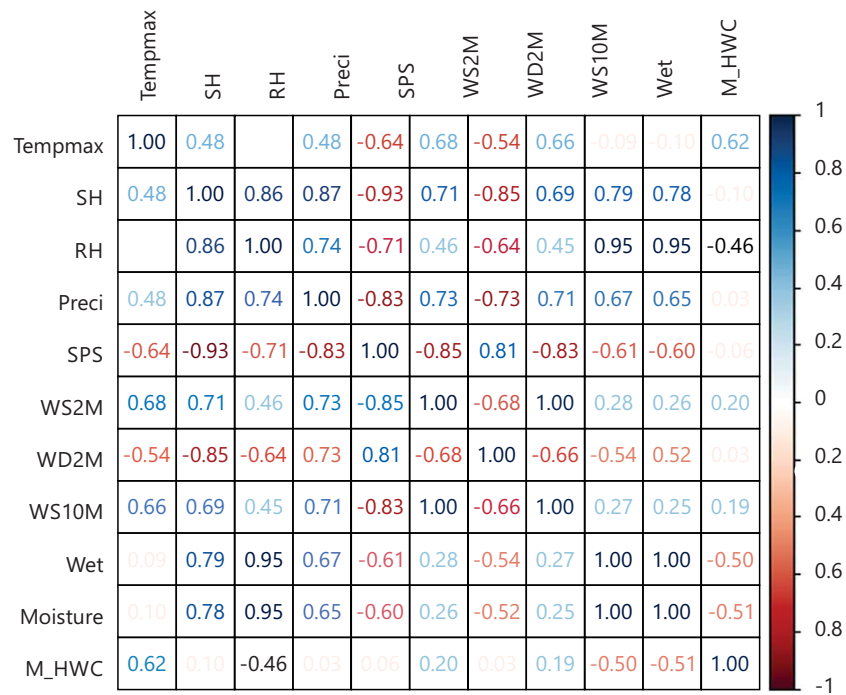


Fig. 6: Correlation matrix of number of heatwave with climate parameters

The monthly duration of heat wave days (HWDs) is illustrated in Fig. 5. The data shows that the size of HWDs is increasing from 2019 to 2023. More specifically, in 2019, March experienced a total of 8 days with temperatures exceeding 36°C, which was the maximum for that year. In 2020, the highest number of HWDs occurred in April, with 6 days exceeding 36°C. In 2021, April saw the maximum number of HWDs with 15 days exceeding 36°C. The year 2022 experienced the most HWDs, with 16 occurring in May. Lastly, in 2023, the maximum number of HWDs in April was 15 days with temperatures greater than 36°C.

Prediction of monthly heatwave using ZIP model: Before fitting the ZIP model in this section, we performed a Spearman’s rank correlation analysis of the number of monthly heatwaves (HW) with other variables identified in the literature as potentially associated with heatwaves. We also conducted a correlation test to identify variables significantly correlated with the occurrence of heatwaves. The references for the literature are provided.

Table 3: Correlation test of MHWC with agroclimatological parameters of POWER data

Climate parameters with MHWC	Spearman's rank correlation coefficient	p-value
Maximum temperature	0.62	0.00***
Specific humidity	0.10	0.37
Relative humidity	-0.46	0.00***
Precipitation	-0.03	0.80
Surface pressure	0.06	0.50
Wind speed at 2 m	0.20	0.06■
Wind speed at 10 m	0.19	0.08■
Wind direction at 2 m	-0.033	0.76
Wetness	-0.50	0.00***
Soil moisture	-0.51	0.00***

***Significant at 0.1%, **Significant at 1% and *5% level of significance

Table 4: Zero inflated poisson model estimations

Count model coefficients with log link			
	Coefficient	Std. Error	p-value
Maximum temperature	0.17	0.06	0.004**
Relative humidity	0.002	0.023	0.927
Wind speed at 2 m	1.29	2.71	0.635
Wind speed at 10 m	-0.98	1.98	0.621
Soil wetness	7.28	2.92	0.012*
Soil moisture	-11.84	4.09	0.003**
Intercept	-3.07	2.66	0.248
Zero-Inflation model coefficients with binomial logit link			
Maximum temperature	-4.8806	2.63	0.063■
Relative humidity	0.2029	0.14	0.128
Wind speed at 2 m	50.1241	46.55	0.281
Wind speed at 10 m	-38.4949	35.37	0.276
Soil moisture	-20.19	15.94	0.205
Intercept	168.2504	15.94	0.077■

***Significant at 0.1%, **Significant at 1% and *5% level of significance

Correlation analysis: In Fig. 6, after conducting a correlation analysis, we have decided to include the variables in the ZIP model. In Fig. 6 M_HWC, the monthly heatwave count (MHWC) is moderately positively correlated ($r = 0.62$) with maximum temperature, and has a moderate negative relationship with relative humidity (RH), soil wetness (WET), and soil moisture (Moisture) with correlation coefficients of -0.46, -0.50, and -0.51, respectively. There is a weak association observed with specific humidity (SH), precipitation (Preci), surface pressure (SPS), wind speed at 2 and 10 m (WS2M), and wind direction at 2 m (WD2M).

In Table 3, we observed that the maximum daily temperature is highly significantly associated with MHWC, and relative humidity, soil wetness, and soil moisture are also highly significantly associated with MHWC with a p-value of 0.000. We found that as the maximum temperature increases, the MHWC will increase. Additionally, we found that an increase in relative humidity, soil wetness, and soil moisture leads to a decrease in MHWC. Unfortunately, we did not find a significant association between the amount of monthly precipitation and MHWC, but it can be inferred from the analysis that an increase in monthly precipitation results in a decrease in MHWC. Moreover, we found a significant positive correlation between wind speed at 2 and 10 m, with p-values of 0.06 and 0.08, respectively. However, we did not find any significant association between surface pressure and wind direction.

Heatwave prediction: In the ZIP model, there are two parts: The count model and the zero-inflated model (binomial logit). Based on the correlation analysis, we included maximum temperature, relative humidity, soil wetness, soil moisture, and wind speed at 2 and 10 m in the count model. These variables, with the exception of wind direction, are included in the zero-inflated model. The data was divided into two parts: A training set from 1982 to 2021 and a validation set from 2022-2023.

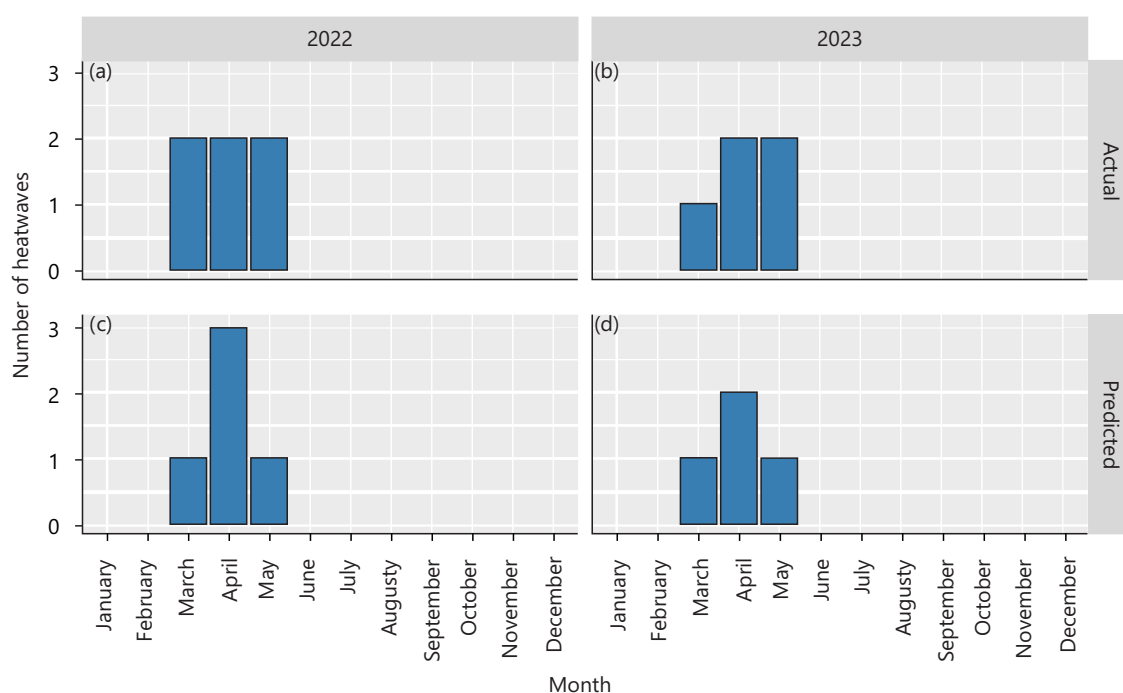


Fig. 7(a-d): (a) Actual number of heatwaves occurred in 2022, (b) actual number of heatwaves occurred in 2023, (c) Predicted number of heatwaves in 2022 using the proposed model, (d) Predicted number of heatwaves in 2023 using the proposed model Actual and predicted number of heatwaves

The results of the ZIP model are presented in Table 4. The count model with a log link showed that maximum temperature ($\beta = 0.17$, $p = 0.004$), soil wetness ($\beta = 7.28$, $p = 0.012$), and soil moisture ($\beta = -11.84$, $p = 0.003$) were significant predictors of the response variable, while relative humidity and wind speeds were not significant. In the zero-inflation (logit) model, no variables were statistically significant at the 5% level, although maximum temperature and the intercept showed marginal significance, indicating a weak contribution to excess zero counts.

Our analysis in Table 3 shows that maximum temperature and soil moisture have a significant influence on the prediction of monthly heatwave count at a 0.1% significance level, with p-values of 0.004 and 0.003, respectively. Additionally, soil wetness is significantly associated with a 1% significance level. In the inflation model, we also found that temperature significantly contributes to the occurrence of zero heatwave counts.

Figure 7(a-d) presents the predicted and actual MWHC for the Gazipur district in 2022-2023 as obtained from the ZIP model. Heatwaves were observed only in March, April, and May. In 2022, the actual MWHC was 2 in March, April, and May (Fig. 7a), while the predicted MWHC was 1, 3, and 1 for March, April, and May respectively (Fig. 7c). In 2023, we observed actual MWHC values of 1, 2, and 2 in March, April, and May respectively (Fig 7-b), while the predicted values were 1, 2, and 1 for the same months (Fig 7d). The accuracy of the ZIP model's predictions was assessed using MAE and MSE. A lower MAE and MSE indicates better predictive performance^{12,27}. The obtained value for the predicted model is 0.1667, which is very close to zero, indicating a strong performance in predicting MWHC.

Effects of MWHC on the yield of summer tomato: Two BARI-developed hybrid varieties namely BARI tomato-4 and BARI tomato-8 are heat-tolerant⁴. However, we would like to investigate the potential impact of MWHCs and MHWs on the yield of summer tomatoes in Bangladesh.

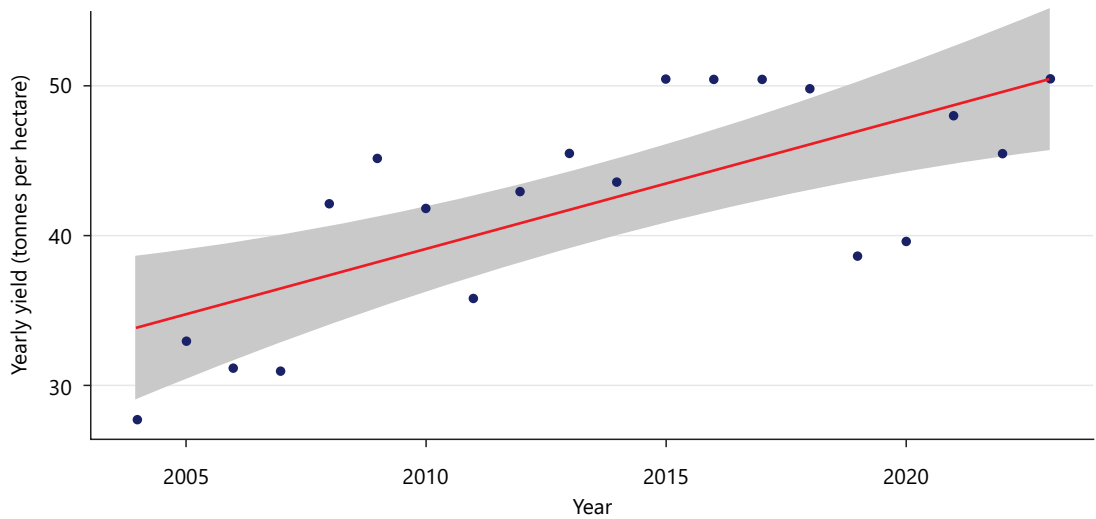


Fig. 8: Line diagram of the yield of summer tomato

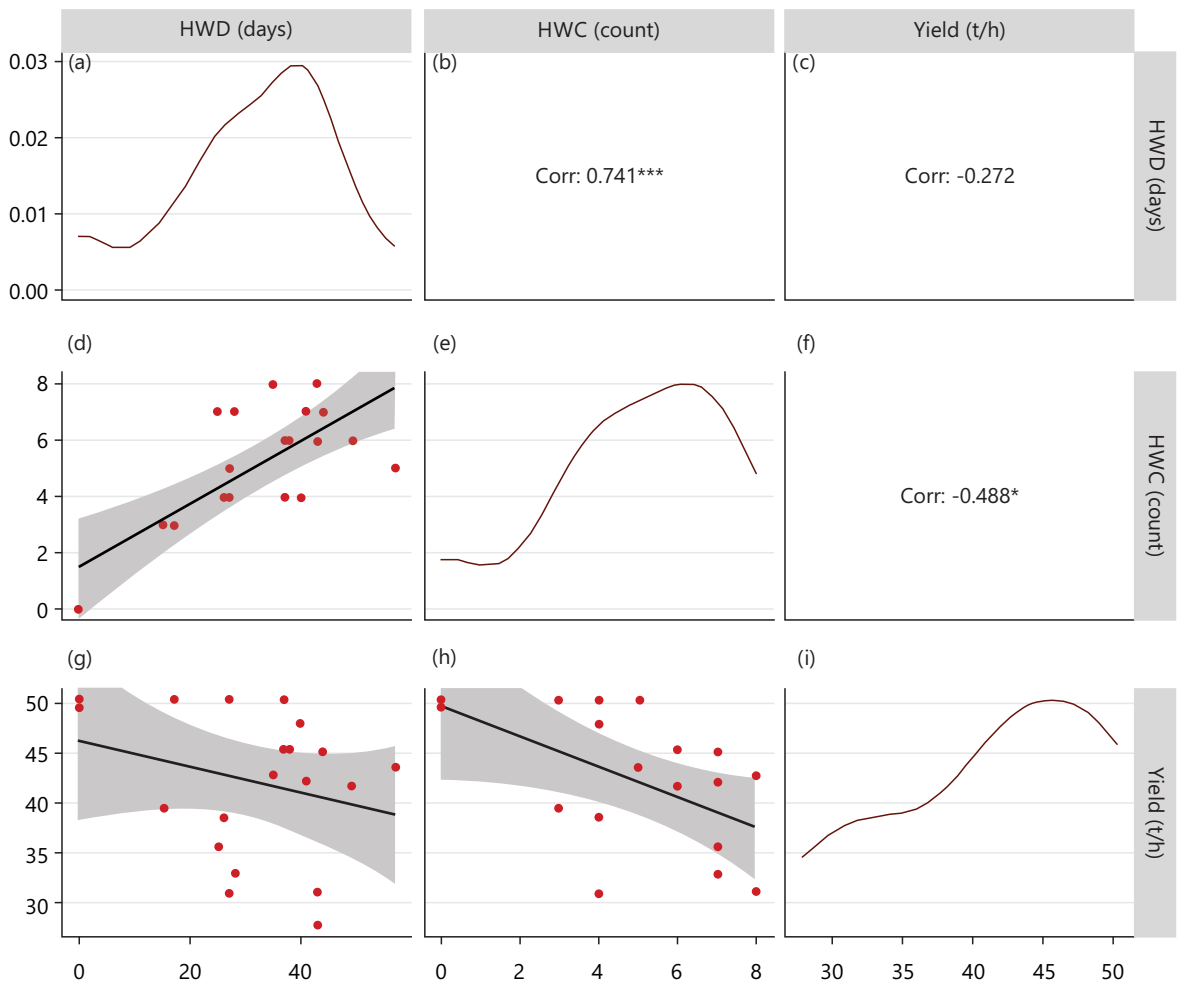


Fig. 9(a-i): (a) Density graph of yearly HWDs, (b) Correlation between yearly HWCs and HWDs, (c) Correlation between yield (t/ha) and HWDs, (d) Scatter plot along with increasing trend line between HWDs and HWCs, (e) Density graph of yearly HWCs, (f) Correlation between yearly yield (t/ha) and HWCs, (g) Scatter plot along with decreasing trend line between HWDs and yield(t/ha), (h) Scatter plot along with decreasing trend line between HWCs and yield(t/ha), (i) Density graph of yearly yield (t/ha)

Table 5: Linear regression estimates of yield of summer tomatoes with HWC

Variables	Coefficients	Std. error	t-value	p-value
HWC	-1.5414	0.6497	-2.373	0.029*
Intercept	49.8320	3.5584	14.004	0.000***

P-value for overall model significance: 0.02901
Adjusted R²: 20%

***Significant at 0.1%, **Significant at 1% and *5% level of significance

The average yield of summer tomatoes was 42.12 tons per hectare, with a standard deviation of 7.24. The minimum and maximum yields were 27.70 tons per hectare and 50.41 tons per hectare, respectively. In Fig. 8, a line diagram illustrating the yearly yield of summer tomatoes, it is evident that there has been an increase in the yield of summer tomatoes.

In Fig. 9(a-i), a correlogram is presented. Scatter plots are visualized in the lower diagonal, density plots are in the diagonal, and the Pearson correlation coefficient with the significance level is displayed in the upper diagonal. We observed that as the yearly HWC and HWD increase, the yield decreases for each pair of scatterplots (Fig. 9(g-h)). We also found that there is a significant negative correlation between the yield and HWC, with a correlation coefficient of -0.488 at a significance level of 5% (Fig. 9f). Additionally, the correlation between HWD and yield is -0.272, indicating a negative linear relationship between them (Fig. 9c). These negative correlation coefficients indicate also that for the increase of HWCs and HWDs, the yield of summer tomato decreases.

The correlation coefficients show the strength of the association between variables, but they do not establish causation³¹. To investigate the causation of yield and HWC, we conducted a linear regression analysis in this study. The LR estimates are presented in Table 5, and we observed that the overall model is significant with a p-value of 0.029. This indicates that the estimated model is more effective than the null model in predicting and explaining the yield of summer tomatoes. The coefficient of determination, adjusted R-squared, is 20% for the model, meaning that only HWC explains 20% of the total variation in the yield of summer tomatoes. Other characteristics influencing yield, such as plant height, number of leaves per plant, number of branches per plant, virus infestation (%), fruit length and diameter, individual fruit weight, number of locules, and total soluble solid (TSS) content, as shown by Biswas *et al.*³² could increase the adjusted R-squared. However, this is beyond the scope of our study³².

Our analysis indicated that the coefficient of HWC is significantly different from 0, as its p-value is 0.029, which is less than 0.05. This provides evidence that HWC has a significant effect on the yield of summer tomatoes in Bangladesh, which was one of the specific objectives of this program. The intercept, 49.8320, is also highly significant with a p-value of 0.000, indicating that the average yield of summer tomatoes in Bangladesh is 49.8320 (t/ha) when no other variables are considered in the model. The coefficient of HWC is -1.5414, meaning that an increase in HWC by one day per year will result in a decrease of 1.5414 (t/ha) in the yield of summer tomatoes.

CONCLUSION

This study developed and evaluated the performance of a ZIP model for monthly heatwave (HW) prediction in Gazipur district, using assimilation model (MERRA-2) agro climatological data. The study also investigated the impacts of HWs on the yield of summer tomatoes. The predictive model performed well in predicting HWs during the validation period, 2022-2023, with very low (0.167 for both) Mean Squared Error (MSE) and Mean Absolute Error (MAE). This study also showed significant negative effects of HWs on the yield of summer tomatoes. The findings suggest that policymakers may utilize the predictive model to anticipate HWs two years in advance, helping to reduce damages to summer tomato production in Bangladesh. By adjusting the sowing and harvest time of summer tomatoes based on the early HW

predictions, the overall yield can be increased, potentially preventing yield reduction. However, it is important to note that the monthly HW predictions are specific to the Gazipur district, and future research may focus on developing region-specific predictive ZIP models for short, mid, and long-term predictions, as well as creating spatial maps of HWs in Bangladesh. Additionally, forecasting the yield of summer tomatoes based on the findings of this study may contribute to a better understanding of growing demand.

SIGNIFICANCE STATEMENT

This study provides a practical framework for predicting heatwave occurrences using a Zero-inflated Poisson model and demonstrates their significant negative impact on summer tomato yield. The findings offer valuable insights for climate-resilient agricultural planning, enabling policymakers and farmers to anticipate extreme temperature events and adjust crop management practices to minimize yield losses and improve productivity under changing climatic conditions.

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