

## **Weather Variations and Productivity Changes in Wheat Yield: Empirical Analysis of an Indian State**

**Md. Shahnawaz and Mohammad Imdadul Haque<sup>1</sup>**

### ABSTRACT

Agriculture is universally prone to climatic variations. This study estimates the weather sensitivity of wheat yield in the Indian state of Bihar using secondary data from 1996 to 2022. Bihar happens to be one of the most backwards states of India. The study regresses wheat yield on the weather variables, that is, temperature and rainfall, and non-weather variables such as irrigation, fertiliser consumption, and farm harvest price, using the method of System GMM (Generalised Method of Moments). The study finds that the maximum temperature, which is below the threshold, has a positive effect, and persistent low temperature, along with foggy events, have a negative effect on wheat yield. The Rabi season receives very little rainfall, and cultivation under irrigation has a positive and significant impact. Fertiliser also plays an important role in improving the wheat yield. The wheat harvest price is also a factor in determining wheat yield. The study recommends the use of fertiliser, enhanced irrigation coverage, and adequate harvest prices to improve wheat yield.

**Keywords:** Weather variations, Climate change, Wheat yield, System GMM

**JEL Codes:** C23, Q11, Q54, O13

### I

#### INTRODUCTION

Climate change has become a significant challenge for scientists and policymakers in recent decades. Indian meteorological data indicate that warming has escalated by 0.5°C per century since the previous century (Government of India 2010b). The majority of this increase can be attributed to the preceding 40 years, i.e., from 1971 to 2010 (Kothawale et al., 2010). Similarly, it is observed that the frequency of low and moderate rainfall has significantly reduced, while the frequency of heavy rainfall has increased (Dash et al., 2009), leading to catastrophic weather conditions, including drought and floods in various regions of the country. The World Bank Report highlights that extreme climate events, such as floods, droughts, and heat waves, are expected to intensify in the future. (World Bank, 2013). Fluctuations in climate directly affect agricultural production and productivity, especially in tropical and subtropical regions. Developing economies such as India exhibit heightened vulnerability to climate shocks, primarily due to their heavy reliance on agriculture and limited financial and technical resources for mitigation (Lal et al., 2012). Climatic factors, particularly drought, were identified as the most prominent issues affecting crop yields in India (Haque & Khan, 2017).

Bihar is among the largest states of India, facing substantial economic challenges, and has an agriculture-based economy, despite abundant natural resources and perennial rivers. It lies in tropical and subtropical regions and is classified into three agro-climatic zones. Paddy, wheat, and maize are among the major crops

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<sup>1</sup>Department of Economics, Aligarh Muslim University, India

cultivated in the state. Although the land is fertile, agricultural productivity remains substantially below the national average. Approximately 90% of the state's population lives in rural areas, where agriculture and related activities are the primary source of livelihood (Bihar State Action Plan on Climate Change, 2015). Around 82 per cent of farmers possess marginal holdings (Agriculture Census Division, Ministry of Agriculture, New Delhi). A significant portion of the state faced drought conditions in four out of five years from 2009 to 2013 (Kisore et al., 2015). The Indian Council of Agricultural Research reveals that 24 of the 38 districts in Bihar are highly susceptible to climate change (Sehgal et al., 2013). Inadequate rainfall during the Kharif season results in incidents of drought even in North Bihar, a region typically prone to flooding (Bihar State Disaster Management Authority, GOB). Conversely, certain regions of the state experience frequent severe flooding. Approximately 73% of Bihar's geographical area, spanning 28 of its 38 districts, is classified as flood-prone (Bihar State Disaster Management Authority, GOB). Weather fluctuations linked to climate change led to short-term crop failures and long-term declines in production (Kishore et al., 2019). The Stern Review (2006) highlights that climate change will exacerbate poverty in developing economies. Although Bihar has sufficient groundwater resources and a widespread irrigation system (covering more than 65 per cent of the area), crop yields in the state are more prone to drought than in the rest of India. This vulnerability is attributed to higher irrigation costs, which render it less affordable (Kishore et al., 2014). This indicates that, while groundwater is physically accessible, it is economically confined. The contribution of agriculture to the state's GDP has remained roughly 20 per cent over the past five years. Therefore, it is essential to analyse agricultural production and productivity in the state, as it supports the livelihoods of a significant portion of the population. It has the potential to create increased employment opportunities and reduce poverty levels.

The frequent occurrence of climate-induced events, such as droughts and floods, may seriously threaten the livelihoods of most people engaged in agriculture and lead to rural poverty, fluctuations in agricultural income, and labour migration from the state. The current study aims to analyse the impacts of climate change on Rabi crop productivity, primarily wheat yields, in Bihar, where wheat is the dominant Rabi crop. This study adds to the literature in the following ways.

The novelty of this study is that, although there is literature on the impacts of climate change on farm productivity at the national level, we need to confirm these impacts at the sub-national level, as India has diverse climatic conditions across its territory. This will support policymakers in designing localised policies for agricultural development and enhancing farm income. The generalised method of moments (GMM) has been employed alongside fixed-effects and random-effects models to address endogeneity arising from the inclusion of a lagged dependent variable among the explanatory variables, while also mitigating heterogeneity.

The rest of the study is organised as follows. The next section presents a review of the literature, followed by the study's objectives. We then discuss the source and types of data employed in the current study, followed by the econometric methodology used to analyse the available data. The next section presents the results and discussion from the econometric analysis. The section pertains to the study's conclusion.

## II

### REVIEW OF THE EXISTING LITERATURE

Dozens of studies have been conducted to evaluate the climate sensitivity of crop yields across various regions and countries. Sanghi A. & Mendelsohn R. (2008) regress net farm income or property values on climate and non-climate factors, attempting to assess how farmers adapt in India and Brazil. They conclude, using district-level secondary data, that global warming may reduce crop yields by 4%- 26% in India and 1%-39% in Brazil annually by the end of this century. Guiteras (2009) examines the effects of annual weather variation on agricultural output in India, employing a panel data approach. They highlight the importance of daily temperature variation in crop growth, as temperature has non-linear effects, and they expect that the negative impact of climate change would suppress consumption among the poor in India by at least 18 per cent.

Hanan et al. (2011) conclude that districts in the northwest of India (relatively well-off regions) will suffer the most, while the northeast region (poor states) will be comparatively less affected by climate change. They opine that a better policy is to reduce the share of rural income that comes from climate-sensitive activities. Birthal et al. (2014) analyse the impact of climate variables, i.e., temperature and rainfall, on the yield of major crops. They establish the relationship between crop yield and climate and non-climate variables using a panel data fixed-effects approach, following Deschenes and Greenstone (2007). They highlight that the climate impact will not be severe in the short run. It is also possible that the effect would be nominal in the long run due to continuous adaptations.

Auffhammer et al. (2012) examine the impact of extreme weather events, floods and droughts using state-level data. It collected data on crop yield and its climatic and non-climatic determinants from 1966 to 2002 across nine states, mostly rainfed areas, and concludes that droughts and floods are very harmful to crop yield.

Guntukula R. (2020) assesses the influence of climatic variables such as rainfall and temperature on the seven major crops: wheat, rice, pulses, rapeseed, mustard, cotton, and sugarcane, and concludes that different crops differ significantly in terms of climate sensitivity. Birthal et al. (2014) assessed the climate sensitivity of Indian Agriculture using district-level panel data from 1967 to 2005. They regress the gross value of output on the crop-growing-period temperature, rainfall, and irrigation, and infer that irrigation is critical for enhancing crops' resilience to extreme

temperatures. About 80% of available water is used for irrigation, and half of the cropped area remains rainfed. Hence, it is equally important to optimise water-use efficiency in irrigation by applying techniques such as micro-irrigation (Sharma et al., 2010).

Birthal et al. (2021a) examine the effects of heat stress on wheat yield in India during the flowering and grain-filling stages, and assess the effectiveness of irrigation in mitigating heat stress. They reach the view that yield losses are increasing over time and that the efficacy of irrigation in combating the harmful effects of climate change is declining. Generally, crops exhibit greater sensitivity during anthesis and grain filling (Zampieri et al., 2017). In addition, crops require different heat and temperature levels at different phases of their growth, and these thresholds vary from region to region. Barlow et al. (2015) think that 33°C is the threshold temperature for wheat. However, there is insufficient evidence on temperature thresholds for different crops in India, and 30°C is often assumed to be the threshold (Zaveri & Lobell, 2019).

Birthal et al. (2021b) examine how farmers shift/alter agricultural land use in response to climate change. Climate change reduces various crop yields at different rates. This induces farmers to grow crops that exhibit greater resilience to temperature, thereby maximising their profits. They regress crop yield on growing degree days, excess degree days, rainfall, soil quality, and farm harvest price using a two-step GMM approach, and argue that an economy with a large share of marginal and small farmers may not adapt by adjusting crop patterns to climate change. Hence, other adaptation techniques, such as crop breeding for stress tolerance, high yield, and resource-use efficiency, should be prioritised.

The efficacy of the diesel subsidy program in Bihar is investigated by Kishore et al. (2015), which was initiated to combat the harmful effects of frequent droughts from 2009 to 2014. They conclude that the drought-relief program was less effective and could not help farmers combat drought-induced harmful effects, unlike canal and electricity-powered irrigation in Punjab and Haryana. Padakandla S. (2016) analyses the climate sensitivity of five primary crops in the former state of Andhra Pradesh using district-level panel data, concluding that Rabi crops are more vulnerable to climate change than Kharif crops. This study assesses changes in weather variables, specifically temperature and rainfall, and examines their annual impacts on wheat, the predominant Rabi crop.

Broadly, there are three important approaches applied to estimate the impact of climate and weather fluctuation on crop yield. (a) The most extensive, detailed, and oldest is the simulation method, which is based on a controlled experiment. In this approach, a crop is exposed to different temperatures, and its yields are compared across temperatures to assess the impact of climate change on temperature and rainfall (Birthal et al., 2014). This method estimates crop damage under controlled

conditions. However, this approach does not account for adaptation techniques used by farmers across different regions (Jacoby et al., 2011). Furthermore, a crop-specific approach is needed; one has to develop a separate approach for each crop. (b) The second method is the Hedonic Approach, initially developed by Mendelson (Mendelson et al., 1994). This approach measures the climate impact on agricultural productivity directly from the land value. If the land market is operating perfectly, crop prices will reflect land value rent. Although this approach accounts for adaptations, the prediction it yields assumes that the technological envelope within which farmers would adapt today should not change in the future (Jacoby et al., 2011). Moreover, agricultural productivity is affected by many unobserved factors. Dropping them from the model can produce omitted variable bias. The approach may conflate the effects of climate with those variables (Deschene & Greenstone, 2007). (c) To overcome the existing drawbacks of the Hedonic Method, Deschene and Greenstone (2007) propose a new method to measure the effects of climate fluctuations on agricultural profits using weather variations. This approach is treated as superior to the former one on the grounds that (I) the Panel data technique can account for time-invariant parameters, including soil elevation. (II) It is also able to capture the effect of short-term adaptation strategies on productivity. (III) Dependent variables (Net/Gross Revenue or land value) are an annual measure rather than the average of cross-sections, as assumed in the Ricardian approach (Birthal et al., 2014).

### III

#### DATA AND METHODOLOGY

The present study extracts data from 1996 to 2022 for 32 districts of Bihar to analyse the impact of weather variation on the most stable Rabi crop, i.e., wheat. Most of the required data used in the present study were collected from the website of the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) (<http://data.icrisat.org/dld/>). The current study includes both weather and non-weather variables that may potentially affect the yield. This includes the average maximum and minimum temperatures, cumulative rainfall (in millimetres), irrigated area, fertiliser consumption, and wheat harvest price. The choice of the variables is consistent with existing studies by Guntukula (2020), Guntukula & Goyari, (2020), Padakandla. (2016), Birthal et al.(2014), and Bhardwaj et al. (2022). Table 1 presents the description of the data and their sources.

Panel data modelling is essential due to the nature of the investigation for the following reasons: First, some factors, like land fertility, that affect agricultural productivity are impossible to quantify. They might also differ between regions and districts. In other words, individual heterogeneity is a characteristic of some factors. Or we may encounter certain variables that can be measured but cannot account for them due to a lack of data. These cause the omission of the important factor from the model. These omitted variables create an autocorrelation problem. Panel data models control for such individual heterogeneity by incorporating district/ region fixed

effects. Second, panel data models capture more information, reveal greater variation, reduce collinearity among variables, and yield more efficient estimates. Third, panel data are better suited to studying the adjustment and dynamics of the model (Baltagi & Baltagi, 2008). Further, various factors change over time, such as cultivation and harvesting technologies, which improve agricultural yields. To account for these factors, time-fixed effect variables are included in the model.

TABLE 1. DESCRIPTION OF DATA

Variables	Definition	Source
InW Yield	Wheat Yield (kg/ha)	ICRISAT
W area	Area Under Wheat	ICRISAT
FHP	wheat Harvest Price (RS/quintal)	ICRISAT
W Irrig	Wheat Irrigated Area in (1000 Hectare)	ICRISAT
R Fert	Rabi Fertiliser in tonnes per Hectare	ICRISAT
MAXT	Rabi Maximum Temperature (°C)	ICRISAT
MINT	Rabi Min Temperature (°C)	ICRISAT
R RF	Rabi rainfall (mm)	INDIA WRIS

Many studies report that weather variables, including temperature and rainfall, influence crop yield nonlinearly (Schlenker & Roberts, 2006; Guiteras, 2009). They suggest adding maximum and minimum temperatures and squared terms for rainfall to the model to capture non-linear effects. So, the basic model of the study is:

$$Y_{it} = a + \beta_1 X_{it} + \beta_2 W_{it} + \mu_{it} \quad i=1, \dots, N; \quad t=1, \dots, T \quad (1)$$

The subscript  $i$  describes the cross-section dimensions, while  $t$  denotes time series elements.  $Y_{it}$  is the wheat yield.  $X_{it}$  represents non-weather determinants and  $W_{it}$  is the weather determinants. Similarly,

$$\mu_{it} = \alpha_i + \varepsilon_{it} \quad (2)$$

Where  $\alpha_i$  is the unobserved district-specific heterogeneity, and  $\varepsilon_{it}$  is the pure disturbance term.

The most common techniques used to analyse panel data are the Fixed Effects and Random Effects models. These models are well-designed to control the district-specific heterogeneity and are applied in empirical studies depending on the Hausman test. However, these two techniques are static and may yield inefficient estimates when dynamic relationships are present. Some studies reveal that the lagged output of a particular crop and the same price can also act as important determinants of current crop production and cultivation area (Birthal et al., 2021), which is well explained by the Cobweb model. The existence of lag values of the dependent variable causes endogeneity and violates the assumption of strict exogeneity. This restricts the use of a static panel data model, as static models can lead to autocorrelation and heteroscedasticity, resulting in inconsistent estimates and

motivating the use of a dynamic panel data model. The dynamic panel data model prominently, Difference and System GMM, are designed to (1) introduce dynamism in the model by incorporating the lag-dependent variable in the set of explanatory variables, (2) deal with the problem of endogeneity, (3) include at least one predetermined variable in the set of explanatory variables, and (4) address the problem of autocorrelation and heteroscedasticity within the individual units (Roodman, 2019).

Hence, the present study will apply the System GMM Model and prefer it over the difference GMM as it provides more efficient. This approach is embedded in the system of equations, i.e., the original and transformed equations, and employs lagged values of the differenced and original variables as instruments to avoid weak instruments (Roodman, 2009). We opt for a log-linear specification to reduce variation in the dependent variable, and the coefficient can be interpreted as a proportional change (Birthal et al., 2014). Wheat, the second most stable and widely cultivated crop, is the dependent variable in the current study assessing climate impacts on the Rabi crop.

The present specifies the following model:

$$\ln Y_{it} = \beta_0 + \beta_1 \max T_{it} + \beta_2 \min T_{it} + \beta_3 RF_{it} + \beta_4 IR_{it} + \beta_5 Fert_{it} + \beta_6 FHP_{it} + \beta_7 W area + \beta_8 \sum_{k=1}^K \ln Y_{it-k} + \mu_i + \varepsilon_{it} \quad (3)$$

Where  $Y_{it}$  is the wheat yield per hectare,  $\max T_{it}$  is the average maximum temperature of the wheat growing period.  $\min T_{it}$  is the average minimum temperature for the wheat-growing period.  $RF_{it}$  is the cumulative rainfall of the same period,  $IR_{it}$  is the wheat irrigated area,  $Fert_{it}$  is the consumption of fertiliser in the rabi season,  $FHP_{it}$  is the wheat harvest price.  $W area$  is the area under wheat cultivation,  $\mu_i$  is the district fixed effect and  $\varepsilon_{it}$  is the error term.

#### IV

#### RESULTS

Table 2 presents the descriptive statistics for the data used in the current study. It is essential in grasping the basic features and patterns of the data employed. It comprises the mean values (central values), minimum and maximum values, and the standard deviation of each variable to capture the variation of individual observations from the central values.

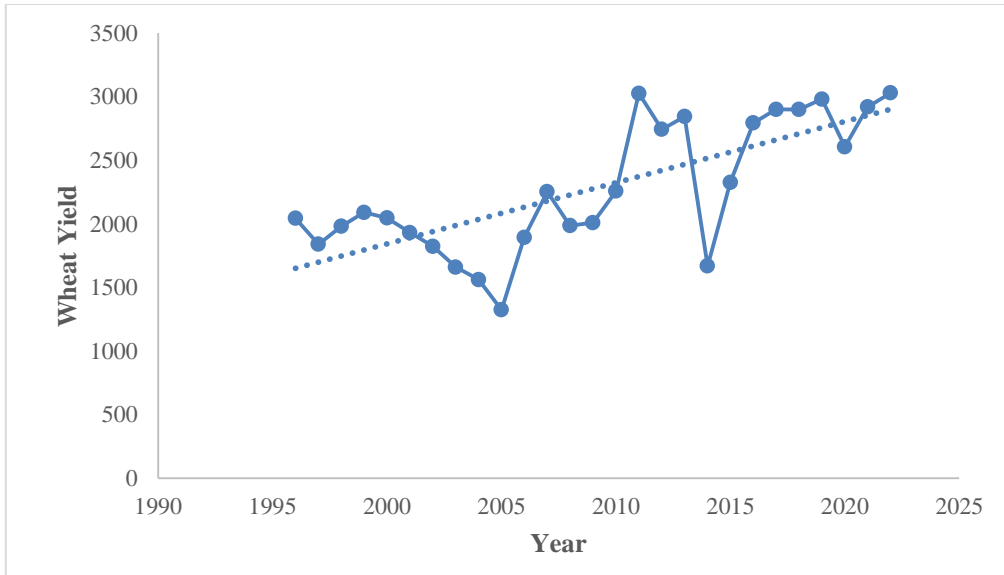


FIGURE 1A. LOG WHEAT YIELD (KG/HA)

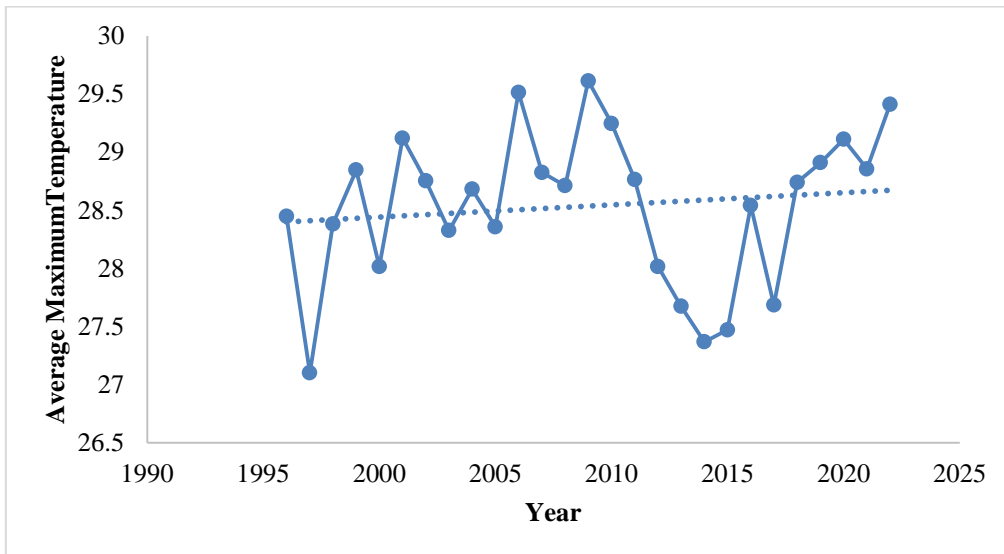


FIGURE 1B. AVERAGE MAXIMUM TEMPERATURE OF RABI SEASON

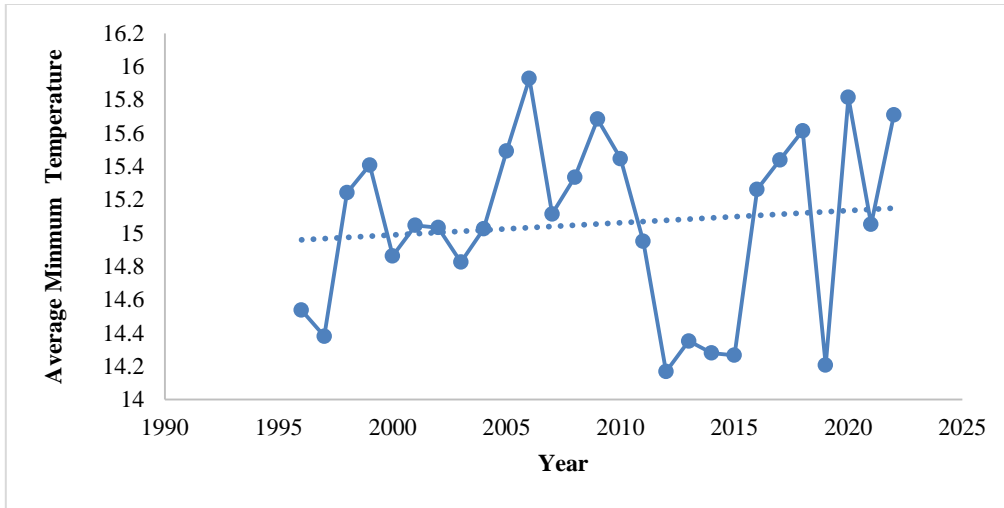


FIGURE 1C. AVERAGE MINIMUM TEMPERATURE OF RABI SEASON

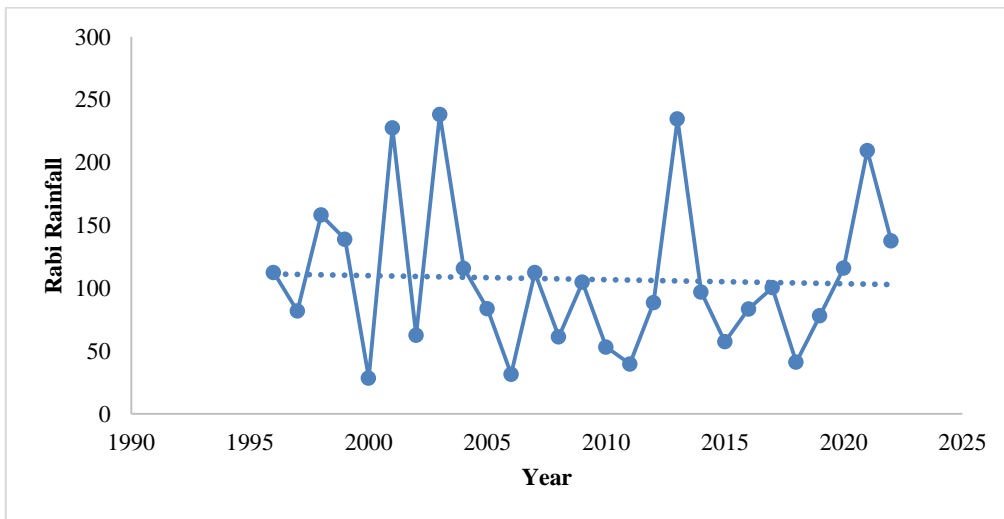


FIGURE 1D. TOTAL RAINFALL DURING RABI SEASON

TABLE 2. DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. dev.	Min	Max
In_wyield	864	7.678059	0.336931	6.401917	8.49699
W Area	864	57.60066	29.45511	7.52	201.076
MAXT	864	28.30559	0.830611	26.27167	31.45333
MINT	864	14.90903	0.679144	13.07667	16.79
R RF	864	107.0835	80.67615	50	588.85
Rabi fert	860	21088.51	14685.57	371	73412
W Irrig	864	53.16339	30.2809	1.568001	297.806
WHP	864	1046.025	502.5746	408	3827

The mean maximum temperature during the wheat-growing period is 28.30°C, with a minimum of 26.27°C and a maximum of 31.45°C. The mean minimum temperature is 14.90°C, with a variation of  $\pm 2^\circ\text{C}$  across almost all districts of Bihar. Cumulative rainfall, measured in millimetres (mm), varies drastically across the districts, with some receiving heavy rainfall and others receiving less. Although fertiliser consumption and irrigated wheat areas are not the primary variables, they are critical for enhancing crop yield and serve as adaptive instruments chosen by farmers. Farm Harvest Price (FHP) is an important factor determining the output level. If the price of wheat increases in the current year, this increased price acts as an incentive to produce more wheat in the next year, and hence, farmers produce more wheat in the subsequent year.

Table 3 reports the correlation matrix, which shows that the variables are related and negates the possibility of significant multicollinearity bias. Table 4 presents the results of the Fixed Effect and Random Effect models, respectively. The fixed-effects result reveals that the two important variables in the model, namely, area under wheat (W Area) and wheat irrigated area, are statistically insignificant. On the other hand, the maximum and minimum temperatures are statistically significant at the five per cent level, while rainfall is significant at the ten per cent level. The Hausman test favours the use of the Fixed Effects model, as it rejects the null hypothesis that the Random Effects model is appropriate.

The modified Wald test for heteroskedasticity demonstrates the existence of heteroskedasticity in the fixed-effect model. The null hypothesis of the test, which posits the absence of groupwise heteroscedasticity in the model, is rejected since the P-value is less than 0.05. Similarly, the Wooldridge test confirms the presence of autocorrelation in the model. Further, adding a lag of the dependent variable itself leads to autocorrelation. To overcome these, we use the System GMM estimator.

TABLE 3. CORRELATION MATRIX

	Ln W Yield	W area	MAXT	MINT	R RF	Rabi Fert	W Irrig	WHP
ln_wyield	1							
W Area	0.152	1						
MAXT	-0.228	-0.200	1					
MINT	-0.132	-0.292	0.720	1				
R RF	-0.070	-0.164	0.0793	-0.013	1			
Rabi Fert	0.398	0.237	-0.175	-0.220	-0.051	1		
W Irrig	0.197	0.950	-0.211	-0.262	-0.160	0.241	1	
WHP	0.478	-0.016	-0.248	-0.192	0.037	0.532	0.040	1

TABLE 4. RANDOM EFFECT AND FIXED EFFECT RESULTS

ln_wyield	Coefficient	Std. err.	z	P>z	[95% conf. interval]
Random Effect					
ln_wyield L1	0.43394	0.032359	13.41	0.000	0.370517 0.497363
warea	-0.0017	0.001124	-1.51	0.13	-0.0039 0.000501
MAXT	-0.01376	0.01662	-0.83	0.408	-0.04633 0.018818
MINT	0.049352	0.020516	2.41	0.016	0.009141 0.089562
R RF	-0.00027	0.000113	-2.39	0.017	-0.00049 -4.9E-05
Rabi Fert	3.04E-06	7.53E-07	4.04	0.000	1.56E-06 4.52E-06
W Irrig	0.002487	0.001071	2.32	0.02	0.000389 0.004586
WHP	0.000156	2.39E-05	6.53	0.000	0.000109 0.000203
_cons	3.769817	0.468391	8.05	0.000	2.851788 4.687846
Fixed Effect					
ln_wyield L1	0.305492	0.03579	8.54	0.000	0.235237 0.375746
W area	-0.00189	0.001516	-1.25	0.212	-0.00487 0.001082
MAXT	0.065435	0.022764	2.87	0.004	0.02075 0.110119
MINT	-0.07634	0.0332	-2.3	0.022	-0.14151 -0.01117
R RF	-0.00021	0.000114	-1.83	0.068	-0.00043 1.57E-05
Rabi Fert	4.42E-06	1.12E-06	3.96	0.000	2.23E-06 6.61E-06
W Irrig	0.001966	0.001268	1.55	0.121	-0.00052 0.004456
WHP	0.000172	2.78E-05	6.19	0.000	0.000117 0.000227
_cons	4.374135	0.53541	8.17	0.000	3.323137 5.425134
Specification Tests					
<b>Items</b>					Static P-Value
Hausman Test (FE vs RE) Chi <sup>2</sup> (7)					97.98 0.000
Modified Wald Test for Group-wise Heteroskedasticity chi <sup>2</sup> (32)					113.63 0.000
Woolridge Test for Autocorrelation Panel Data; F(1, 31)					17.584 0.0002

Table 5 presents the estimated results of equation (3) using a one-step and a two-step GMM model. The inclusion of the lagged dependent variable underscores its significance in crop production. The coefficient of lag for the dependent variable is statistically significant at the one per cent level and is positive, consistent with theoretical expectations. The maximum temperature has a positive effect on wheat yield, which is statistically significant in both the one-step and two-step GMM models at the five per cent significance level. The average minimum temperature during the wheat growing period is also a significant determinant of wheat yield at the 10% and 1% levels of significance, respectively. Rainfall seems to have very little impact, as most of the wheat is cultivated under irrigation, which positively influences wheat yield. Fertiliser plays an important role in enhancing wheat. These factors demonstrate statistical significance at the 1% level. The price of wheat at harvest serves as an incentive for production increases and is statistically significant at the five per cent level.

TABLE 5. RESULTS (TWO-STEP GMM)

ln_wyield	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
<b>One-Step GMM</b>						
ln_wyield L1	0.288234	0.02992	9.63	0.000	0.229592	0.346875
warea	-0.00113	0.001785	-0.63	0.527	-0.00463	0.00237
MAXT	0.041423	0.021022	1.97	0.049	0.000221	0.082624
MINT	-0.05558	0.028611	-1.94	0.052	-0.11166	0.000498
R RF	-0.00014	0.000112	-1.25	0.212	-0.00036	7.99E-05
Rabi Fert	8.16E-06	1.42E-06	5.75	0.000	5.38E-06	1.09E-05
W Irrig	0.001958	0.001586	1.23	0.217	-0.00115	0.005066
WHP	0.000114	3.05E-05	3.75	0.000	5.45E-05	0.000174
_cons	4.80616	0.48291	9.95	0.000	3.859674	5.752647
<b>Two-Step GMM</b>						
ln_wyield L1	0.303527	0.021488	14.13	0.000	0.261412	0.345643
warea	-0.00086	0.001008	-0.85	0.395	-0.00283	0.001119
MAXT	0.045726	0.009622	4.75	0.000	0.026867	0.064585
MINT	-0.05477	0.010804	-5.07	0.000	-0.07595	-0.0336
R RF	-0.00014	5.06E-05	-2.73	0.006	-0.00024	-3.9E-05
Rabi Fert	8.79E-06	1.23E-06	7.15	0.000	6.39E-06	1.12E-05
W Irrig	0.001645	0.001137	1.45	0.148	-0.00058	0.003874
WHP	0.000107	1.68E-05	6.35	0.000	7.36E-05	0.000139
_cons	4.556287	0.307978	14.79	0.000	3.952661	5.159913

Once we estimate the model using GMM, we need to perform post-estimation checks. Broadly, econometricians specify two post-estimation checks for the stability of the estimates. Firstly, the specification of the model suggests that there must be autocorrelation of order one, i.e., AR(1), but not the AR(2) or higher order autocorrelation. Secondly, overidentification restrictions must be satisfied for each

instrument. There are two tests for overidentifying restrictions: the Sargan and the Hansen tests. The null hypothesis of these two tests is that  $H_0$ : overidentifying restrictions are valid. When the P-value  $> 0.05$ , it implies that the overidentifying restrictions are valid.

TABLE 6A. ARELLANO AND BOND TEST FOR AUTOCORRELATION

$H_0$ : There is no autocorrelation.		
Order	Z	Prob > z
1	-4.3834	0.00
2	1.7485	0.0804

Source: Author's calculation

TABLE 6B. SARGAN TEST FOR OVERIDENTIFICATION RESTRICTION

$H_0$ : Overidentifying restrictions are valid;		
chi2(98)	=	30.7769
Prob > chi2	=	1.000

Tables 6A and 6B present the results of post-estimation checks. Table 6A shows the results of the Arellano and Bond autocorrelation test. The null hypothesis,  $H_0$ , is that there is no autocorrelation. The result indicates the existence of autocorrelation of order one (AR(1)), but it does not support the existence of AR(2) and satisfies the first post-estimation criterion. Similarly, Table 6B presents the Sargan test result. The null hypothesis that the overidentification conditions are valid cannot be rejected, as the p-value is 1.000. Consequently, the model satisfies both post-estimation criteria.

## V

## DISCUSSION

We observe that the coefficient on maximum temperature is positive and statistically significant, implying that an increase in maximum temperature has a positive effect on wheat production. This is because we expect a nonlinear influence of temperature on crop production. Initially, we observe a positive relationship between yield and temperature. However, once the temperature reaches the threshold, it begins to harm crop production. The temperature requirements of different crops vary, and these requirements may also be associated with regional factors. Nevertheless, many studies have tried to fix the temperature threshold. Zoveri and Lobell (2019) assume the temperature threshold for wheat in India is 30°C. The maximum temperature is around 30°C across the districts of Bihar; consequently, we observe a positive and statistically significant coefficient for the maximum temperature.

Similarly, the minimum temperature coefficient is negative and statistically significant at the 1% level. This means there exists a negative correlation between wheat yield and low temperature. It is observed that fog events start in November in the Indo-Gangetic Plain, and are at their peak in December and January during the grain-filling time of most Rabi crops. The average number of foggy days varies from 10 to 15 in Bihar (Climate of Bihar, 2015). Foggy hours and foggy days intensify during this period, even in the daytime. The larger events of foggy hours and foggy days lower temperatures for a long period. The steady low temperature harms vegetative growth and may therefore negatively affect winter crops (Sharesha et al., 2018). The coefficient of rainfall is negative, but its magnitude is very small, as the Rabi season receives only 15% rainfall and it is very erratic. The same has also been reported by Birthal et al. (2014) and Birthal et al. (2021). Moreover, wheat is cultivated with irrigation across India. This has also been reported by Birthal et al. (2014). The coefficients of fertiliser is positive and statistically significant at the 1% level, indicating its positive effects on wheat productivity. On the other hand, the coefficient of irrigation, although positive, is not statistically significant. This might be due to suboptimal and untimely irrigation. Kishore & Singh (2021) find that farmers under-irrigate crops, including wheat, due to high irrigation costs in the state. This means higher irrigation and fertiliser consumption lead to higher wheat yield and vice versa. Similarly, the wheat harvest price is both positive and statistically significant. The Farm Harvest Price (FHP) is an important determinant of production levels. A rise in the price of wheat in a given year offers an incentive to farmers to expand production in the upcoming season, as higher prices are directly correlated with profitability. Kishore & Singh (2021) find that 90 per cent of farmers sold their wheat below the MSP in 2017-18, and the median farmer received 19 per cent less than the MSP rate at harvest time in the same year. Higher and more stable prices will encourage farmers to invest in yield-enhancing inputs and adopt input intensification, thereby stimulating wheat productivity.

The results indicate that the coefficient of maximum temperature of the wheat growing period is positive. This finding is not consistent with Birthal et al. (2014). However, in another study, Birthal et al. (2021) report that wheat is the only crop that benefits from growing degree days. This may be due to the fact that the study is conducted at the India level using the district-wise data of all the states of India, where weather conditions vary frequently, while the current study specifically deals with the Bihar region, where weather variations are comparatively significantly minimal. The coefficient on rainfall is negative, consistent with the findings of Birthal et al. (2014). Further, the coefficient of fertiliser is positive, in line with Auffhammer (et al., 2012), and the coefficient of irrigation is positive, in line with Birthal (et al., 2021).

## VI

## CONCLUSION

The present study investigates the consequences of weather variation on wheat, the primary rabi crop in Bihar. Agriculture is a fundamental component of Bihar's economy, with a considerable proportion of the population employed in the agricultural sector. The state demonstrates high vulnerability to climatic extremes, reflected by recurrent flooding in the northern regions and frequent droughts in the western areas. Climatic shocks pose severe risks to farm livelihoods and to the state's overall agricultural development. This study empirically examines the influence of weather volatility in wheat yield, utilising both static and dynamic panel data methodologies, to control endogeneity and heteroscedasticity and avoid biased estimates, to facilitate the development of suitable measures and policies to tackle adverse effects and it may be helpful for minimising the risk to the livelihood of most people residing in the state and improving the performance of the agriculture sector. Variables, namely, average maximum temperature, irrigation, fertilizer and wheat harvest prices, are positively impacting wheat yield in Bihar, while average minimum temperature and rainfall impede the wheat productivity in the region.

Based on the results, this study recommends that instead of bringing more area under wheat cultivation, we need to focus on productivity enhancement by adopting input intensification strategies, as wheat yield is the lowest among the wheat-producing states of India, while the cost of producing wheat is higher than the average cost of wheat production in India, consequently, the net return from wheat is among the lowest in India. Wheat productivity can be improved by promoting balanced use of fertilizer and ensuring the timely availability of subsidized fertilizer for maintaining soil nutrients, and encouraging optimal irrigation, with an affordable cost of irrigation, as the cost of irrigation is very high in Bihar, compared to other states of India, and hence farmers under-irrigate the wheat. Furthermore, the findings suggest that policymakers must ensure that farmers receive a remunerative harvest price, as 90 per cent of farmers sold their wheat below the MSP, with the median farmer getting 19 per cent below it. Hence, Policymakers should ensure that farmers receive higher and more stable prices, which would motivate farmers to invest in yield-enhancing inputs and intensify input use. These measures will stimulate agricultural investment, augment productivity and profitability, and consequently elevate farm revenue, thereby enhancing the welfare of Bihar's inhabitants.

**Acknowledgements:** The author(s) thank the anonymous referees for their careful review, insightful comments, and valuable suggestions, which have significantly contributed to improving the quality and clarity of this manuscript. Their constructive feedback and recommendations for publication are greatly appreciated.

*Received: September 2025*

*Revisions Accepted: February 2026*

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