Chapter-4

Weather Shocks, Crop Productivity, and Crop Diversification: Adaptation Practices in Punjab

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Chapter 4

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4.1 Introduction

In recent years, assessing the nature and relationship of climate shocks with agricultural yield become a great interest for policy-makers and researchers. It is because of the agriculture sector most sensitive to the effect of climate changeability (McCord et al., 2015; Thulstrup, 2015; Tol, 2018). Such an interest is more eminent in those areas where agriculture output is often determined by the whims of nature and crop growers have a lack of adaptive capacity or well information to cope with such extreme shocks (Mendelsohn et al., 2006; Nelson et al., 2009).

A number of studies on weather shocks support the fact that frequent occurrence of weather shocks drastically damaged crop productivity and food supply (IPCC, 2012; Dercon & Christiaensen, 2011). The developing economies like India are more vulnerable to climate shocks due to their deficiency in capital availability, adequate technologies, infrastructure, and organizations to cope with such shocks. In India, studies have reported that climate shocks reduce agricultural productivity by 25 percent (Birthal et al., 2014) and increase poverty by 12-33 percent (Bhandari et al., 2007). Birthal et al. (2015) have further observed that in India 1/3rd of the rice area has been affected by droughts. Similarly, in the context of eastern India, it was noticed that a household income declined by 25-60 percent during a drought year (Pandey et al., 2007). Further, it has been found that the rainfall shocks have reduced agricultural productivity by 42 percent in case of Nigeria (Amare et al., 2018).

However, in the literature, unfavorable effects of high temperature and rainfall on agricultural yield have been widely discussed (Baker et al., 1992; Kumar & Parikh, 2001; Kimball et al., 2002; Jalota et al., 2009; Kaur et al., 2012; Alauddin & Sarkar, 2014; Burke & Emerick, 2016; Chuang, 2019; Shahzad & Abdulai, 2020), and stated that higher variation in temperature or rainfall has threatened livelihoods of agricultural based population. Further, it has been reported that the frequency of occurrence of climate events in state has risen in the recent past and is predicted to rise in the future (Mahajan et al., 2009; World Bank, 2013; Jalota et al., 2014).

In addition, there are a few studies existing in earlier literature that have partly discussed the impacts of timing of monsoon arrival on crop productivity (Binswanger & Rosenzweig, 1993; Sultan et al., 2005; Naylor et al., 2007; Talathi et al., 2008; Gine et al., 2008; Marteau et al., 2011; Jain et al., 2015; Kala, 2017; Detroja et al., 2018; Singh et al., 2020) and they have observed that variation in arrival of timing of monsoon might affect crop productivity. The evidence found from South and Southeast Asia revealed that delayed monsoon arrival from its normal date has adversely affected the crop productivity (Laux et al., 2008). In context of Semi-arid regions in India, it was found that delayed monsoon arrival reduces profits of the cultivators by 15 percent, but the impact being greater on poor farmers (Binswanger & Rosenzweig, 1993). In particular, it is observed that the performance of agriculture is influenced not only by the quantum of rainfall but also by its timing.

In most of the rain-fed areas, farmers depend upon monsoon to begin various agricultural activities. However, untimely rainfall patterns may have serious implications on the overall economy of an agricultural household (Singh et al., 2020). However, it is considered that negative impact of weather shocks on crop productivity could be reduced by applying some risk-coping mechanisms such as infrastructure improvements, management programs, and agricultural insurance in current agriculture systems (Smit & Skinner, 2002; Howden et al., 2007). Besides, other adaptations include viz., diversification into alternative varieties of specific crops (i.e., drought-resistant, early maturing), altering fertilization amount or timing of irrigation, implementing shading, and conservation agriculture such as soil protection, agroforestry (Easterling et al., 2007; Dasgupta et al., 2014; Porter et al., 2014). Some of the studies reported that irrigation has played a significant role in mitigating the effects of extreme climate (Birthal et al., 2014), and also revealed that irrigation may be an endogenous choice sensitive to climate events (Kurukulasuriya et al., 2011). Besides irrigation, crop diversification has widely discussed as an adaptation application to reduce the effects of climatic shocks (Di Falco & Chavas, 2009; Macours et al., 2012; Mitter et al., 2015; Thamo et al., 2017; Asfaw et al., 2018) and also a supporter of sustainable agrarian system (Joshi et al., 2004; Nguyen, 2017). Crop diversification is well documented technology and it seems to be one of the climate smart practices that helps in reducing climate risk, improves food security, and enhances productivity, and helps in mitigation of GHG emissions (FAO, 2013; Rosenstock et al., 2016; Lipper et al., 2017). In the North China plain, it is observed that the suitable diversified cropping systems have a lower carbon footprint (Yang et al., 2014). Accordingly, Birthal and Hazrana (2019) suggested that crop diversification is an important ex-ante adaptation measure to climatic shocks; and its adaptation benefits are more apparent against severe shocks and in the long-run. Therefore, by using various potential risk-coping appliances, farmers can recover the loss of assets in such economies. As in India majority of the farmers have small land holdings and they are economically weak and unable to invest in costlier adaptations; crop diversification is one of the low-cost effective adaptations to avoid productivity loss due to delayed monsoon arrival for these farmers.

The study of Singh et al. (2020) is an exclusive attempt that has seen the impact of delayed onset rainy day on crop productivity in different districts in India at an aggregate level.

However, they ignored the impact of delayed monsoon arrival on regional level and have considered the role played by irrigation in mitigating the adverse effect from climate shocks. The present study adds to this strand of literature by estimating the role of crop diversification as an adaptation practices to minimize these weather effects. Therefore, present study revisits the debate on relationship between weather shocks and crop yield particular in Punjab, and farmers' adaptation measures to cope-up with such losses in productivity due to changes in timing of monsoon arrival. Punjab is agriculturally advanced state and has three times larger land holding size than the national average of 1.15 hectare (Singh et al., 2017). The agricultural development in the Punjab state is clearly visible from the facts that it has the largest proportion of irrigated area (98 percent), highest cropping intensity (about 190 percent) and the most intensive use of chemical fertilizers (246 kg/ha) and other inputs. Rainfall is confined three to four months in a year, and it varies from about 250 mm in South-west parts of the state to about 1000 mm in the northern region of state (Government of Punjab, 2008). By using district level panel dataset (1966-2015) collected from ICRISAT and IMD in Punjab, this study has focused on mainly two issues: - (i) to assess the impact of weather shocks on crop productivity; and (ii) to examine the adaptation benefits of crop diversification against weather shocks.

This chapter contributes to the literature in following way: - First, it examines the impacts of weather shocks on agricultural productivity. Although a significant body of literature has widely studied and intensively debated on the impact of climate change on crop production particular in Punjab as a whole (Hundal, 2007; Kaur et al., 2008; Jalota et al., 2009; Vashisht et al., 2013; Jalota et al., 2014) but impact of timing of monsoon arrival on crop productivity in particular state is rare. There are no rigorous attempts of addressing the issue at micro unit level such as in particular state across districts. The impact of weather change is region-specific issue, therefore, there is a need to strengthen region-specific early warning systems to provide farmers timely information on weather conditions. This chapter accomplishes this gap in the existing literature. It is important to see the extent of timing of monsoon arrival and its regional distribution at micro unit. This would lead to identify the micro level problems of farm sector followed by appropriate policy formation. Second, it examines adaptation effect of other inputs such as fertilizers, and irrigations to cope-up against this weather shocks. This aspect is not explored in the existing studies. In this context, this chapter particular focuses on the role played by crop diversification or other adaptation practices in farming systems to cope-up with weather shock (delayed monsoon).

The remaining part of chapter is organized as: - Section 4.2 describes sources of data, descriptive statistics of the variables, constructed diversification index and extreme monsoon onset day index. Section 4.3 presents the empirical framework of the study. Section 4.4 presents the model results. Finally, the conclusions and policy implications are summarized in Section 4.5.

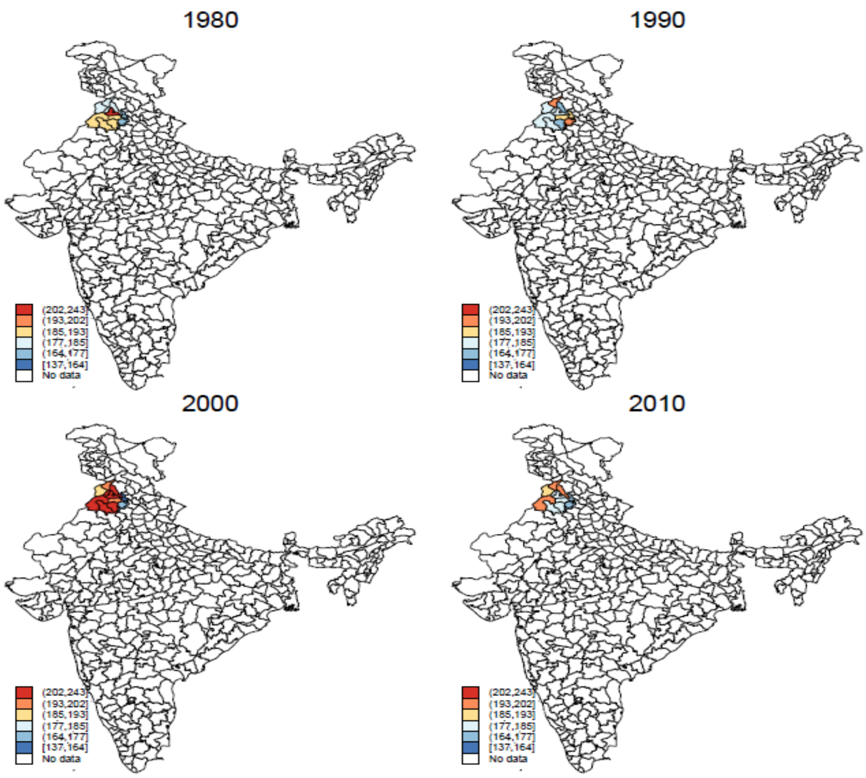
4.2 Data Sources and Descriptive Statistics

4.2.1 Data sources

The present study mainly used two sources of dataset viz., crop production data and weather data. The crop production data on area, yield, and inputs (i.e., fertilizer and share of cropped irrigated area) has been collected primarily from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). This dataset consist of district-level information for 20 states of India with different agriculture and socio-economic characteristics from 1966-2015. However, this study is only concentrated on Punjab state. Detailed information on output and inputs variables viz., crops grown area covered under each crop; inputs like fertilizer, irrigation, and farm harvest prices (FHP) has been collected on major eleven crops (i.e., rice, wheat, sorghum, pearlmillet, maize, fingermillet, pigeonpea, groundnut, chickpea, rapeseed, cotton) for Punjab, which together accounted for 92 percent area of production. The data has been divided into the apportioned and unapportioned database; but this study considered only the apportioned dataset (i.e. data for 1966 district boundaries). However, for analysis the final record of panel data has been set for major 11 districts in Punjab. Secondly, the data on weather variable i.e. rainfall across districts has been extracted from high-resolution (0.25^0 x 0.25^0) daily gridded dataset available from the IMD (India Metrological Department) for the period 1966-2015. In this study, daily rainfall data has been used, and converted into district level. For this purpose, the study has used the district level geographic coordinates to specify the nearest grid point to each district to get information about the monsoon arrival.

Before moving ahead, it tries to observe the distribution of rainfall across districts. The results find that monsoon varies across different districts in the state as shown in Figure (4.1). For the particular case of Punjab, maps are shown in Figure B1 in Appendix B.

Figure 4.1: Variation in monsoon onset day across districts in Punjab



Note: This figure presents the changes in the spatial and temporal pattern of monsoon arrival over 1980-2010 across the districts.

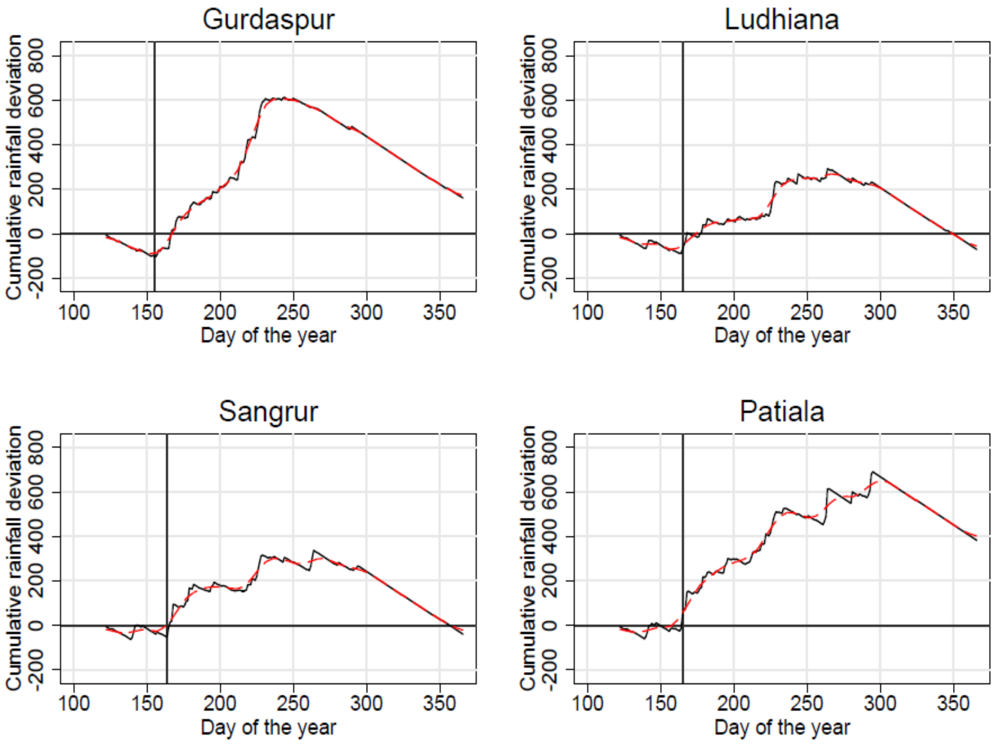
4.2.2 Onset of the rainy season and precipitation index

To measure the structure of onset of rainfall, various indices have been carried out by different studies (Liebmann & Marengo, 2001; Chen et al., 2004; Bombardi & Carvalho, 2009). Thus, in this analysis, methodology used by Boombardi et al. (2017) has been followed to construct the onset of monsoon in different years across districts. This index also captured the combined effect of duration and intensity of rainfall. For this methodology, daily rainfall accumulated anomalies has used at each grid point for each year as the sum of daily rainfall anomalies from *1st May* to the specified day as follows:

$$S(d) = \sum_{t=May,1^{st}}^{d} (P(n) - Pc) \tag{4.1}$$

In Equation *(4.1)*, $S(d)$ represents the accumulated precipitation deviation from the annual mean at day 'd', P *(n)* is the daily rainfall at day 'n', Pc is average of daily rainfall in a particular year. Here, *t* is the starting date of the monsoon. Here, *1st* May or *122nd* day of the calendar year is selected as the arrival day of monsoon. According to India Meteorological Department (IMD), the monsoon does not start before *10th* May. Thus, a date in early May would be appropriate for measuring the onset of rainy day to avoid occurrence of maximum false rainy onsets. In Equation *(4.1)*, the rainy days in the months of the May, June, July, and August (MJJA) are considered, because maximum rain has been recorded in these months (IMD).

Figure 4.2: Arrival of monsoon onset across different districts in Punjab



Note: This figure presents the arrival of monsoon onset across different districts in Punjab.

Figure 4.2 represents the construction of onset rainy day. In this estimation, the onset rainy day is considered as the first inflection point at which the $S(d)$ curve touches its minimum but start turning upward thereafter. In Figure (4.2), vertical blackline display the accumulated rainfall deviation $S(d)$ from the mean. It is observed that the onset rainy day varies across the districts. In case of Gurdaspur, monsoon arrives on 167 day as shown by the vertical line in the Figure (4.2), however in Ludhiana it arrives on the 171 day. By this process, monsoon arrival day in different districts of Punjab can be found.

Table 4.1 represents the summary statistics for the monsoon onset day, various districts show that the onset rainy day varies across districts with an average of 192th days of the calendar years. However, for analysis purposes, we have considered only those days where the onset of rainy day arises with extreme delays, which varies with the mean value of 223 day in Punjab.

Table 4.1: Summary statistics of the monsoon onset day

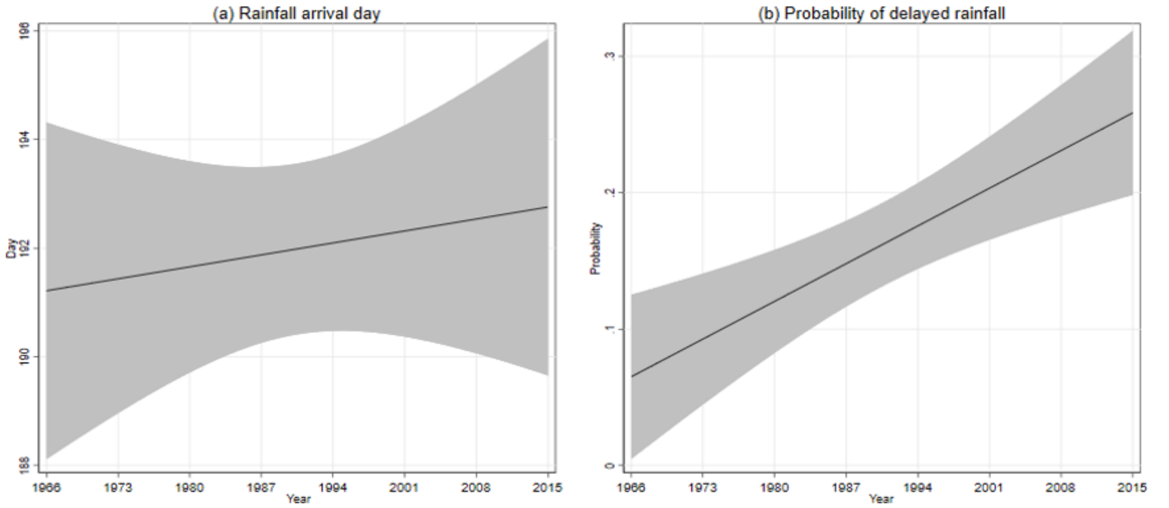
Standardized values	Min	Mean	Max	SD
0	139	185	218	13
1	205	223	243	9
Total	139	192	243	18

Note: this table presents the summary statistics of arrival of monsoon day across different districts in Punjab.

4.2.3 Evidence on climate change

There has been a substantial change in the onset of rainy season across different districts over 1966-2015. In examining the trend and the probability of the onset of rainy day in India, it was found that over time onset of rainy day has moved forward in the later part of the year (Singh et al., 2020). Figure (4.3) depict that the onset day of monsoon has shifted forward by about a day on average over 1966-2015 as shown in part (a) of Figure (4.3). It can be seen that the probability of delay in monsoon onset has also increased over the considered time period.

Figure 4.3: Change in onset of days and probability over 1966-2015 across districts



Note: This figure presents the change in monsoon onset day and probability of monsoon onset day over 1966-2015 across different districts in Punjab.

In part (b) of Figure (4.3), it found that the probability of delay in the onset of monsoon has increased from less than 0.1 in 1966 to 0.27 in 2015. To estimate the day of monsoon arrival over time, regression analysis has been used considering districts fixed effects to control for heterogeneity across different districts; and results are shown in Table 4.2. In the regression analysis, the monsoon onset day and probability of extreme monsoon onset day are regressed on a linear time trend. The outcomes are highlighted in column 1 of Table 4.2 that show a positive but statistically insignificant trend in the arrival of monsoon, which is also displayed in part (a) of Figure (4.3). Overall, the results show that over time the onset of monsoon has shifted forward by about a day on average. Further, it also tests the probability of extreme delay in monsoon, for this purpose, a dummy variable is created. This is defined as 1 if the monsoon arrival day arrives one standard deviation greater than the normal arrival day in a district and 0 otherwise. This dummy variable is regressed on a linear time trend and district fixed effects. The results are presented in column 2 of Table 4.2., and are also displayed in part (b) of Figure (4.3), which shows that the probability of occurring extreme delay in monsoon arrival has increased over time.

Table 4.2: Estimates for change in onset and probability of delayed monsoon across districts

Variables	(1) Monsoon onset day	(2) Extreme monsoon onset day
Year	0.033	0.004***
	(0.060)	(0.001)
Observations	550	550
R-squared	0.001	0.024
District FE	Yes	Yes
Adjusted R-squared	-0.0012	0.0222
F stat	0.294	13.40
Mean of dependent variable	192	0.162

Note: This table represents regression results for change in onset and probability of delayed monsoon occurrence during 1966-2015. In column 1, the district level rainfall arrival days are regressed on a linear time trend while controlling for the district fixed effects. In column 2, the dependent variable is a dummy variable which is coded as 1 if the rainfall arrival day is greater than the mean arrival day in a district and zero otherwise. This dummy variable is regressed on a linear time trend while controlling for district fixed effects.

4.2.4 Diversification measures

Several indices have been used to measures the diversity in cropping system such as Herfindahl Index, Simpson Index, Entropy Index and many more. In spite of their differences, these indices give more or less similar results. In this chapter, Composite Entropy Index (CEI) has been constructed as earlier followed by Shiyani and Pandya (1998).

$$CEI_{it} = -\left(\sum_{i=1}^{N} P * log_N P_i\right) * \{1 - (1/N)\}$$

(4.2)

where, CEI_{it} is the diversity in cropping system; p_i is the area share of crop i in the total cropped area. The range of the index lies between 0 & 1; 0 represents complete specialization, whereas 1 represents complete diversification. Since index uses -$log_N P_i$ as weights, it assign more to lower quantity and less weight to higher quantity. For more clarification see Figure B2 and Figure B3 for different district in Appendix B.

4.3 Empirical Frameworks

There are mainly three approaches that are widely used to estimate the influence of climate shocks on crop yields i.e., (i) Bio-physical crop modelling approach also known as production function approach (ii) Ricardian approach and (iii) Panel data approach. Each of these approaches has its own advantages and limitations. The majority of the previous studies have used panel data approach proposed by Deschenes and Greenstone (2007). It is because of its numerous advantages over others techniques. For instance, by using panel data approach, it is possible to capture the effects of time-invariant variables such as geographical characteristics (i.e., soils and water quality). Moreover, it considers farmers' responses or adaptations to changes in weather change. Further, it is possible to account the short-term effects of adaptations on yield, as in response to yearly variations in weather variables the crop growers can adjust their crop mix, input usages etc. One more benefit to use this approach is that the geographical fixed effect absorbs location-specific time variant determinants of crop yield that may be correlated with climate variables (Deschenes & Greenstone, 2007). Therefore, in this chapter, to examine the impacts of extreme delay in monsoon arrival on agricultural productivity, panel data approach is used.

4.3.1 Extreme monsoon onset day and crop productivity

To estimates the impact of delayed monsoon onset on agricultural productivity, it follows this specification:

$$Y_{it} = a_i + \sigma x_{it} + \sum_{i=1}^{N} \rho_i (a_i \times T) + \beta_1 d\_day_{it} + \varepsilon_{it} \tag{4.3}$$

where, $Y_{it}$is the log of agricultural productivity in district *i* in year *t*. a_i represents the district fixed effect that absorb time-invariant unobserved factors (i.e., geographical characteristics of districts); thus with this fixed effects the predictable coefficients of β*'s* are likely to be unbiased and consistent. x_{it} represents the vector of others additional inputs as controls (i.e., fertilizer and share of crop irrigated area). Further, $(a_i \times T)$ is a district-specific exponential time trend to switch for the district-specific heterogeneity in yield growth due to other technological change; ρ_i is coefficient of time trend across districts. d_day_{it} is a categorical variable for delayed monsoon arrival in district *i* in year *t* named as 'extreme monsoon onset day'; *d_day* is a categorical value where it takes the value 1 if a district *i* in time period *t* receives one standard deviation greater than normal arrival day delay in monsoon arrival and 0 otherwise. ε_{it} is a residual noise term that comprises the effects of other random factors. In

Equation (4.3), $\beta_1$is our main interest parameter that estimates the variation in agricultural productivity due to a one standard deviation delay in the onset of monsoon.

4.3.2 Monsoon onset day, crop productivity, and crop diversification

In Equation (4.3) agricultural productivity is a linear function of the timing of monsoon. However, to test whether crop diversification is an effective adaptation measure to cope with effects of delayed monsoon on agricultural productivity, the modify Equation (4.3) to include an interaction term of extreme delay in monsoon onset day (d_day_{it}) with diversification index (CEI) and specify it as:

$$Y_{it} = a_i + \sigma x_{it} + \sum_{i=1}^{N} \rho_i (a_i \times T) + \beta_1 d\_day_{it} + \beta_2 CEI_{it} + \beta_3 (CEI_{it} \times d\_day_{it}) + \varepsilon_{it}$$

(4.4)

In Equation (4.4), $(\beta_1 d\_day_{it} + \beta_2 CEI_{it} + \beta_3 (CEI_{it} \times d\_day_{it}))$ represents the variation in agricultural productivity due to delayed monsoon and crop diversification; x_{it} is a vector of others additional inputs as controls (i.e., amount of fertilizer and share of crop irrigated area); and ε_{it} is a residual noise term that comprises the effects of other random factors.

4.4 Empirical Results

The results begin with the estimation of Equation (4.3) by using panel dataset regression model after controlling for district and time fixed effects. Equation (4.3) gives us only the impact of delayed monsoon arrival on agricultural productivity. In another, Equation (4.4), it estimates the role of crop diversification as dominant adaptation strategy to cope-up with yields loss due to delayed monsoon arrival. However, in order to check the robustness by including additional inputs, the study is estimates two different specifications of Equation (4.4). In one, diversification index is included and allow it to interact with weather variable, to estimate its effectiveness to cope-up with effects of delayed monsoon on agricultural productivity. In another, other additional input variables (i.e., irrigation, fertilizer) are taken control variables.

4.4.1 Model specification test

Before proceeding further, to know the impact of delayed monsoon onset on agricultural productivity level, and adaptation strategies or risk coping appliance; it is essential to check the specification of the model. It might be possible that variables that are considered in the model seem to be non-stationary which may lead to spurious estimates. To check for stationarity of variables, the panel unit root test has used (see Table B1 in Appendix B). The test statistics modified inverse χ^2 probability estimation shows that null hypothesis of unit root is rejected. Thus, implying that all the variables are stationary and statistical significant at 1 percent level.

Additionally, the error term might be associated with other explanatory variables generating serial correlation and heteroscedasticity problem within cross section units. It may produce less efficient and biased results. Therefore, to check for the existence of these problems, the study tested following (Arellano & Bond, 1991) for serial correlation. Further, to check for heteroscedasticity, Modified Wald test is applied as shown in Table B2 in Appendix B. The variables that are not important deleted from the model. It found χ^2 statistics to be significant at 1 percent level specifying the presence of heteroscedasticity. Therefore, to control for serial correlation and heteroscedasticity, the standard errors have been clustered at the district level.

To check the appropriate model for the estimation of delayed monsoon impact on agricultural productivity, and suitable adaptation practices, the Housman test is conducted. The results of Housman test favour the fixed effect model over the random effect model. Table B3 in

Appendix B presents the specification of Hausman test to check appropriateness for the chosen fixed effect model with district-specific trend. The test rejected the null hypothesis that contain random effect model is appropriate model, therefore, the results favour the fixed effect regression model.

4.4.2 Impact of extreme monsoon onset day and crop productivity

The estimates of Equation (4.3) are presented in Table 4.3. From the estimation, it is found that the coefficients of extreme monsoon onset day is negative and statistically significant for crop-productivity, clearly indicates that a one standard deviation delay in monsoon onset leads to a decline in agricultural productivity. The analysis shows that a one standard deviation delay in monsoon onset lowers agricultural productivity on average of 3.94 percent than the normal arrival day.

Table 4.3: Impact of monsoon onset day and crop productivity

Variables	(1) Crop productivity
d_day	-0.0394**
	(0.0196)
Constant	8.8882***
	(0.0086)
Observations	542
R-squared	0.9824
DIST FE	Yes
DIST x Time Trend	Yes
Adjusted R-Squared	0.982
F stat	4.057

Note: Dependent variable is log productivity; d_day represents the extreme monsoon onset day. The fixed effects associated with specification are shown in the column. ***, **, and * represents the significance level at 1%, 5%, and 10% respectively. Standard errors are in the parentheses. Standard errors are robust to serial correlation and heteroscedasticity within districts.

It is possible that along with climate variables, other inputs such as share of cropped irrigated area and fertilizers also influence crop productivity. To test for the sensitivity of results to these variables, Equation (4.3) is estimated. Here, irrigation and amount of fertilizer are controlled as presented in Table 4.4. From this estimation, the results are comparable to Table 4.3.

Table 4.4: Robustness check with additional control variables of Equation (4.3)

Variables	(1) Crop productivity
d_day	-0.0400**
	(0.0164)
SIRR	-0.4794**
	(0.2361)
FERT	0.0018***
	(0.0002)
Constant	8.9058***
	(0.1188)
Observations	535
R-squared	0.9863
DIST FE	Yes
DIST x Time Trend	Yes
Adjusted R-Squared	0.986
F stat	21.04

Note: presents the estimation of Equation (4.3) with additional variables as a control. Dependent variable is log productivity; d_day represents the extreme monsoon onset day. The fixed effects associated with specification are shown in the column. ***, **, and * represents the significance level at 1%, 5%, and 10% respectively. Standard errors are in the parentheses. Standard errors are robust to serial correlation and heteroscedasticity within districts.

4.4.3 Impact of delayed monsoon arrival and crop diversification as adaptation measure

The main concern of this chapter is to evaluate the effect of crop diversification on crop productivity in situation when there is delay in monsoon arrival from its normal date. Table 4.5 presents the estimation of Equation (4.4). The positive and significant coefficient of interaction term of monsoon onset day with crop diversification (CEI) indicates the significant role of crop diversification in reducing losses in productivity that occurred due to adverse effect of delayed monsoon arrival. Additionally, overall the results hold even after controlling at these variables along with crop diversification i.e., share of crop irrigated area, fertilizer. To test for the sensitivity of these variables, the estimates of Equation (4.4) with controls variables (i.e., share of crop irrigated area and amount of fertilizer) are shown in Table 4.6.

Table 4.5: Estimated regression coefficient of Equation (4.4)

Variables	(1) Crop productivity
d_day	-0.1984**
	(0.0942)
CEI	-0.7634***
	(0.1088)
d_day × CEI	0.1725*
	(0.0913)
Constant	9.6537***
	(0.1076)
Observations	542
R-squared	0.9842
DIST FE	Yes
DIST x Time Trend	Yes
Adjusted R-Squared	0.983
F stat	18.41

Note: Table 4.5 presents the estimates of Equation (4.4) that includes the interaction of the CEI (Composite Entropy Index) with climate variables (Extreme monsoon onset day). The dependent variable is the log of crop productivity. SIRR represents share of crop irrigated area; FERT is amount of fertilizer. Whereas, *** p<0.01, ** p<0.05, * p<0.1 represent the significance level at 1%, 5%, and 10% respectively. Standard errors are in the parentheses.

Table 4.6: Robustness check with additional control variables of Equation (4.4)

Variables	(1) Crop productivity
d_day	-0.1557**
	(0.0767)
CEI	-0.4435***
	(0.0872)
d_day × CEI	0.1254
	(0.0786)
SIRR	-0.5582**
	(0.2407)
FERT	0.0015***
	(0.0003)
Constant	9.4240***
	(0.1635)
Observations	535
R-squared	0.9868
DIST FE	Yes
DIST x Time Trend	Yes
Adjusted R-Squared	0.986
F stat	19.64

Note: Table 4.6 presents the estimates of Equation (4.4) with additional inputs. The dependent variable is the log of crop productivity. SIRR represents share of crop irrigated area; FERT is amount of fertilizer. Whereas, "*** p<0.01, ** p<0.05, * p<0.1 represent the significance level at 1%, 5%, and 10% respectively". Standard errors are in the parentheses.

4.5 Conclusions

Agricultural production is very sensitive to the effects of weather shocks especially timing of monsoon arrival. Untimely monsoon pattern directly and negatively affect the crop productivity. Considering this adverse impact of untimely monsoon arrival on crop productivity, this chapter explored on the link between monsoon onset day and crop productivity. It also revealed that the farmers can reduce crop productivity losses by adopting some risk-coping strategies. Crop diversification has the potential to offset climate risks and improve agrarian sustainability. Such adaptation practice in agriculture is relevant for developing countries such as India where there is deficiency of financial resources. This analysis evolves in two steps: one, to estimate the impact of weather shocks on crop productivity in Punjab; two, to assess the effectiveness of crop diversification to cope-up with such weather risk.

The empirical investigation suggests that the delayed monsoon arrival has a negative and statistically significant impact on crop productivity. But it also found that crop diversification is playing an important role in reducing the loss of crop productivity that occurred due to adverse impact of delayed monsoon.

Therefore, the findings are clearly indicating the importance of crop diversification as well as other additional inputs in minimizing the losses in agricultural productivity. Since agriculture in the regions where farmers are more diversified, those might be less vulnerable to weather shocks. The findings suggest that farmers, besides the irrigation pattern can also use other possible adaptation measures to cope-up with weather shocks viz., crop diversification, rationalising amount of fertilization.

These findings have important implications for agricultural and development policy; and are likely to offer some useful insights for making climate-resilient agricultural practices in the state.