Chapter 4

IMPACT OF CLIMATE ON CROP MEAN YIELD AND VARIABILITY

The chapter overviews the impact of climate parameters i.e., temperature and rainfall on mean crop yield and its variability. Just and Pope production function is discussed. The production function investigates the spatial crop distribution due to climatic variations.

4.1 Introduction

Studies indicate that green-house gases like sulphur dioxide, chlorofluorocarbons, nitrogen dioxide, carbon dioxide, leads to the fluctuating climatic conditions that further influences temperature, rainfall pattern, soil moisture, sea level and precipitation (Aye & Ater, 2012; Houghton et al., 1996). The climatic variations impact the ecological system, economy, and agriculture to a great extent (McCarl et al., 2008; Adam et al., 1999). Thus, to determine the impact of crop yield variability, a mathematical model is developed to investigate the spatial crop distribution due to climatic fluctuations.

Change in climate over a year is one of the major determinants that leads to crop yield variation and its distribution. Due to different crop growth conditions, crops response differently to the varying climatic conditions. Consequently, alternations need to be carried out to make the agriculture sector to deal with the varying climate changes which makes it difficult for the growers to allocate their fields. These alterations become more difficult in a region with scare availability of water resources.

The change in temperature, duration of growing period, level of precipitation impacts the sowing and other operational farm activities. These changes will affect the crop productivity and variability. Thus, a detailed investigation is carried out to evaluate how sensitive is the crop yield and its variability with respect to the weather fluctuations and how it will response to the future climatic variation. For this, it is important to understand how much variations are carried out in crop yield and its distribution because it forms a basis for policy and make the decision-makers to improve the crop yield and reduces its variability. All the mentioned parameters reflect the need of optimal irrigation pattern. Studies has been carried out to determine the impact of climatic variations on crop (Senthold Asseng et al., 2011; Barnwal & Kotani, 2010; Devasirvatham & Tan, 2018).

Along with climate, crop productivity depends on many factors including soil attributes, technological inputs, planting practice and majorly on weather conditions. Thus, a brief literature discussing the impact of soil parameters on crop yield is reviewed in subsequent chapter. Uniform farm operational activities, and adoption of high yielding seed variety make crops more sensitive to weather conditions. Based on weather conditions, crop yield variability can result in the fluctuation in crop production and instable crop prices. (Kim & Pang, 2009) developed a quantitative approach to determine the impact of weather conditions on rice yield variability and mean yield production. Panel Data analysis and Just-Pope stochastic production function were applied for estimating the impact of weather conditions on crop yield and variance. The results of the function indicate that the temperature and rainfall support the rice cultivation in a region.

Earlier studies were carried out to evaluate the impact of changes in climatic variables on mean crop productivity. However, the change in crop yield due to climate parameters is being investigated by only some researchers. Hence, a limited empirical information is available on mean crop yield due to varying climate. Simulation and economic models have been used to determine the relation of these parameters. (Tokunaga et al., 2015) empirically identifies the impact of climatic variations on agricultural crop production using panel data model. The results of the formulated model show that with the rise in temperature there is a reduction in crop production.

The chapter will discuss the impact of climatic parameters on four majorly cultivated crops namely: wheat, mustard, maize and pearl millet in Rajasthan. The state being arid with erratic rainfall often face a fluctuation in crop production, and hence the profit of growers gets impacted. To carry out an analysis Just and Pope production function is applied. The function proposed is the sum of two functions; first one deals with the output level i.e., mean crop yield and second one explains the crop variability. This specification of production function allows decision-makers to differentiate the impact of input on output and risk, offers flexibility to evaluate both positive and negative marginal risks relative to inputs.

To consider the appropriate model that fits the data, Hausman test statistics (Fig. 4.1) is applied that illustrates that the Random Effect Model is more suitable than Fixed Effect model. Further, to choose among Random Effect Model and Pooled OLS model Breusch and Pagan Lagrangian multiplier test is performed that report the superiority of Random Effect over Pooled Model. Moreover, function also depicts those wrong inferences can be drawn if one ignores risk factor that is shown by the interaction term. In such a case, the results can produce a standard error that are often misleading indicating a more precision in estimation than it actually is (Koundouri et al., 2005b).

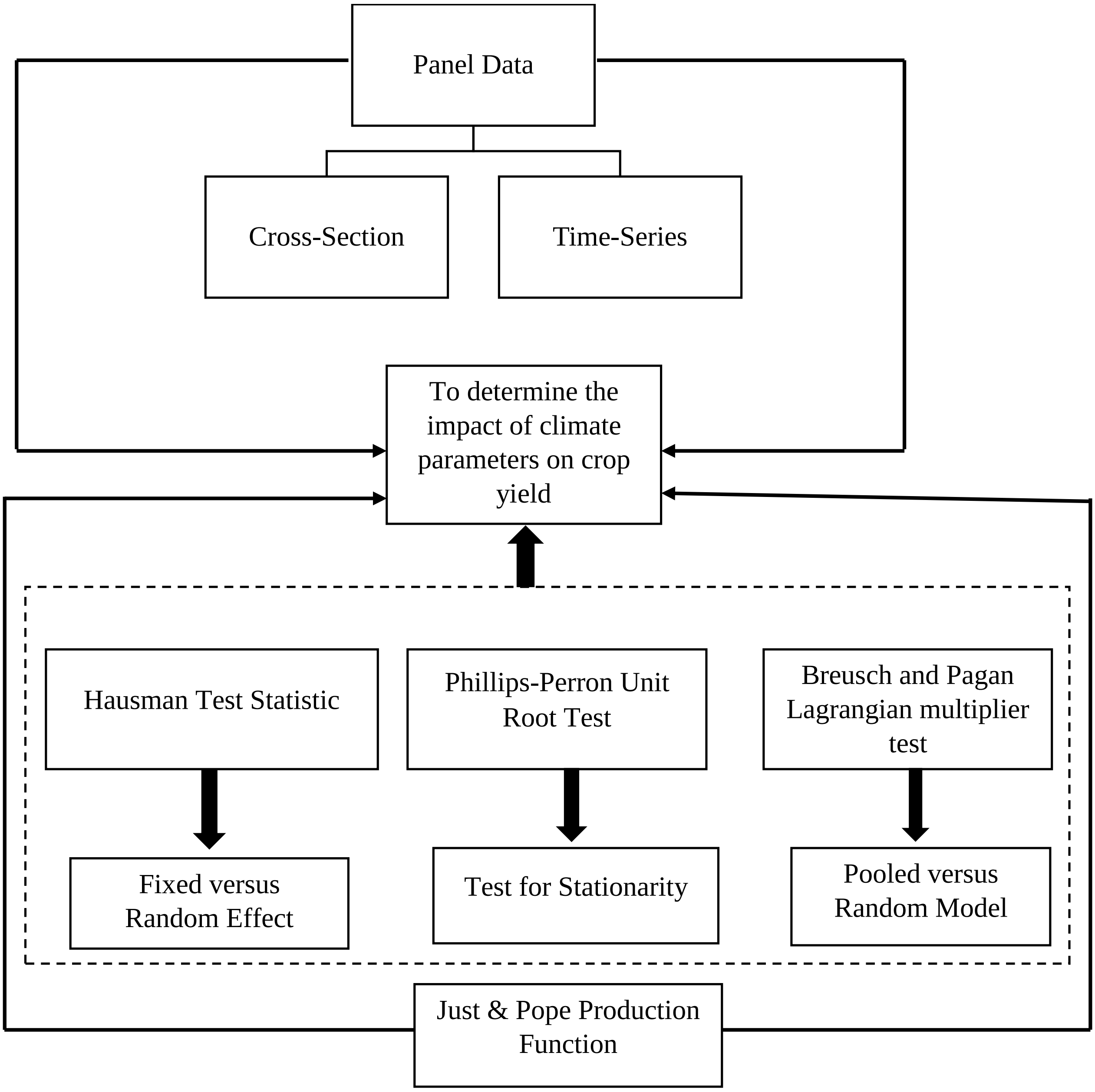


Fig. 4.1: Statistics for Analysis

Thus, study aims to evaluate the impact of climatic variations on crop yield variability and covariance of yield among crop. A secondary data is used to analyze the potential impacts i.e., positive, negative or no impact of weather variables on mean and variance of wheat, mustard, maize and bajra (pearl millets). The production function is defined to determine the impact that will reveal whether the climatic variables will increase or decrease the crop yields.

4.2 Formulation

The impact of climate varies across a region. Consequently, time-series analysis cannot be used to determine such variations. Due to climate variability, such an analysis has its own limitations. Variability in crop yield from one season to another caused by weather conditions over a region, is an important source of production risk (Maharjan & Joshi, 2013). Thus, it is important to understand, how much the yield gets impacted by climatic variations and also, how much the yield variability changes.

A production function of crop yields is considered, that depends on the weather variable (x). Just-Pope stochastic production function is used to represent crop yield in i region at year t (y_{it}) (Just & Pope, 1978).

$$
\begin{aligned}
y_{it} &= f(x_{it};\beta)+\omega_{it}h(x_{it};\delta)^{1/2} \\
E(y_{it}) &= f(x_{it};\beta) \\
V(y_{it}) &= \omega_{it}h(x_{it};\delta)^{1/2}
\end{aligned}
\tag{4.1}
$$

y_{it} is the crop yield in region i in time t; x_{it} is the explanatory variable such as rainfall, maximum & minimum temperature and trend. The first term of equation (4.1) represents the mean crop function and second term represents crop variance. Variance measures crop variability within a region.

ω_{it} is the stochastic variable with zero mean and variance σ^2_{ω} and β & δ are the production function parameters to be determined. In this production function, expected crop yield ($E(_{yit})$) is $f(x_{it};\beta)$ and hence, $f(x_{it};\beta)$ estimates the impact of independent variable on mean crop yield. The crop variance is evaluated by $\omega_{it}\, h(x_{it};\delta)^{1/2}$ i.e. $V(y_{it})$ where $h(x_{it};\delta)$ measures the impact of independent variable on crop yield variance. The variable (x_{it}) that is used for estimation includes constant, temperature and temperature levels (average minimum & average maximum). Both increasing and decreasing risk effects of inputs on output is formulated, as Just-Pope stochastic production function does not restrict risk effects of inputs. Crop yield variability is evaluated by the operator sign associated with function h_x indicates that whether climate variable positively or negatively impact the yield. If the variance of crop yield increases (decreases) under uncertainty then only input is said to be risk increasing (decreasing) [i.e., $h_x > (<) 0$] otherwise decreasing.

(Kumbhakar, 1997; Saha et al., 1997) explains the heteroscedasticity of the Just-Pope production function with the help of following function:

$$y_{it}=f(x_{it};\beta)+u_{it} \quad (4.2)$$

$$V(y_{it})=Var(u_{it})=e^{\delta x_{it}} \quad (4.3)$$

where $u_{it}=\omega_{it}h(x_{it};\delta)^{1/2}$ and $Var(u_{it})=\sigma_{\omega}{}^{2}h(x_{it};\delta)$

To evaluate mean and variance function Just-Pope in (1978), proposed Feasible Generalized Least Squares (FGLS) or Maximum Likelihood Estimation (MLE) method. Traditionally, the stochastic production function is estimated by Feasible Generalized Least Squares approach. However, (Saha et al., 1997) argue that maximum likelihood method is more efficient to get an output, with smaller mean square error than latter. (Saei et al., 2019) determine the impact of climate on crop yield by using Just and Pope stochastic production function.

Model heterogeneity will demonstrate the spatial crop distribution. Heterogeneity explains how stable a variable relationship is, and useful to design, choose and interpret the statistical analysis. Residuals of the model will explain the system heterogeneity. It explains the change in the residual distribution over the range of measured parameter. In simpler words, it can be concluded that heterogeneity of a model is the systematic change in the spread of residuals over the range of measured values. It may be a challenging issue since Ordinary Least Square (OLS) regression assumes that all the residues are extorted from a homogeneous population that has constant variance.

For the model estimation, it is assumed that crop variance follows exponential form: $V(y_{it})=Var(u_{it})=e^{\delta x_{it}}$ with ω_{it} normally distributed i.e., $\omega_{it}\sim.N(0,1)$. In equation (4.2) panel data estimation method is taken into account to investigate the region-specific parameters in the estimation of production function. (T.-H. Huang, 2004; Saha et al., 1997) explains that Monte Carlo experiments shows that the unless residuals show normal distribution the Maximum Likelihood function is more efficient with small mean squared error. The Maximum Likelihood function is represented as:

$$\ln L=\frac{-1}{2}[N*\ln(2\pi)+\sum_{i=1}^{n}\frac{(y_{it}-f(x_{it};\beta))^{2}}{e^{\delta x_{it}}}+\sum_{i=1}^{n}\delta x_{it}] \quad (4.4)$$

MLE estimates the parameter values that maximize the probability distribution for data observation. The method of Maximum Likelihood, estimates those values of the parameters that are most consistent with the sample data. (Chen et al., 2004) evaluate the impact of climatic variations on crop yield variance by using maximum likelihood panel data model. The

Maximum Likelihood model assumes that the error terms show a normal distribution. Several studies are carried out to address the issue that how crop yields are distributed. (Just & Weninger, 1999) proposed a methodology to test the normality of crop yields.

The parameters β and δ is estimated by maximizing equation (4.4). N denotes the total number of observations. To represent the relationship between mean crop productivity and weather variables f(x_{it} ; β), we represent linear and quadratic functional forms. Here we consider only the linear form of variance function δx_{it}. We estimate the stochastic production function for wheat, mustard, pearl millet and maize. Since farmers cultivate the field with more than one crop in a season and adopt crop rotation farm practice, covariance among the crop is estimated. This will provide, variability in the function when the weather parameters (x_{it}) associated with it changes.

By using equation (4.4) a regression analysis will be carried out to estimate the variance of crop k and j respectively.

$$\hat{u}_{kit}\hat{u}_{jit} = x_{it}\alpha + \varepsilon_{kit} + \varepsilon_{jit} \quad (4.5)$$

where, $\hat{u}_{kit} = y_{kit} - f(x_{it};\beta)$ (4.6)

$$\hat{u}_{jit} = y_{jit} - f(x_{it};\beta) \quad (4.7)$$

4.3 Data

We aim to determine the impact of climate parameters (temperature and rainfall) on wheat, mustard, pearl millet and maize in Rajasthan. We obtain a data on crop yield from Ministry of Agriculture Department (2019). The yield data includes average crop yield in Rajasthan at district level. Majorly cultivated districts under these crops were considered for analysis.

Year wise crop production is evaluated for time series from 2014 to 2020. The data on rainfall (R) and temperature (T) are obtained from India Meteorological Department (IMD, 2020). The rainfall data is a time-series data of the total annual rainfall in a state, reflects the average precipitation and inter-seasonal available water within a year. The temperature data includes the varying temperature in growing season i.e., from April to November. The descriptive statistics of the parameters for analysis is illustrated in Table 4.1. By analyzing the climatic trends, we examine the future impacts on crop yield and yield variability.

Fifty-year rainfall data was observed by (Goswami et al., 2006) and it is depicted that the frequency of heavy rainfall significantly increased by 10% per decade and the rate of heavy rainfall raised to about double. From the data revealed by IMD (Indian Meteorological Department) different trends of precipitation is observed during pre-climate and post-climatic changes.

Table 4.1: Descriptive Statistics use for Estimation

	Mean	Standard Deviation	Maximum	Minimum
Wheat (Kg/ha)	3048.75	172.3807	3270	2749
Temperature (℃)	405.9167	128.9196	680	237
Rainfall (in mm)	2.810833	.3065188	3.32	2.29
Mustard (Kg/ha)	1252.833	149.7767	1558	946
Temperature (℃)	28.375	5.266209	36.5	22
Rainfall (in mm)	131.9167	17.25982	160	108
Pearl Millet (Kg/ha)	845.3333	174.4526	1093	394
Temperature (℃)	26.34167	5.951415	15.38	33.18
Rainfall (in mm)	573.1879	59.18868	680.6852	517.1176
Maize (Kg/ha)	1581.333	287.2048	1884	1044
Temperature (℃)	32.525	5.87307	42.1	23.2
Rainfall (in mm)	581.1833	103.491	737.6	378.8

Note: The variation in mean and standard deviation of rainfall and temperature is due to different cultivating season of the crops.*

The time-series data exhibit time trend. Thus, to de-trend the data Phillips-Perron Unit Root test is applied (Fig. 4.2) to determine the stability of variables used for analysis. Results of test is shown in Table 4.2. The results of the test indicate that all the variables used for analysis were stationary, as the p-value < 0.05. Thus, we reject the null hypothesis and conclude that the panel variables are stationary.

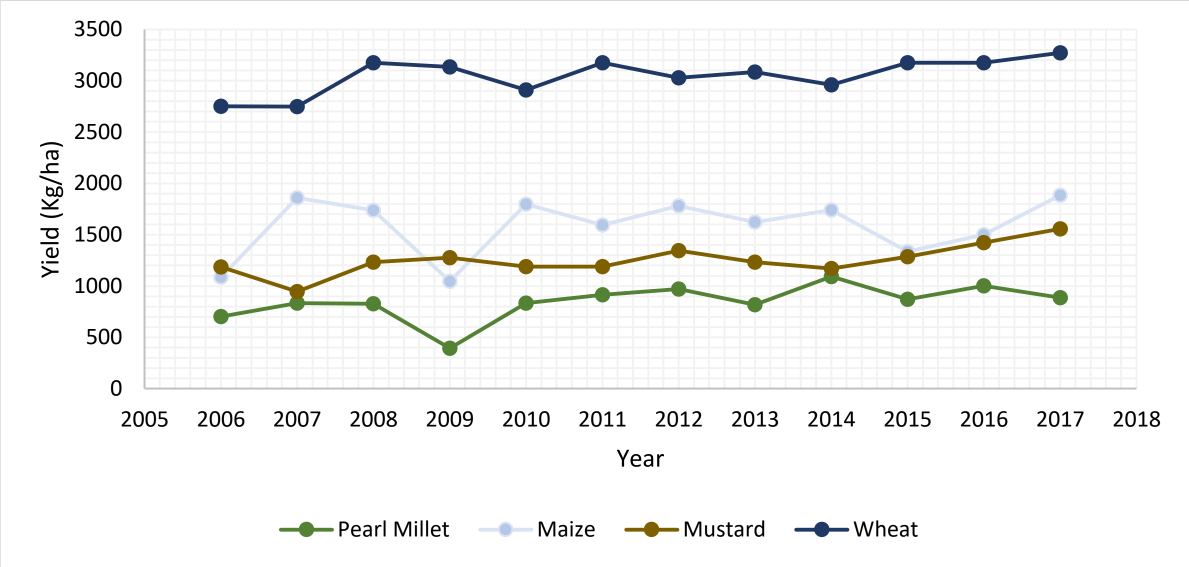


Fig. 4.2.1: Crop Yield Variability

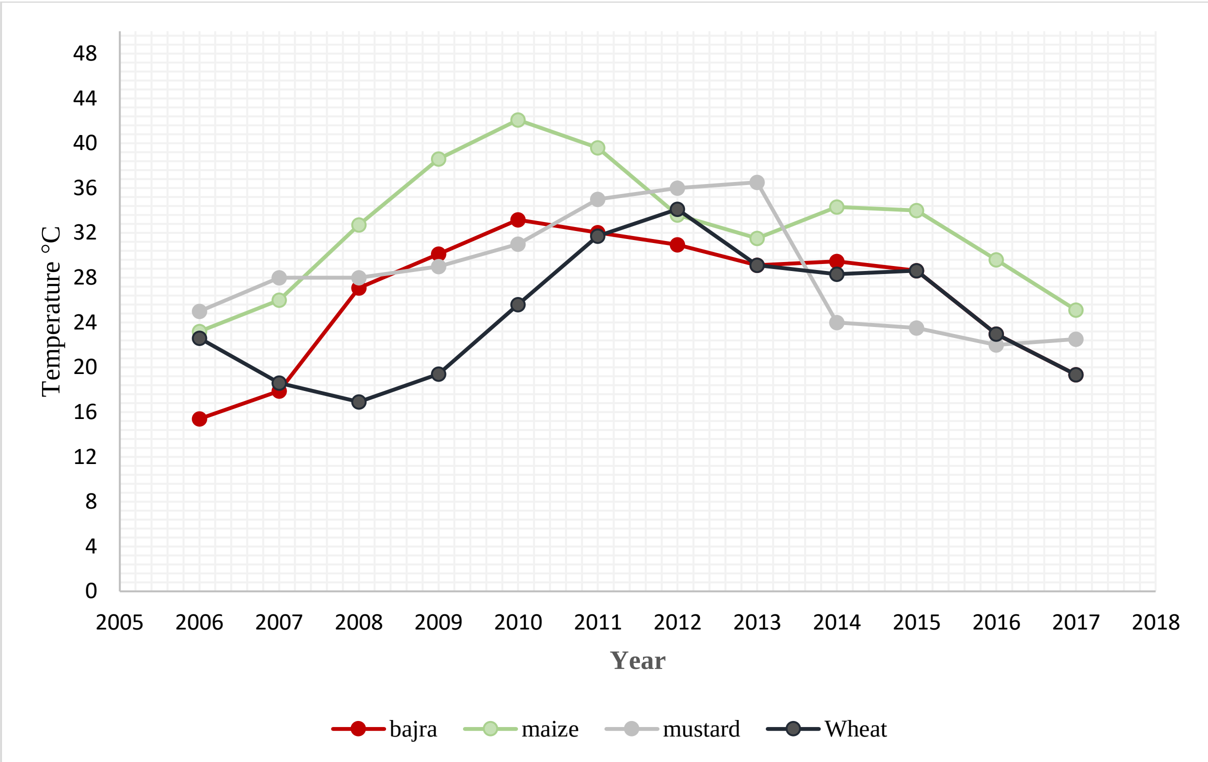


Fig. 4.2.2 Temperature Variability

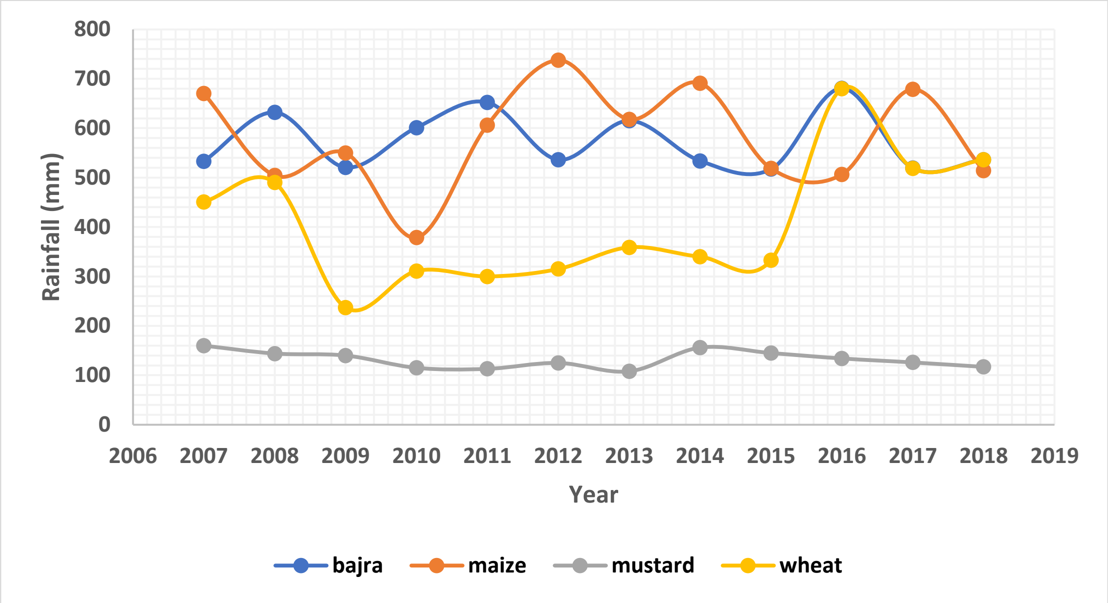


Fig. 4.2.3: Rainfall Variability

Fig. 4.2: Variability in the Estimated Parameters

Table 4.2: Phillips—Perron Unit Root Test Results

		Statistic	p-value	Statistic	p-value	Statistic	p-value
		Yield		Rainfall		Temperature	
Inverse chi-squared (8)	P	32.8713	0.0001	31.6907	0.0001	36.9820	0.0000
Inverse normal	Z	-3.9054	0.0000	-3.1470	0.0008	-4.6659	0.0000
Inverse logit t (24)	L*	-4.5477	0.0001	-4.1893	0.0002	-5.2007	0.0000
Modified inv. chi-squared	Pm	6.2178	0.0000	5.9227	0.0000	7.2455	0.0000

H_0: All panels contain unit roots

H_1: At least one panel is stationary

4.4 Results and Discussion

For the estimation of production function, the panel data model is applied. Panel data model describe the behaviour of a variable both among the variables and over a period of time. The modelled data need to be balanced (same observations for all the group parameters) when parameters are observed over a time period or unbalanced (contain some missing values for some of the group parameters) when individuals are not observed in all time period. It can explain both the common and individual behaviour of the groups. It minimizes the estimation biasness that otherwise, prevails in time-series analysis. The model analysis focusses to represent the likely dependency across data observations within a same group. The panel data model focusses to address the likely dependence across data observations within the same group. The difference between time-series analysis and panel model is that the panel data permits the heterogeneity across the groups and hence, explain individual effect of parameter which is not explained by time-series.

There are three types of panel data model: pooled model, random effects and fixed effects. For the analysis we have to choose the model for the defined data set that best fits the model.

1. **Pooled Model:** In some datasets the individual specific effect can't be observed, implies that all the variables within the group are not correlated thus, a panel data is treated as one large pooled dataset. This linearly independency within the panel groups, is unlikely and hence the pooled OLS (Ordinary Least Squares) model is rarely acceptable for panel data models (Erica, 2020) .
2. **Fixed Effect Model:** Fixed effects are the variables that are constant across a panel, these variables don't change or changes at a constant rate over a period of time. Hence, they are termed as fixed. By evaluating the changes within the group over a period of time, the fixed effect model removes the variable biasness by including dummy variable for unknown values of the variable. In fixed effect model group mean is a unique quantity.

   The regression equation of fixed effects model panel data is as follows:

   $$y_{it} = \alpha_i + \beta' x_{it} + \varepsilon_{it} \qquad \forall\ i=1,2,3,\ldots,N\ ;\ t=1,2,3,\ldots,T \qquad (4.8)$$

   N represents the number of parameters and T is the number of time period. In fixed effect model the individual specific effect is estimated. x_{it} is an observed random parameter over a time t and y_{it} is the dependent random variable.

3. **Random Effect Model:** Random effect model are statistical model in which the parameters that define a decision space exhibit a randomness or random variation. In statistics, the models describe the variations in observed values to be significant or not. Randomness in model arises due to different values of parameters for each group. This model will estimate the panel data where the variables are interconnected between time and parameters. Thus, it is assumed that there is an intercept for each individual and the intercept is a random

variable. Thus, the model has two residual components one is residual due to cross-section and time-series and another one due to the randomness of a parameter. Unlike fixed effect model, random effect model uses the principle of maximum likelihood or general least square.

The random effect equation is given as follows:

$$X_{it} = \alpha_i + \beta' y_{it} + u_i + \varepsilon_{it} \qquad \forall\ i=1,2,3,\ldots,N\ ;\ t=1,2,3,\ldots,T \qquad (4.9)$$

u_i: is the individual residual which is the random characteristic; ε_{it} is the overall residual

Thus, in random effect model, it is the randomness of individual specific effect of parameters that is to be estimated.

Hausman test statistics is used to determine the correct panel data model by testing random effects versus fixed model effects. For this testing of model we considered an hypothesis that random effect is consistent and efficient for wheat, pearl millet, maize, and rapeseed & mustard (Johnston & Dinardo, 1997). Under a null hypothesis the random effect is consistent and efficient.

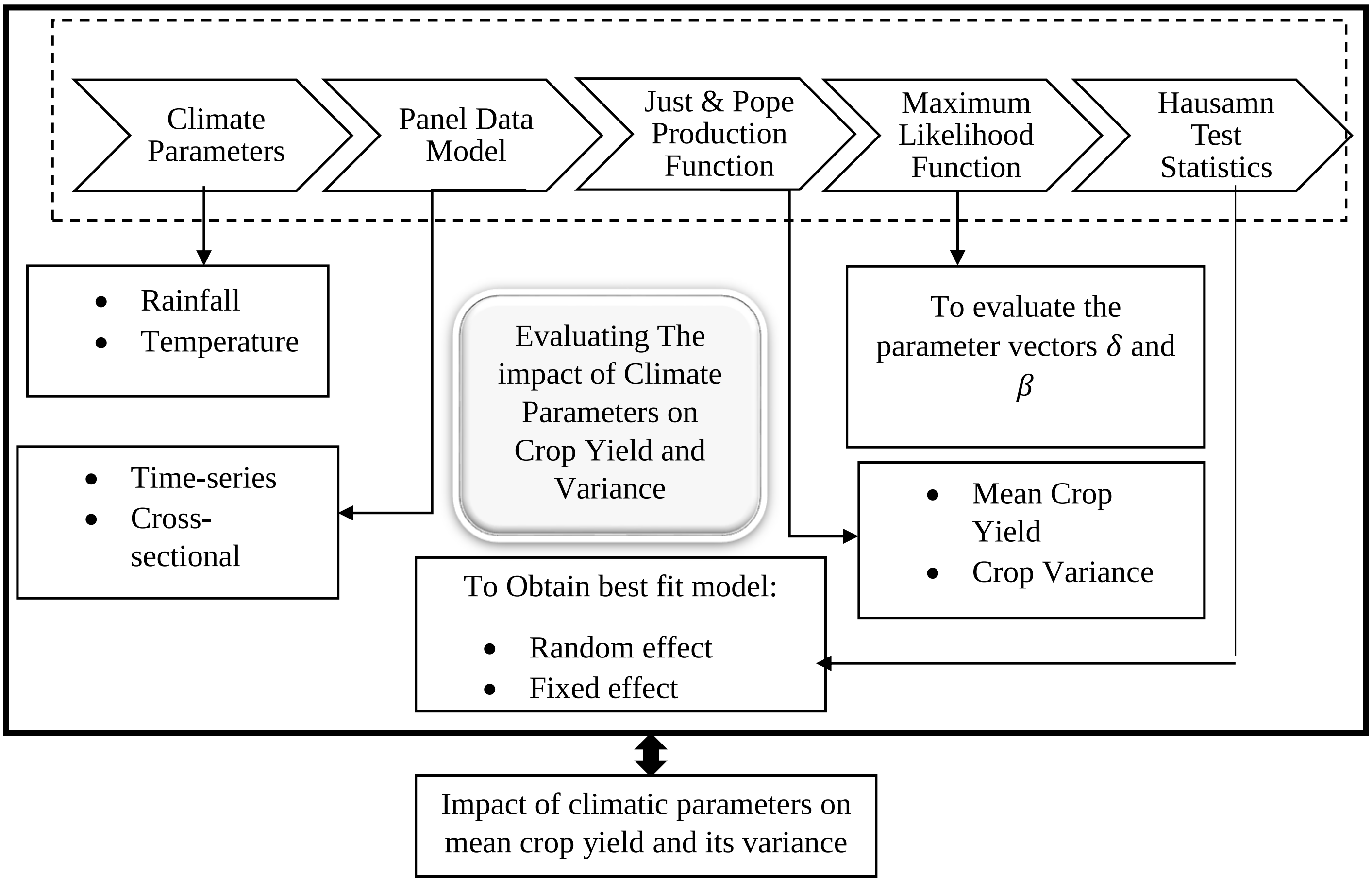


Fig. 4.3: Mathematical Framework for Evaluation of Climate Parameters

Hausman test statistics shows asymptotic distribution as chi-squared analysis with m degrees of freedom. The Hausman test statistic and its p-value indicate that we fail to reject null hypothesis, that the random effect model is consistent and more efficient for the crops under consideration. Thus, for all the estimated production function random effect is appropriate model.

For the estimated yield equations, random effect is more appropriate than fixed effect model. The random effect models are estimated by using maximum likelihood method. It can be evaluated by the value of R^2 that the data fits the model appropriately. To select the correct functional forms Akaike's Information Criterion (AIC) is used.

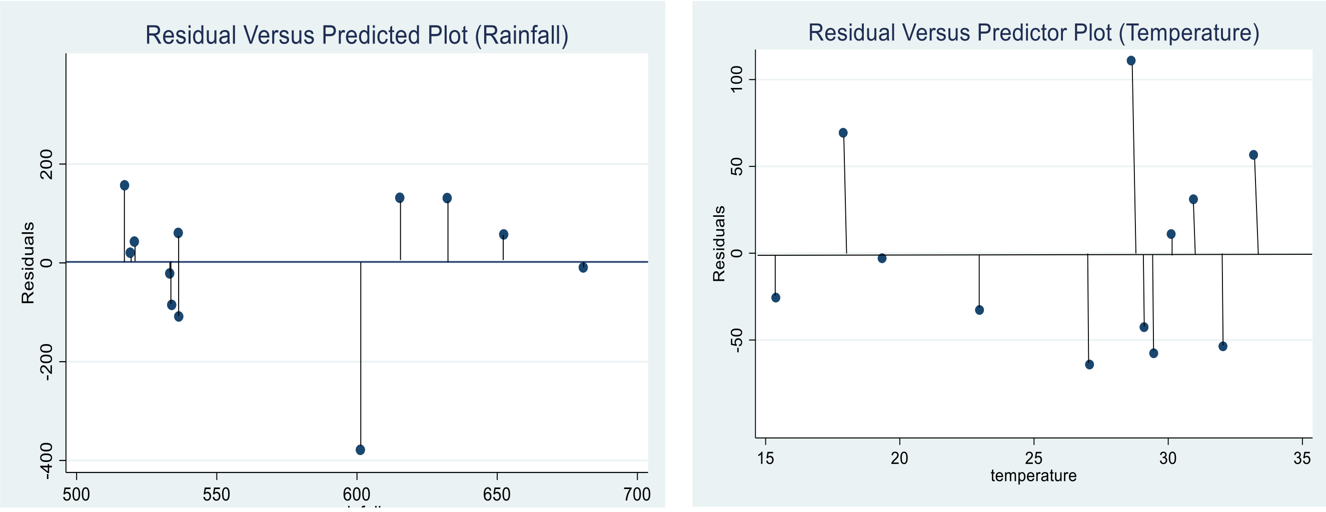
The impact of climatic variables can be calculated by the tables listed below. The two alternative functions linear and quadratic is represented. The estimated coefficient for temperature and rainfall in the mean yield varies between the two functions. The coefficients of two alternative functions i.e., linear and quadratic is shown in tables will determine the impact of rainfall and temperature on crop yield. A positive coefficient for the linear term and a negative coefficient for the quadratic term indicate that an intermediate value has the greatest positive value on yield distribution. The trend time variable added in the model estimates the impact of technological progress on crop yield. For most of the crops the technology trend is approximated by first order polynomial. As heteroskedasticity, violets some of the basic assumptions of statistical techniques hence, to make-up for this the yields are expressed on a log basis, which means that anomalies percent differences from the linear trend rather than absolute differences, as log(a)-log(b)=log (a/b) (D. Lobell, 2010).

The sign and the significance of the estimated coefficients for temperature in the mean pearl millet yield is differ in both functional forms (Table 4.3). Rainfall has a negative impact on the mean pearl millet yield though it is statistically significant in both the functional forms. The temperature in linear function is positively related to mean yield but it is not statistically significant however, in quadratic production function it is statistically significant. In quadratic mean yield function, the interaction term between rainfall and temperature is positive and is statistically significant at 1% level. The interaction term in regression analysis provides an insight on the mean crop yield is impacted by the effect of both rainfall and temperature simultaneously. The R^2 values indicates the 22.19% and 30.71% variations in crop mean yield and variance respectively.

In variance function the coefficients estimated, indicates that increase in rainfall reduce the variability of yield and increase in temperature increases the yield variability. The results imply that the rainfall is risk-decreasing and temperature is a risk-increasing inputs in production of pearl millets. Thus, it can be concluded that the results of the study remain consistent in the region with low precipitation and high temperature. The trend has a positive impact on both mean yield and variance. The error terms of the model are illustrated in Graph 4.1.

Table 4.3: Impact of climate on mean and variance of Pearl Millet in Rajasthan

Mean	**Pearl Millet (Bajra)**			
Variable	**Linear Coeff.**	**Standard Error**	**Quadratic Coeff.**	**Standard Error**
R	-.0005733**	.0001841	-.0418115***	.0064511
T	.0016238	.0018722	-.0153336***	.0284264
R^2	-	-	.0000418***	5.53e-06
T^2	-	-	.0039358***	.0005988
R*T	-	-	.0003088***	.0000421
Trend	.0290009***	.0029427	.0381445***	.0040209
Constant	6.831015	.1078942	18.8126***	1.997304
Variance				
R	-.482548	.7393119	-.0003922	.000628
T	.6097855	7.417653	.0162421	.1516204
Trend	24.66381**	11.96865	24.80915 **	11.85319
constant	945.5465**	430.9541	802.4049***	228.3937
R^2	0.2219	-	0.3071	-
Log Likelihood	-76.22711	-	-76.246538	-
AIC	437.106	-	343.3324	-



Graph 4.1: Residual Versus Predicted Plots (Pearl Millet)

In mean function the coefficient of rainfall is statistically significant in both functional form and has a positive impact on mean maize yield (Table 4.4). The sign of coefficients for temperature indicates that with the rise in temperature the mean yield decreases, however it is not statistically significant in linear function but is significant in quadratic functional form. In quadratic mean yield function, the interaction term between rainfall and temperature is positive and is statistically significant at 1% level. The crop variance coefficients indicate that the rainfall is a risk-decreasing input and temperature is a risk-increasing input.

The coefficient of trend variable in case of variance, is positive but not statistically significant in both functional forms, indicating that technological progress does not bring a larger variability. However, the trend coefficient in case of mean crop yield is positive and statistically significant in linear production function but not in quadratic function indicating that the technological progress does not contribute much in mean maize yield.

Table 4.4: Impact of climate on mean and variance of Maize in Rajasthan

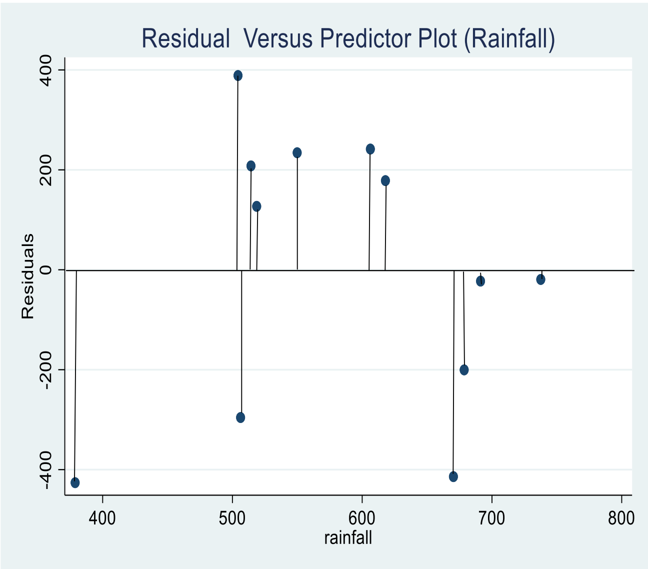
Mean	**Maize**			
Variable	**Linear Coeff.**	**Standard Error**	**Quadratic Coeff.**	**Standard Error**
R	.0001855*	.0000738	.0771137*	.0166939
T	-.0001782	.0013029	-.0771137***	.0166939
R^2	-	-	-8.14e-06***	7.89e-07
T^2	-	-	-.0007852***	.0002469
R*T	-	-	.000224***	.0000151
Trend	.0127749***	.0021078	.0008769	.0023124

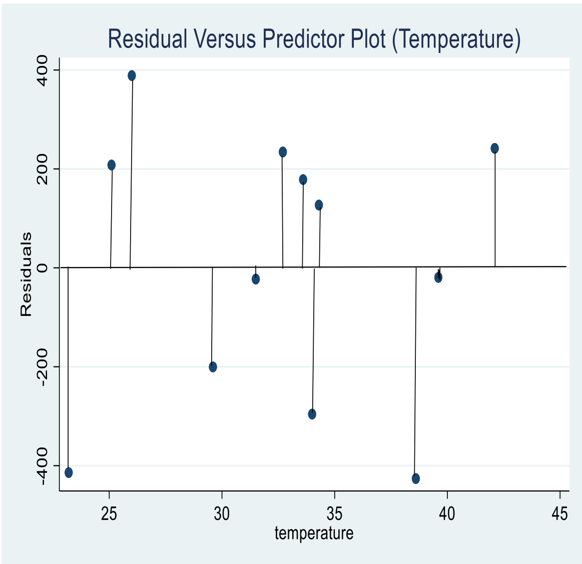
constant	7.179788***	.0630841	8.227828***	.4746374
Variance				
R	.2880376	.771125	.0001163	.0006764
T	-.418767	13.57379	-.0117087	.2091482
Trend	20.15828	22.11197	20.37985	22.20854
constant	1296.522**	658.0201	1421.198 ***	365.8323
R^2	0.0617	-	0.6837	-
Log Likelihood	-83.944291	-	-83.998451	-
AIC	684.9996	-	242.2099	-

*Notes: ***, **, and * indicate that the parameter is significant at the 1%, 5%, and 10% levels, respectively.*

***** the smaller value of R^2 for the linear model indicates that the independent variable (rainfall& temperature) is correlated with dependent variable (yield) but they do not explain the variability in crop yield.*

Graph 4.2 illustrates the residual versus predicted values of the climate parameters





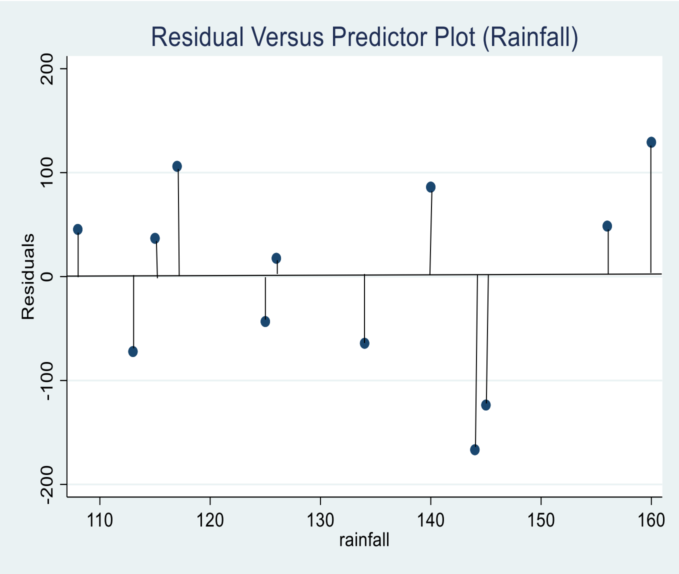
Graph 4.2: Residual Versus Predicted Plots (Maize)

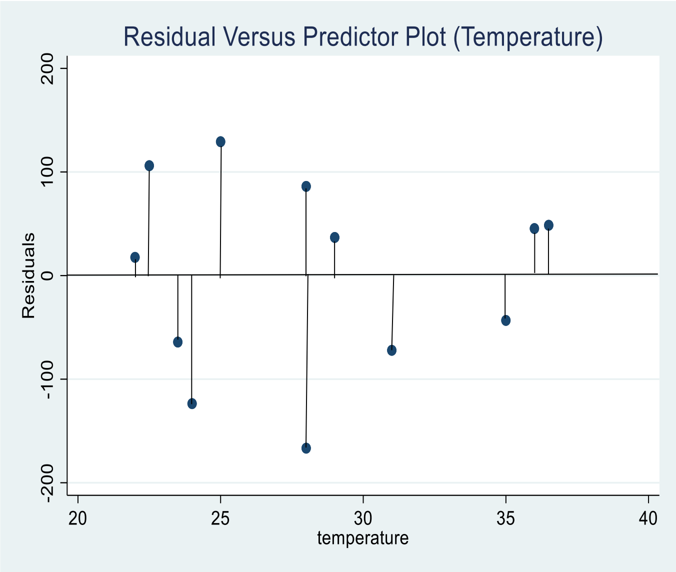
The estimated equation for mustard (Table 4.5) shows that both rainfall and temperature have a negative impact on mean and the variance of crop yield. In both functional forms the coefficients are statistically significant. Relatively low rainfall and temperature supports the mustard production. In quadratic mean yield function the interaction term is positive and statistically significant. The negative coefficients of rainfall and temperature in variance function indicates that in mustard production both the parameters are risk-decreasing inputs.

The coefficient of trend variable in case of variance, is positive and statistically significant at 5% level of significance in both functional forms, indicating that technological progress brings a larger variability. However, the trend coefficient in case of mean crop yield is positive and statistically significant in linear production function but not in quadratic function indicating that the technological progress does not contribute much in mean mustard yield.

Table 4.5: Impact of climate on mean and variance of Mustard in Rajasthan

Mean	**Mustard**			
Variable	**Linear Coeff.**	**Standard Error**	**Quadratic Coeff.**	**Standard Error**
R	-.0023424***	.0005413	-.0502784 ***	.0126676
T	-.0029007*	.001756	-.2453459***	.0681931
R^2	-	-	.0001341**	.0000457
T^2	-	-	.0032119**	.0010336
R*T	-	-	.0003535 **	.0001194
Trend	.0191796 ***	.0026979	-.0029041	.0074345
constant	7.395786 ***	.1062008	14.3834***	1.21113
Variance				
R	-2.871518*	1.688921	-.0099232	.006389
T	-4.303855	5.509146	-.0609408	.0929767
Trend	23.81016**	8.364046	24.51785**	8.366781
constant	1598.99 ***	330.9625	1319.476***	181.0643
R^2	0.3951	-	0.5135	-
Log Likelihood	-70.931013	-	-71.134751	-
AIC	192.6921	-	162.539	-





Graph 4.3: Residual Versus Predicted Plots (Mustard)

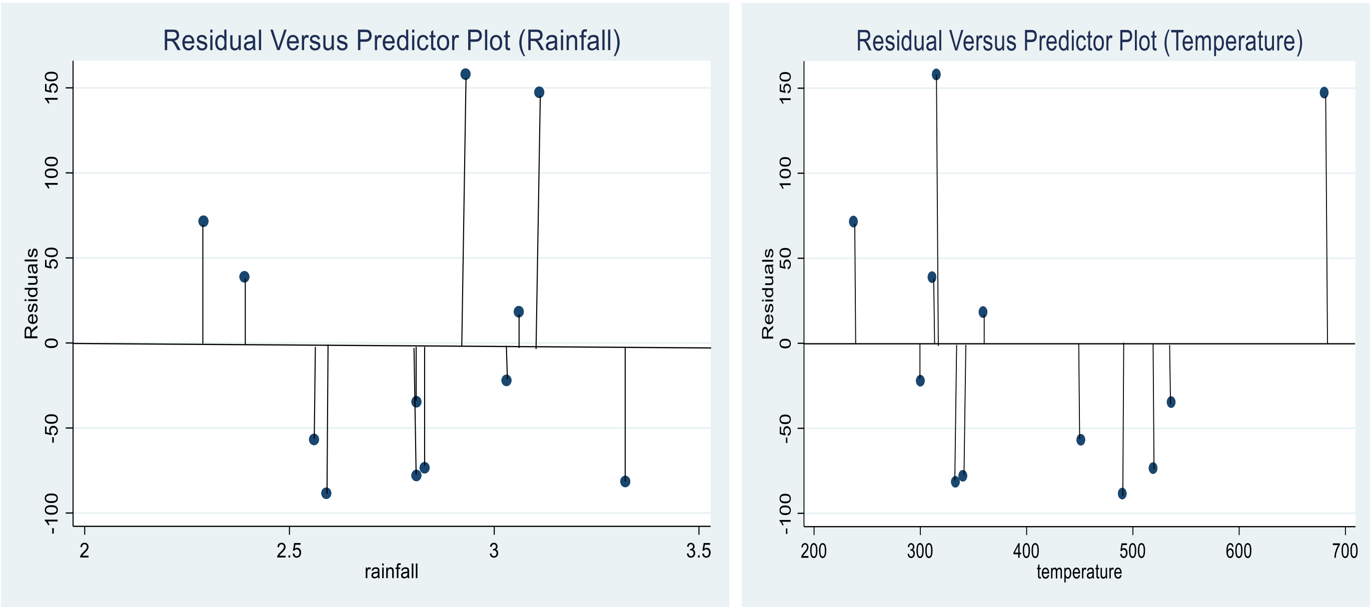
The sign and significance of the rainfall and temperature for wheat differ between the two production functional forms (Table 4.6). The temperature has a negative impact on the mean wheat yields in both the linear and quadratic models, but the rainfall has a negative effect in the linear model and positive impact in the quadratic model.

In the linear model, all the variables are statistically significant. The effect of rainfall on wheat yield variability is negative and statistically significant, while the effect of temperature is positive, but not statistically significant. The trend term in both mean yields is positive and statistically significant in both linear and quadratic function.

Table 4.6: Impact of climate on mean and variance of Wheat in Rajasthan

Mean	**Wheat**			
Variable	**Linear Coeff.**	**Standard Error**	**Quadratic Coeff.**	**Standard Error**
R	-.1126365***	.022331	.3966366**	.4309194
T	-.0001424**	.000048	-.0024813**	.0008531
R^2	-	-	-.1315394*	.076783
T^2	-	-	2.67e-07	1.29e-06
R*T	-	-	.0007188	.0006516
Trend	.0184841 ***	.0020837	.015847***	.0026656
constant	8.275652***	.0589697	7.98684***	.5886723

Variance				
R	-348.3748**	104.1085	-60.60112**	19.86884
T	-.415918**	.2198014	-.0003702	.0002599
Trend	56.2995***	9.632431	54.25793***	10.32778
constant	3830.855***	274.8665	3246.72***	137.6124
R^2	0.3502	-	0.4345	-
Log Likelihood	-70.185041	-	-78.189917	-
AIC	155.4918	-	142.3601	-



Graph 4.4: Residual Versus Predicted Plots (Wheat)

Table 4.7 represents the test statistic of the climate parameters in pooled, random and fixed effect models respectively.

Table 4.7: Test statistics of Pooled, Fixed and Random Model

Parameters	**Pooled OLS Estimation**		**Fixed effect**		**Random Effect**	
	Linear coefficient	Standard error	Linear coefficient	Standard error	Linear coefficient	Standard error
Rainfall	-.1755137	.6255553	.0508999	.3551254	.0484709	.3465892
Temperature	-24.1144	20.34638	-.8766728	5.510678	-.9229622	5.395994
Constant	2431.582	619.9538	1685.078	216.6509	1687.402	782.3913

Panel data analysis is carried out to determine best fit model. Table 4.7 presents the results of different model. Hausman test statistic is employed to choose among Fixed-Effect Model and Random-Effect Model to evaluate whether the unobserved variable is correlated or not. The test results (Table 4.8) indicate that p value is greater than 0.05 thus, we fail to reject null hypothesis. Hence, for a defined dataset, Random Effect Model is consistent and appropriate. Since unobserved values are uncorrelated with error terms there is a need to determine how appropriate and consistent the random effect model for estimation of model parameters. Since values are uncorrelated than OLS model can be preferred (Adewole & Struthers, 2018).

Table 4.8: Hausman Test Results

	Coefficients			
	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Rainfall	.0509008	.0484718	.002429	.077395
Temperature	-.8766729	-.9229623	.0462894	1.118399

b = consistent under Ho and Ha;

B = inconsistent under Ha, efficient under Ho;

Test: Ho: difference in coefficients not systematic

$chi^2(2)=(b-B)^{¢}[(V_b-V_B)^{(-1)}](b-B)$

$= 0.00$

$Prob>chi^2 = 0.9987$ (> 0.05)

For this, estimation of selection of OLS over Random effect model, Breusch and Pagan Lagrangian multiplier test is carried out. The null hypothesis of test is that the variance across the model variables is equal to zero and if so OLS is more appropriate model than Random Effect Model. The results of the is shown in Table 4.9. Since the p-value is less than 0.05 we reject the null hypothesis and thus, conclude that random effect is the right estimation for a model.

Table 4.9: Estimated results for Breusch and Pagan Lagrangian multiplier

Variables	Var	sd = sqrt(Var)
yield	743909.9	862.5021
e	43185.42	207.811
u	2365612	1538.055

Test: Var(u) = 0

chibar2(01) = 221.53

Prob > chibar2 = 0.0000

Table 4.10 summarizes the elasticities of total rainfall and temperature for two production functional forms. The elasticities are estimated at the mean values of the independent variables. The elasticities of rainfall vary from -2.8 to 13.9 in the mean crop yield function and -3.6 to 10.80 in the variance functions. Thus, the response of all the four crops is inelastic in linear function and elastic for quadratic function except for wheat. The calculated elasticity of rainfall in the mean yield functions is higher for pearl millet and wheat than those of mustard and maize.

The elasticity of temperature ranges from -0.85 to 2.85 in the mean crop yield function and -0.09 to 2.10 in the variance function. The estimated elasticities of temperature for both mean yield and variance function is inelastic for linear production function. In quadratic production function, the variance of wheat and maize, in both mean yield and variance is inelastic however that of pearl millet and mustard is elastic. Elasticities estimated will tell how much change in the yield is affected due to change in climatic parameters.

Table 4.10: Elasticities of Rainfall and Temperature

Climate Variables	**Crops**	**Linear**	**Quadratic**
Mean Yield			
Rainfall	Bajra	-.3286132	13.86577
	Maize	.1078183	-2.830775
	Mustard	-.3090045	2.333806
	Wheat	-.3166025	-.8800641
Temperature	Bajra	.0427743	2.85876
	Maize	-.0057964	-.8554286

	Mustard	-.082307	1.918074
	Wheat	-.0577955	.2917308
Variance			
Rainfall	Bajra	-.3271972	10.80461
	Maize	.1058617	-3.633025
	Mustard	-.3023555	2.21447
	Wheat	-.3211885	-.8581512
Temperature	Bajra	.0190017	1.283771
	Maize	-.0086132	-.0358325
	Mustard	-.0974766	2.107798
	Wheat	-.0553762	.2827015

4.5 Conclusion

The greenhouse gases, induced change in climatic conditions, predict the increase in temperature and rainfall levels which will influence the mean, variance and covariance of crop yields. Factors other than climate too influence the crop yield variability. (Hazell, 1984b) argues that the use of high-yielding variety of seed, common or uniform cultivation practices and cultivation of same variety of crop make the crop more sensitive towards climatic variations. This give rise to a question how sensitive is the inter-annual crop yield to a climate change? The answer will be evaluated by estimating the current statistical results.

For producing optimum yield, each crop has its own agro-climatic needs, thus, incorporating the impact of climatic changes on mean crop yield and variability will support the decision makers to opt an appropriate crop combination.

Thus, Just and Pope stochastic production function is used to determine the mean crop yield and variance. The functions $f(x_{it})$ and $h(x_{it}, \alpha)$ could be linear or non-linear. The reason behind specifying the linearity and non-linearity nature of function explains that the effect of input on output is not prior to the effects of input on the variability of output. equation (4.1) represents the impact of input on mean crop yield and equation (4.2) represents the effect of inputs on crop variance. Thus, to sum up it can be said, that E(y) = f(x) and V(y) = h(x) are two independent effects. Since no constrains is imposed by Just-Pope function on risk input effect thus, the function deals with both increasing and decreasing risk effects of inputs on output.

The sign of α determines the increasing or decreasing crop yield variability due to fluctuating climate variables. An input is said to be risk increasing if α is positive otherwise vice-versa.

The results of the function indicate that the impact of temperature and rainfall vary across crops. The trend has a positive impact on both the mean yield and variance of pearl millet, maize, wheat and mustard. The mean yield of crop considered for analysis will be supported by the increased temperature rainfall and low precipitation. The climate change has a significant impact on crop variability. Change in crop variance affects the crop allocation due to differential impact of climate on mean crop yield, the crop combination and allocation of land under each crop is likely to change. Farmers will prefer to cultivate the crop with more mean yield and less variability, in response to climate change. Production of wheat, mustard and pearl millet will likely to increase and production of maize is likely to decrease. The reason for this is that the farmers to reduce the risk, will prefer the crop with low variability. Hence, the crop with more mean yield and less variability is preferred by growers.