

Impact of Climate Change on Rice and Wheat Yield in Punjab State of India: A District-Level Analysis

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2 **District-Level Analysis**

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26 **Abstract**

27 The present study aims to examine the impact of climate change on wheat and rice yield of the Punjab state of
28 India. Using district-level panel data from 1981 to 2017, the study employs fully modified ordinary least squares
29 (FMOLS), dynamic ordinary least squares (DOLS), and pooled mean group (PMG) approaches. The Pedroni
30 cointegration has established a long-run relationship of climate variables with rice and wheat crops. The results
31 of FMOLS and DOLS show that minimum temperature has a positive effect on both wheat and rice, while
32 maximum temperature is found to be negatively contributing to both the crops. Rainfall has a significant adverse
33 effect on wheat yield. Seasonal rainfall has been detrimental to wheat and rice yield in the study period, indicating
34 that excess rainfall proved counterproductive. Pooled mean group (PMG) model confirms the robustness of the
35 results obtained by FMOLS and DOLS techniques. Moreover, Dumitrescu-Hurlin causality test has revealed a
36 unidirectional causality running from minimum temperature, rainfall & maximum temperature to rice and wheat
37 yield. The findings of the study suggest that the government should invest in developing stress-tolerant varieties
38 of wheat and rice, managing crop residuals to curb further environmental effect and sustain natural resources for
39 ensuring food security.

40 *Keywords:* Punjab; Rice; Wheat; FMOLS; DOLS
41

Impact of Climate Change on Rice and Wheat Yield in Punjab State of India: A District-Level Analysis

Abstract

The present study aims to examine the impact of climate change on wheat and rice yield of the Punjab state of India. Using district-level panel data from 1981 to 2017, the study employs fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), and pooled mean group (PMG) approaches. The Pedroni cointegration has established a long-run relationship of climate variables with rice and wheat crops. The results of FMOLS and DOLS show that minimum temperature has a positive effect on both wheat and rice, while maximum temperature is found to be negatively contributing to both the crops. Rainfall has a significant adverse effect on wheat yield. Seasonal rainfall has been detrimental to wheat and rice yield in the study period, indicating that excess rainfall proved counterproductive. Pooled mean group (PMG) model confirms the robustness of the results obtained by FMOLS and DOLS techniques. Moreover, Dumitrescu-Hurlin causality test has revealed a unidirectional causality running from minimum temperature, rainfall & maximum temperature to rice and wheat yield. The findings of the study suggest that the government should invest in developing stress-tolerant varieties of wheat and rice, managing crop residuals to curb further environmental effect and sustain natural resources for ensuring food security.

Keywords: Punjab; Rice; Wheat; FMOLS; DOLS

Introduction

Agriculture plays a predominant role in developing an economy like India, where 50 per cent of the population depends on agriculture as a source of livelihood (Ministry of Agriculture, 2020). Besides the importance of food security and employment, agriculture also boosts the growth of other interlinked sectors, reduces rural poverty, and increases exports of agricultural commodities and foreign exchange (Tripathi et al., 2009; Vyas, 2003). Despite such favourable effects, the agriculture sector has grown on an average of 3.64 per cent after 1980 till 2019 (World Bank, 2020). During the pre-independence, it grew at 1 per cent, while it has grown at 2 per cent per annum in the post-independence era (Tripathi et al., 2009). Infrastructure, technological, and environmental concerns, as well as a lack of political commitment and policy implementation, could all be contributing factors to this stagnation (Kakarlapudi, 2012). On the other side, one of the biggest concerns today worldwide is climate change, which has threatened global stability. According to the ‘Intergovernmental Panel on Climate Change’, “a change in the state of the climate that can be identified (e.g., using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. It refers to any change in climate over time, whether due to natural variability or as a result of human activity” (IPCC, 2007).

Over the last centuries, human activities like deforestation for agricultural and industrial use, excess use of unrefined petrochemicals, and increased use of air conditioners have resulted in the rapid release of greenhouse gases (GHGs) (Morton 2007). It has played a significant role in the changing composition of the atmosphere, leading to global warming and change in the climate (Lobell et al., 2008). Thus, the climate change in the 1970s has attributed to warm in climate systems, disturbances in precipitation received, and frequent occurrence in otherwise rare extreme weather events, melting of ice in the arctic circle, an increase in oceanic temperature along

79 with sea levels and weather extremes (Brown and Funk, 2008; Kotschi 2007). Extreme weather events (flooding
80 & droughts) often lead to the obliteration of crops and food shortage (IPCC, 2018). As a result, both developed
81 and developing countries are affected by climate change. India is known to be one of the developing nations that
82 are most vulnerable to climate change owing to its immense reliance on agriculture for jobs. The dependency on
83 climate variables like temperature and rainfall makes agriculture production very sensitive to changes in climate.
84 In India, more than half the agricultural land and about 70–80 per cent of the total land is irrigated through
85 groundwater (Falkenmark and Molden, 2008). Thus, rainfall received as predicted is considered a boon to the
86 nation and extreme events a natural hazard. Approximately 80 per cent of the annual rainfall in India takes place
87 between June and September during the South West Monsoon. A good amount of precipitation is very
88 determinantal in maintaining sufficient groundwater levels. The changes in climatic condition result in
89 variabilities in precipitation which in turn changes the groundwater levels. Since the agriculture sector is the most
90 affected sector of the economy by climate, it is vital to study the relationship and the impacts of future climate
91 change that might affect the existing pattern.

92 When Indian agriculture is considered, Punjab is found to be among the front-runner states in terms of total
93 production and the producer of major food grains (wheat and rice). So, studying the regional conditions of the
94 climate of Punjab is very crucial. Punjab falls under India's most fertile land regions; the climate is semi-arid
95 tropical, mostly winter (November–March) and summer seasons (April–June). The precipitation usually begins
96 from late June to early September. The achievement of the green revolution in Punjab leads to the state being
97 turned into a food basket by the government to contribute highly to national food security. But over the years, the
98 climate of the state has gone under some very noticeable climate changes. Rainfall has shown increasing trend
99 and high variation in spatial-temporal pattern, increasing the chances of drought and flood in the economy. Along
100 with rainfall, minimum temperature has also been observed to increase with no definitive increasing or decreasing
101 change in maximum temperature. But the increasing humidity and cloudy weather have negatively impacted the
102 crops, especially the rice crop in the region (Kaur et al., 2013). Whereas, on the one hand, a narrow study
103 conducted only on one district has shown no such adverse effect of change in temperature on wheat productivity
104 (Sidhu & Kamal, 2013). While, on the other hand, the broader picture has shown opposite results, where rising
105 temperature and falling rainfall led to a significant adverse effect on the production efficiency of wheat and rice
106 crop in Punjab from 1986–2015 (Kumar and Sidana, 2019). In light of this, this paper aims to look into the effects
107 of climate change on rice and wheat yields in Punjab from 1981 to 2017. The fully modified ordinary least square
108 (FMOLS), dynamic ordinary least square (DOLS), and pooled mean group (PMG) econometric models are used
109 in this paper. Dumitrescu-Hurlin (2012) panel granger causality is also used for granger causality among variables.
110 The study contributed to the existing knowledge in the following ways. First, this will be a first-panel study in
111 Punjab, which has used the panel of 12 districts of Punjab. Second, most of the cited studies in the literature use
112 the average annual temperature as a proxy for climate change. But we have considered only crop season average
113 temperature, which will contribute to the existing literature of Punjab. Third, we use robust econometrics methods,
114 i.e., FMOLS, DOLS and PMG, in which we found similar results across models. Earlier studies use only a single
115 model; they have not verified their finding with other models. The next section deals with the “Review of
116 Literature” presenting the related studies. After that, the variables used in the study and the research methods have
117 been discussed in the “Data and Methods” section. Using the methods, the results obtained have been deliberated
118 in the “Results and Discussion” section followed by the “Conclusion and Policy Implications” of the study.

119 **Review of Literature**

120 This section deals with a summary of the literature related to climate change and agricultural production. We have
121 included those studies which directly or indirectly investigated the effects of climate change on wheat, rice, and
122 cereal crops at regional, single country, and multiple countries levels. Table 1 provides the important results of
123 the literature review.

124 Insert [Table 1]

125 All the above-reviewed studies have shown that climate change is affecting agriculture production either
126 positively or negatively. Studies of Olayide et al. (2016), Chandio et al. (2020b), Loum & Fogarassy (2015),
127 Kaimakamis et al. (2013) are based on a single country. Asian country-based studies (Praveen & Sharma, 2019;
128 Baig et al., 2020; Janjua et al., 2014; Ahsan et al., 2020) and Punjab region-specific studies (Grover & Upadhyay,
129 2014; Hundal & Kaur, 2007; Kumar & Sidana, 2019; Mahmood et al., 2012) have shown that rainfall and
130 temperature are affecting rice, wheat and other crops positively and negatively depending upon when the extreme
131 or scarce rainfall is received, variation in maximum and minimum temperature. Kumar et al. (2021), Kumar &
132 Sidana (2019); Appiah et al. (2018); Zaied & Zouabi (2015) have looked into all of the concerns, including serial
133 correlation, panel group-wise heteroscedasticity, and cross-sectional dependence. But there is a notable paucity
134 of empirical research focusing specifically on analysing the impact of changing climate pattern on most cultivated
135 crops in Punjab, i.e., wheat and rice. After 1980, due to the seasonal variation in climatic factors like maximum
136 and minimum temperature, rainfall on crops. Most of the studies have only been limited to either a few districts
137 or single districts of Punjab taking the average temperature at the place of seasonal maximum or minimum
138 temperature. At last, a large period of time is considered while tackling all panel data problems for authentic
139 regression analysis. With this motivation, the study aims to investigate the impact of climate change on wheat and
140 rice yields in Punjab during 1981–2017. To overcome the methodological issues, FMOLS, DOLS and PMG
141 models are employed in this study.

142 **Data and Methods**

143 *Data and Model Specification*

144 Given the importance of wheat and rice as major crops of Punjab in providing food security, we take the data for
145 wheat and rice separately for the analysis. Our panel data covers 12 major wheat and rice producing districts of
146 Punjab during the period of 1981–2017. Table 2 describes the variables, their symbols, units and their sources
147 through which data have been collected. From the literature, maximum and minimum temperature along with
148 rainfall have been identified as the key determinants of rice and wheat yield. The trends of these key dependent
149 and independent variables have been shown in Figure 1–8. Apart from that, the production of these crops also
150 depends on the cultivated area, which relates to how much area these crops are sown in. Therefore, based on these
151 variables, the following model specifications are framed:

$$152 \quad RY_{it} = f(RMxT_{it}, RMiT_{it}, RP_{it}, RA_{it}) \quad (1)$$

$$153 \quad \ln RY_{it} = \beta_0 + \beta_1 \ln RMxT_{it} + \beta_2 \ln RMiT_{it} + \beta_3 \ln RP_{it} + \beta_4 \ln RA_{it} + u_{it} \quad (2)$$

154 Where RY : rice yield, $RMxT$: the average maximum temperature during the rice harvesting season, $RMiT$: the
 155 average minimum temperature during the rice harvesting season, RP : the average precipitation (rainfall) during
 156 the rice harvesting season, RA : area cultivated for rice, β : coefficients, u : error term, subscript i : the cross sections
 157 which are 12 districts of Punjab selected for the study and subscript t : time which is 1981–2017 for the study.

$$158 \quad WY_{it} = f(WMxT_{it}, WMiT_{it}, WP_{it}, WA_{it}) \quad (3)$$

$$159 \quad \ln WY_{it} = \beta_0 + \beta_1 \ln WMxT_{it} + \beta_2 \ln WMiT_{it} + \beta_3 \ln WP_{it} + \beta_4 WRA_{it} + u_{it} \quad (4)$$

160 Where WY : wheat yield, $WMxT$: the average maximum temperature during the wheat harvesting season, $WMiT$:
 161 the average minimum temperature during the wheat harvesting season, WP : the average precipitation (rainfall)
 162 during the wheat harvesting season, WA : area cultivated for wheat, β : coefficients, u : error term, subscript i : the
 163 cross sections which are 12 districts of Punjab selected for the study and subscript t : time which is 1981–2017 for
 164 the study. From the above-framed model specifications, we move on to the methodology that has been used for
 165 the estimation of the models specified.

166 Insert [Table 2]

167 Insert [Figure 1]

168 Insert [Figure 2]

169 Insert [Figure 3]

170 Insert [Figure 4]

171 Insert [Figure 5]

172 Insert [Figure 6]

173 Insert [Figure 7]

174 Insert [Figure 8]

175 *Panel Unit-Root Test and Cointegration Test*

176 Before estimating the impact of climate change on the main crops of Punjab, it is imperative to check the
 177 stationarity of the variables so as to avoid any biased results. For estimation, the first-generation unit-root test
 178 given by Levin, Lin and Chu (LLC), and Im, Pesaran and Shin (IPS) were used, which assume the statistical
 179 independence of each cross-sectional data series in the study (Barbieri, 2008).

180 The equation for LLC is following:

$$181 \quad \Delta y_{i,t} = \phi_i y_{i,t-1} + \sum_{N=1}^{p_i} \psi_{i,N} \Delta y_{i,t-N} + \alpha_{m,i} \beta_{m,t} + \epsilon_{i,t} \quad (5)$$

182 Where y refers to the variable being tested for unit root, Δ denotes the differentiated form of the variable, ϕ_i is less
 183 than zero for the non-existence of unit root against the null hypothesis of $\phi_i \geq 0$.

184 The equation for IPS is following:

$$185 \quad y_{i,t} = (1 - p_i) \alpha_i + p_i y_{i,t-1} + \epsilon_{it} \quad (6)$$

186 Where the null hypothesis is that $p = 1$.

187 The null hypothesis under the above methods has stated the existence of unit root (stationarity), while the
 188 alternative has shown non-stationarity in the panel data (Akpolat, 2014). If non-stationarity exists, then
 189 cointegration is estimated to get a consistent and efficient estimation. For cointegration, the Pedroni cointegration
 190 method is applied, which has developed seven different tests to determine the existence of panel cointegration.

191 The equation for Pedroni Cointegration is:

$$192 Y_{i,t} = \alpha_i + \delta_i t + \beta_{1i} X_{1i,t} + \beta_{2i} X_{2i,t} + \dots + \beta_{Ki} X_{Ki,t} + \mu_{it} \quad (7)$$

193 From the above-estimated equation, the residuals $\hat{\mu}_{i,t}$ are tested through the following equation:

$$194 \Delta \hat{\mu}_{i,t} = p_i \Delta \hat{\mu}_{i,t-1} + \sum_{k=1}^n \phi_{i,k} \Delta \hat{\mu}_{i,t-k} + v_{i,t} \quad (8)$$

195 There is a presence of cointegration when p_i is significantly different from zero.

196 *FMOLS and DOLS Model*

197 Panel cointegration methods have evolved the long-run economic relationship between the variables often
 198 projected in economic theory. Thus, the long-run coefficients test whether the variables satisfy the theoretical
 199 restrictions or not (Mohapatra & Gopaldaswamy, 2016). After determining cointegration or long-run relationship,
 200 the direction and magnitude of the long-run relationship among variable can be quantified by applying the fully
 201 modified ordinary least square method (FMOLS) & dynamic ordinary least square (DOLS) methods.

202 The equation for FMOLS and DOLS are:

$$203 \hat{\beta}_{FMOLS}^* = N^{-1} \sum_{n=1}^N \hat{\beta}_{FMOLS,n}^* \quad (9)$$

204 Here $\hat{\beta}_{FMOLS}^*$ represents FMOLS regression parameter applied in n countries.

205

$$206 \hat{\beta}_{DOLS}^* = N^{-1} \sum_{n=1}^N \hat{\beta}_{DOLS,n}^* \quad (10)$$

207 Here $\hat{\beta}_{DOLS}^*$ represents DOLS regression parameter applied to cross-sections n.

208 The FMOLS is a non-parametric technique, and the DOLS is a parametric procedure used to eliminate the
 209 problems of serial correlation and endogeneity (Akpolat, 2014; Othman & Masih, 2015). The applicability of
 210 these methods is subjected to the pre-conditions of unit root tests of all variables in the same order and the
 211 existence of cointegration among the independent variables (Othman & Masih, 2015). Further, FMOLS is
 212 sensitive to simultaneous bias but adjusts the unit-specific fixed effects, short-run dynamics and give efficient and
 213 consistent estimation (Mohapatra & Gopaldaswamy, 2016). At the same time, DOLS is used by taking cross-
 214 sectional leads of dependent variables and lagged values of explanatory variables to reduce endogeneity.

215 *Pooled Mean Group (PMG) Model*

216 After getting the coefficients with FMOLS & DOLS, Pooled Mean Group (PMG) method is used to estimate both
 217 the short and long-run coefficients as it examines the existing heterogeneity present in the dynamic panel data
 218 (Tatoglu, 2011; Rafindadi, 2017). It becomes important so that in the long run, the impact of climate change on

219 area & production of various crops is homogenous. In the short run, the different districts taken in the study might
 220 have shown heterogeneity in the area and production due to the availability of different requirements of water,
 221 fertility of the land, mechanisation etc. (Rafindadi, 2017). Further, PMG estimation supports the estimated
 222 coefficients of FMOLS & DOLS by eliminating the problem of endogeneity with the inclusion of sufficient lag
 223 of all variables (Asteriou et al., 2020).

224 *Dumitrescu-Hurlin Panel Causality Tests*

225 After FMOLS, DOLS and PMG, Dumitrescu-Hurlin (2012) panel causality test has been used to identify the
 226 causality amongst the variables used in the study. Dumitrescu-Hurlin (2012) has given an advanced version of the
 227 Granger causality test where a homogenous non-causality hypothesis was tested, which implies there is no such
 228 causal link between two variables in all the cross-sections units (Ndoricimpa, 2014), whereas the alternative
 229 hypothesis shows that a causal relationship exists among the variables (Kumar et al., 2021). The test can be
 230 represented in the following equation:

231
$$y_{it} = \alpha_i + \sum_{i=1}^k \gamma_i^{(k)} y_{i,t-k} + \sum_{i=1}^k \beta_i^{(k)} x_{i,t-k} + \varepsilon_{it} \quad (11)$$

232 Where $\beta_i = (\beta_i^{(1)}, \beta_i^{(2)}, \dots, \beta_i^{(k)})$ α_i represents individual effects, which are supposed to be fixed in the time
 233 dimension, k denotes the lag orders and is assumed the same for all cross-sectional units, $\gamma_i^{(k)}$ and $\beta_i^{(k)}$,
 234 respectively, represent lag and slope parameters that differ across groups.

236 **Results and Discussion**

237 Table 3 and 4 presents the descriptive statistics for all the variables corresponding to wheat and rice from 1980–
 238 2017. As shown in the table, the highest variation is observed in rice yield and wheat yield in comparison to the
 239 other variables, i.e., 575.803 and 731.957, respectively. Further, all the variables under wheat and rice have shown
 240 more symmetrical distribution except the production of wheat and rice that have shown a movement slightly
 241 towards left tail and inclusion of some exceptional years high or less production. Besides the distribution of
 242 various variables, rice yield is showing a 28% association with minimum temperature, while wheat is observed to
 243 be 36% correlated with maximum temperature. The other variables have shown an association with the
 244 productivity of rice and wheat in the range of 4% to -15%.

245 Insert [Table 3]

246 Insert [Table 4]

247 Insert [Table 5]

249 In order to determine the long-run relationship among the variables, it is necessary to fulfil the pre-conditions of
 250 possessing unit root (non-stationarity) among all variables, either at level or at first difference. Table 5 has shown
 251 unit root tests by using Levin, Lin and Chu (LLC) & Im, Pesaran and Shin (IPS) Tests. The benefit of estimating
 252 unit root by IPS over LLC is that, where the latter assumes homogeneity (independence among cross-section
 253 panel), the former assumes heterogeneity (dependency among cross-section panel) across the panel (Libanio,
 254 2005). Thus, variables viz. RY, WY, RMxT, RMiT, WMiT, RP, WP, RA, are found to be stationary at the level
 255 and first difference among both the tests. While variables viz. WMxT and lnWA are stationary at the first

256 difference in both LLC & IPS. Thus, all variables are stationary, which states a long-run relationship among
257 variables, and the independent variable can be regressed on the dependent variable without spurious regression.

258 Insert [Table 6]

259 Insert [Table 7]

260 Table 6 and 7 show cointegration estimation of wheat and rice crop with various climate variables in the long run.
261 For cointegration, a robust & heterogenous Pedroni test is used, which gives seven different statistics. The
262 estimation has shown that cointegration within the panel and between panel statistics is statistically significant at
263 a one per cent level in both rice and wheat. However, some exceptional results have been observed under panel
264 v-statistics and group rho-statistics for rice and wheat where data failed to show any cointegration, which could
265 be due to different time period (T) and places that have caused different relationship among the variables (Chien
266 et al., 2014). Otherwise, overall estimation has established the long-run relationship among various climate
267 variables and the production of wheat and rice according to Pedroni's seven different tests (Ageliki et al., 2016;
268 Neal, 2014)

269 *Impact on Rice Yield*

270 As the study has included different districts and a long time period, it increases the chance of autocorrelation &
271 heteroscedasticity. So, after determining cointegration & avoiding spurious regression, DOLS and FMOLS
272 cointegrating equation estimations have been used to estimate or quantify the long-run relationship among the
273 variables (Othman, 2015). Panel FMOLS is a non-parametric test to control the problem of endogeneity and
274 correlation that arise due to cross-section variables (Ramirez, 2006; Akpolat, 2014). In comparison, panel DOLS
275 is a parametric test used to estimate long-run coefficients by preventing the trend in variables by specifications in
276 regressors (Mitic et al., 2017; Akpolat, 2014).

277 Insert [Table 8]

278 Table 8 has shown FMOLS & DOLS long-run estimations or the impact of various climatic variables described
279 in Table 1 on the productivity of rice. The empirical estimations of FMOLS have presented that the coefficient of
280 minimum temperature has shown a positive change in rice yield, which is statistically significant at 1% level.
281 Additionally, a 1° C increase in temperature has increased rice yield by 2.309%. The findings of the paper can be
282 supported by various national, regional and international empirical estimations. As the countries possessing
283 similar characteristics to India like Pakistan & Bangladesh have shown that an increase in the minimum
284 temperature in Pakistan has positively affected the rice yield due to the growth of crop at the replantation stage
285 during the vegetation phase, and in Bangladesh, its impact is neutral on different varieties of rice (Abbas & Mayo,
286 2021; Chowdhury & Khan, 2015). Whereas in China, the exact opposite results can be observed where the
287 minimum temperature has shown a negative impact on yield although insignificant, and it happens due to an
288 increase in respiration loss during night time (Zhang et al., 2010). While in Punjab, the study has shown a positive
289 non-significant effect of an increase in average temperature above normal (Hundal & Kaur, 2007).

290 The coefficient of maximum temperature is found to be negatively affected the rice yield, where a 1°C increase
291 in maximum temperature decreased rice yield by 2.606%. The findings of the same coefficient are supported by
292 various studies done on Punjab. Grover & Upadhyya (2014) and Saseendran et al. (2000) has observed a negative

293 impact of the increase in rice productivity due to a rise in the average temperature, enhanced due to an increase in
294 the level of warming. Similarly, a district-level study conducted by Kumar & Sidana (2019) has shown that
295 maximum and minimum temperature has negatively impacted rice yield, but the negative effect of maximum
296 temperature can be eliminated due to an assured irrigational facility in Punjab. The same conclusion has been
297 observed by Zhang et al. (2010) that the maximum temperature leads to the falling of rice yield due to short crop
298 duration.

299 The coefficient of rainfall is showing a negative impact on rice productivity at 10% level. It is contradicting to
300 various studies which have shown a positive effect of increased rainfall on agricultural productivity (Kumar et al.,
301 2021). Further, the negative impact can be observed due to an increase in rainfall during the ripening stage (Abbas
302 & Mayo, 2021). Due to heavy rainfall in the month of August in Meghalaya shows a significant and -0.46% impact
303 on rice (Dkhar et al., 2017) and an increase in rainfall from 5% to 15% in the month of September–October has
304 negatively impacted rice yield in Punjab (Mahmood et al., 2012).

305 Similarly, the coefficient of the land has a positive impact on rice productivity, where 1% increase in the land has
306 improved the productivity by 0.223%. A study conducted in China, the leading rice producer, has shown that an
307 increase in average land size/plots will increase the technical efficiency in the long run (Tan et al., 2010). Further,
308 a positive relationship can be seen between ownership of land and rice yield in India (Koirala, 2014) and land
309 inequality suppressing the farmers to use resources and affecting rice productivity adversely (Prasanna et al.,
310 2009). Additionally, the estimations of DOLS have analysed that 1% increase in minimum temperature brought a
311 positive and significant change of 3.474% in rice. Further, maximum temperature and rainfall are affecting rice
312 negatively by 3.87% and 0.034% but insignificantly. The reason for the negative impact might be due to a decrease
313 in the number of plants at the ripening stage, tillering or stem elongation stage (Abbas & Mayo, 2021) and heavy
314 rainfall in the maturity stage (Mahmood et al., 2012).

315 *Impact on Wheat Yield*

316 Table 9 has given the estimations of FMOLS and DOLS on wheat as similar estimations have been done on rice
317 yield. Estimating the effect of the dependent variable on the independent variable, the FMOLS estimator is used,
318 which has shown that the minimum temperature coefficient is increasing wheat yield by 2.520%, while an increase
319 in maximum temperature depresses wheat yield by 2.012% due to 1° C change. Various studies have shown that
320 the average increase in the temperature has deteriorated the wheat yield due to an increase in temperature at the
321 grain-filling stage (Asseng, 2011). A low temperature and high radiation will positively impact wheat grain
322 production (Amir, 1991), and wheat yield is adversely affected during the increase in temperature in the month of
323 February & March (Jha & Tripathi, 2011). Besides, in lieu of increasing temperature and the absence of a proper
324 irrigation facility, groundwater dependence leads to a sustainability crisis and depresses the wheat yield as well
325 (Sudmeyer et al., 2016). Further, it becomes very important to understand that how and why the wheat yield is
326 offsetting or improving under low or high temperature. Wiersma (2018) has written that daytime cooler
327 temperature is positively increasing the yield, but the increasing temperature during tillering decreases the
328 productivity of wheat by negatively affecting spikelets. Whereas Kleinjan (2021) has discussed that lower
329 temperature is generally having low resistance towards lower temperature when it has already grown and at
330 maturity stage, while high resistance towards lower temperature is at reproductive stage.

331

Insert [Table 9]

332 The coefficient of rainfall is negatively determining the wheat yield at 5%, which is empirically tested or discussed
333 under various studies and discussion, because of change in rainfall intensity which is significantly correlated with
334 the type of soil, i.e. sandy & lower mineral at an early stage (Tataw et al., 2016), untimely rainfall triggered the
335 quality. A decrease in rainfall in the vegetative stage and an increase in the reproductive stage reduce wheat
336 production (Yu, 2013). Lastly, the coefficient of land is detrimental to wheat yield as it can be observed that with
337 1% change in the land would negatively impact the wheat yield by 0.164%. Various reasons may lead to such
338 situations, and supporting the estimation of the current study as land degradation is offsetting more than climate
339 change (Raimondo et al., 2021). Further, a positive relationship can be seen between ownership of land and rice
340 yield in India (Koirala, 2014) and land inequality suppressing the farmers to use resources and affecting rice
341 productivity adversely (Prasanna et al., 2009).

342 Additionally, the estimations of DOLS have presented that 1% increase in minimum temperature brought a
343 positive and significant change of 2.745% in the productivity of wheat. Further, maximum temperature, area and
344 rainfall are affecting rice yield by 2.909%, 0.157% and 0.102% significantly at 5, 10 and 1% level, respectively.

345

Insert [Table 10]

346

Insert [Table 11]

347 Table 10 and 11 have shown the short and long-run dynamics of change in the variable in the study on the
348 productivity of rice and wheat. PMG is supporting the FMOLS, and it is preferred over DOLS due to its
349 assumption of homogeneity in the long run and maintaining the property of heterogeneity in the short run. It helps
350 us to show how an independent variable determines the dependent variable in the short and long run while tackling
351 the problem of endogeneity and variable specific effects (Samargandi et al., 2014). Thus, the results of the PMG
352 estimator have shown a similar impact in the long run as of FMOLS & DOLS except for the variation in the
353 minimum temperature that has brought an insignificant change in the rice yield. All other variables have similar
354 significant positive and negative impact on the productivity of rice. On the contrary, change in area in the short
355 run does not have any significant impact on rice productivity.

356 The short and long-run relationship of different variables in wheat productivity has shown similar results as in the
357 FMOLS and DOLS. Here, all variables, in the long run, have the same negative and positive effect on yield.
358 While, in the short run, change in production has a positive and significant impact on wheat productivity. The rest
359 of the variables, i.e. change in the area, minimum and maximum temperature, caused an insignificant effect on
360 the productivity of wheat. Meanwhile, comparing the impact of variation in the independent variables like
361 minimum temperature, maximum temperature, area and production have shown a more vibrant effect on the
362 productivity of rice and wheat than in the long run.

363

Insert [Table 12]

364

Insert [Table 13]

365 The Dumitrescu-Hurlin panel causality test is also used to investigate the causal relationship among variables.
366 The causality test verifies the findings by establishing a causal relationship between the majority of the variables

367 (Chishti et al., 2021). The results in Table 12 have shown a bi-directional causal relationship between rice and its
368 corresponding variables, i.e., area to yield & rainfall to minimum temperature. Similarly, rice yield to the
369 maximum temperature, rice yield to rainfall, maximum to minimum temperature, rice area to rainfall & rice area
370 to maximum temperature have shown unidirectional causality at 1%, 5 and 10% level of significance, respectively.
371 The results of Table 13 have shown a unidirectional causal relationship between wheat and various variables like
372 yield to minimum temperature, maximum temperature to wheat yield, rainfall to yield, wheat area to wheat yield,
373 maximum to minimum temperature, wheat rainfall to minimum temperature and maximum temperature at 1%
374 level.

375 **Conclusion and Policy Implications**

376 The study aims to examine the impact of climatic variables on the major crops, i.e., rice and wheat, in the Punjab
377 state of India during the time period 1981–2017. Pedroni cointegration technique has been used to identify the
378 long-run relationship between climate variables and rice and wheat yields. The long-run association between the
379 variables is tackled with FMOLS & DOLS techniques are employed for empirical estimation, while the PMG
380 model is used for robustness purpose. The estimated results have shown the long-run relationships between
381 climatic factors as of Minimum Temperature, Maximum Temperature, Rainfall & control variables, i.e. area under
382 rice and wheat crops in Punjab. Further, FMOLS & DOLS models have shown that minimum temperature and
383 harvested area contribute positively to the yield of rice. On the contrary, the maximum temperature and rainfall
384 have a deteriorating impact on rice productivity. In the case of the wheat crop, maximum temperature and rainfall
385 are detrimental to wheat productivity in the study area during the time under consideration. However, the
386 minimum temperature is the only variable that is observed to be enhancing the wheat yield. The results of the
387 PMG model supports the findings of FMOLS and DOLS, which ensures the robustness of the estimated models.
388 Dumitrescu-Hurlin causality test reveals a bidirectional causality between rice yield and harvested area of rice,
389 while a unidirectional causality runs from the harvested area of wheat to wheat yield.

390 As shown above, most of the climatic factors except minimum temperature and control variable have a negative
391 effect on rice and wheat. So, it is an alarming stage to address the issue of agricultural sustainability. Because if
392 rainfall is affecting the yield adversely, either in the case of wheat or rice, then the concern for the government
393 and policymakers is to follow adaptative and mitigation policies which will help farmers to sustain their income
394 without affecting the sustainability of natural resources. Rainwater harvesting, creating awareness among farmers,
395 broadening the view of extension department for various adaptative policies to combat the climate impact on
396 wheat and rice (Mahmood et al., 2012). Meanwhile, to prevent the damage or death of plants at maturity stage or
397 reproductive stage either by increase/decrease in minimum or maximum temperature on wheat and rice can be
398 controlled by using water-saving (stress-tolerant varieties of seeds & crop diversification), carbon management
399 (managing the legumes and crop residual), knowledge or smart movement like (extension program and emphasis
400 on research) can help to minimize the impact of climate change to some extent (Malhi et al., 2021). Therefore, the
401 Punjab government should take appropriate policy measures to maintain the consistency of the largest shareholder
402 in the food basket of the country after the green revolution and also to manage the water-led facility.

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List of Tables

Table 1. Summary of Relevant Studies on Climate Change and Agricultural Production

Author(s)	Time	Country (ies)	Econometric model (s)	Results
Olayide et al. (2016)	1970–2012	Nigeria	Descriptive analyses	Rainfall => + but insignificant on agriculture
Zaied & Zouabi (2015)	1980–2012	Tunisia	FMOLS, Panel Cointegration	Temperature => - on agriculture Rainfall => - on agriculture,
Dumrul & Kilicarlan (2017)	1961–2013	Turkey	ARDL	Rainfall => +ve on agriculture Temperature => -ve on agriculture
Vyankatrao (2017)	1991–2016	India	Crop Simulation model	Temperature => - on rice yield
Sarker et al. (2014)	1972–2009	Bangladesh	pope production function	Maximum temperature => + on rice yield
Zhang et al. (2010)	1980–2010	China	Regression Model	Temperature=> - on rice yield
Kaimakamis et al. (2013)	1977–2007	Greece	Multiple linear regression	Temperature => - but insignificant on agriculture Rainfall => - but insignificant on agriculture
Loum & Fogarassy (2015)	1960–2013	Gambia	Just and Pope modified Ricardian production functions	Rainfall, Temperature => - on cereals yield
Praveen & Sharma (2019a)	1967–2016	India	Multiple regression analysis	Temperature => - on maize and wheat Rainfall => + but insignificant on maize and wheat
Praveen & Sharma (2019b)	1967–2016	India	ARIMA	Temperature => - on wheat and rice production
Guntukula & Goyari (2019)	1956–2015	Telangana, India	FGLS	Minimum temperature => - on maize yield Maximum temperature, rainfall => + on maize but insignificant

Guntukula (2019)	1961–2017	India	Regression	Rainfall => - on food crops except pulses, + on non-food crops Maximum temperature => on food and non-food crops except rice Minimum temperature => - on non-food crops, + on food crops.
Chandio et al. (2020a)	1968–2014	Turkey	ARDL, Granger Causality	Temperature => - effect on cereal yield Rainfall: + on cereal yield
Attiaoui & Boufateh (2019)	1975–2014	Tunisia	ARDL, Granger Causality	Rainfall => - on cereal yield Temperature => + on cereal yield
Abbas & Mayo (2020)	1981–2017	Punjab, Pakistan	Cobb-Douglas production function	Maximum temperature => - on rice yield Minimum temperature => + on rice yield Rainfall => + on rice yield
Peng et al. (2004)	1979–2003	Philippines	Simulation method	Minimum temperature => - on rice yield
Baig et al. (2020)	1990–2017	India	ARDL	Maximum temperature => + on all crops except for wheat Minimum temperature=> + on cereal yield Temperature => + on wheat and cereal yield, - on rice yield Rainfall => - on cereals yield, +ve on wheat yield
Ahsan et al. (2020)	1971–2014	Pakistan	ARDL	CO ₂ emissions, cultivated area and => + on Cereals Production
Chandio et al. (2020b)	1982–2014	China	ARDL, Johansen Cointegration	Temperature, Rainfall => - on agriculture. Land => + on agriculture
Zhai et al. (2017)	1970–2014	China	ARDL	Rainfall => - on wheat yield Land Size => + on wheat yield Temperature => - but insignificant on wheat yield
Janjua et al. (2014)	1960–2009	Pakistan	ARDL	Temperature => + but insignificant on wheat yield Rainfall => + but insignificant on wheat yield

Grover & Upadhyay (2014)	1972–2010	(Ludhiana District) Punjab	Cobb-Douglas production function	Maximum temperature => - on paddy yield Minimum temperature, Rainfall => + on paddy yield
Hundal & Kaur (2007)	1970–199	Punjab	CERES models	Minimum and maximum temperature => - on paddy, wheat yield
Kumar & Sidana (2019)	1986–2015	Punjab	Fixed effect regression	Temperature => - on rice & wheat yield Rainfall => - on wheat yield
Mahmood et al. (2012)	1978–2007	Punjab	Cobb-Douglas production function	Rainfall => - on rice yield
Kumar et al. (2021)	1971–2016	Lower-Middle-Income Countries	FGLS, FMOLS, DOLS, and Driscoll-Kraay standard regression	Temperature => - cereals production Rainfall => + cereals production

Note: =>: unidirectional relationship, (+): positive effect and (-): negative effect, PMG: pool mean group, FGLS: feasible generalized least square, ARDL: autoregressive distributed lag, DOLS: Dynamic Ordinary Least Square and FMOLS: Fully Modified Ordinary Least Square, LLC: Levin-Lin-Chu Unit-root test, IPS- Im-Pesaran-Shin Unit-root test

1 **Table 2.** Variables Description

Variables	Symbol	Unit	Source
Rice Yield	RY	hg/ha	Food and Agriculture Organisation (FAO)
Wheat Yield	WY	hg/ha	FAO
Rice Season Average Maximum Temperature	RMxT	Degree Celsius	National Aeronautics and Space Administration (NASA) Climate Portal
Rice Season Average Minimum Temperature	RMiT	Degree Celsius	NASA Climate Portal
Wheat Season Average Maximum Temperature	WMxT	Degree Celsius	NASA Climate Portal
Wheat Season Average Minimum Temperature	WMiT	Degree Celsius	NASA Climate Portal
Rice Season Average Annual Rainfall	RP	mm	NASA Climate Portal
Wheat Season Average Annual Rainfall	WP	mm	NASA Climate Portal
Rice Cultivated Area	RA	ha	FAO
Wheat Cultivated Area	WA	ha	FAO

2

3 **Table 3.** Descriptive Statistics and Correlation Matrix for Rice Crop

	RY	RMxT	RMiT	RA	RP
Mean	3459.619	38.328	26.882	158.225	114.334
Median	3456.500	38.620	26.955	158.500	107.401
Maximum	4873.000	43.345	29.560	367.000	298.578
Minimum	1593.000	30.808	23.488	8.000	29.015
Std. Dev.	575.803	2.143	1.217	86.719	45.750
Skewness	-0.024	-0.456	-0.359	0.216	0.814
Kurtosis	2.961	3.158	2.650	2.053	3.929
Observations	444	444	444	444	444
	lnRY	lnRMxT	lnRMiT	lnRA	lnRP
lnRY	1.000	0.049	0.263	0.135	-0.033
lnRMxT	0.049	1.000	0.892	0.288	-0.892
lnRMiT	0.263	0.892	1.000	0.377	-0.749
lnRA	0.135	0.288	0.377	1.000	-0.126
lnRP	-0.033	-0.892	-0.749	-0.126	1.000

4

5 **Table 4.** Descriptive Statistics and Correlation Matrix for Wheat Crop

	WY	WMiT	WMxT	WA	WP
Mean	3963.601	10.729	25.360	228.624	19.000
Median	4059.500	10.784	25.413	226.000	15.457
Maximum	6651.000	12.538	27.928	422.000	93.444
Minimum	1998.000	8.898	20.828	23.000	2.198
Std. Dev.	731.957	0.710	1.421	100.394	13.674
Skewness	-0.288	-0.121	-0.458	0.169	1.643
Kurtosis	2.918	2.325	2.621	1.945	6.720
Observations	444	444	444	444	444

	lnWY	lnWMxT	lnWMiT	lnWA	lnWP
lnWY	1.000	0.360	0.280	0.111	-0.159
lnWMxT	0.360	1.000	0.373	0.365	-0.663
lnWMiT	0.280	0.373	1.000	-0.081	-0.191
lnWA	0.111	0.365	-0.081	1.000	-0.126
lnWP	-0.159	-0.663	-0.191	-0.126	1.000

6

7 **Table 5.** Unit Root Test Results

Variables	LLC		IPS	
	At Level	At first Difference	At Level	At first Difference
lnRY	-3.408***	-12.876***	-4.298***	-17.460***
lnRMxT	-7.486***	-15.268***	-5.994***	-18.866***
lnRMiT	-8.298***	-16.041***	-6.751***	-19.501***
lnRA	-4.333***	-10.884***	-2.341***	-9.608***
lnRP	-6.742***	-14.522***	-6.742***	-20.742***
lnWY	-2.243**	-9.233***	-4.373***	-16.907***
lnWMxT	2.244	-6.551***	-8.532***	-19.758***
lnWMiT	-1.437*	-10.768***	-4.178***	-16.386***
lnWA	-0.694	-11.828***	-0.925	-11.352***
lnWP	-3.631***	-13.420***	-8.175***	-16.199***

8 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively.

9 **Table 6.** Pedroni Cointegration Test for Rice Crop

		Unweighted Statistic	Prob.	Weighted Statistic	Prob.
Within Panel	Panel v-Statistic	-1.243	0.893	-2.052	0.980
	Panel rho-Statistic	-2.030**	0.021	-2.037**	0.021
	Panel PP-Statistic	-6.952***	0.000	-6.608***	0.000
	Panel ADF-Statistic	-3.272***	0.001	-2.591***	0.005
Between Panel	Group rho-Statistic	-0.969	0.166		
	Group PP-Statistic	-7.273***	0.000		
	Group ADF-Statistic	-2.912***	0.002		

10 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively.

11 **Table 7.** Pedroni Cointegration Test for Wheat Crop

		Un-Weighted Statistic	Prob.	Weighted Statistic	Prob.
Within Panel	Panel v-Statistic	0.900	0.184	0.278	0.391
	Panel rho-Statistic	-3.033***	0.001	-2.581***	0.005
	Panel PP-Statistic	-9.039***	0.000	-8.473***	0.000
	Panel ADF-Statistic	-2.280**	0.011	-2.173**	0.015
Between Panel	Group rho-Statistic	-1.199	0.115		
	Group PP-Statistic	-8.146***	0.000		
	Group ADF-Statistic	-1.581*	0.057		

12 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively.

13 **Table 8.** Regression Results (*Rice Yield is the dependent variable*)

Variables	Rice			
	FMOLS Model		DOLS Model	
	Coefficient	Prob.	Coefficient	Prob.
lnRMiT	2.319*** (0.074)	0.000	3.474*** (0.824)	0.000
lnRMxT	-2.606*** (0.060)	0.000	-3.879*** (0.887)	0.000
lnRP	-0.125* (0.075)	0.093	-0.034 (0.116)	0.772
lnRA	0.128*** (0.019)	0.000	0.103*** (0.036)	0.004
R ²	0.80		0.79	
Adjusted R ²	0.76		0.77	

14 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively. Standard error is in
15 parentheses.

16 **Table 9.** Regression Results (*Wheat yield is the dependent variable*)

Variables	FMOLS Model		DOLS Model	
	Coefficient	Prob.	Coefficient	Prob.
lnWMiT	2.520*** (0.273)	0.000	2.745*** (0.487)	0.000
lnWMxT	-2.120*** (0.532)	0.000	-2.909** (1.193)	0.015
lnWP	-0.053** (0.022)	0.015	-0.102* (0.057)	0.075
lnWA	-0.164*** (0.043)	0.000	-0.157*** (0.057)	0.007
R ²	0.87		0.86	
Adjusted R ²	0.84		0.83	

17 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively. Standard error is in
18 parentheses.

19 **Table 10.** Pooled Mean Group (PMG) Model (*Rice yield is the dependent variable*)

Variables	Coefficient	Std. Error	Prob.
	Long Run Equation		
lnRMiT	0.120	0.696	0.864
lnRMxT	-3.840***	0.780	0.000
lnRP	-0.251***	0.092	0.007
lnRA	0.121***	0.035	0.001
	Short Run Equation		
ECT	-0.419***	0.039	0.000
ΔlnRMiT	0.641**	0.304	0.036
ΔlnRMxT	0.434***	0.154	0.005
ΔlnRP	0.070***	0.015	0.000
ΔlnRA	-0.154	0.153	0.315
Constant	9.368***	0.867	0.000

20 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively.

21

22 **Table 11.** Pooled Mean Group (PMG) Model (*Wheat yield is the dependent variable*)

Variables	Coefficient	Std. Error	Prob.
Long Run Equation			
lnWMiT	0.821*	0.426	0.055
lnWMxT	-1.700*	0.941	0.072
lnWP	-0.106**	0.046	0.022
lnWA	-0.170***	0.048	0.000
Short Run Equation			
ECT	-0.308***	0.056	0.000
Δ lnWMiT	-0.094	0.099	0.341
Δ lnWMxT	-0.147	0.206	0.477
Δ lnWP	0.029***	0.006	0.000
Δ lnWA	-0.135	0.159	0.394
Constant	4.032***	0.731	0.000

23 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively.

24

25 **Table 12.** Dumitrescu-Hurlin Panel Causality Tests (*Rice yield is the dependent variable*)

Hypothesis	W-Stat.	Zbar-Stat.	Prob.
lnRMiT \nRightarrow lnRY	0.884	-0.396	0.692
lnRY \nRightarrow lnRMiT	0.596	-1.027	0.304
lnRMxT \nRightarrow lnRY	0.887	-0.388	0.698
lnRY \nRightarrow lnRMxT	5.206***	9.072	0.000
lnRP \nRightarrow lnRY	1.111	0.101	0.919
lnRY \nRightarrow lnRP	4.556***	7.648	0.000
lnRA \nRightarrow lnRY	2.082**	2.229	0.026
lnRY \nRightarrow lnRA	2.025	2.105	0.035
lnRMxT \nRightarrow lnRMiT	0.288*	-1.700	0.089
lnRMiT \nRightarrow lnRMxT	4.691***	7.943	0.000
lnRP \nRightarrow lnRMiT	2.981***	4.197	0.000
lnRMiT \nRightarrow lnRP	6.154***	11.148	0.000
lnRA \nRightarrow lnRMiT	1.190	0.274	0.784
lnRMiT \nRightarrow lnRA	0.764	-0.658	0.511
lnRP \nRightarrow lnRMxT	1.453	0.850	0.395

$\ln RMxT \Rightarrow \ln RP$	1.038	-0.059	0.953
$\ln RA \Rightarrow \ln RMxT$	2.655***	3.484	0.001
$\ln RMxT \Rightarrow \ln RA$	0.805	-0.569	0.569
$\ln RA \Rightarrow \ln RP$	5.275***	9.223	0.000
$\ln RP \Rightarrow \ln RA$	0.951	-0.248	0.804

26 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively.

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28 **Table 13.** Pairwise Dumitrescu-Hurlin Panel Causality Tests (Wheat yield is dependent variable)

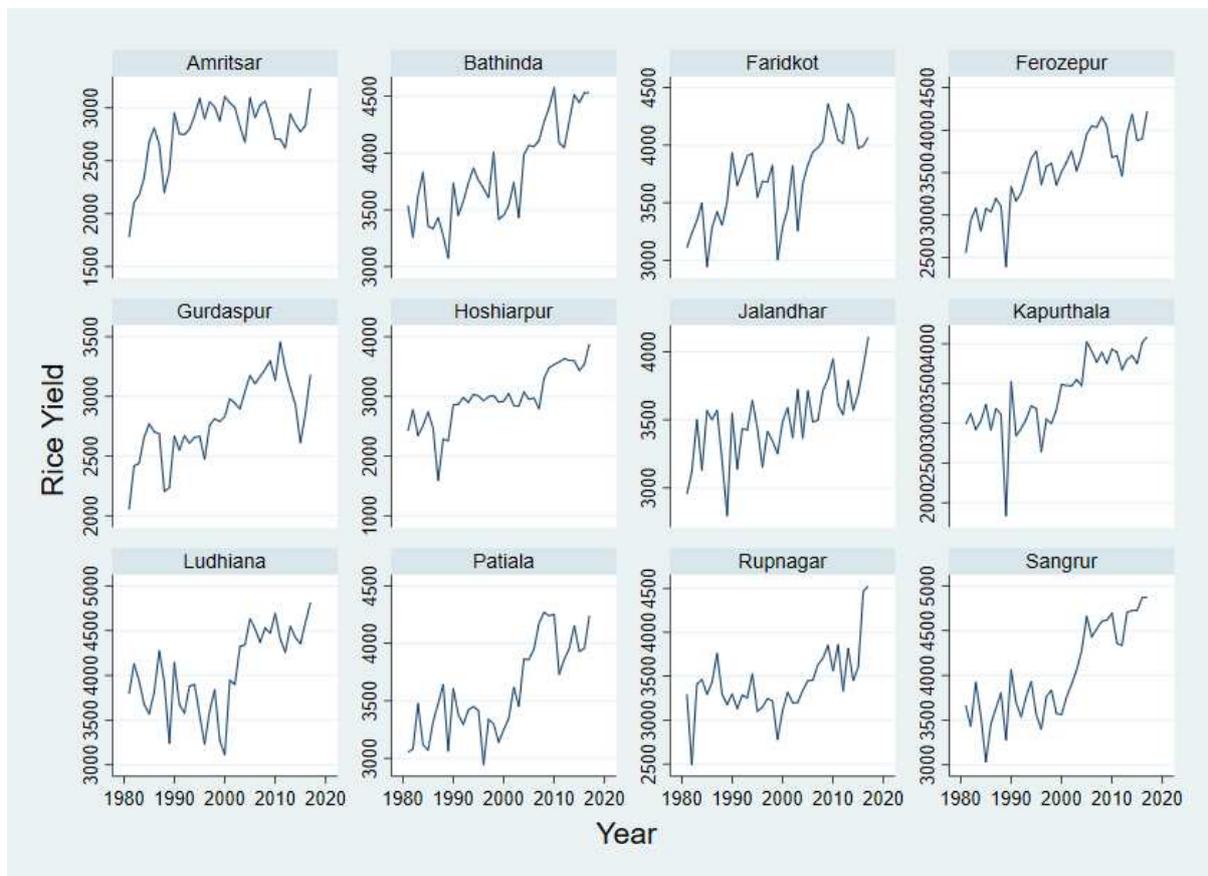
Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.
$\ln WMiT \Rightarrow \ln WY$	1.397	0.727	0.467
$\ln WY \Rightarrow \ln WMiT$	5.762***	10.290	0.000
$\ln WMxT \Rightarrow \ln WY$	3.102***	4.464	0.000
$\ln WY \Rightarrow \ln WMxT$	1.690	1.371	0.171
$\ln WP \Rightarrow \ln WY$	4.384***	7.272	0.000
$\ln WY \Rightarrow \ln WP$	0.737	-0.717	0.473
$\ln WA \Rightarrow \ln WY$	2.148**	2.372	0.018
$\ln WY \Rightarrow \ln WA$	1.577	1.122	0.262
$\ln WMxT \Rightarrow \ln WMiT$	2.643***	3.457	0.001
$\ln WMiT \Rightarrow \ln WMxT$	1.650	1.282	0.200
$\ln WP \Rightarrow \ln WMiT$	2.576***	3.311	0.001
$\ln WMiT \Rightarrow \ln WP$	0.494	-1.250	0.211
$\ln WA \Rightarrow \ln WMiT$	1.410	0.758	0.449
$\ln WMiT \Rightarrow \ln WA$	1.577	1.123	0.261
$\ln WP \Rightarrow \ln WMxT$	3.540***	5.423	0.000
$\ln WMxT \Rightarrow \ln WP$	1.233	0.369	0.712
$\ln WA \Rightarrow \ln WMxT$	0.632	-0.947	0.344
$\ln WMxT \Rightarrow \ln WA$	1.228	0.358	0.720
$\ln WA \Rightarrow \ln WP$	0.428	-1.394	0.163
$\ln WP \Rightarrow \ln WA$	0.550	-1.126	0.260

29 Note: *, **, and *** show the significance level at 10%, 5%, and 1% respectively.

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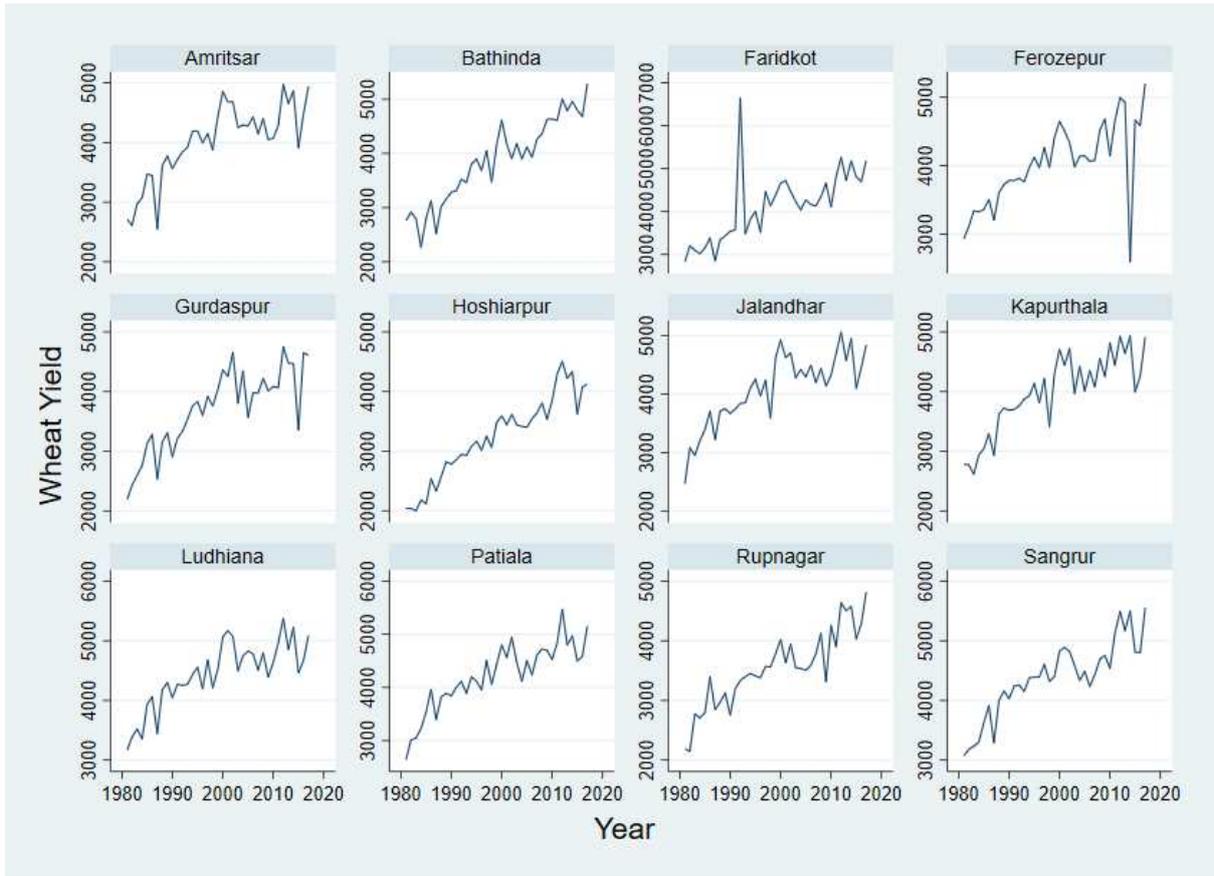
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Figure 1. Trends in Rice Yield in Punjab during 1981–2017

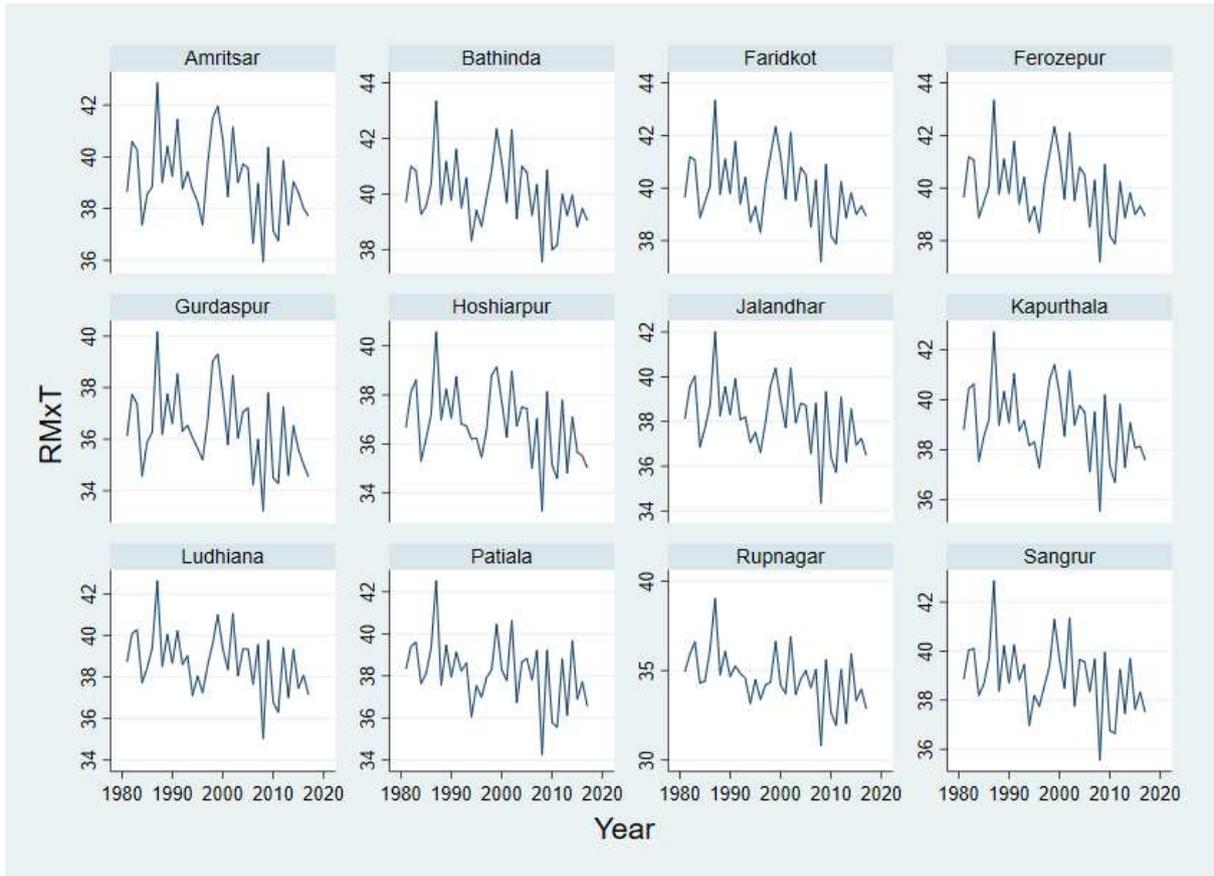


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Figure 2. Trends in Wheat Yield in Punjab during 1981–2017

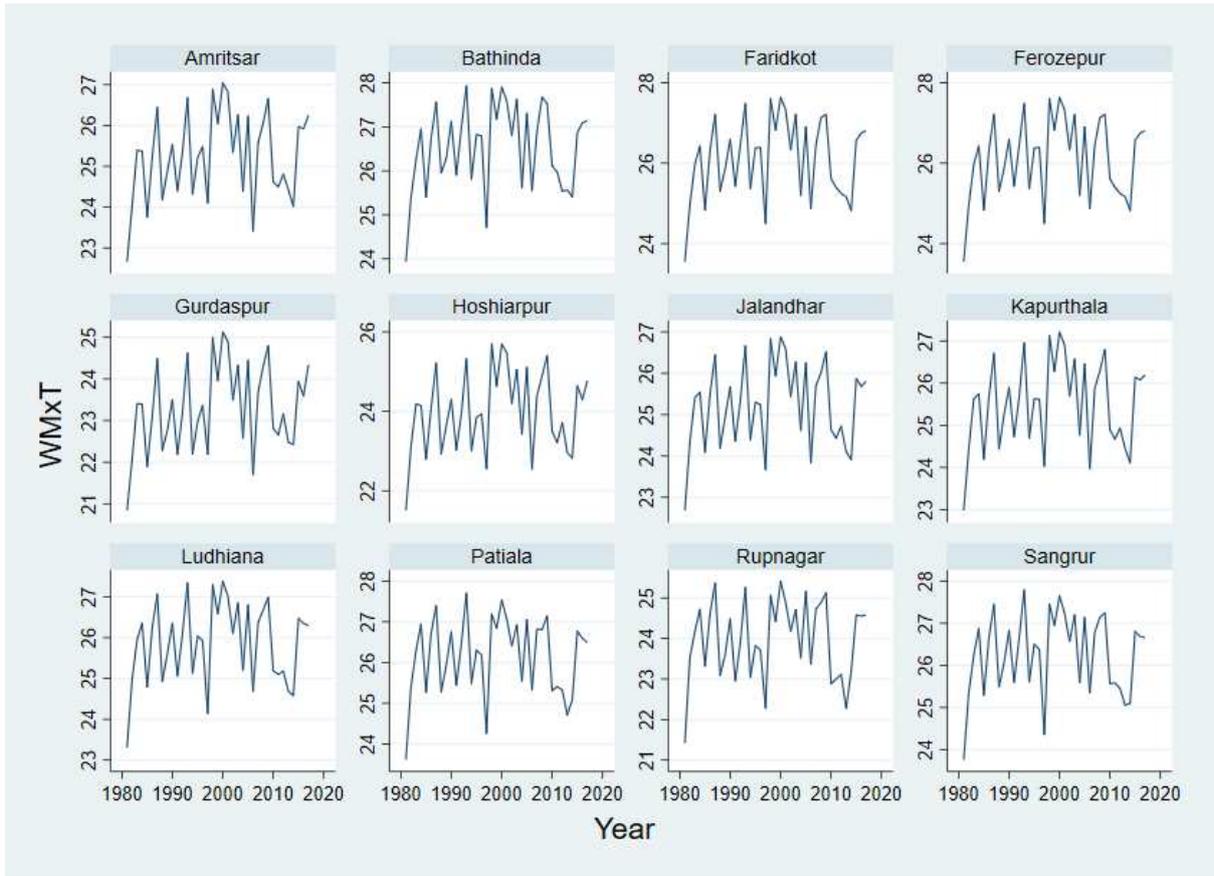
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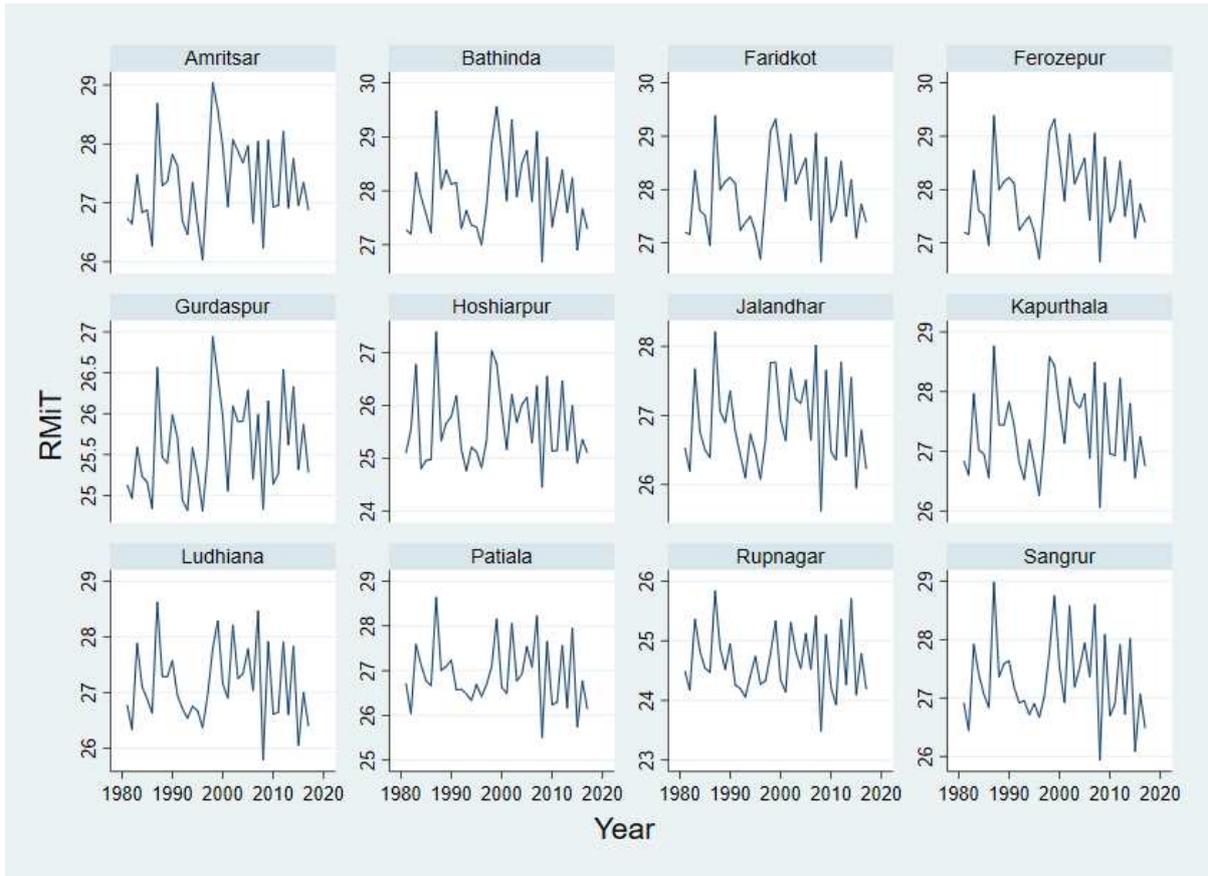
Figure 3. Trends in Rice Average Maximum Temperature in Punjab during 1981–2017



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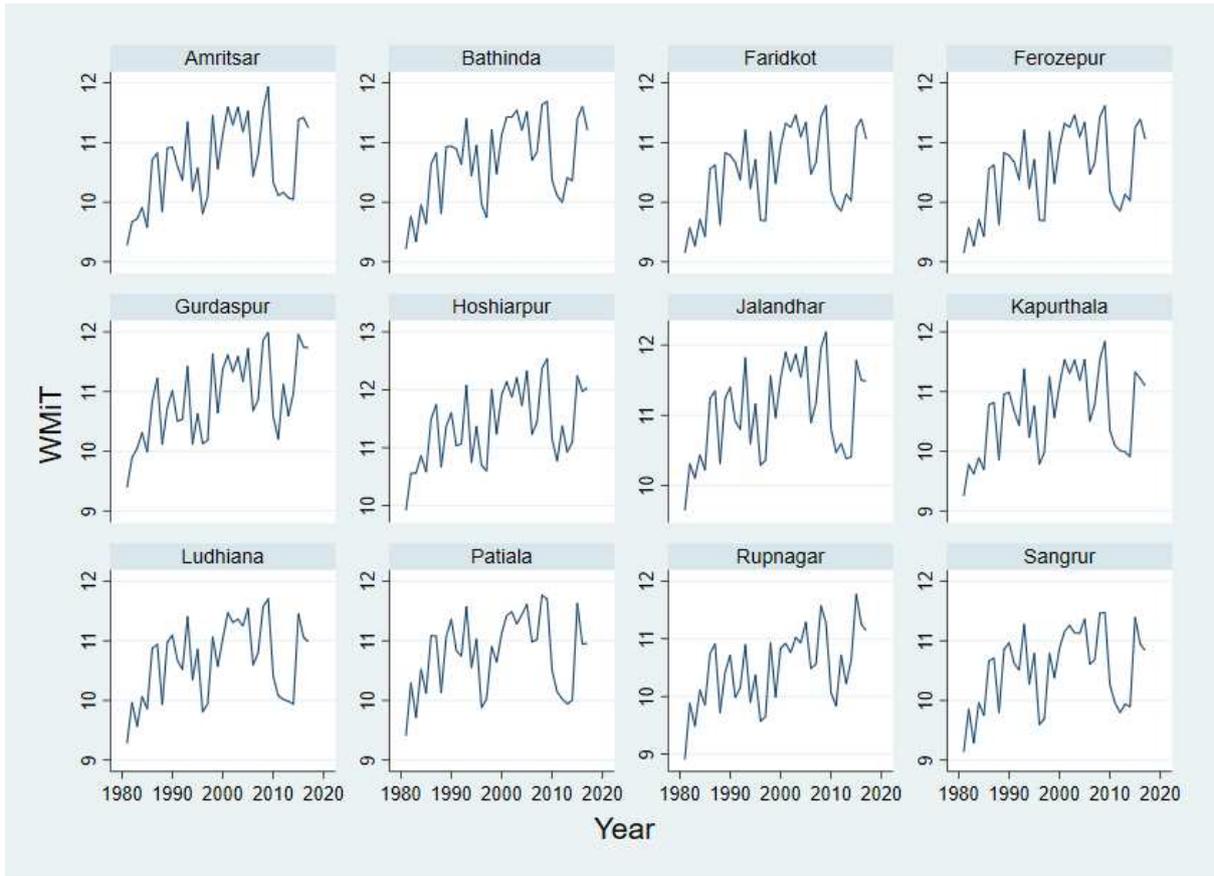
Figure 4. Trends in Wheat Average Maximum Temperature in Punjab during 1981–2017



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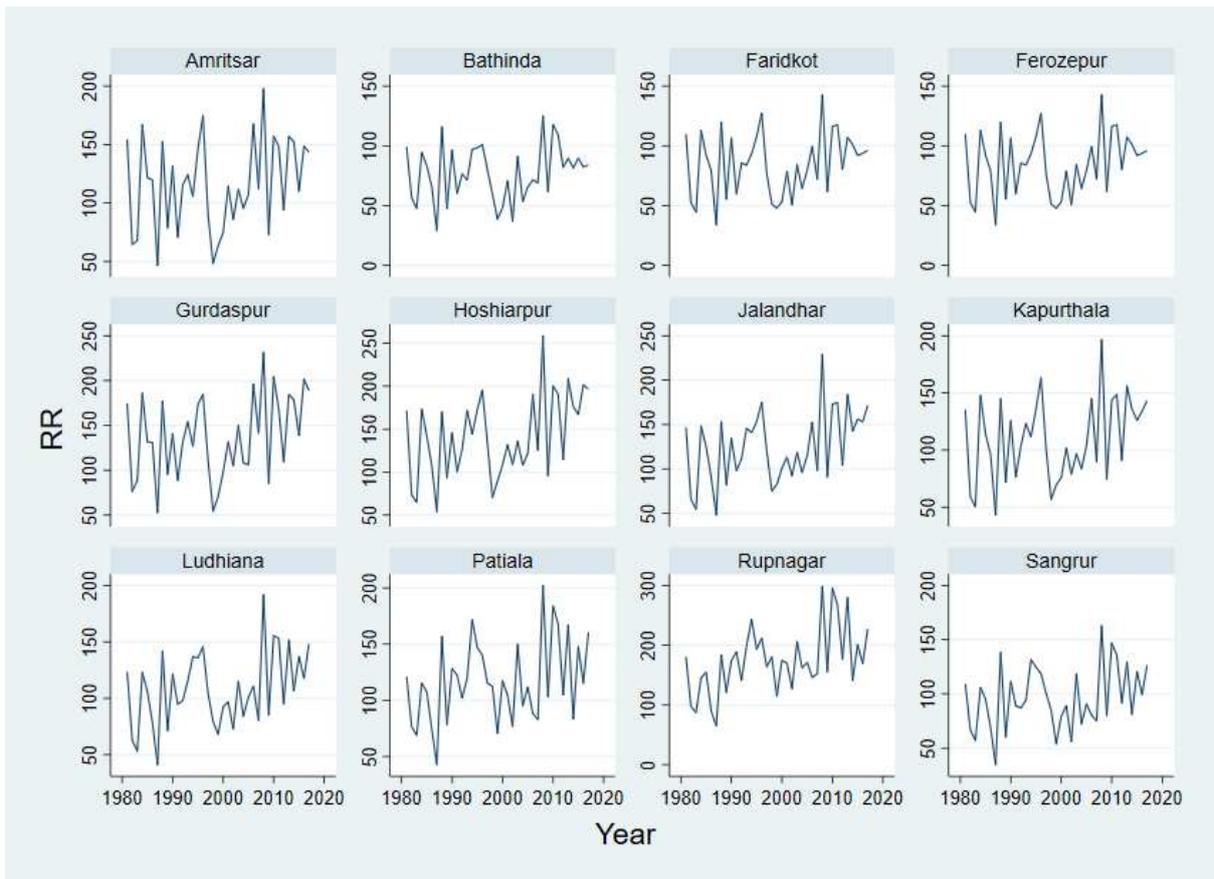
Figure 5. Trends in Rice Average Minimum Temperature in Punjab during 1981–2017



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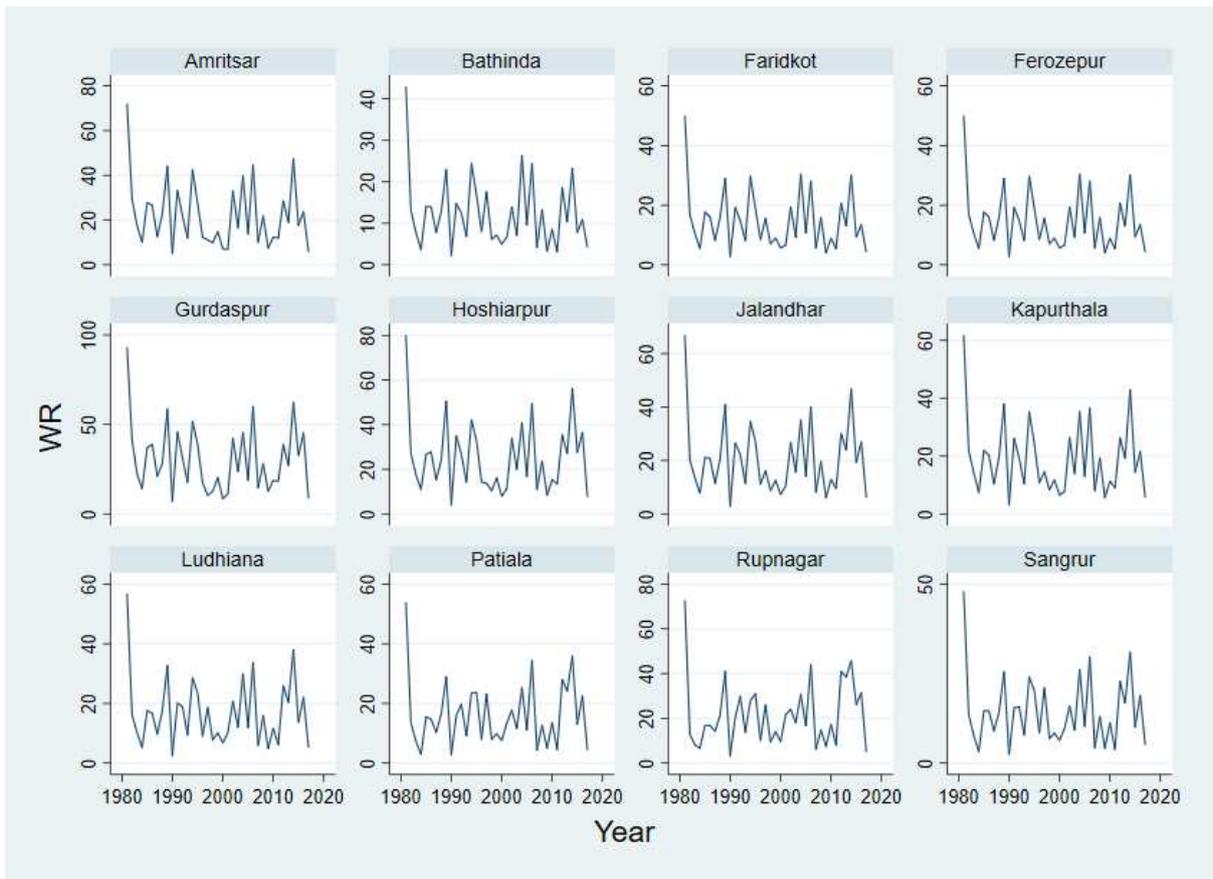
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Figure 8. Trends in Average Annual Rainfall during Wheat Season in Punjab during 1981–2017

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