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# The Impact of Climate Change on Agricultural Employment, Evidence from South Asian Countries based on Pooled Mean Group Estimation of Dynamic Heterogeneous Panel

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## ABSTRACT

Being the most populous region, South Asia is home to one-fourth of the population in the world. Along with the aforementioned feature, South Asia is becoming one of the most climatic-hazard-prone regions on the planet. Hence, this study attempts to analyse empirically how economic performance and climate change affect employment in the agriculture sector. The study includes seven South Asian countries' data, excluding the Maldives, from 1992 to 2021 by applying the most widely used Panel ARDL, which involved pooled mean group (PMG) estimation. In the short run, the effect of past-year employment and temperature is positive, whereas GDP per capita is negatively related to agricultural employment and rainfall is insignificant. However, in the long run, the error correction coefficient is significant, and overall data has been able to establish a long-run relationship. The study concludes that, with the long-run impact for each country, agricultural employment is negatively affected by GDP per capita and temperature. Lastly, the effect of temperature in the long run reveals that climate change has long-term impacts on agriculture employment. We believe that the findings of the study have important implications for policymakers in the future.

**Keywords:** PMG Model, Climate Change, Agricultural Employment, Climate Refugee JEL Classification: C13; C23; E24; 013; Q15; Q54; Q56.

## INTRODUCTION

Undoubtedly, global warming earned the recognition of being the leading evil of all externalities in the sense that it affects everyone and everything existing on the planet. That is why the decade of the 1940s is often marked as the beginning of the "Anthropocene", a new geological era in human history, because of the "Great Acceleration," which signifies the steeper rise in most of the climatic variables since World War II (WW-2) (Baldwin *et al.*, 2020). The main feature of this anthropogenic epoch is that human dominance is becoming more destructive to nature and the beings around it. Moreover, the special feature of climate change is that it is as global as it is long-lasting. So, it is often hard to capture its impact on only a particular country or region. Yet attempts were made to take appropriate measures to tackle the various types of crises stemming from anthropogenic climate change in coastal countries like India, Bangladesh, and the Maldives. Though developing nations like South Asia contribute less to global greenhouse gas emissions, they suffer greatly from the consequences (Metcalfe, 2003). A recent study reveals that Bangladesh is going to be the victim of recurring floods and cyclones because of climate change's frequent cyclonic activity in the Bay of Bengal and the increased melting of the Himalayan snowpack (Jenkins, 2003).

To make an inclusive society, necessary steps should be taken because the poorest people in society have to bear the burden of climate change, which in turn intensifies regional and global inequality. From that perspective, to fulfill the various targets of the Sustainable Development Goals (SDGs), climate change deserves more in-depth and empirical investigation, which will try to figure out its different sorts of associations with other socio-economic variables. Being one of the most vulnerable regions to climate change, South Asia is frequently threatened and hurt by intense floods, droughts, storms, acute salinity, and tropical cyclones. A recent study shows that Bangladesh is now confronting the high frequency of tropical cyclones more than five times (Haque *et al*., 2016). Due to the lethal impacts of extreme weather events like floods and cyclones, South Asia is becoming a regional hub of climate refugees through forced displacement and migration. Consequently, urban poverty and pollution are being heightened, with a subsequent decrease in the quality of life in urban society. In addition to its economic costs, various types of socio-political consequences are being felt to a greater extent in the coastal region. For instance, those who migrated from the immediate disaster-torn area to a suburban or urban city are being convicted of no crime. Hence, judicial rights are being violated by the so-called refugees (Ahsan, 2019).

To sense the extent of the environmental degradation in South Asia, we may look into the recent Global Liveability Index (2022), which shows that Dhaka (fourth) and Karachi (sixth) occupy the worst positions in the world. Further weather vulnerability can be observed from another index named the Global Climate Risk Index (2020) (Eckstein et al., 2021). It has been developed to measure to what extent countries and regions have been affected by extreme weather-driven calamities. The study segregates its risk intensity into two parts: the short-term and long-term Climate Risk Index (CRI). If we take into account the long-term (1999–2018) CRI, it appears that Pakistan (5th), Bangladesh (7th), and Nepal (9th) remain among the top worst countries, which are becoming more vulnerable day by day. The report further explored that India and Sri Lanka ranked 5th and 6th in 2018 in terms of encountering climatic hazards. The list of impacts of climate change is very long; we will only restrict ourselves to finding the link between climate change and agricultural employment. Of the various sectors, agriculture became the hardest victim of climate change. Moreover, because of the sea-level rise, river erosion, loss of cultivable land, and frequent floods, people are becoming unemployed through forced migration, which is affecting employment in agriculture.

Unfortunately, policymakers are not able to distinguish between domestic migration and climate change migration. But it is urgent to examine a link between climate-induced migration and its impact on agricultural employment.

Therefore, the study aims to find a long-term relationship between climatic variables (temperature and precipitation) and agricultural employment in South Asia, comprising 7 countries. The reason the South Asian nations were chosen for the study is that South Asia is warming up faster than the world average, which would likely lead to more frequent and severe extreme weather incidents (Vinodan, 2010). Though different aspects of climate research were addressed previously, the link between climate change and agricultural employment remained undiscovered in the context of South Asia. To do so, the pooled mean group estimation (PMGE/ARDL) model was used. The paper is designed with the following outline: Section 1 begins with an introduction, and Section 2 involves the literature review. Section 3 describes the methodology, followed by Section 4, which explains the empirical results. And Section 5 gives the concluding remarks and future research scope.

## LITERATURE REVIEW

Because of its wide-ranging effects, the literature on climate change is vast, which proves its significance among climate scientists and energy economists. Hence, climate economics became a popular destination for upcoming economists. To trace the date of the literature on national welfare and climate change, we may get back to the early days of economics, when it was observed that hot countries would tend to be poor. Thus, it was attempted to have a link between temperature and poverty (Montesquieu, 1751). Exploring the connection between both variables continued even at the dawn of the 20th century (Huntington, 1924). To measure the well-being of any nation, GDP remains the most favorable variable. Thus, from the very beginning, the central focus of climate economists was to evaluate the impact of climate change on GDP. In doing so, they introduced a special model called Integrated Assessment Models (IAMs) (Nordhaus, 1993). Since the early estimates understated the economic effects of climate change, they were modified later. However, it was surely established that the temperature rise would result in a negative relationship between temperature and income, where it was seen that a 1-degree rise in temperature is accompanied by a 1.1 percentage point decrease in GDP (Dell *et al*., 2008). The same study shows that poor nations are mostly heated by climate change, whereas there are few effects of climate change on developed countries, which in turn indicates an increase in global inequality between the poor and rich countries in the long run (Dell *et al*., 2009). Moreover, the Stern review projected that if immediate action is not taken, the world might lose 5% of GDP every year. In addition to that, in cases of greater risk, the effect of climate change would lead to a 20% loss of world GDP (Stern, 2006). A similar kind of relation has been found in the case of Bangladesh, where it was observed that a 1-degree Celsius increase in temperature would lead to a 0.44% decrease in GDP (Roy *et al*., 2019). Because of the complexity of climate change, it affects many sectors in many ways. Of them, the agricultural sector is the hardest hit. Maybe the earliest study on agriculture from an economic perspective was done by Adams, whose impacts on agriculture were inconclusive (Adams, 1989). But a recent study shows that crop yields in Africa could be reduced by 50% due to climate shock (Tol, 2020). Surprisingly, the impact of climate change on agriculture is not the same in all regions around the world. For instance, it was observed that variation in temperature and precipitation in the United States resulted in annual profits in agriculture in 2002, which amounted to 1.3 billion USD (Deschênes *et al*., 2007). But the problems with those studies are that they did not consider the cases of coastal, dry, and poor countries where negative impacts on agriculture are utterly visible due to land loss by river erosion and sea-level rise. From this observation, we may say that in the short run, climate change might bring some gains for those who depend on rain-fed agriculture and those who spend substantial money on heating, particularly in the winter season. But in the long run, these short-term gains will be negligible compared to the economic burden posed by environmental degradation (Tol, 2020).

Another horizon where the impact of climate change was analyzed is the connection between climate change and its subsequent effects on healthcare expenditure. A recent study on South Asia shows that climate change due to carbon emissions can lead to a substantial increase in healthcare expenditure (Azad et al., 2018). As a result, climate change threatens human security in both direct and indirect ways, with increased salinity in the water as a result of increased climatic change (Zakar *et al*., 2020). Moreover, climate change has an impact on food security. According to one study, a decrease in cereal production as a result of climate change ultimately leads to an increase in cereal prices (Yan *et al*., 2022).

There is another stream of literature that focuses on the relationship between economic growth, carbon emissions, and energy consumption. A recent study in the case of Sri Lanka from 1971–2006 suggests a long-run causal relationship between carbon emissions and energy consumption (Uddin *et al*., 2016). Therefore, a number of environmental organizations expressed their support for a global system of environmental norms, though developing countries maintain lower standard norms than developed countries (Tisdell, 2003).

Unfortunately, less focus has been given to linking employment with climate change. Most of the studies used computed general equilibrium (CGE) models while examining the nexus between employment and climate change. To analyze the unemployment effects of anthropogenic climate change, it was observed that carbon emission restrictions would increase the unemployment rate if supportive policies were not taken, like wage subsidies for those who were associated with the carbon-emitting industries. This study assumed labor market flexibility. Otherwise, sectorial shipment of labor would not be plausible (Babiker *et al*., 2006). A similar kind of conclusion was drawn in the case of OECD countries using the CGE model, whereas the previous study used a dynamic CGE model (Château *et al*., 2011).

Though there were different types of models developed to analyze the impact of climate change, many of them were criticized later by the researchers due to methodological flaws. We would like to give a quick review of them. Under the umbrella of Integrated Assessment Models (IAMs), a set of special methods were developed to analyze the effects of climate change from various aspects and to evaluate the extent of carbon pricing. The first of them is Dynamic Integrated Climate Economy (DICE), which is followed by Regional Integrated Climate Economy (RICE), PAGE 1995, PAGE 2002, and FUND, which are often dubbed cost-benefit integrated assessment models. The primary goals of these models were to calculate the social costs of carbon (SCC) for carbon pricing policies. To do so, they relied mostly on the marginal social costs of carbon, which were criticized later because the marginal analysis underestimated the economic costs of carbon emissions. Instead, the average calculation of SCC suggested that the economic costs almost doubled (Pindyck, 2019).

IAMS, along with other CGE models, were also criticized for not taking macro-data of climatic variables, where these models were built on a set of growth functions and damage equations. As a result, they underestimated the welfare loss of the global economy. Moreover, in most of the studies, economic costs were calculated based on an estimate of a 3-degree Celsius increase, whereas they might exceed that threshold. Therefore, recent models prefer methods that are based on macro-data, which are more realistic for displaying the causal relationship among the variables (Tol, 2009).

To the best of our knowledge, research on climate change and its impact on agricultural employment is undiscovered in the context of South Asia. Therefore, this paper examines the possible effect of climate change on agricultural employment in South Asia.

## METHODOLOGY

### Data

Secondary data are used in the study. The balanced panel consists of annual data for employment in agriculture measured in percentage of total employment, GDP (gross domestic product) per capita at current US dollars, mean annual temperature (Celsius) calculated from monthly data, and mean annual rainfall (millimeter) calculated from monthly data, including seven selected South Asian countries, namely Afghanistan, Bangladesh, India, Pakistan, Nepal, Bhutan, and Sri Lanka from 1992 to 2016, and data on each variable. The data on employment in agriculture and GDP per capita are gathered and verified from the World Development Index (WDA), the World Bank, and monthly temperature and rainfall data are collected from the Climate Change Knowledge Portal (CCKP), the World Bank. The variation of climate change data in the Maldives is rare enough to increase the power of interpretation of the model, and including it may be misleading. Since South Asia is mostly dependent on agricultural and natural resources and is a region with many climate-related hazards, investigating the link between these two is one way to improve the literature on climate and agriculture.

### Model Specification

In this paper, we pool cross-section and time-series data to study relationships between the labor market in the agricultural sector and independent variables such as GDP per capita and mean temperature. We get the following equation:

$Agro\_employ = f(GDPPC, Tem$[1]$, Rain,$-----------------(1)

Where Agro_employ is the percentage of employment in the agriculture sector out of total employment in the economy, GDPPC expresses each country's gross domestic product divided by each country's total population, and Tem is temperature measured by giving half weight to the monthly average maximum and minimum temperature, then aggregating the average monthly average temperature divided by a number of the total month. Rain is measured as the average annual precipitation among the countries, which is calculated from the monthly average precipitation. GDP per capita is the proxy variable of economic performance, which is an important explanatory variable because if the number of economic activities is increasing in a country, the employment of labor would be more concentrated in the manufacturing and service sectors, thus the number of jobs in agriculture would fall. Among the many climate change variables, temperature and rainfall are more widely used. The effects of climate change are reflected in high or low temperatures, irregular seasonality, irregular rainfall, and floods. The most commonly used proxy variables, temperature and rainfall, are directly affected by climate change. The empirical model form for this specification is given by:

$Agro\_employ_{it} = \beta_0 + \beta_1 GDPPC_{it} + \beta_2 Tem_{it} +$
$\beta_3 Rain_{it} + \varepsilon_{it}$-------------------------------------------------(2)

As defined earlier in Equation (1), Agro employ, GDPPC, Tem, and Rain. A constant term, $\beta_0$ is present, and the GDPPC coefficient, $\beta_1$ which is expected to be negative, is present. The expected negative effects of Tem would be reflected by $\beta_2$, and $\beta_3$ is the impact of Rainfall, which is likewise expected to be negative.

t is a time-series data, *i* is a cross-section data that differs from country to country, and $\varepsilon_{it}$ is an error term.

### Estimation Procedure

It is required to validate the unit root for each variable because the data are panel and include long-term data. Non-stationary variables not only cause erroneous regression but also make estimating moments explosive. In order to make sure the panel cointegration, it is first required to ascertain whether the data series contains unit roots. We have selected the Im, Pesaran and Shin (IPS, hereinafter), a method based on the well-known Dickey-Fuller approach, for this study.

[1] Tem stands for temperature

Im, Pesaran, and Shin denoted IPS (Levin *et al*., 2002) proposed a test for the presence of unit roots in panels that makes use of information about both the time-series dimension and cross-section dimension, reducing the number of time observations needed for the test to be statistically significant. We will also use this method in our study because economics experts have shown the IPS test to have greater test power for analyzing long-run relationships in panel data. IPS starts by providing a distinct ADF regression for each cross-section with unique effects and no time trend:

$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + \varepsilon_{it}$ -------------(3)

where $i = 1, \ldots, N$ and $t = 1, \ldots, T$

For each of the N cross-section units, IPS performs a separate unit root test. Their analysis is based on statistics from the Augmented Dickey-fuller (ADF) model that are averaged over groups. Following the estimation of the unique ADF regressions. The testing coefficient's primary concern is $\rho_{i.}$ The variable may have a unit root and be non-stationary if strong evidence indicates that $\rho_{i.}$ is not statistically different from zero. This is because the null hypothesis is that $\rho_i$ is equal to zero, while the alternative hypothesis is that $\rho_i$ is less than zero. The Dickey-Fuller test statistics are left-biased and dependent on the model specification since the addition of intercept and trend strengthens the null hypothesis and prevents rejection of the null hypothesis.

**Panel Cointegration Tests**

The long-term relationship between the non-stationary variables must be run with cointegration. Despite the non-stationarity of the variables, their combination may nonetheless have the motivation to return to a certain value. Most frequently employed are panel cointegration tests, which Pedroni recommended conducting to determine whether there is a long-run cointegration between employment in agriculture and the independent variables (1999). We will employ Pedroni's seven-panel cointegrations since he normalizes the panel statistics using correction terms before deciding which tests to perform on the estimated residuals from a cointegration regression.

According to Pedroni's suggested methodologies, calculated residuals from the predicted long-run regression will have the following form:

$y_{i,t} = \alpha_i + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \cdots + \beta_{Mi} x_{Mi,t} + e_{i,t}$ ------------------------------------(4)

*for* $t = 1, \ldots, T$; $i = 1, \ldots, N$; $m = 1, \ldots, M$,

where T is the total number of observations across time, N is the total number of cross-sectional units in the panel, and M is the total number of regressors. The member-specific intercept or fixed-effects parameter in this setup varies across different cross-sectional units. The same is true for member-specific time effects and slope coefficients. Testing the Augmented Dickey-Fuller test for residuals conditioning where all variables are cointegrated with the same order, either I(0) or I (1)

$e_{it} = \theta_i e_{it-1} + \sum \phi_{ij} \Delta e_{it-1} + v_i$ ------------------------------------------------------(5)

If the test statistic can reject the null hypothesis, variables are cointegrated with order zero, I(0), otherwise there is no cointegration among the variables. The null hypothesis is that there is no integration against the alternative hypothesis that cointegration exists.

**Autoregressive distributed lag model**

Before estimating the ARDL model, the unit root and cointegration tests have to be completed. The ARDL model consistently applies to short sample periods and distinguishes between short-run and long-run coefficients. Equation (6) is now shown as a panel ARDL (p,q1,q2,q3) equation because p denotes the lags of the dependent variable and q denotes the lags of the independent variables. The panel ARDL equation is shown as follows.

$$Agro\_empoy_{it} = \alpha_i + \sum_{j=1}^{p} a_{1,ij} Agro\_employ_{i,t-j} + \sum_{j=1}^{q_1} a_{2,ij} GDPPC_{i,t-j} + \sum_{j=1}^{q_2} a_{3,ij} Tem_{i,t-j} + \sum_{j=1}^{q_3} a_{4,ij} Rain_{i,t-j} + \varepsilon_{it} \text{ ------------(6)}$$

where i = 1,2,3,...N and t = 1,2,3,...T, $\alpha_i$ represents the fixed effects, $\alpha_2 - \alpha_4$are the lagged coefficients of the independent variables and the regressors and $\epsilon_{it}$ is the error term which is assumed to be white noise and varies across countries and time.

In a panel error correction (ECM) representation equation (7) is formulated as follows:

where t = 1, 2, 3, N and I = 1, 2, 3, N T, $\alpha_i$ stands for the fixed effects, $\alpha_2 - \alpha_4$are the lagged coefficients of the independent variables and regressors, and $\epsilon_{it}$ is the error term, which is taken to be random noise that fluctuates across nations and over time. Equation (7) in a panel error correction (ECM) format is written as follows:

$$\Delta Agro\_empoy_{it} = \alpha_i + \sum_{j=1}^{p} a_{1,ij} \Delta Agro\_employ_{i,t-j} + \sum_{j=1}^{q_1} a_{2,ij} \Delta GDPPC_{i,t-j} + \sum_{j=1}^{q_2} a_{3,ij} \Delta Tem_{i,t-j} + \sum_{j=1}^{q_3} a_{4,ij} \Delta Rain_{i,t-j} +$$

$\beta_{1,ij} Agro\_employ_{i,t-1} + \beta_{2,ij} GDPPC_{i,t-1} + \beta_{3,ij} Tem_{i,t-1} + \beta_{4,ij} Rain_{i,t-1} + \varepsilon_{it}$ ------------------------(7)

Where Δ is the first difference of variables, also $\alpha_2 - \alpha_4$ are the short-run coefficients while $\beta_1 - \beta_4$are the long-run coefficients of Agro_emloy, GDPPC, Tem and Rain respectively. Once, a long-run relationship is established between the dependent variables and the regressors, the panel ECM model (equation (8) can be expressed as follows:

$\Delta Agro\_empoy_{it} = \alpha_i + \sum_{j=1}^{p} a_{1,ij} \Delta Agro\_employ_{i,t-j} + \sum_{j=1}^{q_1} a_{2,ij} \Delta GDPPC_{i,t-j} + \sum_{j=1}^{q_2} a_{3,ij} \Delta Tem_{i,t-j} + \sum_{j=1}^{q_3} a_{4,ij} \Delta Rain_{i,t-j} + \theta_i ECM_{i,t-j} + \varepsilon_{it}$ ----------------------------------------------(8)

where the $\theta_i$ stands for the ECM coefficient, which measures how quickly the economy adjusts each year to reach long-run equilibrium. The appropriate lag duration for the ECM model is determined by Akaike's lag selection criteria with only a few annual data.

**Pooled Mean Group Estimation**

The primary feature of PMG is that while long-run slope coefficients are constrained to being homogeneous across nations, short-run coefficients, such as the intercept, the rate of adjustment to the long-run equilibrium values, and error variances are allowed to be heterogeneous country by country. This is especially helpful when there is cause to believe that different countries' long-run equilibrium relationships between variables are similar. Pooled mean group estimate is more often recognized than mean group estimation and dynamic fixed estimation.

This study uses the Pesaran method of pooled mean group estimation (PMGE) of dynamic heterogeneous panels to calculate the effects of climate change on agricultural employment (1999). Panel study using the ARDL model's unrestricted specification for periods t = 1, 2, and T and groups I = 1, 2 and N, with y as the dependent variable

$y_{it} = \sum_{j=1}^{p} \pi_{ij}\, y_{i,t_{-1}} + \sum_{j=0}^{q} \gamma_{ij}' x_{i,t_{-j}} + \mu_i + \epsilon_{it}$ ---------(9)

Where $y_{it}$ is a scalar dependent variable, $x_{it}$ is the k × 1 vector of explanatory variables for group i, $\mu_i$ denotes the fixed effects, $\pi_{it}$ are scalar coefficients of the lagged dependent variables, $y_{ij}$

$\Delta yit = \emptyset iyi,t-1 + \beta i' xi,t-1 \sum_{j=1}^{p} \pi ij \Delta yi,t-1 + \sum_{j=0}^{q} \gamma' ij \Delta xi,t-j + \mu i + \epsilon it$-----------------------------(10)

It is assumed that the disturbance terms of $\epsilon it$ are independently distributed across i and t, with zero means and $\sigma_i^2 > 0$ variances. It is assumed further that $\emptyset < 0$ for all i's. Thus, there exists a long-run relationship between $y_{it}$ and $x_{it}$. The long-run adjustment would be negative showing a negative trend to return to long-run equilibrium.

With zero means and $\sigma_i^2 > 0$ variances, it is believed that the disturbance terms of it are independently distributed across i and t. In addition, it is assumed that $\emptyset < 0$ for all i's. As a result, yit and xit have a long-term relationship. A negative long-run adjustment would indicate a downward tendency toward long-run equilibrium.

**EMPIRICAL RESULTS AND FINDINGS**

**Descriptive Analysis and Summary Statistics**

The data consists of 196 observations about employment in the agricultural labor market, 198 for GDP per capita, 210 for rainfall, and 210 for temperature, and contains the overall condition of south Asian countries' climate change and economic activity. Table 1 indicates the pooled summary statistics, and subsequent Appendices 1 and 2 indicate the categorical countries' conditions. The higher mean agriculture employment (54.22 percent) in South Asia reflects that the region is the most agriculturally productive. Most South Asian countries are growing so fast; therefore, the average GDP per capita has reached approximately 948.72 dollars. The tropical belt is more prone to extreme weather, resulting in higher rainfall (more than 1000 millimeters per year) and an asymmetric temperature trend (nearly 20 degrees Celsius per year).

Table 1. Pooled summary statistics.

| *Variable* | *Observation* | *Mean* | *Std. Dev* | *Min* | *Max* |
|---|---|---|---|---|---|
| Agro_employ | 196 | 54.22 | 13.25 | 24.98 | 82.1 |
| GDP Per capita | 165 198 | 1111.22 | 948.72 | 170.57 | 4077.044 |
| Temperature | 210 | 19. 57 | 6.31 | 9.51 | 27.02 |
| Rainfall | 210 | 1255.96 | 699. 86 | 187.52 | 2664.2 |

Source: Author's estimation from WTO and CCKP data.

The graph in Appendix 2 shows the mean amount of agricultural employment, rainfall, temperature, and GDP per capita. Bangladesh and Bhutan show the highest rainfall in South Asia, while Nepal, Bhutan, and Afghanistan show relatively lower temperatures in the South Asian region. The graph in Appendix 2 contains the climate variable over the year, where rainfall in each country is continuously increasing and has a positive trend. On the other hand, temperature is fluctuating for most of the countries around a particular range, mostly 20 to 30. It is clear from the graph that the negative trend in agriculture employment and the positive trend in rainfall imply a negative relationship between agriculture employment and rainfall. Moreover, the temperature and rainfall in each country do not belong to a predicted trend. The rapid fluctuation of these two climate variables indicates the effect of climate change in South Asian countries.

**Testing multi-Collinearity:**

Multi-collinearity is a common problem in time series data. To estimate the efficient parameters, perfect or near-perfect multi-collinearity should be minimized. Here, the pairwise correlation has been tested, which indicates that there is a tolerable level of multicollinearity and no perfect collinearity among the independent variables. Therefore, the data could be used for estimation purposes.

Table 2. Pairwise correlation.

| Variables | Agro_employ | GDPPC | Tem | Rain |
|---|---|---|---|---|
| Agro_employ | 1 | | | |
| GDPPC | -0.54 | 1 | | |
| Temperature (Tem) | -0.63 | .15 | 1 | |
| Rain | .13 | .26 | 0.16 | 1 |

Source: Author's estimation from WTO and CCKP data.

**Testing variables Behavior**

Table 3 shows the results of the IPS panel unit root test at the level proving that the variables Tem and Rain are I (0) in the constant and constant plus trends of the panel unit root test. These findings unequivocally demonstrate that, depending on the lag time, it is not possible to reject the null hypothesis of a panel unit root at the level of the series. Assumed is the absence of any time trend. In order to test for stationary, we take into account a constant plus-time trend. Again, we discovered that, in the absence of a constant plus time trend, the null hypothesis of a panel unit root is not frequently rejected in all series at the level form and different lagged lengths. Tem and Rain are non-stationary at the level, according to the findings of the panel unit root tests, whereas Agro employ and GDPPC's variables are confirmed to be non-stationary at the level.

Table 3. Panel Unit Root Test – Im, Pesaran and Shin (IPS).

| *Variable* | *Level* | | *First-order difference* | |
|---|---|---|---|---|
| | Constant | Constant + Trend | Constant | Constant + Trend |
| Agro-Employ | -4.42 (1.00) | -.24 (0.40) | -7.40 (0.00***) | -6.00 (0.00***) |
| GDPPC (current us $) | -6.33 (1.00) | -09 (.47) | -8.36 (0.00***) | -7.93 (0.00***) |
| TEM | -5.54 (0.00***) | -5.80 (0.00***) | - | |
| RAIN | -12.53 (0.00***) | -11.69 (0.00***) | | |

Source: Author's estimation from WTO and CCKP data

*Note:*

***, ** and * indicate rejection of the null hypothesis of no-unit root at 1% and 5% and 10%, levels of significance.

The findings of the IPS test at the first difference for the constant and constant plus time trends are also shown in Table 3. We can see that the unit root test's null hypothesis for these two non-stationary variables is rejected at a critical value of 95%. (5 percent level) Therefore, there is substantial evidence that these two series are integrated into order one based on the IPS test. Given the findings of the IPS tests, the autoregressive distributed lag model (ARDL) is used to identify both short- and long-term associations since all variables are not cointegrated in the same order.

**Cointegration Result**

We must execute a panel cointegration test to see whether the ARDL (p,q,n,m) model contains a stable long-run relationship. Pedroni (1999) is used to determine whether long-run steady-state or cointegration exists between the variables, and Table 4 shows that at a constant plus trend level, 1 out of 7 statistics reject the null hypothesis, indicating that no cointegration exists at the 1, 5, and 10% level of significance. Because all statistics rule out cointegration, we conclude that there is no long-run cointegration among variables in South Asian nations, and Pedroni's panel non-parametric (t-statistic) and parametric (ADF-statistic) statistics are more trustworthy in constant plus time trend.

Table 4. The Pedroni Panel Cointegration Test.

| *Test* | *Constant* | *Constant + Trend* |
|---|---|---|
| Panel *v*-Statistic | -1.32 (0.90) | 5.14 (0.00***) |
| Panel *ρ*-Statistic | 1.14 (0.87) | 1.43 (0.92) |
| Panel *t*-Statistic: (non-parametric) | 1.21 (0.89) | .68 (0.76) |
| Panel *t*-Statistic (*adf*): (parametric) | 0,89 (0.81) | .52 (0.70) |
| Group *ρ*–Statistic | 2.02 (0.98) | 2.56 (0.99) |
| Group *t*-Statistic: (non-parametric) | 1.54 (0.94) | 1.66 (0.95) |
| Group *t*-Statistic (*adf*): (parametric) | 0.98 (0.84) | 1.48 (0.94) |

Source: Author's estimation from WTO and CCKP data

*Note:* ***, ** and * indicate rejection of the null hypothesis of no-co-integration at 1% and 5%, and 10% levels of significance.

Therefore, it is impossible to draw a long-term link between the dependent and independent variables from this data set. If all the variables are not integrated in the same order and if there is no cointegration among the variables, then we can use the ARDL model to find out the short-term and long-term relationship between climate and employment in agriculture. We then run the ARDL model to see if climate change has an influence on agricultural employment.

**Estimation of Short and Long-run Coefficient**

Based on the Akaike information criterion (AIC) in Appendix 3, the best way to explain the model is ARDL (2, 2, 2), where the second minimum penalty exists, and it fits the data with minimum information loss. Based on the model of pooled mean group estimation, the result of the estimation is presented in Table 5, where there is the steady-state long-run relationship, the coefficient of long-run convergence is significant at a 1 percent significance level, and the long-run impact of climate change and GDP per capita is significant at a 1 percent and 10 percent significant level, which is negative by direction. But in the short run, the coefficient of the first lag of Roleplay has a positive impact on agriculture employment, which means that employment in the past year has positively affected current employment in the agriculture sector.

In the short run, rainfall is seen to have a positive impact on Agro-employees, but this result proves insignificant. But the finding is also true for GDP, which has a negative and significant impact on employment in the short run. However, the result indicates temperature has a positive impact on agricultural employment. This creates a contradiction between the short run and the long run. One interpretation is that even though the temperature has a positive short-term effect, it is perceived as a large amount of irregularity over the long term; as a result, if the temperature is erratic and more or less than expected, it must have a negative long-term effect. In the long run, these two variables' test coefficients are statistically different from zero, bearing the evidence that GDP per capita and temperature have a causal effect on agriculture employment.

Table 5. Baseline estimation ARDL (2,2,2,2).

| *Variables* | *The long-run impact on D(Agro_employ)* | *The short-run coefficient on D(Agro_employ)* |
|---|---|---|
| Convergence coefficient | -0.1367(0.0064***) | |
| GDPPC | -0.0045 (0.0000***) | |
| TEM | -3.0263 (0.0691*) | |
| RAIN | -0.0042 (.2018) | |
| D(Agro_employ(-1) | | 0.4635 (.0025***) |
| D(GDPPC) | | -0.0002 (0.8093) |
| D(GDPPC (-1)) | | -0.0017 (0.4217) |
| D(TEM) | | 0.5051 (0.0676*) |
| D(TEM (-1) | | .6712 (0.0094**) |
| D(RAIN) | | 0.0010 (0.1030) |
| D(RAIN (-1) | | 0.0011 (0.2664) |

Source: Author's estimation from WTO and CCKP data
Note: *** and ** and * significant with 99% and 95%, and (90%) confidence level

PMG is assumed long-run homogeneity among the country but short-run heterogeneity. Short-run results would be different from country to country due to different economic policies taken by each country. Table 6 contains, that even though the speed of adjustment is statistically insignificant in the overall result but each county's incentive toward long-run stable value is significant. We can reject the null hypothesis with a 1 per cent significant level of each adjustment coefficient for each country. It means that for a long time, each country is affected negatively by GDP per capita and temperature.

Table 6. Long-run convergence of each country.

| *Country* | *Coefficient of adjustment* |
|---|---|
| Afghanistan | 0.06 (0.02***) |
| Bangladesh | -0.03 (0.00***) |
| Bhutan | -0.32 (0.00***) |
| India | -0.03 (0.00***) |
| Nepal | -0.03 (0.00***) |
| Pakistan | -0.18 (0.00***) |
| Sri Lanka | -0.31 (0.01***) |

Source: Author's estimation from WTO and CCKP data
Note: ***,** and * significant with 99%, 95% and 90% confidence level

**DISCUSSION**

South Asia is a region that is heavily dependent on agriculture, making it vulnerable to the effects of climate change because it lowers agricultural production. The study's findings confirm the widely held belief that, over time, the effects of climate change on agriculture employment are negative. In this study, the annual patterns of rainfall and temperature have been irregular. The rising air temperature and the rising tendency in the intensity and frequency of extreme events characterize the temperature variability in South Asia (Sivakumar *et al*., 2010). Rainfall has been erratic, falling substantially during the monsoon season and less so during the dry season (Mirza, 2011). As a result, the productivity of agriculture may be significantly impacted by temperature and rainfall. Numerous studies on the effects of climate change on agricultural employment have been conducted in each nation. Even if the study emphasizes the temperature's long-term effects, the remaining rainfall has been deemed insignificant. In addition, the study sought to determine the short-term effects of climate change but found none, even if it discovered long-term effects. There might be both micro-level studies and country-level studies identified to establish the short-term impact on One study conducted in Bangladesh shows the impact of climate change on agricultural productivity (Iqbal *et al*., 2015). There is scope for a micro-study of other countries.

**CONCLUSION**

Science has confirmed that climate change is real and not just a myth. The world temperature is increasing every day, and the world is more than warmer than the pre-industrial level (World Bank, 2013). Climate change has caused regular droughts, sea level rise, and river erosion in South Asia. Additionally, as a result of global warming, the intensity of saline intrusion into farmlands in coastal areas is increasing. Agriculture and natural resources are extremely important to South Asian nations. As a result of the rising temperature, the expected climate for agricultural output is disrupted, which has an impact on it. Agriculture employment is therefore impacted by agricultural production. In addition, climate change results in both heavy and irregular rainfall, and in south Asia, the severity and frequency of floods and flash floods have already increased. Employment in agriculture is impacted by unpredictable rainfall since agriculture output depends on expected rainfall and the necessary amount of rain to increase overall production.

Since climate change and global inequality remain the foremost problems in the 21st century, we must tackle them with the utmost sincerity. Moreover, being a junction of developing countries, South Asia needs special treatment for adaptation and mitigation policies. Because, like other developing countries, the agricultural sector in South Asian countries dominates its leading economic indicators. So, to keep agriculture production growing, farmers have to follow the adaptation method to mitigate the effects of climate change. The two methods that are most frequently used to combat climate change are locally led adaptation (LLA) and nature-based solutions (NbS). LLA is the framework for collaboration among the various stakeholders, including governments, donors, civil society organizations, and private sector organizations, to identify, prioritize, plan, carry out, assess, and learn from adaptation measures to combat climate change. NbS is on the other side, reducing carbon emissions by planting diverse mangrove trees, shifting from using fossil fuels to renewables, and improving eco-friendly technology.

**LIMITATIONS AND FURTHER RESEARCH**

A drawback of this study is the inability to find a statistically significant relationship between rainfall and agricultural employment. Additionally, rainfall has no effect on employment in agriculture in the short run, whereas temperature has a positive effect. But in the long run, the temperature has a negative impact. There is a contrast between the short run and the long run. Microdata can be used to form short-term relationships and could solve the short- and long-run contrast. The benefit of the microdata is that, rather than focusing on the overall situation in South Asia, it shows how the impact of climate change on agricultural employment varies for each country.

As climate variables, only temperature and rainfall were used in this study. Sunshine and humidity are additional significant climate variables that might be included in future research to better understand the effects of climate change in particular. The econometric approach might also be a future study topic; later studies could use mean group estimation (MG) rather than pooled mean group estimation (PMG).

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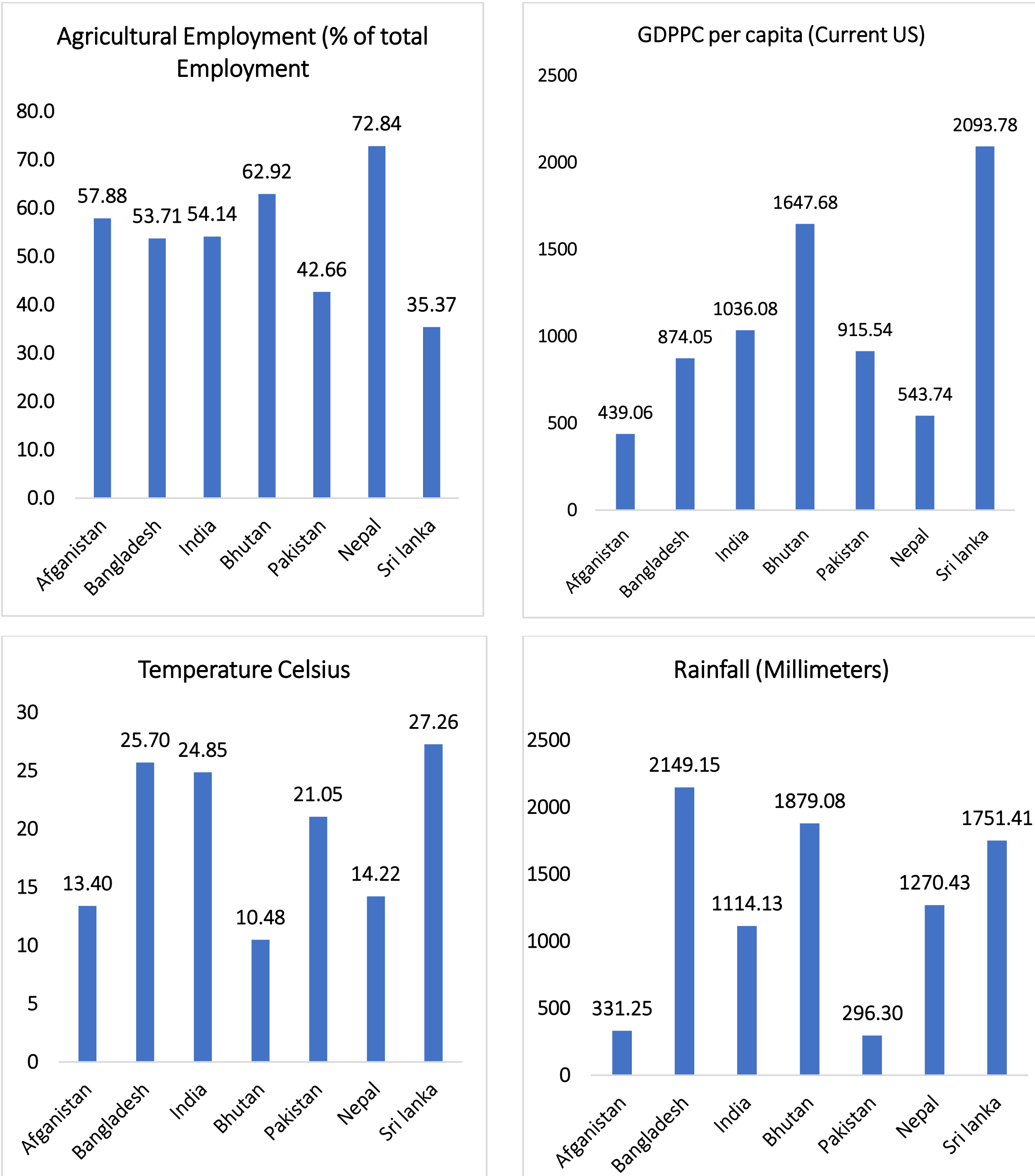
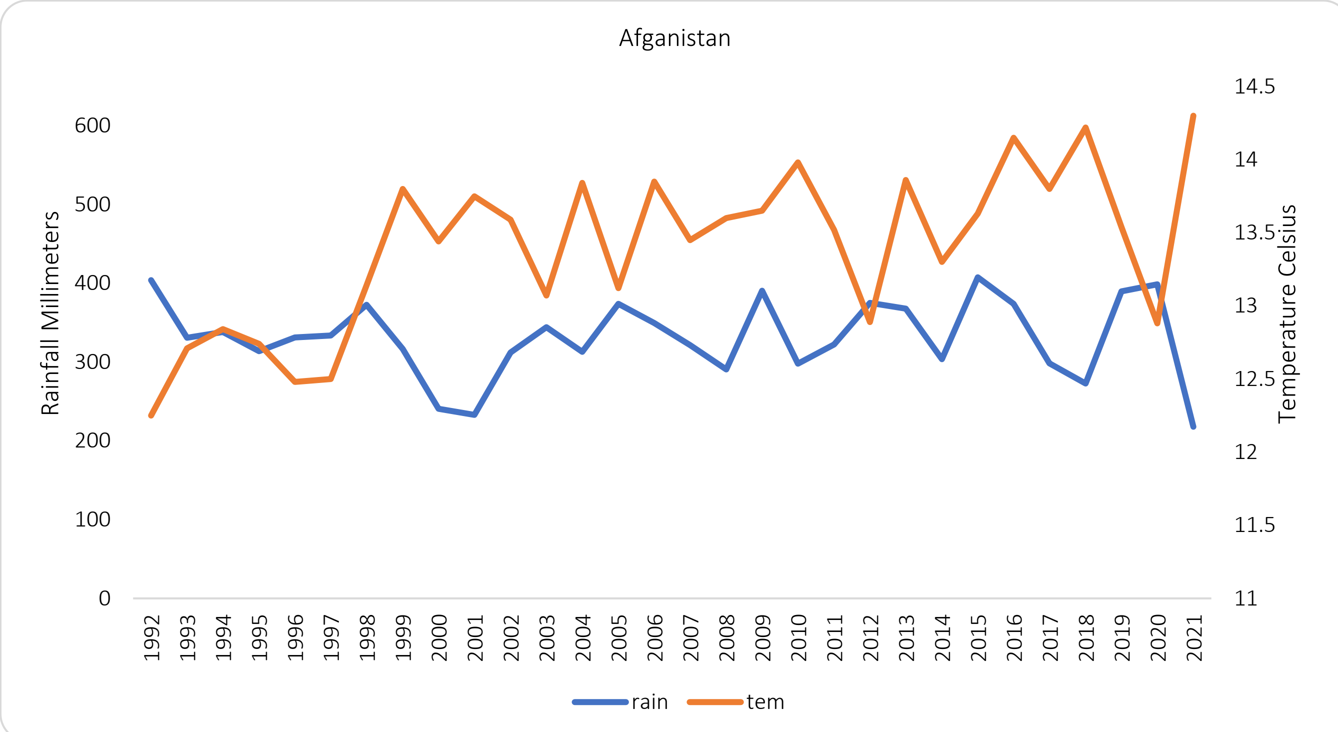
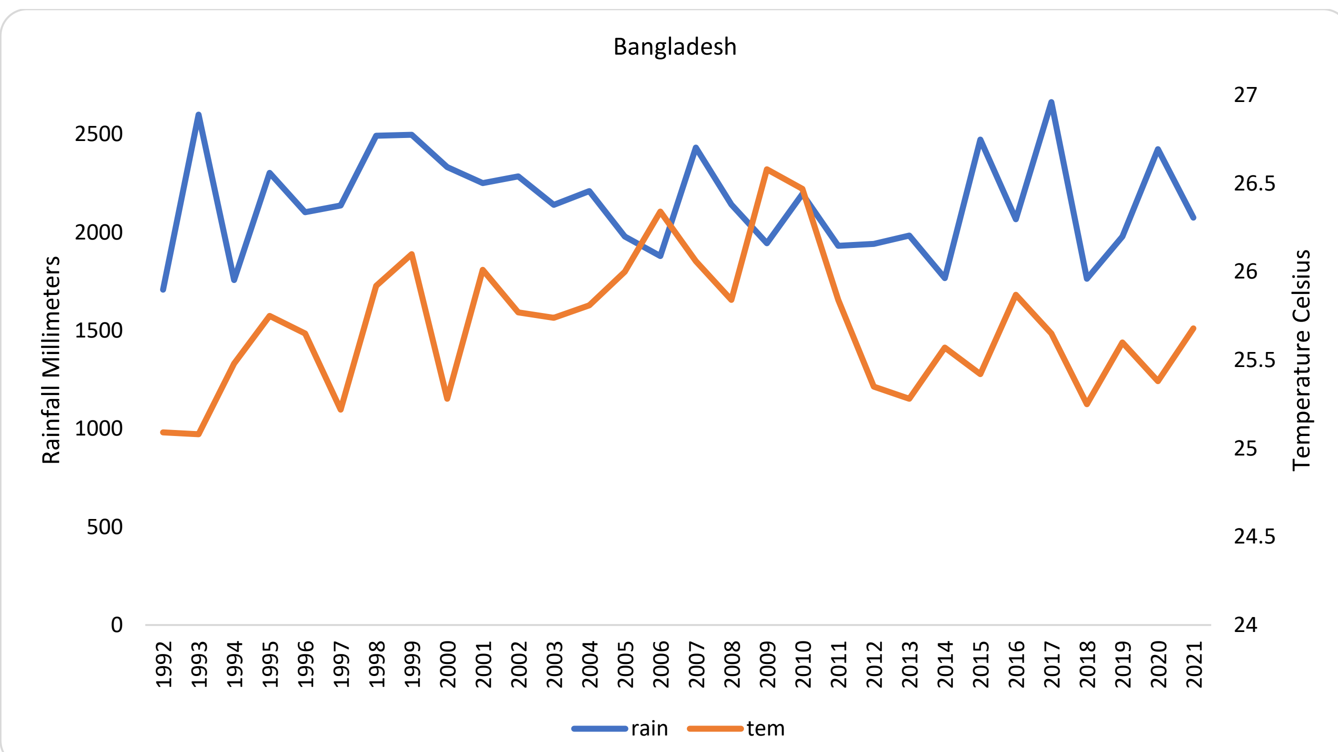
Appendix 1. Mean of the variables among the countries.



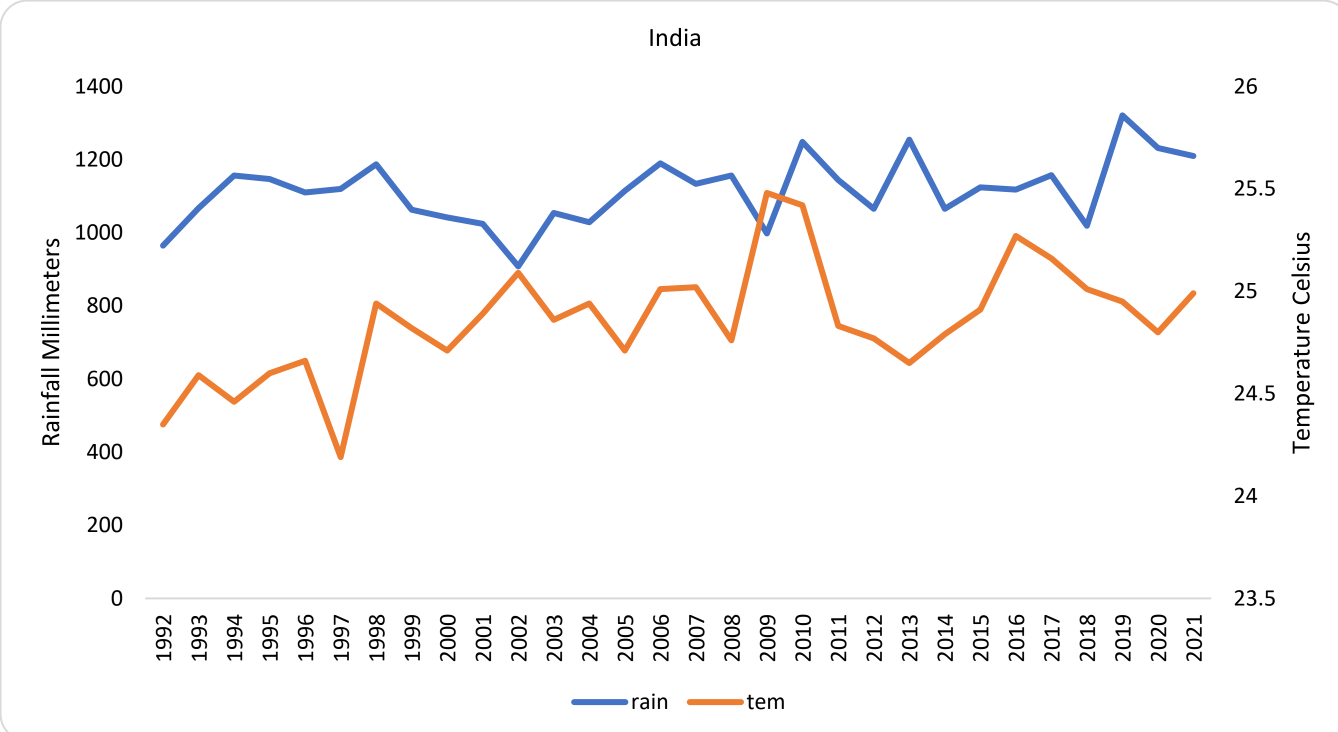
Appendix 2(a). Trend among rainfall, temperature, and Agricultural employment.



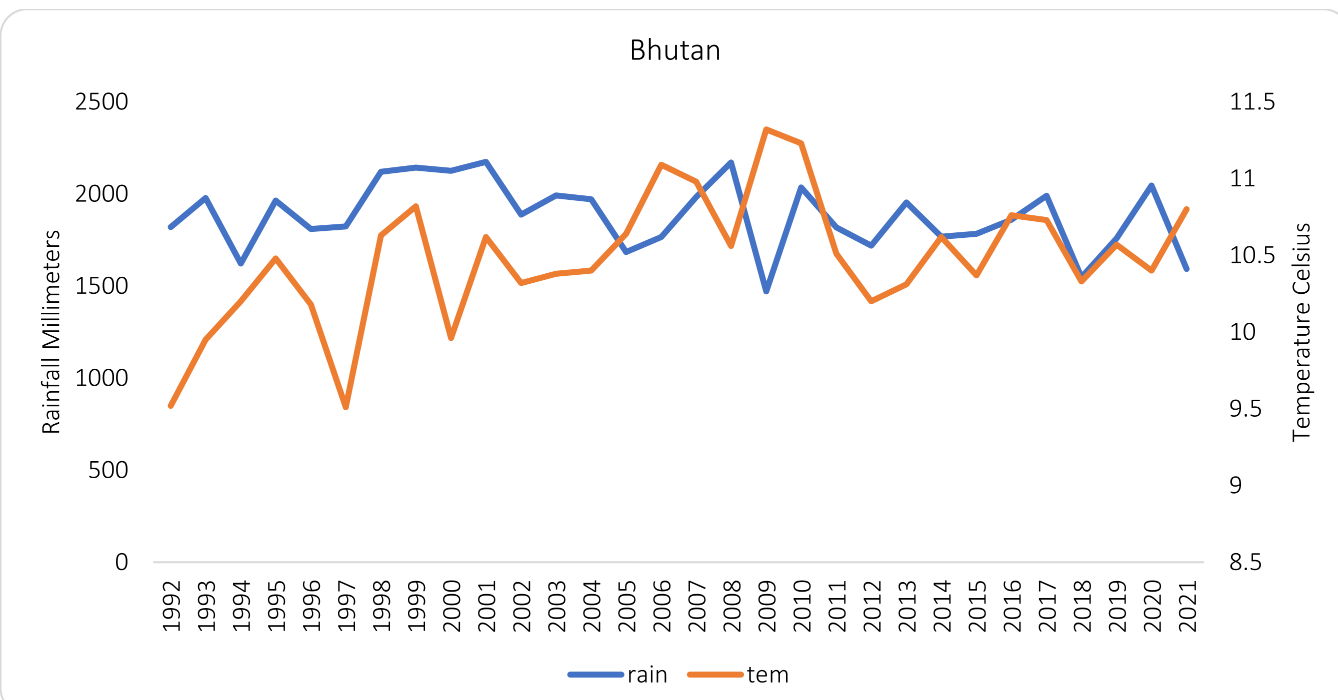

Appendix 2(b). Trend among rainfall, temperature, and Agricultural employment.



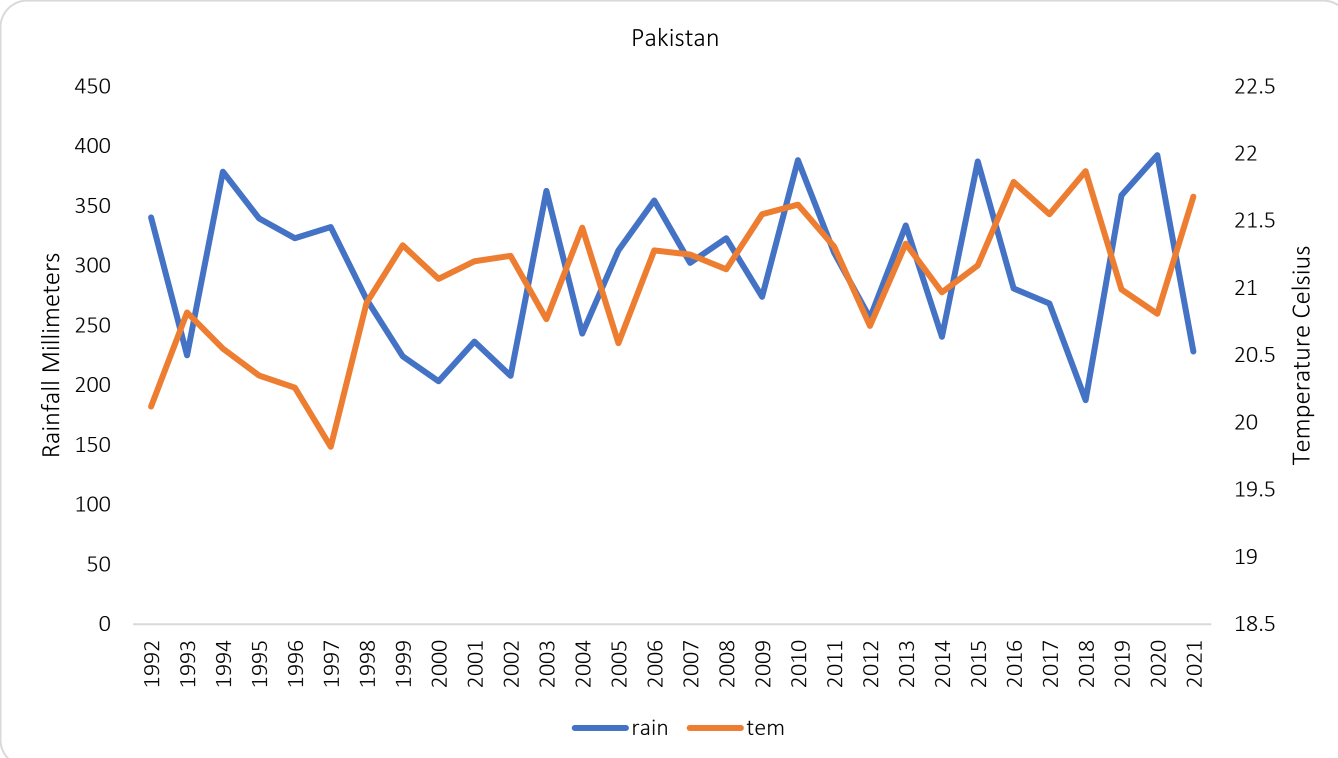
Appendix 2(c). Trend among rainfall, temperature, and Agricultural employment.



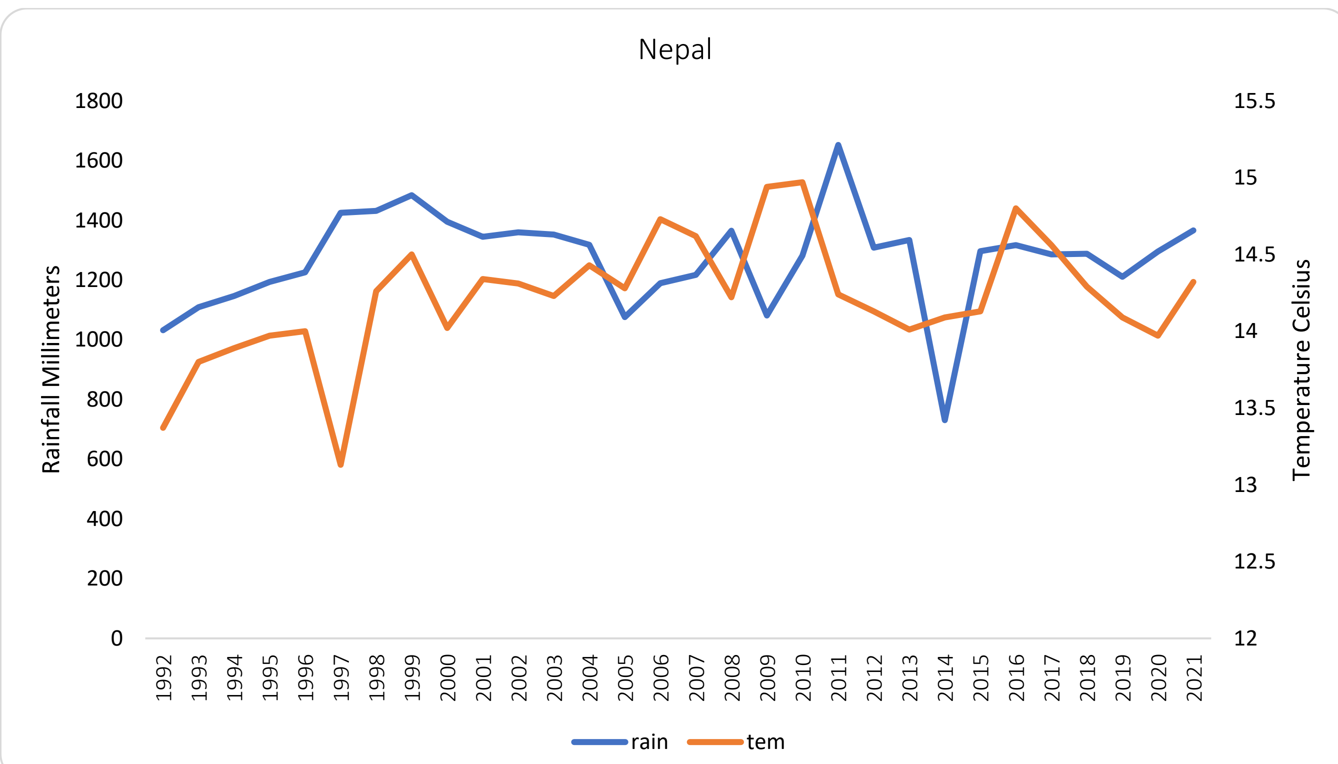

Appendix 2(d). Trend among rainfall, temperature, and Agricultural employment.



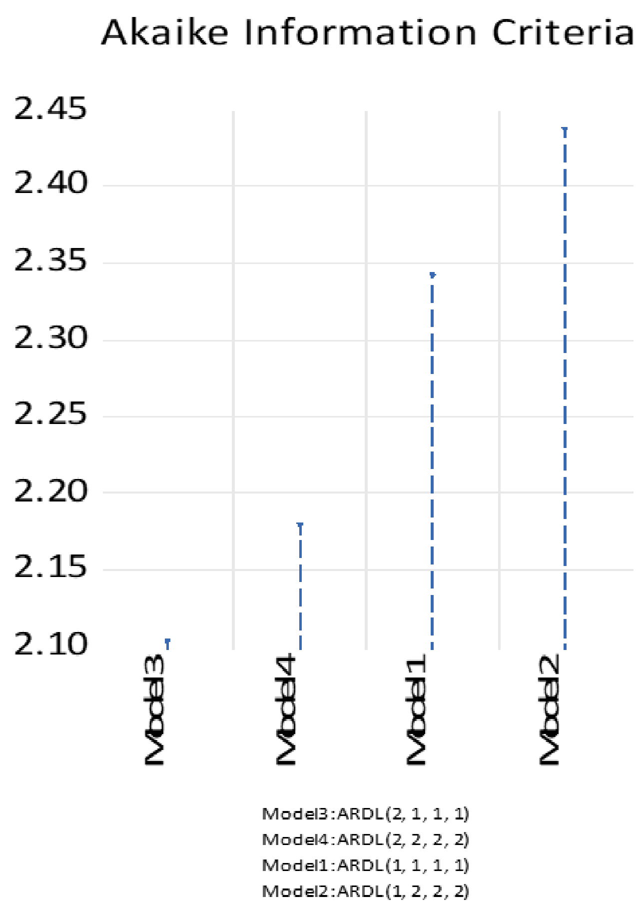
Appendix 2(e). Trend among rainfall, temperature, and Agricultural employment.




Appendix 2(e). Trend among rainfall, temperature, and Agricultural employment.



Appendix 3. Model selection.

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