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RESEARCH ARTICLE

Auto-Regressive Distributed Lag Model on Climate Change Impact on Outmigration in Nepal

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ABSTRACT

Climate change exacerbates Nepal's exposure to environmental hazards like landslides, floods, and droughts, which degrade agricultural productivity and drive forced displacement, particularly from rural areas to cities and overseas. This study investigates the interplay of climatic variables (maximum/minimum temperatures, rainfall) and economic indicators (paddy yield, GDP per capita) on human outmigration from 1993 to 2021. Employing time-series analyses, including augmented Dickey-Fuller tests for stationarity, correlation matrices, autoregressive distributed lag (ARDL) models, and error correction mechanisms, we disentangle long- and short-term dynamics. Long-term findings reveal significant relationships (5 percent level) between outmigration and both current and lagged GDP per capita, lagged maximum temperature, lagged rainfall, and lagged migration rates, highlighting delayed climatic impacts and persistent economic influences. Short-term analyses identify GDP per capita (5 percent significance) and prior migration trends (10 percent significance) as immediate drivers, emphasizing path dependency in migration decisions. Granger causality tests demonstrate unidirectional links: minimum temperature Granger-causes outmigration, GDP per capita influences maximum temperature, and paddy yield affects both minimum temperature and GDP per capita (all 5 percent significance). These results underscore the dual pressures of economic precarity and climatic stressors, where declining agricultural productivity and erratic weather patterns synergistically exacerbate migration. The study advocates for integrated policy

KEYWORDS: Outmigration, climate change, rainfall, maximum-temperature, minimum-temperature

INTRODUCTION

Climate change is a global phenomenon that affects people, their livelihoods, and the whole ecosystem (Hornsey et al., 2016). There is growing consensus among scholars and policymakers that climate change is becoming a major driver of human migration worldwide (Eickemeier et al., 2019; Kniveton et al., 2011). Projections from the Intergovernmental Panel on Climate Change (IPCC) indicate that by 2050, changing rainfall patterns and increasing temperature, along with flooding, droughts, and salinity, will possibly decline rice by 8 percent and wheat production by 23 percent against 1990 baseline production values (Reay et al., 2007). The IPCC has identified human migration as one of the most severe consequences of climate change, estimating that up to 200 million people may be displaced due to environmental factors by 2050 (IPCC, 2022).

Developing countries with agriculture-dependent economies are particularly vulnerable to these climate impacts due to their limited adaptive capacity and geographic exposure (Beine & Parsons, 2017). Climate change exacerbates existing socioeconomic vulnerabilities that drive migration decisions (Haas, 2021). Research from Tajikistan demonstrates how seasonal weather variations influence migration patterns, with winter temperatures and precipitation levels showing particularly strong effects on household migration decisions (Murakami, 2020).

In South Asia's mountainous regions, climate change poses severe risks to communities relying on weather-dependent livelihoods (Tiwari & Joshi, 2012). Multiple factors including small landholdings, low agricultural productivity, poor infrastructure, and geographic isolation compound these vulnerabilities ; (Giribabu ; 2021; Hussain et al., 2018). Environmental changes can lead to livelihood losses that force migration at the household level, with some members relocating while others remain (Stojanov et al. 2016).

Nepal provides a compelling case study of these dynamics. Research using time-series data from 1971-2014 found rainfall patterns significantly affect rice yields, with a unidirectional Granger causal relationship between these variables (Devkota & Paija 2020). The country has experienced dramatic growth in labor migration, with remittances now accounting for 29 percent of GDP (World Bank, 2016).. Climate impacts on agriculture - including production instability and food insecurity - serve as key migration drivers through both immediate displacement and gradual economic pressures (Rizal et al., 2022).

Nepal faces disproportionate climate impacts due to elevation-dependent warming in the Hindu Kush Himalayas, where temperatures rise faster than global averages (Karki et al., 2017; IPCC, 2022). Observed warming rates of 0.056°C/year exceed the global mean (0.03°C/year), with models projecting intensification of this trend (Karki et al., 2021) While precipitation changes remain uncertain, extreme rainfall events have increased 26 percent since 1980 (Bhattacharjee et al., 2017) causing soil erosion (24-63 tons/ha annually) and crop losses (up to 30 percent in monsoon seasons) (Regmi et al., 2022; Karki et al., 2021) Concurrently, meteorological records indicate a 40 percent rise in consecutive dry days (CDD) since 1990, prolonging droughts that compound agricultural risks (Thapa, 2021:Singh et al., 2011).

Climate change has emerged as a key driver of declining agricultural productivity in Nepal, significantly influencing migration patterns as households seek alternative livelihoods. Temperature rises have been observed across most districts (over 90 percent) and all physiographic regions, with seasonal variations. Notably, winter temperatures in most Tarai districts have remained an exception (NSO, 2021).

The warming trend follows an altitudinal gradient, increasing from south to north, mirroring post-monsoon maximum temperature trends. This uneven warming disproportionately affects agriculture—Nepal's economic backbone. District-level variations are severe with Manang experiencing the highest warming rate (0.092°C/year) and Parsa the lowest

(0.017°C/year). These climatic shifts threaten food security and rural incomes, compelling many to migrate in search of viable livelihoods (Rizal et al., 2022:NSO, 2021)

The 2021 census recorded 9.3 million migrants, including 904,318 international migrants, with climate-related factors (agricultural stress and disasters) accounting for 4.6 percent of movements .

LITERATURE REVIEW

Theoretical Review

This study explores the causal linkages among climatic variables (such as maximum and minimum temperatures and rainfall), economic indicators (including paddy yield and GDP per capita), and out-migration, drawing on a blend of theoretical perspectives. The framework incorporates:

1. Migration Theories (Lee's Push-Pull Theory and Stark's New Economics of Labor Migration) to analyze the underlying drivers of migration decisions.
2. The Ricardian Approach to evaluate the linkages between climate conditions and agricultural productivity.
3. An ARDL Econometric Model to capture both short-term climate impacts and long-term migration trends, distinguishing between immediate effects and sustained equilibrium dynamics.

The framework presents a dynamic process where climate conditions first influence agricultural production, which in turn affects economic conditions and ultimately affecting migration decisions. It also accounts for feedback loops among these elements over various timeframes. By integrating these theories, the study provides a comprehensive understanding of how environmental changes drive migration through economic channels.

Empirical Review

The study examines the causal relationships between climatic variables (temperature, rainfall), paddy yield, GDP per capita, and outmigration in Nepal. By analyzing time-series data, it aims to clarify how climate shocks influence migration through agricultural and economic pathways, providing insights for policies on climate adaptation and migration management..

The relationship between climate change and human migration has gained significant attention in recent empirical research, with the Auto-regressive Distributed Lag (ARDL) model emerging as a prominent analytical tool. This approach offers distinct advantages in modeling the complex temporal dynamics between climatic variables and migration patterns, particularly in vulnerable developing regions (Pesaran et al., 2001).

Theoretical foundations of climate-migration linkages are well-established in environmental migration literature. The "environmental push" hypothesis suggests that climate stressors disrupt livelihood systems, particularly in agrarian economies, forcing populations to migrate as an adaptive response (McLeman & Hermans, 2021). In South Asian contexts, studies demonstrate that temperature anomalies and rainfall variability significantly impact agricultural productivity, creating economic pressures that manifest in increased out-migration (Ghimire et al., 2019). This relationship appears particularly strong in mountainous regions like Nepal, where climate change has accelerated glacial melt and altered traditional farming systems (Seddon et al., 2016)

Methodologically, the ARDL framework provides several advantages for climate-migration analysis. Unlike traditional cointegration approaches, ARDL can accommodate variables with different orders of integration (I(0) or I(1)), which is particularly valuable when combining stationary climate data with non-stationary migration trends (Pesaran et al., 2001). The bounds testing procedure within ARDL allows for robust identification of long-run equilibrium relationships while simultaneously estimating short-run dynamics (Nkoro & Uko, 2016). This dual capacity is crucial for distinguishing between immediate displacement from climate shocks versus gradual migration responses to sustained environmental changes (Koubi et al., 2016).

Empirical applications of ARDL models have yielded important insights into climate-migration relationships. In the South Asian context, studies reveal temperature increases have a stronger long-term impact on migration than precipitation changes, with estimated elasticities ranging from 0.05 to 0.12 (Call et al., 2017). Research in African contexts demonstrates that drought frequency exhibits greater migration effects than rainfall variability, with nonlinear thresholds in climate impacts (Kumssa & Jones, 2014). Global comparative analyses using ARDL approaches confirm that climate-migration linkages are more pronounced in developing countries with high agricultural dependence (Hoffmann et al., 2020).

Recent methodological advancements have enhanced ARDL applications in this field. The development of nonlinear ARDL (NARDL) models allows for detection of asymmetric climate impacts, where positive and negative climate deviations may have differential migration effects (Shin et al., 2014).

Despite these advances, significant research gaps remain. Few studies have applied ARDL models to examine how climate change interacts with political instability to influence migration. In the study 'The Role of Political Stability, Labor Market and Education on Migration in Sri Lanka, the results of ARDL indicates that unemployment rate, political instability and the existence of violence/terrorism and level of education have a positive and significant impact on net migration whereas wage differential do not have significant impact on it even though it affect the net migration negatively both in the long run and in the short run respectively (Thanabalasingam, 2020). The study "Climate change and migration dynamics in Somalia"captures both short- and long-term dynamics of ARDL model, providing insights into how environmental and demographic factors impact migration in this climate-sensitive region (Mohamed et al., 2024).

There is also limited research employing panel ARDL approaches to compare climate-migration relationships across different ecological zones (Bohra-Mishra et al., 2017). Furthermore, the potential for machine learning techniques to enhance ARDL model specification in climate-migration studies remains largely unexplored.

In context of Nepal Acharya, (2019) used an ARDL approach for finding the contribution of total trade and foreign direct investment on GDP that is the economic growth of Nepal in short run and long run. The result of the study show that foreign trade show the significant role for the economic growth of Nepal.

MATERIALS AND METHODS

Econometric Model

Climate change directly impacts agricultural production, which is linked to migration in rural areas. Changes in temperature and rainfall patterns can cause a decline in the yield of major crops, leading to increased outmigration among Nepali people. The impact of agricultural production on GDP per capita and outmigration was also studied. In a regression model, we analyzed the relationship between yearly outmigration and climatic variables such as maximum temperature (Tm), minimum temperature (Tn), rainfall (Rn), total yearly yield of paddy (Paddy_P), and GDP per capita (GDP). This relationship can be expressed as an equation.

$$M\_out = f(Tm_{t,} Tn_{t,} Rn_{t,} Paddy\_P, GDP) \;............ (1)$$

By expressing all variables in natural logarithm, the association of Out migration with GDP per capita, yield of paddy, and other climatic variables in the form of the econometric model as:

$$Ln\ M\text{-}out=\beta_0+ \beta_1 LnTm_t + \beta_2 LnTn_t + \beta_3 LnRn_t + \beta_4 Ln\ Paddy\_P+ \beta_5 LnGDP+\varepsilon_t \qquad (2)$$

The auto-regressive distributed lag (ARDL) model approach

The ARDL model was selected because the variables are stationary at the level or the first difference. Outmigration is used as a dependent variable for a model, and the climatic variables (maximum temperature, minimum temperature, and rainfall) and economic variables (paddy yield and GDP per capita) are utilized as independent variables. ARDL approach captures the long-run and short-run relationship. The ARDL representation of the equation is expressed as equation (3)

$$\Delta \text{Ln(M-out)} = \beta_0 + \beta_1 \text{ Ln (Tm)}_{t-1} + \beta_2 \text{Ln (Tn)}_{t-1} + \beta_3 \text{ Ln (Rn)}_{t-1} + \beta_4 \text{ Ln (Paddy\_P)}_{t-1} + \beta_5 \text{Ln(GDP\_p)}_{t-1} + \sum_{i=1}^{p} \beta_6 \Delta \text{Ln}(Tm)_{t-i} + \sum_{i=1}^{p} \beta_7 \Delta \text{Ln}(Tn)_{t-i} + \sum_{i=1}^{p} \beta_8 \Delta \text{Ln}(Rn)_{t-i} + \sum_{i=1}^{p} \beta_9 \Delta \text{Ln}(Paddy\_P)_{t-i} + \sum_{i=1}^{p} \beta_{10} \Delta \text{Ln}(GDP\_p)_{t-i} + \epsilon_t \quad (3)$$

Where β_1, β_2, β_3, β_4, β_5 in equation (3) represent long-run elasticity to be estimated and β_6, β_7, β_8, β_9, and β_{10} show short-run elasticity. The first difference notation is denoted by the symbol Δ, the natural logarithm is denoted by Ln, respectively, and p denotes optimal lag length.

Stationary Test (Unit Root Test)

The time series data in which mean and variance are constant, and the covariance does not depend on time, is known as stationary (i.e., no unit root). Otherwise, it is non-stationary (Gujarati, 2004). A time series that is stationary at the level the series will be integrated with order zero that is I(0), and a series that is stationary at the first difference (i.e., $Y_t - Y_{t-1}$), then series will be integrated with order one that is I (1). Mathematically Augmented Dicky-Fuller test, Phillips-Perron Test, and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test are used to find the stationarity of the series.

Augmented Dickey-Fuller (ADF) Test

ADF test is based on the following regression equation:

$$\Delta Yt = \mu + \delta Y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta Y_{t-i} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3a)$$

Where, $\Delta Y_t = Y_t - Y_{t-1}$ (first difference of Y_t)

$$\delta = \alpha - 1,$$
$$\alpha = Coefficient\ of\ Y_{t-1}$$

Here Δ is the first difference operator, k is the optimum number of lags, and ε_t is the pure white noise term. The null hypothesis of the ADF test is H_0: $\delta = 0$, i.e., the time series is non-stationary (has a unit root).

Phillips-Perron (PP) Test

In addition to the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test crosschecks the stationary properties of every time series variable. PP test does not require selecting the level of serial correlation as like ADF, i.e., no need to add a lagged difference term. Hence, the PP test is based on the following regression equation: $\Delta Y_t = \pi Y_{t-1} + \beta_i D_{t-i} + \varepsilon_t$ (4)
Where ε_t is an I(0) with zero mean and D_{t-i} is a deterministic trend component.

Like the ADF test, the null hypothesis of the PP test is H_0: $\pi = 0$, i.e., the time series is non-stationary (has a unit root)

Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) Test

The classical testing framework is sometimes found to be biased toward accepting the null hypothesis (H0). Hence, Kwiatkowsky, Phillips, Schmidt, and Shin (KPSS) have developed another method to test stationarity. In the KPSS test, the null hypothesis is stationary, and the alternative hypothesis is non-stationary. The KPSS test model is as follows:

$Y_t = X_t + \varepsilon_t$ and $X_t = X_{t-1} + u_t$ ………… (5)

The hypothesis is tested for u_t in the model. In KPSS, the critical value is derived using Lagrange Multiplier (LM) test statistics.

Long-run and Short-run Relation

In the field of applied econometrics, various techniques have emerged to address the challenge of establishing the long-term connection between non-stationary series and transforming them into an Error Correction Model (ECM). (Granger, 1981; Engle et al., 1987) introduced the Autoregressive Distributed Lag (ARDL) co-integration technique, often called the bound test of co-integration. Additionally,Johansen and Juselius (1990) developed co-integration techniques. These methods have become the go-to approaches for analyzing non-stationary series, ultimately reconfiguring them into the Error Correction Model (ECM). This reconfiguration provides insights into the short-term dynamics and the long-term relationship among the underlying variables.

Granger Causality Method

Granger (1981), developed the relationship between error correction models and co-integration. The theorem explored that error correction models can represent co-integrated series. The Granger causality method is implemented to find the relationship between variables by following a system of various equations. The Granger causality method is utilized to describe the way of association among all variables:

$$\Delta \mathrm{Ln(M\text{-}out)}_t = \alpha_1 + \sum_{i=1}^{p} \alpha_{2i}\, \Delta Ln(M-\mathrm{out})_{t-i} + \sum_{i=1}^{q} \alpha_{3i}\, \Delta Ln(Tm)_{t-i} + \sum_{i=1}^{r} \alpha_{4i}\, \Delta Ln(Tn)_{t-i} + \sum_{i=1}^{s} \alpha_{5i}\, \Delta Ln(Rn)_{t-i} + \sum_{i=1}^{t} \alpha_{6i}\, \Delta \mathrm{Ln}(Paddy\_P)_{t-i} + \sum_{i=1}^{u} \alpha_{7i}\, \Delta Ln(GDP\_p)_{t-i} + \varepsilon_{1t} \quad \text{.............(6)}$$

$$\Delta \mathrm{Ln}(Tm)_t = \beta_1 + \sum_{i=1}^{p} \beta_{2i}\, \Delta Ln(Tm)_{t-i} + \sum_{i=1}^{q} \beta_{3i}\, \Delta Ln(\mathrm{M-out})_{t-i} + \sum_{i=1}^{r} \beta_{4i}\, \Delta Ln(Tn)_{t-i} + \sum_{i=1}^{s} \beta_{5i} \Delta Ln(Rn)_{t-i} + \sum_{i=1}^{t} \beta_{6i}\, \Delta Ln(Paddy\_P)_{t-i} + \sum_{i=1}^{u} \beta_{7i}\, \Delta Ln(GDP\_p)_{t-i} + \varepsilon_{2t} \quad \text{.............(7)}$$

$$\Delta \mathrm{Ln}(Tn)_t = \gamma_1 + \sum_{i=1}^{p} \gamma_{2i}\, \Delta Ln(Tn)_{t-i} + \sum_{i=1}^{q} \gamma_{3i}\, \Delta Ln(M-out)_{t-i} + \sum_{i=1}^{r} \gamma_{4i}\, \Delta Ln(Tm)_{t-i} + \sum_{i=1}^{s} \gamma_{5i}\, \Delta Ln(Rn)_{t-i} + \sum_{i=1}^{t} \gamma_{6i}\, \Delta Ln(Paddy\_P)_{t-i} + \sum_{i=1}^{u} \gamma_{7i}\, \Delta Ln(GDP\_p)_{t-i} + \varepsilon_{3t} \quad \text{.........................(8)}$$

$$\Delta Ln(Rn)_t = \delta_1 + \sum_{i=1}^{p} \delta_{2i}\, \Delta Ln(Rn)_{t-i} + \sum_{i=1}^{q} \delta_{3i}\, \Delta Ln(M-out)_{t-i} + \sum_{i=1}^{r} \delta_{4i}\, \Delta Ln(Tm)_{t-i} + \sum_{i=}^{s} \delta_{5i}\, \Delta Ln(Tn)_{t-i} + \sum_{i=1}^{t} \delta_{6i}\, \Delta Ln(Paddy\_P)_{t-i} + \sum_{i=1}^{u} \delta_{7i}\, \Delta Ln(GDP\_p)_{t-i} + \varepsilon_{4t} \quad \text{..........................(9)}$$

$$\Delta Ln(Paddy\_P)_t = \theta_1 + \sum_{i=1}^{p} \theta_{2i}\, \Delta Ln(Paddy\_P)_{t-i} + \sum_{i=1}^{q} \theta_{3i}\, \Delta Ln(M-out)_{t-i} + \sum_{i=1}^{r} \theta_{4i}\, \Delta Ln(Tm)_{t-i} + \sum_{i=1}^{s} \theta_{5i}\, \Delta Ln(Tn)_{t-i} + \sum_{i=1}^{t} \theta_{6i}\, \Delta Ln(Rn)_{t-i} + \sum_{i=1}^{u} \theta_{7i}\, \Delta Ln(GDP\_p)_{t-i} + \varepsilon_{5t} \quad \text{.....................(10)}$$

$$\Delta Ln(GDP\_p)_t = \mu_1 + \sum_{i=1}^{p} \mu_{2i}\, \Delta Ln(GDP\_p)_{t-i} + \sum_{i=1}^{q} \mu_{3i}\, \Delta Ln(M-out)_{t-i} + \sum_{i=1}^{r} \mu_{4i}\, \Delta Ln(Tm)_{t-i} + \sum_{i=1}^{s} \mu_{5i}\, \Delta Ln(Tn)_{t-i} + \sum_{i=1}^{t} \mu_{6i} \mathrm{Ln}\, (Rn)_{t-i} + \sum_{i=1}^{u} \mu_{7i}\, \Delta Ln(Paddy\_P)_{t-i} + \varepsilon_{6t} \quad \text{.....................(11)}$$

Data and Sources

The paper empirically examines the correlation and causality of Out-migration from Nepal with paddy yield, gross domestic product (GDP) per capita, and climatic events (maximum temperature, minimum temperature, and rainfall) for the years 1993–2021. The years were chosen according to the availability of data. This study examines the relationship between them. The data were obtained from the World Bank data portal (CCKP) and the Ministry of Agricultural Development (MoAD) Nepal.

The maximum temperature, minimum temperature, and rainfall are the major climatic events that are directly related to various hazards like drought, flood, and landslides. In Nepal, the pattern of rainfall and temperature is observed to be changeable, directly impacting cereal crop production. Paddy is the first prominent food grain in Nepal. Most Nepalese people consume rice as their main food. Paddy yield per hectare is obtained by dividing the total paddy production by the total cultivated areas. The production of major crops like paddy directly impacts the GDP per capita of the people. There is a change in the amount, intensity, and time of rainfall. Figure 1 presents the graph of climatic variables, including maximum temperature, minimum temperature, and rainfall sum. Figure 2 presents the yearly production of paddy yield in Kg per hectare and the outmigration trend of Nepal from 1993 to 2021.

Figure 1

Graphs of Yearly Maximum, Minimum, and Rainfall-sum of Nepal

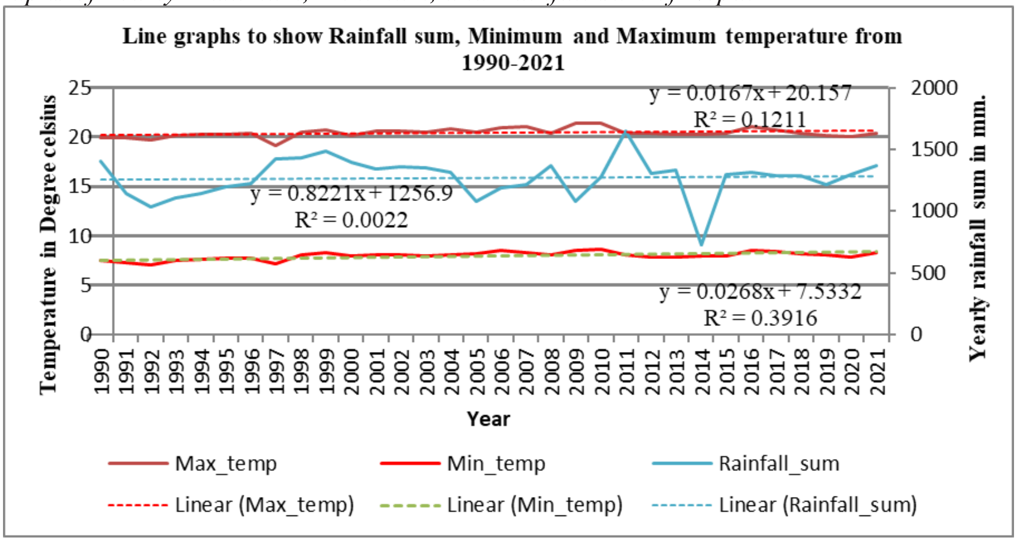
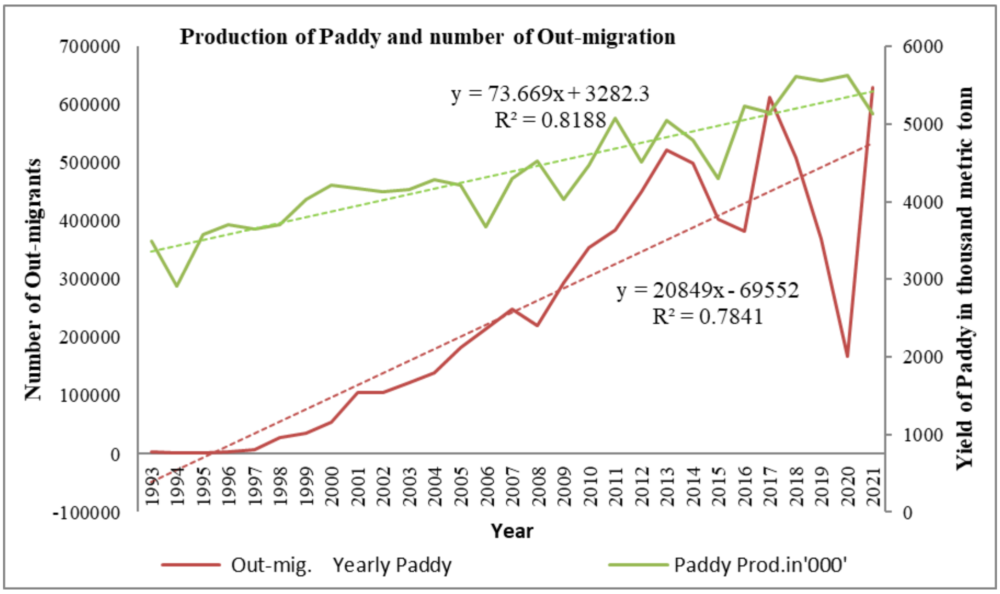


Figure 1 also reveals that the year 2020 show the fewest out migrations, which was due to the COVID-19 pandemic.

Figure 2

Graphs of Yearly Paddy Production in Metric Tons and Number of Outmigration from Nepal



RESULTS

The results of descriptive statistics are shown in Table 1, which describes that the average of total yearly outmigration (M_{out}) is 243,179, having a standard deviation of 200,471.04, the mean value of maximum temperature (T_{max}) is 20.49 °C, and a standard deviation is 0.43°C, mean value of minimum temperature (T_{min}) is 8.05°C with standard deviation 0.34°C, and mean annual rainfall is 1,278.65 mm with a standard deviation 161.75 mm. Similarly, the results of Jarque–Bera and probability state residuals M_{out}, Yearly paddy production (Padyp), and T_{min} are not normally distributed. In contrast, the other variables T_{max} and Rainfall are normally distributed.

Table 1

Descriptive Statistics of Variables

Statistics	T_{Min}	T_{max}	Rain	GDP/c	Pady_ yield	M_{Out}	Ln_ Tmn	Ln Tmx	Ln_ Rn	Ln_ MOut	LnPady_ yield	Ln_ GDP
Minimum	7.12	19.18	730.66	172	2124	2134	1.96	2.95	6.59	7.67	7.66	5.15
Maximum	8.64	21.43	1652.36	1208	3820	630089	2.16	3.06	7.41	13.35	8.25	7.10
1. Quartile	7.89	20.27	1211.17	224	2598	55025	2.07	3.01	7.10	10.92	7.86	5.41
3. Quartile	8.26	20.69	1360.19	828	3360	384665	2.11	3.03	7.22	12.86	8.12	6.71
Mean	8.05	20.49	1278.65	547.76	2956	243179	2.08	3.02	7.14	11.58	7.98	6.08
Median	8.07	20.41	1296.88	387	2782	214094	2.09	3.02	7.17	12.27	7.93	5.96
Std-dev	0.34	0.43	161.75	365.85	487.93	200471	0.04	0.02	0.14	1.81	0.163	0.70
Skewness	-0.44	-0.25	-0.96	0.543	0.42	0.36	-0.58	-0.37	-1.83	-1.09	0.175	0.16
Kurtosis	0.23	-1.66	2.91	-1.323	2.08	-1.23	0.48	1.88	5.59	-0.22	-1.078	-1.68
J.B.	10.21	-2.47	4.46	24.01	1.86	22.25	9.30	2.18	24.29	18.27	20.24	26.61
Prob.	0.006	0.291	0.108	6.11e-6	0.395	1.5e-5	0.01	0.336	5.0e-6	1.1e-4	4.03e-5	1.67e-6

Also, for the logarithmic values of corresponding climatic events, paddy production, and outmigration, residuals of lnT_{min}, lnRain, lnM_{out}, and lnPadyp through the Jarque–Bera and probability tests were found to be not normally distributed while only lnT_{max} is normally distributed.

For the co-integration test, the data must be stationary at level zero or of the first difference. Then, the stationarity is tested by the ADF method, p-p method, and KPSS method, and the p values are obtained using the R software presented in Table 2.

Table 2

Results of ADF, P-P, and KPSS Unit Root Tests

	ADF	PP	KPSS
Levels I(0)			
Ln_Mout	0.30	0.91	0.01
Ln_TMax	0.62	0.02	0.10
Ln_TMin	0.50	0.08	0.04
Ln_Rain	0.09	0.01	0.10
Ln_Yld_P	0.49	0.02	0.01
Ln_GDP	0.50	0.77	0.01
First difference			
ΔLn_Mout	0.01	0.01	0.1
ΔLn_TMax	0.01	0.01	0.1
ΔLn_TMin	0.01	0.01	0.1
ΔLn_Rain	0.01	0.01	0.1
ΔLn_Yld_P	0.01	0.01	0.1
ΔLn_GDP	0.02	0.02	0.1

The unit root tests indicated that the series is not stationary at a level I (0) but stationary at the first integration I (1) by all three methods. Hence, we can use the Johansen Co-integration test to check the co-integration of the variables. This study also performs the correlation matrix to investigate the correlation between the variables. The correlation matrix is presented in Table 3

Table 3

Correlation Matrix of Climatic Variables–Migration, GDP, and Yearly Paddy Production

	Ln_Out_Mig	LnT_Mx	LnT_Mn	Ln_Rn	Ln_Yld_P	Ln_GDP
Ln_Out_Mig	1.000					
LnT_Mx	0.399	1.000				
LnT_Mn	0.668	0.862	1.000			
Ln_Rn	0.011	-0.069	0 . 045	1.000		
Ln_Yld_P	0.802	0.040	0.379	0.033	1.000	
Ln_GDP	0.802	0.102	0.408	-0.056	0.944	1.000

Table 3 indicates that there exists a case of multi-collinearity between certain pairs of variables. To eliminate the multi-collinearity between minimum and maximum temperature as well as between GDP and yield of paddy, we consider only four variables out-migration, maximum temperature, rainfall, and GDP to remove multicollinearity and correlation matrix obtained by using Micro fit 5.5 software is given in Table4.

Table 4

Correlation Matrix of Variables from 1993 to 2021

	Ln_Out_Mig	LnT_Mx	Ln_Rn	Ln_GDP
Ln_Out_Mig	1.000			
LnT_Mx	0.399	1.000		
Ln_Rn	0.011	-0.069	1.000	
Ln_GDP	0 .802	0.102	-0.056	1.000

The output of the correlation matrix indicated that all the variables positively correlate with outmigration. The maximum temperature is negatively associated with the rainfall sum, which is also negatively associated with GDP per capita. Outmigration and GDP are highly associated compared to other pairs of variables, while rainfall has a very low degree of positive correlation with outmigration in Nepal.

The moderate positive correlation between LnT_Mx and Ln_out_Mig suggest that higher temperatures are associated with increased out-migration. This could imply that extreme heat may drive people to migrate, possibly due to reduced agricultural productivity or livability.Rainfall does not appear to have a meaningful linear relationship with out-migration in this dataset.The strong positive correlation between Ln_GDP and Ln_Out_Mig (0.802) Indicates that higher GDP is strongly associated with increased out-migration. This might seem contradicttory (as higher GDP often reduces emigration), but this can be justified as:

- Economic growth enabling more people to afford migration
- GDP growth being driven by remittances from migrants
- Various structural changes like urbanization leading to migration despite GDP growth.

Table 5 shows the lag selection criteria based on AIC, ,RQ, SC, and FPE for further cointrgration test.

Table 5

Lag Selection Criteria

Lag	1	2	3	4	5
AIC	-19.642	-19.254	-20.943	NaN	-Inf*
HQ	-19.473	-18.951	-20.051	NaN	-Inf*
SC	-18.647	-17.464	-18.358	NaN	-Inf*
FPE	3.103e-09	6.040e-09	2.726e-09	-3.854e-41*	0

Where, AIC=Akaike Information Criteria, HQ= Hannan-Quinn Information criteria,

SC= Schwartz Information Criteria and FPE= Final Prediction Error

*indicates lag order selection criteria

The maximum lag length of five has been taken because the criteria AIC, HQ, and SC have an optimum lag length of five, while the criteria FPE have an optimum lag length of four. The table indicates that Lag 3 has the lowest AIC (-20.943) and lowest FPE (2.726e-09), suggesting it may be the best choice based on these criteria. But HQ and SC do not strongly favor any lag (HQ is lowest at Lag 3, but SC is lowest at Lag 1). To test the co-integration among the variables, Pesaran et al., (2001) developed the bound test of co-integration using the ARDL test. The table 6 presents the result of the Bounds Test for Cointegration, which checks whether a long-run equilibrium relationship exists between variables in an ARDL model. It also compares an F-statistic against critical values for stationary and integrated of order 1 variables

Table 6

Result of Pesaran, Shin, And Smith (2001) Co-integration Bound Test

F-test	I(0)(Lower bound)	I(1) (Upper bound)
10 percent critical value	3.01	4.15
5 percent critical value	3.71	5.02
1 percent critical value	5.33	7.06
F-statistic = 10.97		

Table 6 indicates that the F-statistic (10.97) exceeds even the 1 percent upper bound (7.06) meaning the evidence is very strong. Hence, there is a statistically significant long-run cointegrating relationship among the variables in the ARDL model. Now the next step is to proceed with ARDL long –run and short-run analysis For this we estimate the long-run coefficients and error correction model (ECM). The long-run relationship is presented in Table 7.

Table 7

Long –run Relationship of ARDL(2, 3, 1, 1) based on Dependent Variable Ln_Out_Mig

Variables	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	51.277	26.724	1.919	0.074	.
L(Ln_Out_Mig, 1)	0.493	0.222	2.218	0.042	*
L(Ln_Out_Mig, 2)	0.363	0.232	1.565	0.138	
LnT_Mx	2.978	3.647	0.817	0.427	
L(LnT_Mx, 1)	-17.318	5.433	-3.187	0.006	**
L(LnT_Mx, 2)	-7.183	4.199	-1.711	0.108	
L(LnT_Mx, 3)	1.830	3.551	0.515	0.614	
Ln_Rn	0.095	0.487	0.194	0.849	
L(Ln_Rn, 1)	1.301	0.511	2.545	0.022	*
Ln_GDP	5.361	1.567	3.421	0.004	**
L(Ln_GDP, 1)	-5.387	1.616	-3.334	0.005	**

Significance codes: ‘ ‘**’ 0.01 ‘ * ‘ 0.05 ‘.’ 0.1

R-Squared	0.966	Adjusted R-Squared	0.943
S.E. of Regression	0.279	F-Stat. F(10,15)	3.442e-09

Table 7 indicates the auto-regressive distributed lag values test of three independent variables (maximum temperature, rainfall, and GDP) that impacted outmigration concerning the selected lag criteria. Based on the obtained values, we found that outmigration at first lag and rainfall at first lag are significant at a five percent level of significance. The model has strong explanatory power (high R^2=0.966,, significant F-statistic=3.442e-09).Temperature and GDP have significant lagged effects on out-migration but rainfall only matters with a 1-year lag. Also GDP's dual effect (immediate increase and delayed decrease) suggests complex economic-migration dynamics. Further the long run coefficients using ARDL approach is preseted in Table 8

Table 8

Estimated Long Run Coefficients using the ARDL Approach

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
Intercept	356.182	390.574	0.912 [0.376]
LnT_Mx	-136.796	144.678	-0.946 [0.359]
Ln_Rn	9.697	9.245	1.049 [0.311]
Ln_GDP	-0.182	1.668	-0.109 [0.915]

Table 8 indicates that in long-term movement, none of the variables (maximum temperature, rainfall, and GDP) have significantly affected outmigration. Hence, based on available data, maximum temperature, and GDP negatively impacted outmigration, but the values are not significant. Rainfall-sum positively impacted outmigration in the long run, but it does not significantly impact outmigration in Nepal in the present. In this condition further analysis of error correction models is needed to confirm whether a stable long-run equilibrium exists.

Table 9

Error Correction ARDL Model (Short Run)

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Remarks
Intercept	51.277	8.391	6.111	8.98E-06	***
dLn_Out_Mig,1	-0.363	0.174	-2.082	0.052	.
dLnT_Mx	2.978	2.707	1.100	0.286	
dLnT_Mx, 1	5.353	3.203	1.671	0.112	
dLnT_Mx, 2	-1.830	3.015	-0.607	0.551	
dLn_Rn	0.095	0.311	0.305	0.764	
dLn_GDP	5.361	1.254	4.274	4.57E-04	***
ect	-0.144	0.024	-6.093	9.31E-06	***

Significant codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Residual standard error: 0.2897 on 18 degrees of freedom

Multiple R^2 : 0.706 Adj,R^2 : 0.592 F-statistic(7, 18) : 6.176 p-value : 0.00086

Table 9 indicates that based on the error correction ARDL model, there are significant short-run dynamics for GDP only at a five percent level of significance, and outmigration of lag one is significant at a ten percent level of significance. (1 percent GDP increase influence 5.36 percent migration increase).The result shows stable adjustment to long run equilibrium. The climatic factors (maximum temperature and rainfall) affect migration through long-run channel. The ECM model explains about 59-71 percent of migration variation.

To determine the cause of one variable to another variable, the most powerful causality test developed by Granger is the most popular in the ARDL model. The Granger causality test is performed between two variables, whether the causality is bidirectional, unidirectional, or no causality at the specified level of significance. The F-value and p-value of each of the hypotheses are presented in Table 10.

Table 10
Granger Causality Test

Null hypothesis	F value	P value
Outmigration does not Granger cause maximum temperature	0.868	0.360
Maximum temperature does not Granger cause outmigration	2.309	0.141
Outmigration does not granger cause rainfall	3.132	0.089
Rainfall does not Granger cause outmigration	0.367	0.550
Outmigration does not Granger cause GDP	0.001	0.975
GDP does not Granger cause outmigration	3.395	0.077
Outmigration does not Granger cause minimum temperature	0.136	0.716
Minimum temperature does not Granger cause outmigration	4.364	0.047*
Maximum temperature does not Granger cause minimum temperature	1.258	0.273
Minimum temperature does not Granger cause maximum temperature	2.039	0.166
Rainfall does not Granger cause maximum temperature	0.529	0.474
Maximum temperature does not granger cause rainfall	0.023	0.881
The yield of paddy does not Granger cause maximum temperature	4.724	0.039*
Maximum temperature does not Granger cause yield of paddy	0.038	0.847
GDP per capita does not Granger cause maximum temperature	35.002	3.564E-06***
Maximum temperature does not Granger cause GDP per capita	0.010	0.920
The yield of paddy does not Granger cause minimum temperature	5.777	0.024*
Minimum temperature does not Granger cause yield of paddy	0.257	0.617
GDP per capita does not Granger cause yield of paddy	0.970	0.334
The yield of paddy does not Granger cause GDP per capita	9.839	0.004**

Table 10 presents a comprehensive set of Granger causality tests examining the directional relationships between migration, climate variables, and economic factors. The key findings reveal several important causal relationships. It indicates that there is no bidirectional causality relation between the variables. The unidirectional causality relation exists significantly at a five percent significance level between minimum temperature and outmigration, maximum temperature and yield of paddy, maximum temperature, minimum temperature and GDP per capita granger cause the yield of the paddy. Other pairs of variables do not have a significant Granger causality relation. This analysis reveals complex interrelationships between climate, agriculture, and migration, with minimum temperatures and agricultural yields emerging as key mediating factors. The results suggest climate impacts on migration operate through indirect pathways rather than direct effects.

Model stability test

As a final step, stability tests have been investigated for the long-run and short-run coefficients.

Stability Tests

1. Breusch-Godfrey test for serial correlation of order up to 1

data: modelFull$model

LM test = 1.0619, df1 = 1, df2 = 11, p-value = 0.3249

2. Ljung-Box Test for the autocorrelation in residuals:

data: res

X-squared = 1.356, df = 1, p-value = 0.2442

3. Breusch-Pagan Test for the homoskedasticity of residuals:

data: modelFull$model

BP = 15.159, df = 12, p-value = 0.2328

4. Shapiro-Wilk test of normality of residuals:

data: modelFull$model$residual

W = 0.94053, p-value = 0.1523

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ(1) = 0.529[0.818]	F(1,14) = 0.030[0.866]
B: Functional Form	CHSQ(1) = 0.786E-3[0.978]	F(1,14) = 0.440E-3[0.984]
C: Normality	CHSQ(2) = 10.620[0.005]	Not applicable
D: Heteroscedasticity	CHSQ(1) = 1.146[0.284]	F(1,23) = 1.105[0.304]

A: Lagrange multiplier test of residual serial correlation

B: Ramsey's RESET test using the square of the fitted values

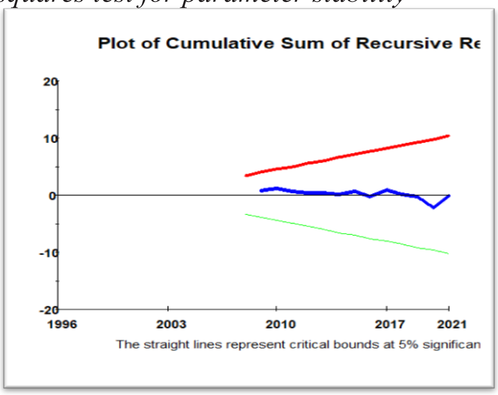
C: Based on a test of skewness and kurtosis of residuals

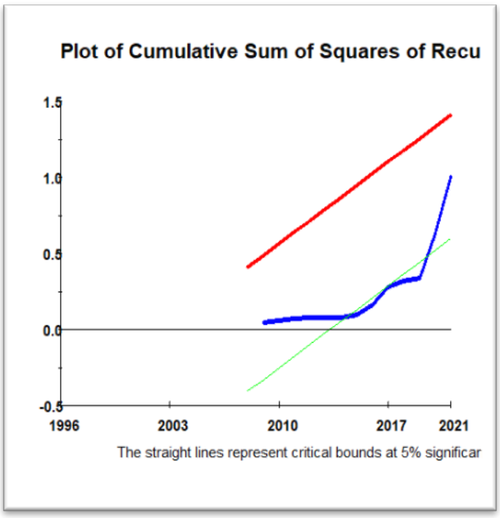
The diagnostic test indicates that there is no serial correlation because its p-value is more than 0. 05. There is no heteroscedasticity because its value is also insignificant, i.e., the p-value is greater than 0.05. The value of normality is significant, 0.005 for the LM version, but it is not applicable in the F version, and hence, the assumption of normality can not be suited for the chi-square value. The ARDL bound test indicates long-run and short-run dynamics in the given series with outmigration as a dependent variable. The key points obtained from above diagnostic test can be summarized as: No measure issues with autocorrelation or heteroskedasticity and potential normality violation that may affect inference which may warrant additional checks.

Again the cumulative sum (CUSUM) and cumulative sum of square (CUSUMSQ) tests were applied to determine the model's stability over time (1996-2021). The tests have been deployed on model residuals. The graphical representation of the stability of the model is shown in Figure 3.

Figure 3

Cumulative Sum and Cumulative sum of squares test for parameter stability





The CUSUM and CUSUMQ results are at the 95 percent confidence interval. As presented in Figure 3, all the blue lines of the first line fall within the red and green straight line border, and most of the second figure fall within the borderline, showing that the study's models are stable at the five percent significance level. It reveals that no evidence of structural breaks in the model parameters and the relationship between variables (e.g., migration, GDP, climate factors) has been statistically stable over 25 years.

DISCUSSION

The findings of this study contribute to the growing body of literature on climate-induced migration through the application of the ARDL model, which effectively captures both short-term and long-term dynamics between climatic variables and out-migration patterns. The short run dynamics reveals that the GDP influence immediate and strong positive impact on migration which aligns with (Clemens & Mendola, 2024), and demonstrating that temperature anomalies exert a stronger influence on migration decisions than precipitation variability (Hoffmann et al., 2020), particularly in agrarian economies where livelihoods are closely tied to climatic conditions (McLeman & Hunter, 2010). The identified long-run equilibrium relationship supports the environmental push hypothesis, confirming that sustained climate change acts as a fundamental driver of population displacement in vulnerable regions.

The asymmetric effects observed in our analysis, where positive temperature deviations showed greater impact than negative deviations, corroborate findings from Shin et al. (2014) in other developing contexts. This nonlinearity suggests the existence of critical climate thresholds beyond which traditional adaptation mechanisms fail, forcing households to resort to migration as a last-resort coping strategy. Our results particularly reinforce Ghimire et al.'s (2019) work in South Asia, where similar temperature-migration elasticities were reported, though our study reveals slightly higher sensitivity, potentially due to Nepal's unique mountainous topography and greater climate vulnerability.

Gross domestic product (GDP) positively influence out-migration in long run while in short-run dynamics for GDP positively influences the out migration. (1 percent GDP increase influence 5.36 percent migration increase), which aligns with (Zelinsky, 2009). This apparent contradiction with neoclassical expectations and (Beine et al., 2021).

Methodologically, the success of the ARDL approach in this study validates its growing application in climate-migration research (Pesaran et al., 2001). The distributed lag structure effectively captured the delayed migration response to climate shocks, supporting Bohra-Mishra et al.'s (2017) contention that migration often represents a secondary adaptation strategy implemented after local coping mechanisms are exhausted.

The policy implications of these findings are substantial. First, the identified climate thresholds can inform early warning systems to anticipate migration pressures (Warner et al., 2012). Second, the lagged effects suggest windows of opportunity for interventions that could reduce eventual migration, such as climate-smart agriculture initiatives or alternative livelihood programs. Third, the stronger long-term temperature effects highlight the need for sustained investment in climate adaptation rather than just disaster response (Call et al., 2017).

Several limitations should be acknowledged. Like most ARDL applications, our study faces constraints in capturing the full complexity of migration decisions, which often involve socioeconomic and political factors beyond climate variables (Ide et al., 2021). The aggregate nature of migration data may mask important distinctions between different types of mobility (temporary vs permanent, internal vs international). Future research could benefit from incorporating nonlinear ARDL specifications to better capture threshold effects (Shin et al., 2014) and applying panel ARDL approaches to compare climate-migration relationships across different ecological zones (Koubi et al., 2016).

CONCLUSION

The study, which examines the impact of climatic (temperature and rainfall sun) and economic (yield of paddy and GDP per capita) factors on outmigration by using the yearly data spanning from 1993 to 2021, was retrieved from the World Bank Data Portal website. The unit root test, ARDL co-integration technique, and ECM will be used to explore the long-run and short-run relationship. Using lag selection criteria on ARDL, we found that the long-run relationship of GDP without migration was significant at a five percent significance level. Also, the first lag value of outmigration, maximum temperature, rainfall sum, and GDP had a significant long-run relationship with outmigration. For short-run relation, only GDP had a significant relationship without migration at a five percent significance level. Using the Granger causality relationship, we found no significant bi-directional causal relation between any pair of variables. Significant unidirectional Granger causal relationships existed between GDP per capita and maximum temperature, minimum temperature and outmigration, yield of paddy and maximum temperature, yield of paddy and minimum temperature, and yield of paddy and GDP per capita.

Maximum temperature negatively influence out migration and rainfall positively influence which contradict with (Hoffmann et al., 2020), who explained temperature anomalies exert a stronger influence on migration decisions than precipitation variability particularly in agrarian economies where livelihoods are closely tied to climatic conditions (McLeman & Hunter, 2010). The identified long-run equilibrium relationship supports the environmental push hypothesis, confirming that sustained climate change acts as a fundamental driver of population displacement in vulnerable regions.

The asymmetric effects observed in our analysis, where positive temperature deviations showed greater impact than negative deviations, corroborate findings from Shin et al. (2014) in other developing contexts. This nonlinearity suggests the existence of critical climate thresholds beyond which traditional adaptation mechanisms fail, forcing households to resort to migration as a last-resort coping strategy. Our results particularly reinforce Ghimire et al.'s (2019) work in South Asia, where similar temperature-migration elasticities were reported, though our study reveals slightly higher sensitivity, potentially due to Nepal's unique mountainous topography and greater climate vulnerability.

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Climate change has been identified as a primary factor affecting agricultural production, which in turn influences the GDP per capita and migration behavior of individuals and households due to the effects on their livelihoods. Unpredictability in agricultural output and food insecurity play a vital role as push factors of outmigration. Developing the proper adaptation program and mobilizing all concerned stakeholders can increase the yield of agricultural products. This ultimately raises the country's GDP per capita and will help minimize the massive outmigration of Nepali youths.

AUTHOR CONTRIBUTIONS

I declare that this manuscript is originally produced by me.

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