Bartin University Journal of Education
https://doi.org/10.14686/buefad.1847859

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Research Article

The Relationship Between Climate Change, Migration and Education for the NBR of The Gambia

Gambiya'nın Kuzey Banka Bölgesi'nde Iklim Değişikliği, Göç ve Eğitim Arasındaki Ilişki

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Citation: Mbowe, A., Fanneh, M., & Kayode, A. (2026). The relationship between climate change, migration and education for the NBR of The Gambia. *Bartın University Journal of Faculty of Education, 2026(3)*, 1255-1272. https://doi.org/10.14686/buefad.1847859

Article Information

Article History

Received:
29 December 2025
Accepted:
25 April 2026
Published:
08 July 2026

Keywords

Climate change
Migration
Educational attainment
Partial least squares
Structural equation model
North Bank Region
The Gambia

Abstract

Purpose: *Climate change–related extreme events have compelled many people to leave their homes in search of safer and more favourable environments. At the same time, migration linked to climate shocks continues to rise as these events become more frequent and intense worldwide. This study analyses the relationships between climate change, migration, and education in The Gambia, addressing a notable research gap in this context.* ***Method:*** *Structured household questionnaires were used to collect data, and Structural Equation Modelling (SEM) was applied to establish relationships among the three constructs. Findings: The findings suggest that as climate change intensifies, migration rates decrease. However, there is a positive relationship between migration and education, indicating that individuals with higher educational attainment are more likely to migrate.* ***Conclusion:*** *The study highlights the pressing need for climate adaptation strategies, enhanced access to education, and socioeconomic reforms to address the challenges of climate-induced migration. These results offer valuable insights for targeted interventions to mitigate climate impacts and support sustainable development in The Gambia.*

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Makale Bilgisi

Makale Tarihçesi

Geliş Tarihi:
29 Aralık 2025
Kabul Tarihi:
25 Nisan 2026
Yayımlanma Tarihi:
8 Temmuz 2026

Anahtar Kelimeler

İklim değişikliği
Göç
Eğitim düzeyi
Kısmi en küçük kareler
Yapısal eşitlik modeli
Kuzey Banka Bölgesi
Gambiya

Öz

Amaç: *İklim değişikliğine bağlı aşırı olaylar, birçok insanı daha güvenli ve elverişli ortamlar arayışıyla evlerini terk etmeye zorlamıştır. Aynı zamanda, bu olayların dünya çapında daha sık ve yoğun hale gelmesiyle birlikte iklim şoklarına bağlı göç artmaya devam etmektedir. Bu çalışma, Gambiya'da iklim değişikliği, göç ve eğitim arasındaki ilişkileri inceleyerek bu bağlamda önemli bir araştırma boşluğunu ele almaktadır.* ***Yöntem:*** *Yapılandırılmış hanehalkı anketleri kullanılarak veri toplanmış ve üç yapı arasındaki ilişkileri belirlemek için Yapısal Eşitlik Modellemesi (SEM) uygulanmıştır.* ***Bulgular:*** *Bulgular, iklim değişikliği şiddetlendikçe göç oranlarının azaldığını göstermektedir. Ancak, göç ile eğitim arasında pozitif bir ilişki vardır; daha yüksek eğitim düzeyine sahip bireylerin göç etme olasılığı daha yüksektir.* ***Sonuç:*** *Çalışma, iklim kaynaklı göçün zorluklarını ele almak için iklim uyum stratejilerine, eğitime erişimin artırılmasına ve sosyoekonomik reformlara duyulan acil ihtiyacı vurgulamaktadır. Bu sonuçlar, iklim etkilerini hafifletmeye ve Gambiya'da sürdürülebilir kalkınmayı desteklemeye yönelik hedeflenmiş müdahaleler için değerli içgörüler sunmaktadır.*

Introduction

The importance of studying climate change and its impact on human systems cannot be overstated. Climate change has emerged as one of the most pressing global challenges of the 21st century, with far-reaching consequences for environmental sustainability, economic development, and human well-being. According to the Intergovernmental Panel on Climate Change (IPCC, 2021), global temperatures have risen significantly due to anthropogenic greenhouse gas emissions, resulting in increased frequency and intensity of extreme weather events such as heatwaves, floods, droughts, and storms. These changes pose serious threats to livelihoods, food security, water availability, and social stability, particularly in vulnerable regions of the world.

Developing countries are disproportionately affected by climate change due to their limited adaptive capacity, high dependence on climate-sensitive sectors, and existing socioeconomic challenges. In sub-Saharan Africa, climate change has intensified existing vulnerabilities, undermining key sectors such as agriculture, water resources, health, and education. The region's heavy reliance on rain-fed agriculture makes it especially sensitive to climate variability, including erratic rainfall patterns and prolonged droughts (Demski et al., 2017). These environmental stressors contribute to declining agricultural productivity, food insecurity, and rising poverty, thereby constraining economic growth and development.

In The Gambia, the impacts of climate change are increasingly evident. Rising temperatures, unpredictable rainfall, and recurrent extreme weather events have disrupted agricultural production, the primary source of livelihood for a large proportion of the population. Sea-level rise poses additional risks to coastal communities,

threatening settlements, infrastructure, and fertile agricultural land, particularly in low-lying areas along the River Gambia (Mbowe, 2025). In recent years, the country has experienced more frequent and intense climate-related hazards, including flooding, extreme heat, and prolonged droughts, which have significantly affected health, education, and overall well-being, especially among rural populations (Bayo & Mahmood, 2023). Rural households, particularly women and children, are among the most vulnerable groups, as they often have limited access to resources and adaptive capacities.

One of the key social responses to climate change is migration. The relationship between climate change and migration is complex and multidimensional. While climate stressors can act as "push factors" that encourage people to move in search of better livelihoods, they can also constrain mobility by limiting the financial and social resources required for migration (Black et al., 2011; Cattaneo et al., 2019). In many cases, households adopt migration as an adaptation strategy to diversify income sources and cope with environmental shocks (Hermans & McLeman, 2021). However, not all individuals can migrate; some become "trapped populations," unable to move despite facing significant climate risks due to poverty, cultural ties, or lack of opportunities.

In The Gambia, migration has become an increasingly prominent phenomenon, particularly among young people. Many youths migrate from rural areas to urban centres or attempt irregular migration routes, commonly referred to as the "backway," in search of better economic opportunities. The North Bank Region (NBR) has recorded some of the highest migration rates in recent years. While migration can serve as a livelihood strategy, it also has significant social implications, particularly for education. The relationship between migration and education is both direct and indirect. On one hand, migration can disrupt education by leading to school dropouts, especially among youths who leave school prematurely to migrate. On the other hand, migration can positively influence education through remittances, which may support school-related expenses and improve access to educational resources (Adams & Cuecuecha, 2010; de Haas, 2010).

Despite the growing body of literature on climate change, migration, and education as separate areas of study, there remains a significant gap in understanding how these three variables interact, particularly within the context of The Gambia. Most existing studies focus on sector-specific impacts without adequately examining the interconnected pathways through which climate change influences migration decisions and, in turn, educational outcomes. Addressing this gap is crucial for developing integrated and context-specific policy responses.

This study aims to examine the interrelationships between climate change, migration, and educational attainment in the North Bank Region of The Gambia. Specifically, it seeks to understand how climate change influences migration patterns and how both climate change and migration affect educational outcomes.

Literature review

Climate change has emerged as one of the most critical global challenges, significantly influencing human mobility patterns across the world. According to the Intergovernmental Panel on Climate Change (IPCC), the increasing frequency and intensity of climate-related hazards, including hurricanes, floods, droughts, and rising sea levels are contributing to large-scale displacement of populations. These climatic changes compel individuals and communities to migrate as a coping strategy in response to environmental stress. Similarly, the International Organisation for Migration (IOM) Environmental Migration Portal (2020) describes climate change as a "threat multiplier" that exacerbates existing socio-economic vulnerabilities and drives migration. Environmental stressors combined with socioeconomic challenges have therefore become major drivers of migration in many parts of the world (Rana & Ilina, 2021).

Empirical studies across different regions further demonstrate the link between climate change and migration. For example, Bell et al. (2021) documented migration patterns in coastal Bangladesh, where rising sea levels have forced communities to relocate. Likewise, Campbell and Warrick (2015) examined the relocation of communities in the Pacific Islands as an adaptive response to climate change. These studies illustrate how environmental changes are reshaping population mobility, particularly in vulnerable coastal and island regions.

Climate change also has significant implications for educational outcomes. Extreme weather events frequently disrupt educational infrastructure and schooling processes. According to the Intergovernmental Panel on Climate Change (2022), climate-related disasters displaced approximately 17 million children from schools in 2018 alone. Such disruptions often force families to prioritise immediate survival over long-term educational goals. In many developing regions where agriculture is the primary source of livelihood, climate variability and extreme events can reduce household incomes, thereby compelling children to withdraw from school to contribute to household survival (Deuster, 2021). As a result, climate-induced shocks can significantly undermine educational attainment.

Migration, which often occurs as a response to climate-related stress, may further influence educational outcomes. When families relocate, children frequently experience interruptions in schooling during the transition period, leading to learning gaps and lower educational attainment. Research by McKenzie and Rapoport (2011) found that children from migrant households in Mexico were less likely to be enrolled in school compared to their non-migrant peers due to the instability associated with migration. Similarly, earlier studies by Quinn (2005) and Massey (1997) highlighted that migration can negatively affect the educational attainment of migrants. Supporting this argument, Davis and Brazil (2020) found that international remittances associated with migration may reduce school enrolment in some contexts. McKenzie and Rapoport (2011) further observed that migration had a significant negative effect on schooling attendance and attainment among boys aged 12–18 and girls aged 16–18 in rural Mexico.

While migration is often viewed as a common response to climate change, not all populations can move. The concept of trapped populations has therefore gained increasing attention in climate migration research. Trapped populations refer to individuals or communities who remain in environmentally high-risk areas despite facing climate-related threats because they lack the resources or opportunities to relocate (Fernand & Gholamzadeh, 2024). Studies indicate that socioeconomic and demographic factors strongly influence climate immobility. For instance, Cai et al. (2016) found that flooding in India had a moderate impact on mobility, particularly among women and poorer households. The study also revealed that individuals aged 36–45 years and those above 55 years were more likely to remain climate immobile.

Similarly, research by Christopher and Appiah (2025) showed that income levels significantly influence climate immobility, with low-income individuals having higher odds of remaining trapped in environmentally vulnerable areas. Evidence from Peru further suggests that people become increasingly vulnerable to being trapped when climate impacts gradually erode the ecosystems on which they depend for their livelihoods (Thiede, 2024; Pearson et al., 2023). Cultural and social factors also contribute to immobility. Deep-rooted traditions, attachment to ancestral lands, limited access to relocation assistance, and uncertainty surrounding migration decisions can discourage relocation (dos Santos, 2023; Upadhyay et al., 2024). In addition, Williams and Williams (2020) highlighted cases of spontaneous immobility in parts of the Northern Triangle, where families remain in their places of origin despite severe food insecurity.

Overall, the literature demonstrates a complex relationship between climate change, migration, and education. Climate change can act as a catalyst for migration, while both climate shocks and migration processes may disrupt educational attainment. At the same time, socioeconomic constraints may prevent vulnerable populations from migrating, leaving them trapped in climate-sensitive areas. These dynamics highlight the importance of understanding how climate change shapes both mobility and immobility and the broader social consequences associated with these processes.

Methodology

Research Design

Sampling Technique and Sample Size

The study employed a multi-stage sampling method to determine the sample to be included in the North Bank Region (NBR). Stage 1: Regional Selection; Purposive sampling was used to select the North Bank Region as the study area, given its vulnerability to climate change impacts and migration patterns. Stage 2 Community Selection: A simple random sampling technique was applied to select 30 communities across the six districts of NBR. Communities with fewer than 50 households were excluded to ensure adequate representation and data sufficiency. Stage 3 Household Selection: A probability proportionate to size (PPS) sampling technique was employed to select households

within the chosen communities. This ensured that the number of households sampled in each district was proportional to the district's total household population.

Sample Size

Using Yamane's (2003) formula: $n = N/ 1+Ne^2$; where N=267,043 (total household population of NBR) and e=0.05 (margin of error), the calculated sample size was 399.4 households. This was rounded to 400 households for practicality. A minor sampling error of 15 households was noted during fieldwork.

Data Collection

To ensure transparency and replicability, the following steps were taken during data collection.

Household surveys were conducted between June and September 2022, coinciding with the rainy season when climate change impacts such as flooding and windstorms are most pronounced. Structured questionnaires were administered to household heads or knowledgeable adult members. The questionnaire was designed to capture demographic information, climate change experiences, migration drivers, and educational outcomes.

A team of trained enumerators was recruited from the region. They underwent a two-day training workshop covering survey ethics, interview techniques, and the use of digital data collection tools (tablets with preprogrammed survey forms).

Prior to full deployment, the questionnaire was pilot-tested in two communities outside the selected sample to refine wording, sequencing, and clarity. Within each selected community, households were chosen using systematic random sampling. Enumerators used household listing data from the Gambia Social Registry (2021) as a sampling frame. The sampling interval was determined by dividing the total number of households in the community by the allocated sample size. Supervisors conducted spot-checks and daily reviews of completed questionnaires to ensure accuracy and consistency. Any discrepancies were corrected through revisits or clarifications with respondents.

Data Analysis

Furthermore, the partial least squares structural equation modelling (PLS-SEM) method, SMARTPLS 4software was employed to develop the SEM model and examine the associations between climate change, migration, and education.

Furthermore, the measurement model was assessed, starting with the factor loadings to establish the reliability of individual items. Additionally, the model's internal consistency reliability was established with construct reliability and validity. Cronbach's Alpha, composite reliability (ρ_a), and (ρ_c) were examined to determine construct

reliability. The validity of the concepts was also measured by examining the construct's convergent validity (using Average Variance Extracted (AVE)) and discriminant validity (using the Heterotrait-Monotrait Ratio (HTMT) matrix). Additionally, the model's explanatory power was assessed using R-squared, Fsquared and SRMR. The total effect was used to establish the relationship between climate change, education and migration, as it gives a vivid insight into both the direct and indirect effects.

Variables

To examine the relationship, a set of indicators was developed for each construct. The intensity and frequency of flooding, rainfall, windstorms, and heatwaves were indicators used to assess climate change. These indicators have been empirically proven valid in climate-induced migration studies. They are familiar with climate change literature and have been found to disrupt schooling and displace people, making them appropriate for measuring climate change impacts on families' livelihoods.

Climatic interruption, reduced number of schoolings, youth migration, agricultural damage, damage to school buildings, economic instability, language barriers and cultural differences were the indicators used to measure the external factors affecting educational attainment. They reflect multidimensional barriers that hamper students' success in school. Additionally, agricultural damage and economic instability indicate the economic instability of farming households, which impacts their children's schooling. Similarly, language barriers and cultural differences are indicators found to be used in migration and education literature. Migrant families find language and cultural differences limiting their educational attainment.

Finally, Loss of employment, Employment of spouse, marriage, studies, Disaster/Conflict, Trade, business, and lack of land were the indicators used to measure the motivating factors of migration. These indicators are drawn from established migration theories, such as the push-pull, which was used in this study. They highlight the social, economic and environmental drivers influencing migration.

Findings

Structural equation modelling is a group of statistical analysis techniques, as described by Hoe (2008), which are utilized to model complex relationships among measured variables and latent variables using Smart PLS 4. SEM is useful for inferential data analysis and testing hypotheses when the inter-relationships among the study constructs are defined beforehand and founded on established theory (Hoe, 2008). The analysis method examines how changes in one variable are related to changes in one or more other variables, using correlation coefficients. SEM is preferred for this purpose because it measures multiple variables and their interrelationships at the same time, making it more flexible than other multivariate techniques, as it can handle multiple dependent relationships among variables simultaneously (Bonell et al., 2022). Similarly, compared

to regression techniques, SEM provides more precise information about the level of support the research model receives from the data (Gefen et al., 2000).

Assessment of the Measurement Model

The measurement model is evaluated to weigh the value of the constructs. The quality criteria assessment starts with considering the factor loadings, followed by construct reliability and construct validity. A good measurement model should have high factor loadings, which indicate that the variables are well-represented by the items in the model. Construct reliability ensures that the measurement model consistently measures the intended construct, while construct validity assesses the extent to which the model reflects the intended theoretical construct.

Factor Loadings

Table 1 and Figure 1 examine the factor loadings of the model. They were examined to assess indicator reliability. Loadings greater than 0.70, which illustrate that a construct describes above 50% of the indicator's variance, are acceptable. Schamberger et al. (2020) maintained that, in general, when assessing indicators, it is advisable to consider removing loadings ranging from 0.40 to 0.70 if doing so would help improve the composite reliability of the scale to reach the recommended threshold. However, considerations need to be made on the impact removing an indicator will have on the validity. At times, weaker indicators are kept in the scale owing to their contribution to content validity. Nevertheless, indicators of enormously low loadings of 0.40 or below must always be removed from reflective scales. Hence, all indicator loadings used were found to be above the thresholds and kept.

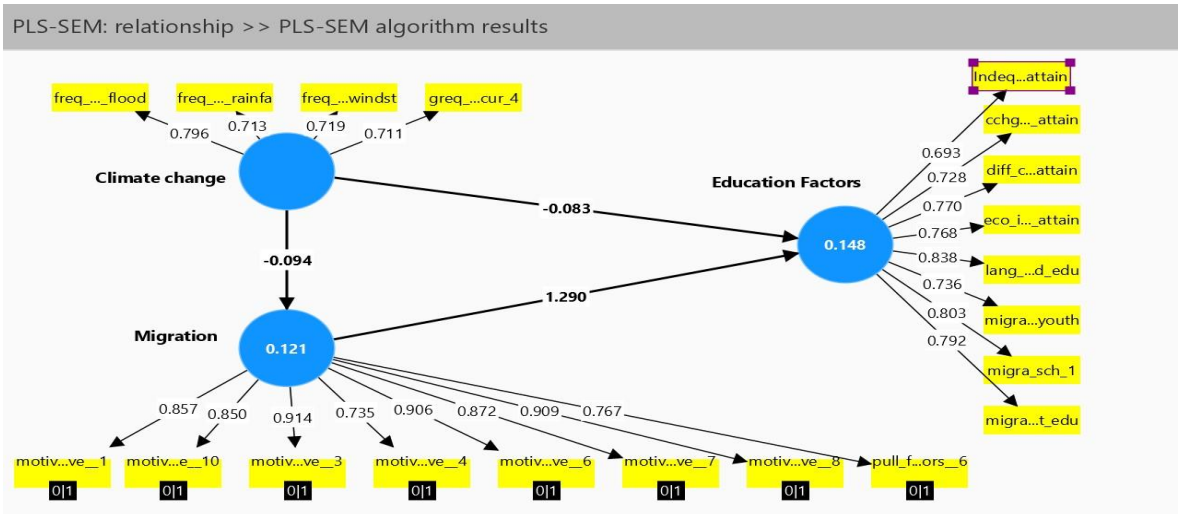
In this study, the measurement model's factor loadings were consistently high, ensuring that the constructs were reliably and validly represented. The retained indicators provide a robust and reliable measurement of the underlying constructs, allowing for meaningful analysis of the relationships among the variables. By maintaining the integrity of these indicators, the model achieves a high level of accuracy and validity.

Table 1. *Latent Constructs and Their Observed Indicators*

	Climate change	Education attainment	Migration
Inadequate policies		0.693	
Climate change_impact		0.728	
Cultural difference		0.770	
Agricultural disruption		0.768	
Language_barrier_		0.838	
Migration reduces_school yrs		0.736	
Political refugee		0.803	
Migration_distraction		0.792	
frequency_of floods	0.796		
Frequency of drought	0.713		
Frequency of_windstorm	0.719		
Frequency of heat waves	0.711		
Loss of employment			0.857

Lack of employment	0.850
Employment of spouse	0.914
Mariage	0.735
Education	0.906
Disaster/ Conflict	0.872
Lack of Land	0.909
Employment opportunity	0.767

Figure 1. *Latent Constructs and Their Observed Indicators*



Source: Primary data (2023), SmartPLS 4 (Yan Piaw Chua) Indicator loadings

Construct Reliability

Table 2 highlights the construct reliability. The internal consistency reliability for the model was assessed using the traditional method of Cronbach's alpha (Cronbach & Meehl, 1955). Nonetheless, Schamberger et al. (2020) recommend composite reliability simply because composite reliability presumes that all indicator loadings of a population are equal, while Cronbach's alpha does not; this is consonant with the PLSSEM algorithm's operating principle of ranking indicators based on their reliabilities during model estimation.

Additionally, Cronbach's alpha frequently tends to underestimate reliability due to its sensitivity to the number of items in the scale. PLS-SEM can solve these limitations by using composite reliability. Schamberger et al. (2020) express composite reliability as liberal, while Cronbach's alpha may be excessively conservative, and the actual reliability of the construct is often thought to lie somewhat within the range defined by these two extremes.

Accordingly, Dijkstra and Henseler's rho (pa), put forward by Dijkstra and Henseler (2015), is generally between the composite reliability and Cronbach's alpha, forming an excellent compromise. As a result, all three reliability metrics were computed and evaluated. According to Nunny and Berndtein (1994), reliability scores between 0.60 and 0.70 are deemed acceptable for exploratory studies, while scores from 0.70 to 0.90 are viewed as satisfactory for research at more advanced stages. However, "Values above

0.90 (and definitely above 0.95) are not considered since they are typically the result of semantically redundant items, which somewhat reshape the same question." Hence, Table 1 shows that the reliability values are above 0.60. Moreover, all the composite reliability values, which are more consistent with the PLS-SEM algorithm's operation, are more than the satisfactory level of 0.70. Hence, the values range from 0.717 to 0.956. Therefore, construct reliability is established.

Table 2. *Internal Consistency and Reliability Statistics for Latent Variables*

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
Climate change	0.717	0.722	0.825
Education Factors	0.903	0.956	0.919
Migration	0.946	0.950	0.955

Construct Validity

The validity of the constructs was measured by examining the construct's convergent and discriminant validity.

Convergent Validity

Table 3 shows the convergent validity of the model. The notch of agreement among numerous efforts to measure the same concept is known as convergent validity. According to Bogazzi et al (1991), measures of the same thing should be highly covarying if they are valid measures of the concept. On the other hand, convergent validity refers to the degree to which a measure positively correlates with others in the construct Hair, (2016). The convergent validity of an individual construct is measured using the Average Variance Extracted (AVE). It is assured when each construct's AVE is 0.50 or higher. A construct with an average variance extracted (AVE) of 0.50 or higher explains 50% or more of the variation of the indicators making up the construct. The Average Variance Extracted (AVE) values for the constructs are above 0.50; therefore, convergent validity is assured.

Table 3. *Assessment of the Average Variance Extract (AVE)*

	AVE
Climate change	0.541
Education Factors	0.589
Migration	0.729

Discriminant Validity

Table 4 indicates the discriminant validity of the model. "The level to which measures of individual concepts are distinct is known as the Discriminant validity. According to Bagozzi et al, measures should not be highly correlated if concepts are unique. Additionally, according to Hair (2016), discriminant validity measures the degree to which constructs are different by empirical standards. Recently, Fornell and Larcker's point of reference has been mainly used when examining discriminant validity. Studies

have shown this metric is inappropriate for assessing discriminant validity, particularly when indicator loadings on the construct are marginally different. However, Henseler et al (2015) proposed an accurate Heterotrait-monotrait ratio, which has been applied in the study. Hence, when the HTMT is 0.85 or below, it is said that the discriminant validity in the model is established. The study highlighted that the HTMT values are less than 0.85. Hence, discriminant validity is established.

Table 4. *Discriminant Validity Assessment Using the Heterotrait-Monotrait Ratio (HTMT) - Matrix*

	Climate change	Education Factors	Migration
Climate change	0.41		
Education Factors	0.261	0.326	
Migration	0.42	0.363	0.510

Structural Model Assessment

The structural model is evaluated by examining the coefficient of determination (R2), However, the structural model must first be assessed for any potential issues related to collinearity.

Collinearity

Table 5 shows the collinearity statistics of the model. Collinearity is assessed by calculating the variance inflation factor (VIF) to ensure unbiasedness. Hair et al. (2019) state that VIF values of 5 or less are acceptable, while values close to 3 or less are more appropriate. Hence, all the VIF values for the model are less than 3, and thus, the multicollinearity is apt.

Table 5. *Path Coefficient of the Structural Model*

	Variance inflation factor (VIF)
Climate change -> Education Factors	1.137
Climate change -> Migration	1.000
Migration -> Education Factors	1.137

The Model's Explanatory Power

The explanatory strength of a model depends on how well it aligns with the available data, typically assessed through the association strength indicated by the PLS path model (Shmueli et al., 2016). The most widely used indicator for evaluating a structural model's explanatory capacity is the coefficient of determination (R^2), and it ranges from 0 to 1; higher values reflect stronger explanatory power (Hair et al., 2022). As a general guideline, R-squared values of 0.25,0.50 and 0.75 correspond to weak, moderate, and

substantial explanatory accuracy (Henseler et al., 2009; Hair et al., 2011). However, the acceptable threshold can differ by discipline in certain fields; values as low as 0.10 may be deemed sufficient. Moreover, the R-squared values tend to increase with the number of predictor constructs included in the model (Hair et al., 2022).

In Table 6, the R^2 values for the endogenous latent variables, Education Factors, and migration, are reported. The R^2 value of 0.248 (weak) for education factors and 0.321 (moderate) for migration was obtained. However, both values can be considered satisfactory as they are above the minimum threshold of 0.10, thus supporting the model's explanatory power.

Table 6. *R-squared (The Coefficient of Determination)*

	R-square	R-square adjusted
Education Factors	0.248	0.244
Migration	0.321	0.319

Cohen's f^2 is used to determine the effect size by evaluating changes in the R^2 value, specifically when the endogenous construct is detached from the model. If removing a construct significantly decreases the R^2 value of the endogenous construct, it shows that the predecessor construct has a substantial impact (Hair et al., 2022). According to Cohen (1988), the values 0.35, 0.15, and 0.02 signal large, medium, and small f^2 effect sizes. When the effect size is below 0.02, it means "there is no measurable effect" (Hair et al., 2022, p. 195). However, considering Aguinis et al. (2005)'s review, even these values may be optimistic.

F-square (effect size)

Table 7 highlights the f2 values of all combining predictor constructs and matching endogenous constructs. The results show that climate change affects education factors (0.307) and migration (0.237), while migration has a medium effect on education factors.

Table 7. *R-squared (The Coefficient of Determination)*

	f-square
Climate change -> Education Factors	0.307
Climate change -> Migration	0.237
Migration -> Education Factors	0.125

The Standardised Root Mean Square Residual (SRMR)

Table 8 presents the Standardised Root Mean Square Residual (SRMR), which is a measure used to assess the overall fit of a structural equation model. The SRMR represents the standardised difference between the observed correlations and the

correlations predicted by the model. In other words, it indicates how closely the model reproduces the observed data. Lower SRMR values suggest a better model fit.

According to Li-tze Hu and Peter M. Bentler (1999), an SRMR value below 0.08 indicates an acceptable model fit, while values below 0.05 indicate a good model fit.

In this study, the model produced an SRMR value of 0.08, which suggests that the model meets the acceptable threshold for model fit. This means that the discrepancies between the observed correlations and the correlations predicted by the model are relatively small, indicating that the model adequately represents the data.

However, it is important to note that SRMR does not measure the percentage of variance explained or the predictive power of the model. Instead, it simply reflects how closely the model-implied relationships match the observed relationships in the dataset.

Table 8. *Model's Predictive Power*

Saturated model	
Standardised root mean square residual (SRMR)	0.08

The Relationship Between Climate Change, Educational Attainment and Migration

The relationships between climate change, migration, and educational attainment presented in Table 9 are assessed using the total effects within the PLS-SEM model. The total effect represents the sum of the direct and indirect effects and is particularly useful in studies that seek to identify the overall influence of multiple driver constructs on a given outcome through one or more mediating variables.

The results reveal that climate change has an inverse relationship with educational attainment (β = –0.083). This finding suggests that climate-related stressors negatively affect education, either directly or indirectly. Such impacts may include the destruction of school infrastructure, the loss of teaching and learning materials, or increased economic pressure on households, which may force students to drop out of school. Consequently, as extreme weather events become more frequent or severe, school access, attendance, and overall educational attainment are likely to decline.

Similarly, climate change exhibits a negative relationship with migration (β = –0.094), indicating that increased climate-related challenges are associated with reduced migration in the study context. This suggests that as the effects of climate change intensify, individuals or households may face financial or logistical constraints that limit their ability to migrate.

In contrast, the positive relationship between migration and educational attainment (β = 1.290) indicates that higher levels of education are associated with a greater likelihood of migration. This may reflect the idea that individuals with higher

educational attainment possess the knowledge, aspirations, or resources necessary to pursue opportunities elsewhere.

Table 9. *Total Effect*

	Education Factors	Migration
Climate change	-0.083	-0.094
Migration	1.290	

Discussion and Conclusion

The relationships between climate change and educational attainment, climate change and migration, and migration and educational attainment were assessed using the total effects generated from the model. The findings reveal that climate change and educational attainment exhibit an inverse relationship, indicating that climate-related stressors negatively affect educational outcomes. This relationship reflects the multifaceted ways in which environmental shocks disrupt education systems. For instance, extreme weather events such as floods and storms can damage school infrastructure, destroy teaching and learning materials, and lead to prolonged school closures (UNESCO, 2020; UNICEF, 2021). At the household level, climate-induced economic pressures-particularly those arising from crop failure, declining agricultural productivity, and loss of livelihoods-often compel families to reallocate resources away from education, thereby increasing dropout rates and reducing school attendance (Behrer et al., 2021; Jensen, 2000).

Moreover, climate-related factors such as heat stress have been shown to impair students' cognitive performance and concentration, further undermining learning outcomes (Park, Behrer & Goodman, 2021). Despite these negative effects, the weak correlation observed in this study suggests that climate change is not the sole determinant of educational attainment. Rather, educational outcomes are shaped by a broader set of social, economic, and institutional factors, including household income, parental education, quality of schooling, and government policy interventions (Glewwe & Kremer, 2006). This finding aligns with the broader literature emphasizing the multidimensional nature of educational achievement. Consequently, there is a critical need to strengthen climate adaptation strategies within the education sector. Such measures may include the construction of heat-resilient classrooms, investment in hazard-resistant infrastructure, improved drainage systems in flood-prone areas, and the establishment of effective early warning systems to minimize disruptions and enhance system resilience (World Bank, 2021).

Furthermore, the results indicate a negative relationship between climate change and migration, suggesting that climate stressors, rather than encouraging migration, tend to reduce it in the study region. This finding supports the concept of "trapped populations," where vulnerable individuals are unable to migrate despite facing significant environmental risks (Black et al., 2011). According to Fernand and Gholamzadeh (2024), immobility is often influenced by strong attachment to place, as individuals may be reluctant to leave behind their families, social networks, and property.

Older populations tend to emphasize deep religious, cultural, and emotional ties to their place of origin, which reinforces their decision to remain.

This finding deviates from the dominant scholarly narrative that climate change acts primarily as a driver of migration (IOM, 2022). Although households in the study area experience substantial agricultural losses, many still prefer to remain within their communities. This preference may be explained by cultural norms that discourage relocation, as well as by the financial constraints associated with migration. Indeed, climate-related economic losses can significantly reduce households' capacity to finance relocation and establish new livelihoods elsewhere (Cattaneo et al., 2019). As a result, migration is not always a viable adaptation strategy, and environmental stress may instead exacerbate immobility.

These findings highlight that decisions to migrate are shaped not only by environmental conditions but also by social ties, cultural values, and economic capabilities. In this context, vulnerable populations may become "trapped" not necessarily due to low exposure to climate risks, but because of limited adaptive capacity and restricted access to resources. Therefore, there is a pressing policy need for governments to develop frameworks that facilitate safe, orderly, and affordable migration pathways for populations affected by environmental hazards. Such policies could include financial support mechanisms, skills training, and institutional arrangements that reduce the barriers to mobility while protecting migrants' rights (IOM, 2022; Black et al., 2011).

In contrast, the study reveals a strong positive relationship between migration and educational attainment, indicating that higher levels of education are associated with a greater likelihood of migration. This finding is consistent with human capital theory, which posits that education enhances individuals' capacity to access opportunities beyond their immediate environment (Sjaastad, 1962). Educated individuals are more likely to possess the skills, information, and resources necessary to migrate successfully, whether internally or internationally.

Additionally, migration can generate positive feedback effects on education through remittances and knowledge transfer. Households receiving remittances from migrants are often better able to finance educational expenses, including school fees, uniforms, and learning materials, thereby improving educational access and outcomes (Adams & Cuecuecha, 2010). Furthermore, migrants exposed to new socio-economic contexts may develop a stronger appreciation for education and encourage investment in schooling among family members left behind (de Haas, 2010).

This strong positive relationship suggests that migration can serve as an important adaptation strategy that enhances household resilience to climate change while simultaneously supporting educational advancement. However, it also underscores existing inequalities, as only households with sufficient resources and human capital can benefit from migration opportunities.

Considering these findings, it is recommended that the Ministry of Education integrate climate-risk mapping and early warning information into the Education Management Information System (EMIS). Such integration would enhance data-driven decision-making, improve preparedness for climate-related disruptions, and support targeted interventions in vulnerable areas. Additionally, cross-sectoral collaboration between education, environment, and migration institutions will be essential to develop holistic policies that address the interconnected challenges of climate change, mobility, and educational development.

Limitations

Like all studies, this work has the following limitations to be considered.

1. The use of a cross-sectional research design employed by the researcher limits the causal interpretation of results.
2. The survey data collected is not free from respondent bias, which can influence the accuracy and reliability of the data.
3. The PLS_SEM model constructs were operationalized with the use of indicators, which may not have captured the multi-functionality of migration, climate and education.
4. The study cannot be generalised for the whole country because the data was concentrated in one region.

Ethical Approval

During the research, the ethical principles of the publication process were complied with.

Author Contributions

Authors	Literature Review	Method	Data Collection	Data Analysis	Results	Conclusion
Author 1	x		x	X	x	
Author 2		x				
Author 3						x

Conflict of Interest

No conflict of interest.

Plagiarism Checks

The current article meets BUEFAD similarity standards.

Grant Support

There was no grant support.

Artificial Intelligence Usage Statement

Artificial Intelligence was not used.

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