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Investigating the complex landscape of climate finance in least developed countries (LDCs)

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Abstract
This study aimed to investigate the complex landscape of climate finance, assessing the adequacy, predictability, and implications for sustainable development in least developed countries (LDCs). This study is motivated by the pressing need to assess the adequacy, predictability, and implications of climate finance for sustainable development in least developed countries (LDCs). Employing an econometric framework, this study utilizes ARIMA models to analyze time series data (from 2000 to 2021) on climate finance. The analysis revealed a notable gap between the needed and actual climate funding received by LDCs. Despite an annual requirement of $93.7 billion according to the UK-based International Institute for Environment and Development (IIED), LDCs have only received an average of $14.8 billion annually since 2015. The study suggests that climate funding for LDCs lacks predictability and falls short in meeting their needs, potentially facing an 80% decrease by 2030 under certain scenarios. It advocates for a strategic revamp in climate finance mechanisms to ensure adequacy and predictability, urging policymakers and international funding bodies to adopt more robust, fair, and needs-based approaches to climate financing. This research emphasizes the responsibility of developed nations and global agencies in bridging the considerable funding gap faced by LDCs. By integrating advanced forecasting techniques with a comprehensive analysis of global economic and political factors, this study sheds light on the challenges LDCs encounter in securing stable and sufficient climate finance, stressing the urgency for systemic reforms in global climate finance policies.

Keywords Climate finance · ARIMA models · Sustainable development · Funding gap · Global climate policy

1 Introduction

Climate change represents a monumental challenge of contemporary times, transcending geographical and socioeconomic boundaries, as articulated by [1]. Its repercussions extend far beyond environmental realms, posing a multifaceted threat to global stability and progress, as highlighted by [2]. The severity and frequency of its impacts, ranging from extreme weather events to rising sea levels and shifting weather patterns, underscore its profound implications for natural ecosystems, agricultural productivity, water resources, and human health and safety, as noted by [3]. Various international accords and scientific reports emphasize the urgency of mitigating climate change's worst impacts, given the narrowing window for effective action, as outlined by [4].

As articulated by, developing nations, particularly least developed countries (LDCs), bear a disproportionate burden of climate change effects due to their limited financial resources, infrastructure, and institutional capacities [5]. Climate

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change compounds existing challenges such as poverty, food security, and health issues, exacerbating vulnerabilities in LDCs, as noted by [6]. Despite historically contributing less to global greenhouse gas emissions, these nations are more vulnerable to climate change impacts, further accentuating the unfairness of the phenomenon, as observed by [7]. The lack of resources hinders LDCs' ability to effectively respond and adapt to climate change, leaving their citizens inadequately protected, as highlighted by [8]. Therefore, climate finance has emerged as a critical tool for addressing these disparities, aiming to support mitigation and adaptation actions in LDCs through various financial instruments and funding mechanisms, as emphasized by [9].

Within the framework of climate finance in least developed countries (LDCs), it is imperative to recognize the profound implications of climate change for both socioeconomic development and the attainment of sustainable development goals (SDGs) by 2030. Climate change poses significant challenges to LDCs, exacerbating existing vulnerabilities and hindering progress toward sustainable development objectives [10, 11]. Extreme weather events, rising sea levels, and shifts in weather patterns not only threaten critical ecosystems, agricultural productivity, and water resources but also jeopardize human health, food security, and livelihoods within these nations. Consequently, the adverse impacts of climate change undermine efforts to achieve the SDGs, particularly those related to poverty eradication, health, food security, clean water and sanitation, and sustainable cities and communities [12]. Addressing the climate finance gap in LDCs is therefore essential not only for building resilience and adaptation capacities but also for advancing broader development agendas and ensuring the realization of the SDGs by 2030.

The pressing need to address climate change in LDCs warrants a deeper investigation into the landscape of climate finance. Understanding the intricacies of financial flows in these vulnerable regions is crucial for informing policy interventions and ensuring the effective allocation of resources to support adaptation and mitigation efforts. By shedding light on the inadequacies and challenges within the current climate finance framework, this study aims to contribute to more targeted and impactful strategies for sustainable development in LDCs.

The urgency of studying climate finance in LDCs is underscored by the theoretical underpinnings of environmental justice and shared but differentiated responsibilities. The disproportionate impacts of climate change on vulnerable populations highlight the moral imperative for economically advantaged nations to support their less affluent counterparts. Moreover, the narrowing window for effective action, as emphasized by international accords and scientific reports, accentuates the importance of timely and targeted interventions to mitigate the worst impacts of climate change. Over the past two COP gatherings, COP27 and COP28, significant strides have been made in advancing global efforts to address climate change. COP27 witnessed a heightened emphasis on enhancing ambition and accelerating action to limit global temperature rise, with several countries committing to more ambitious emissions reduction targets under the Paris Agreement. Additionally, COP27 saw increased recognition of the need to support vulnerable nations, particularly least developed countries (LDCs), in adapting to the impacts of climate change through enhanced financial and technical assistance. Building on these foundations, COP28 further solidified the international commitment to climate action by fostering increased collaboration and innovation in climate finance mechanisms. The conference facilitated the mobilization of additional resources to support mitigation and adaptation initiatives, particularly in regions most vulnerable to climate change impacts. Together, these achievements represent significant progress toward fulfilling the objectives outlined in the Paris Agreement and demonstrate a growing global consensus on the urgency of addressing climate change through concerted multilateral efforts.

The context of climate finance in LDCs presents a unique and significant area of study due to the intersecting challenges of poverty, vulnerability, and environmental degradation. These countries not only face acute risks from climate-related hazards but also encounter barriers in accessing and utilizing financial resources to build resilience and adapt to changing conditions. Understanding the dynamics of climate finance within this context is essential for designing tailored solutions that address the specific needs and challenges of LDCs.

Despite the growing recognition of the importance of climate finance, there is a noticeable gap in in-depth analysis tailored to the socioeconomic and environmental contexts of LDCs. Existing research has focused primarily on broad trends and global mechanisms, overlooking the nuanced challenges and opportunities unique to LDCs. This gap highlights the need for a more comprehensive understanding of climate finance dynamics in these vulnerable regions. This study aims to fill the aforementioned gap in the literature by providing a detailed examination of the complex landscape of climate finance in LDCs. By integrating financial analysis with the specific demands of climate change adaptation and mitigation, this research seeks to offer insights that can inform more targeted and effective interventions to support sustainable development in LDCs. The main purpose of this study is to investigate the complex landscape of climate finance in LDCs and assess its adequacy, predictability, and implications for sustainable development, thereby contributing to a more nuanced and actionable understanding of climate finance in the context of the world's most vulnerable regions.

By filling the existing research gap, this study aims to contribute to a more nuanced understanding of climate finance dynamics in LDCs and provide insights that can inform policy and practice in supporting sustainable development efforts.

2 Literature review

2.1 Theoretical findings

In examining the complexities of climate finance in the context of least developed countries (LDCs), the adoption of a multidisciplinary theoretical framework is deemed imperative. This framework integrates the principles of environmental justice with the tenets of dependency theory to comprehensively elucidate the challenges and opportunities inherent in addressing climate-related issues in LDCs. Environmental justice principles underscore the ethical imperative of rectifying the disproportionate burden of climate change impacts borne by marginalized populations in LDCs, emphasizing the need for equitable distribution of resources and decision-making processes. Simultaneously, dependency theory illuminates the structural inequities perpetuated by historical patterns of exploitation and unequal power dynamics in the global economic system, emphasizing the importance of addressing underlying systemic injustices in climate finance initiatives targeted at LDCs. Through the synthesis of these theoretical perspectives, a nuanced understanding emerges, guiding the formulation of more equitable and effective strategies for climate finance allocation and implementation in LDCs.

2.1.1 Environmental justice theory

Environmental justice theory underscores the imperative of equitable distribution of environmental benefits and burdens, prioritizing fairness and inclusivity [13–15]. It accentuates the disproportionate exposure to environmental risks and ramifications endured by marginalized communities, frequently stemming from factors such as race, income, or social standing. This theoretical framework advocates the implementation of policies and practices aimed at rectifying these disparities, thereby ensuring uniform access to a salubrious environment and averting the imposition of unjust environmental hazards [15, 16].

In the specific context of climate finance in least developed countries (LDCs), the theory of environmental justice assumes critical importance due to the disproportionate impact of climate change on these nations. This necessitates an approach to resource allocation that prioritizes mitigation and adaptation to climate change while ensuring that the benefits extend to the most marginalized communities. Moreover, the theory prompts a meticulous examination of climate finance mechanisms, advocating for rigorous scrutiny of the representation of vulnerable populations in climate funding policies [15, 16]. By integrating this theory into the study, a more comprehensive understanding emerges regarding the impact of these financial instruments on sustainable development in LDCs.

Incorporating environmental justice theory into the analysis of climate finance in LDCs enriches the scholarly discourse by providing a nuanced perspective on the intersection of environmental issues and social equity. This approach underscores the imperative of addressing not only the environmental dimensions of climate change but also the social injustices exacerbated by its impacts. By illuminating the inequities inherent in current climate finance mechanisms, scholars and policymakers can devise more effective strategies to ensure that the benefits of climate finance reach those who are most in need, thereby advancing the overarching goal of sustainable development [11, 14, 15].

2.1.2 Dependency theory

Dependency theory, which originated in the mid-twentieth century, offers a framework for understanding the structural inequalities that persist between developed and developing nations [17, 18]. At its core, this theory contends that the economic advancement of less industrialized countries is impeded by their reliance on more advanced and economically dominant nations. Such reliance perpetuates a cycle of dependency, wherein developing nations find themselves marginalized within the global economic system, lacking the autonomy to pursue sustainable development on their own terms [19–21]. Dependency theorists argue that this unequal distribution of economic power and resources sustains a state of economic subordination, inhibiting the growth and self-sufficiency of developing nations [22].

In the context of climate finance and sustainable development in least developed countries (LDCs), the principles of dependency theory resonate deeply. LDCs often face economic vulnerabilities stemming from the historical legacies of exploitation and underdevelopment. These nations frequently find themselves locked into patterns of dependency on external sources of finance and expertise, inhibiting their ability to pursue sustainable development trajectories that align with their own priorities and needs [19–21]. Dependency theory underscores the need for structural reforms within the global economic system to rectify these disparities and empower LDCs to chart their own paths toward climate resilience and sustainable development.

Moreover, an analysis of dependency theory in the context of climate finance prompts a critical examination of power dynamics within international negotiations. This study sheds light on how asymmetries in economic power influence the allocation of climate finance and the formulation of development strategies in LDCs [17, 18]. By interrogating these power imbalances, policymakers and scholars can better understand the long-term efficacy and sustainability of climate finance initiatives aimed at fostering resilience and sustainable development in LDCs, thereby contributing to more equitable and inclusive outcomes in the global pursuit of climate justice [22].

2.2 Nexus between climate finance and environment

Climate finance in least developed countries (LDCs) represents a critical aspect of global efforts to mitigate and adapt to climate change. The unique challenges faced by LDCs, including limited financial resources, weak institutional capacity, and vulnerability to climate impacts, underscore the importance of understanding the complex landscape of climate finance within these nations [23]. Despite the urgent need for climate finance in LDCs, the literature highlights various barriers and gaps that hinder effective financial flows to support climate action in these countries. These barriers encompass both internal challenges, such as inadequate policy frameworks and institutional capacity, and external factors, including global economic dynamics and the dominance of traditional funding mechanisms [24].

Furthermore, the mobilization of climate financing in LDCs is intricately linked to broader development goals, necessitating a holistic approach that considers the synergies and trade-offs between climate action and development priorities [25]. While international climate finance mechanisms, such as the Green Climate Fund (GCF) and bilateral aid, aim to support climate-related projects in LDCs, their effectiveness in addressing the diverse needs and priorities of these countries remains a subject of debate [26]. Moreover, the fragmented nature of climate finance, characterized by overlapping funding sources and competing priorities, poses challenges for coordination and coherence in LDCs' efforts to access and utilize financial resources for climate adaptation and mitigation [27].

In light of these complexities, there is a growing call for enhanced transparency, accountability, and effectiveness in climate finance governance mechanisms to ensure that resources are allocated efficiently and equitably to address the specific needs and priorities of LDCs [28]. Addressing the challenges associated with climate finance in LDCs requires not only financial investments but also institutional reforms, capacity-building initiatives, and innovative financing mechanisms tailored to the context and capabilities of these nations [25]. By examining the dynamics of climate finance in LDCs through a multidisciplinary lens that integrates insights from economics, political science, and development studies, policymakers and practitioners can develop more robust strategies to accelerate climate action and promote sustainable development in the world's most vulnerable regions.

In comparison to other regions, sub-Saharan Africa (SSA) has contributed the least to greenhouse gas accumulation but is more susceptible to climate change impacts [29]. Adaptation to climate change is expected to cost African countries at least $18 billion a year between 2010 and 2050, but funds reaching African countries are far below what is needed [30]. Agriculture, health, and water are negatively impacted by climate change in Africa, which poses a major threat to development [31, 32]. Climate aid promises of $100 billion to developing countries have not been met by developed countries by 2020, and the deadline for mobilizing these funds has been extended through 2025 [33]. To implement its NDCs, Africa will need $2.8 trillion between 2020 and 2030, with mitigation accounting for the largest share, whereas adaptation will only account for 24% of the total [34].

Climate finance has been a crucial component of climate accords since 2009, and it is crucial to maintaining commitment and encouraging greater ambition among many emerging markets and developing countries [35]. As a result of delivering the $100 billion commitment, we will be able to go from "billions to trillions" and mobilize private capital on a whole new level [36]. According to Article 2.1c of the Paris Agreement, parties must align financial flows with a path to climate-resilient development and low greenhouse gas emissions [37]. The implementation of sustainable investments can enhance productivity and generate co-benefits, including reduced co-benefits and ecosystem and biodiversity protection [38]. Creating and implementing comprehensive stimulus packages that will drive strong recovery and build a better future is an exceptional opportunity for economic decision-makers [35].

Whether it is bilateral, MDB, multilateral climate funds, DFIs, domestic financing, or private financing, all aspects of climate finance must align with this imperative [39].

According to the Copenhagen Accord, developed countries should provide sufficient financial resources to support adaptation in developing countries [40]. In the literature, "adequacy" is generally defined as the amount needed to meet the adaptation needs of developing countries or sufficient funding to cover adaptation costs in developing countries [41]. Developing countries need predictable funding to formulate adaptation strategies and implement activities [42]. To facilitate predictability, the Accra Agenda for Action (2008) requires donor countries to provide timely information about annual expenditures and to develop a three- to five-year plan in advance [43]. Predictability is not about changing funding amounts but about whether recipients can expect future adaptation funding [40].

Global mitigation measures to reduce greenhouse gases are estimated to cost between $200 billion and 210 billion in 2030. The share of the global GDP of Africans between 2005 and 2010 was estimated to be 5 billion dollars per year in terms of financial resources [44]. A total of US$2.5 billion was approved for mitigation projects in Africa between 2008 and 2012, while approximately US$510 million was allocated annually [45]. Africa requires at least US$18 billion every year to adapt between 2010 and 2050, whereas the AfDB estimates Africa's adaptation costs to be between $20 and $30 billion per year [46]. It has been shown that financial flows to climate change adaptation activities in Africa are not adequate in comparison with the continent's needs [47].

Climate funds are used to fund projects in Africa, but the consistency of the amounts committed, deposited, approved, and disbursed is a source of academic debate [44, 48]. Projects funded by bilateral funds have a mean disbursement ratio of 35% (45%), while multilateral projects have a mean disbursement ratio of 50% (47%) [44, 47]. According to [44, 49], it takes approximately 2 years (1.2 years) for projects funded by bilateral funds to receive their first payment. Multilateral funds may have better financial flow predictability than bilateral funds due to delays caused by bureaucratic processes [44, 47, 50]. Generally, bilateral funds are approved and allocated at the highest level, while multilateral funds are usually managed by trustees [44, 47, 50]. Multilateral projects are primarily implemented by international organizations and nongovernmental organizations, such as the United Nations Development Program and the United Nations Environment Program [44, 49].

Using three mitigation scenarios, the revenue of the financing proposals is calculated to assess adequacy and predictability. According to [51], a financing mechanism must generate at least USD 10 billion per year to qualify as adequate. In contrast to [51, 52] assessed climate funding predictability from a broader perspective. Müller [51] evaluated the predictability of climate funding mainly based on domestic revenue, while [52] assessed the predictability of climate funding based on the revenue generated by the financing proposals of three different mitigation scenarios, each having a different level of mitigation effort. To do so, a framework called the Framework to Assess International Regimes (FAIR) was used. In the FAIR mode, climate regimes are analyzed with regard to their environmental and economic impacts [52]. Furthermore, the model focuses on assessing the costs of environmental and abatement measures under different climate regimes. Consequently, the model accounts for the use of Kyoto mechanisms in linking long-term climate targets and global reduction goals with regional emission allowances and abatement costs [52, 53].

3 Methodology

This study uses an OECD climate finance dataset covering global annual climate-related development finance from 2000 to 2021, providing a historical perspective on how financial resources have been allocated to address climate change and support sustainable development. The annual data are converted into quarterly data. The conversion of annual data into quarterly data is a common practice in econometric analysis, especially for estimating dynamic models. This is due to the limitations of the small sample size of annual data, which can lead to over-parameterization and loss of degrees of freedom, compromising the robustness and reliability of the analysis. However, this process also introduces assumptions and interpolations that can introduce complexities and potential biases. Despite these challenges, the conversion to quarterly data remains a valuable statistical solution for addressing the constraints of limited data in dynamic econometric modeling.

3.1 Unit root test

The concept of unit root testing is a pivotal aspect of time series analysis and is primarily used to ascertain the stationarity of a dataset. Stationarity, a fundamental characteristic of time series data, implies that statistical properties such as the mean, variance, and covariance remain constant over time. This lack of trend in the data denotes a stationary series, whereas the presence of a trend indicates nonstationary. The significance of establishing the stationary nature of a time series cannot be overstated, especially in the context of regression analysis. Nonstationary data can lead to spurious regression results, thereby undermining the reliability of any conclusions drawn. To address this, the method of differencing is often employed. Differencing stabilizes the mean of a time series by eliminating or reducing trends, effectively removing changes in the level of the series. This process is crucial for ensuring the validity and accuracy of the analysis performed on time series data. The stationarity of the data is examined by utilizing the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests.

3.2 Autoregressive integrated moving average (ARIMA)

The ARIMA (autoregressive integrated moving average) method, also known as the Box–Jenkins method, relates to fitting a mixed ARIMA model to a given dataset. Furthermore, ARIMA is a class of models that explain a given time series based on its own lags and lagged forecast errors [54, 55]. Based on the contributions of Yule and Wold, Box and Jenkins devised a practical approach for performing ARIMA models [56, 57]. In Box–Jenkins theory, there are three iterative steps: (a) identifying the model, (b) estimating the parameters, and (c) testing the model. In general, if a time series is acquired from the ARIMA technique, it should have some theoretical autocorrelation properties [57–61]. Then, for a given time series, one or several possible models should be identified by matching theoretical and empirical autocorrelation patterns [62–64]. For identifying the order of the ARIMA model, Box and Jenkins recommend using the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the sample data [65, 66].

For the identification step, a stationary time series must be produced to determine the ARIMA model. A stationary time series has constant statistical characteristics, including the mean and autocorrelation structure [62, 67–70]. As a result, differencing and power transformation are usually necessary to remove the trend and stabilize the variance before fitting an ARIMA model [57, 62, 71, 72]. Then, the model parameters can be estimated, and the model can be specified. Finally, the adequacy of the model was evaluated by diagnostic testing. A diagnostic statistic and residual plot can then be used to determine if future values match the current data. Parameters should be estimated, and the model should be validated if it is inadequate. Using diagnostic information can help us develop new models. According to the Box–Jenkins model, a strategy of repeating until a high degree of satisfaction and error reduction is achieved [73–77].

Statistical models such as moving averages, exponential smoothing, and ARIMA can be used to model time series [62, 78, 79]. Since the future values are linear functions of the past values, these models are linear. The ARIMA (short for autoregressive integrated moving average) method, also known as the Box–Jenkins method, relates to fitting a mixed ARIMA model to a given dataset [72, 80–82]. Based on the contributions of Yule and Wold, Box and Jenkins devised a practical approach for performing ARIMA models [56, 57]. In Box–Jenkins theory, there are four iterative steps: (a) identifying the model, (b) estimating the parameters, (c) testing the model, and (d) forecasting the model (see Table 1).

The future value of a variable in an ARIMA model is a linear combination of its past values and errors. This process can be represented as follows:

$$Y = \varnothing_0 + \varnothing_1 Y_{t-1} + \varnothing_2 Y_{t-2} + \cdots + \varnothing_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots - \theta_q \epsilon_{t-q}$$

where Y_t = the actual value. ε = the random error at time t. $\varnothing_i and \theta_j$ = the coefficients. p = AR. q = MA.

The methodological flowchart (Fig. 1) for the application of the ARIMA model in climate finance primarily involves a systematic approach to analyzing univariate time series data, which is pivotal for understanding and forecasting trends crucial for financial decisions impacted by climatic variables. The process commences with assessing the stationarity of the data, as ARIMA models necessitate a stationary series to ensure consistency in statistical properties over time. Nonstationary data undergo transformations such as differencing to achieve stationarity, followed by the computation of the autocorrelation function (ACF) and partial autocorrelation function (PACF) to determine the appropriate ARIMA model parameters. Once the model coefficients are estimated, rigorous diagnostic checks are conducted to validate the model's accuracy in capturing the data characteristics without overfitting. The suitability of ARIMA for climate finance analysis stems from its predictive

Table 1 Box–Jenkins four iterative steps

Modeling Phase	Description
ARIMA Modeling: Step 1—Identification	The initial step in ARIMA (Autoregressive Integrated Moving Average) modeling involves identifying the appropriate lags for AR and MA components using correlograms. The goal is to identify a model with few parameters, a principle known as parsimony, for reliable forecasts and avoiding overfitting, crucial for effective ARIMA modeling
ARIMA Modeling: Step 2—Estimation	The ARIMA (Autoregressive Integrated Moving Average) modeling process involves estimation, based on the principle of parsimony. It emphasizes simplicity and reliability over overparameterization. Balancing complexity and explanatory power is crucial, ensuring robustness and effectiveness for forecasting purposes by selecting a model that captures essential time series characteristics
ARIMA Modeling: Step 3—Diagnostics	The ARIMA (Autoregressive Integrated Moving Average) modeling process includes Diagnostics to avoid overfitting. It involves selecting the appropriate model and scrutinizing residuals correlograms for unexplained information. The Box−Jenkins methodology emphasizes parsimony, balancing simplicity and effective time series capture, aiming for robust forecasting
ARIMA Modeling: Step 4—Forecasting and Validation	The ARIMA model's fourth step, Forecasting and Validation, is crucial for transitioning from theoretical to practical application. The model uses historical data and patterns to forecast future values, validates its accuracy through out-of-sample testing, and undergoes refinement. This stage bridges the gap between statistical analysis and practical forecasting

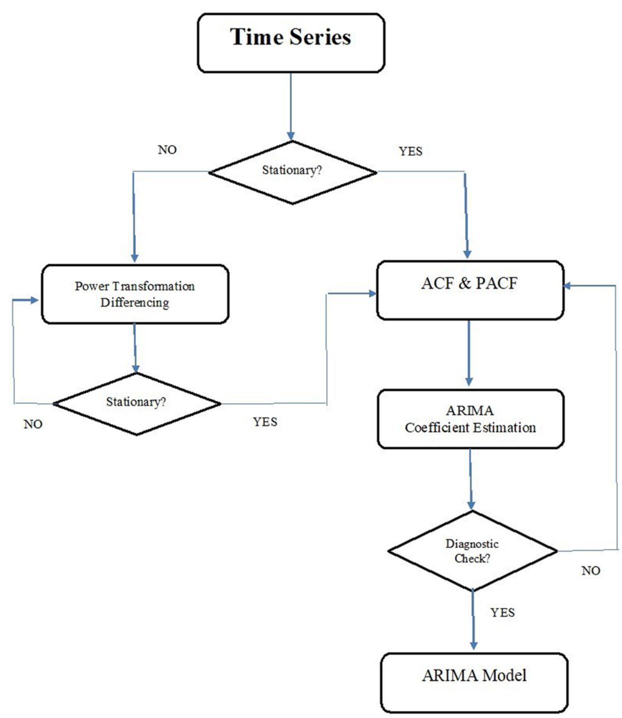


Fig. 1 Methodological flow chart

capabilities, flexibility in handling different data behaviors, and statistical rigor, making it invaluable for forecasting and hypothesis testing of financial variables influenced by environmental factors. This robust statistical framework thus supports more informed and evidence-based decision-making in the domain of climate finance.

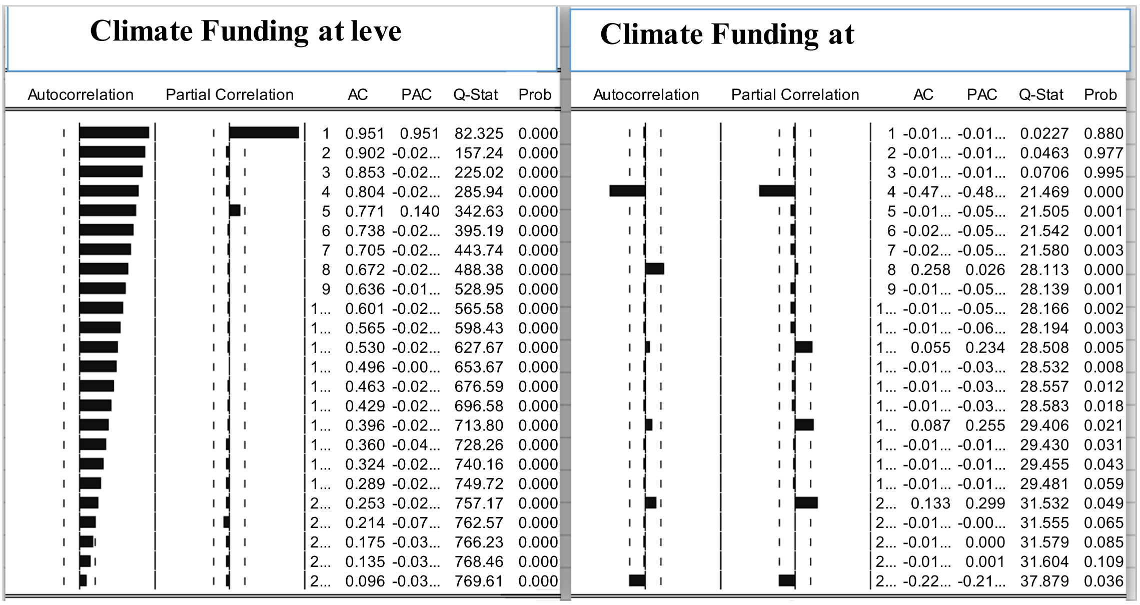
Ljung–Box test: In ARIMA modeling, Ljung and Box (1978) proposed the Ljung–Box Q test. The residuals are used instead of the original series in a fitted ARIMA model. Thus, it tests a hypothesis that the residuals from the ARIMA model do not have autocorrelation, or it tests the lack-of-fit hypothesis for misspecification of the model using the Q statistic:

$$Q = N(N+2)\sum_{j=1}^{L}\frac{\hat{\rho}_j^2}{(N-j)}$$

Table 2 Unit root analysis

Variable	Augmented Dickey-Fuller (ADF) test	Phillips-Perron test
At Level I(0)		
CF	− 1.7348	− 2.6671
At 1st Difference I(1)		
CF	− 8.0238***	− 9.3105***

***Indicates significance at the 1% level



Climate Funding at leve

	AC	PAC	Q-Stat	Prob
1	0.951	0.951	82.325	0.000
2	0.902	-0.02...	157.24	0.000
3	0.853	-0.02...	225.02	0.000
4	0.804	-0.02...	285.94	0.000
5	0.771	0.140	342.63	0.000
6	0.738	-0.02...	395.19	0.000
7	0.705	-0.02...	443.74	0.000
8	0.672	-0.02...	488.38	0.000
9	0.636	-0.01...	528.95	0.000
1...	0.601	-0.02...	565.58	0.000
1...	0.565	-0.02...	598.43	0.000
1...	0.530	-0.02...	627.67	0.000
1...	0.496	-0.00...	653.67	0.000
1...	0.463	-0.02...	676.59	0.000
1...	0.429	-0.02...	696.58	0.000
1...	0.396	-0.02...	713.80	0.000
1...	0.360	-0.04...	728.26	0.000
1...	0.324	-0.02...	740.16	0.000
1...	0.289	-0.02...	749.72	0.000
2...	0.253	-0.02...	757.17	0.000
2...	0.214	-0.07...	762.57	0.000
2...	0.175	-0.03...	766.23	0.000
2...	0.135	-0.03...	768.46	0.000
2...	0.096	-0.03...	769.61	0.000

Climate Funding at

	AC	PAC	Q-Stat	Prob
1	-0.01...	-0.01...	0.0227	0.880
2	-0.01...	-0.01...	0.0463	0.977
3	-0.01...	-0.01...	0.0706	0.995
4	-0.47...	-0.48...	21.469	0.000
5	-0.01...	-0.05...	21.505	0.001
6	-0.02...	-0.05...	21.542	0.001
7	-0.02...	-0.05...	21.580	0.003
8	0.258	0.026	28.113	0.000
9	-0.01...	-0.05...	28.139	0.001
1...	-0.01...	-0.05...	28.166	0.002
1...	-0.01...	-0.06...	28.194	0.003
1...	0.055	0.234	28.508	0.005
1...	-0.01...	-0.03...	28.532	0.008
1...	-0.01...	-0.03...	28.557	0.012
1...	-0.01...	-0.03...	28.583	0.018
1...	0.087	0.255	29.406	0.021
1...	-0.01...	-0.01...	29.430	0.031
1...	-0.01...	-0.01...	29.455	0.043
1...	-0.01...	-0.01...	29.481	0.059
2...	0.133	0.299	31.532	0.049
2...	-0.01...	-0.00...	31.555	0.065
2...	-0.01...	0.000	31.579	0.085
2...	-0.01...	0.001	31.604	0.109
2...	-0.22...	-0.21...	37.879	0.036

Fig. 2 ACF and PACF

4 Analysis of results

4.1 Tests of the unit roots hypothesis

To construct an econometric model for climate funding (CF), it is crucial to determine the stationary characteristics of variables through unit root testing. The augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used to diagnose nonstationary in the time series data (see Table 2). This implies that the data may show trends or heteroscedasticity, potentially undermining the reliability of inferential statistical techniques. However, the CF time series does not negate the null hypothesis at level, confirming its nonstationary nature. This validates the use of differencing to achieve stationarity, making the data suitable for subsequent analyses such as ARIMA modeling.

4.2 Model identification

The data analysis shows a strong serial correlation between climate funding for LDCs and past funding amounts (see Fig. 2). The ACF plot shows a gradual decline but remains positive across many lags, suggesting a nonstationary time series. The PACF plot shows a significant spike at lag 1, followed by nonsignificant values at subsequent lags, suggesting an autoregressive process of order 1, AR(1). The AC and PAC values show the actual autocorrelation coefficients for the respective lags, with a high autocorrelation at lag 1 and a partial autocorrelation coefficient at lag 1. The Q-statistics are high, rejecting the null hypothesis of no autocorrelation at all lags. The ARIMA model for this time series might start with an AR(1) term, suggesting that past funding amounts are a strong predictor of future funding. However, differencing is needed to achieve stationarity (as also reported in the unit root section).

The ARIMA (4, 1, 5) model was chosen as the best choice due to its optimal balance between data fit and simplicity (see Table 3). It had the most significant coefficients, demonstrating robustness in capturing time series data dynamics. The model also had the highest adjusted R-squared value, indicating superior explanatory power. It also had the lowest volatility, indicating higher precision in predictions due to reduced variability. Additionally, it had the lowest Akaike information criterion (AIC) score, which penalizes overfitting. Thus, the ARIMA (4, 1, 5) model was the most suitable for the dataset under study.

4.3 Model estimation

The results from the ARIMA (4, 1, 5) model, as summarized in Table 4, provide comprehensive insight into the time series behavior under study. The model includes four autoregressive (AR) terms and five moving average (MA) terms. The AR terms show varying degrees of influence: AR(1) has a strong negative relationship with the previous value (B = −0.6714; t-statistic = −2.5909). AR(2), AR(3), and AR(4) are statistically insignificant. For the MA terms, MA(1), MA(3), and MA(5) are statistically significant (B = 0.6673; t-statistic = 3.2630; B = 0.5363; t-statistic = 2.1985; B = −0.6370; t-statistic = −4.2811). In contrast, MA(2) and MA(4) are not statistically significant. The R-squared value of 0.33 indicates that approximately 33% of the variance in the dependent variable is explained by the model, while the adjusted R-squared of 0.24, which accounts for the number of predictors, suggests a moderate fit. Overall, the ARIMA model elucidates a multifaceted interaction between historical data points and corresponding errors, highlighting the importance of specific lagged values in shaping the current series outcome. The model's coefficients suggest that certain lags exert a disproportionately significant influence, thereby indicating a non-uniform dependency across the temporal sequence. Such findings underscore the complexity inherent in the time series, revealing that the predictive power of past observations varies markedly, potentially due to underlying cyclical patterns or external influences that affect the series at different intervals. This nuanced understanding aids in refining the model's parameters for enhanced forecasting accuracy.

4.4 Model diagnostics

The Ljung–Box Q statistic is a statistical test used to determine whether a model, such as an ARIMA model, has autocorrelation in a time series dataset (see Fig. 3). It is useful for checking residual randomness, as random residuals indicate that the model captures all patterns without autocorrelation for further prediction. The results are interpreted using the Q-Stat and Prob columns, with low p values indicating significant autocorrelation and high p values indicating random residuals, indicating model validity.

4.5 Model forecasting and verification

Forecast comparison graph: The time series visualization (Fig. 4) compares actual and predicted climate funding values, showing substantial volatility in the actual data. The forecasting model fails to fully capture this variability, suggesting underestimation. The predicted values maintain a steady course around the zero line, suggesting that the model may represent the overall direction but lacks granularity to reflect finer details and subtler trends. The use of differencing in the data transformation process suggests an attempt to convert a nonstationary time series into a stationary one.

Figure 5 shows a significant discrepancy between the actual and predicted climate funding values over four quarters of 2021. The blue line (ClmFin) shows a flat trend, suggesting a constant level of funding, while the red line (CLMFINF) shows a positive trend, indicating a predicted increase. Possible reasons include model overfitting, exogenous factors, data anomalies, and predictive challenges.

The ARIMA model analysis offers valuable insights into climate funding dynamics for least developed countries (LDCs). The model's diagnostic plot shows the inverse roots of the AR and MA polynomials, indicating stability and invertibility (see Fig. 6). The roots of ARs show temporary deviations from long-term climate funding trends, while the roots of MAs account for unexpected shocks such as policy changes or economic shifts. This predictability and stability are crucial for long-term climate initiatives in LDCs.

4.6 Summary of the results

Climate change poses a significant challenge for least developed countries (LDCs), which often lack resources and infrastructure. Assessing the current climate finance framework is crucial to ensure that it aligns with their unique vulnerabilities and urgent needs in the face of climate change.

Table 3 Model comparison

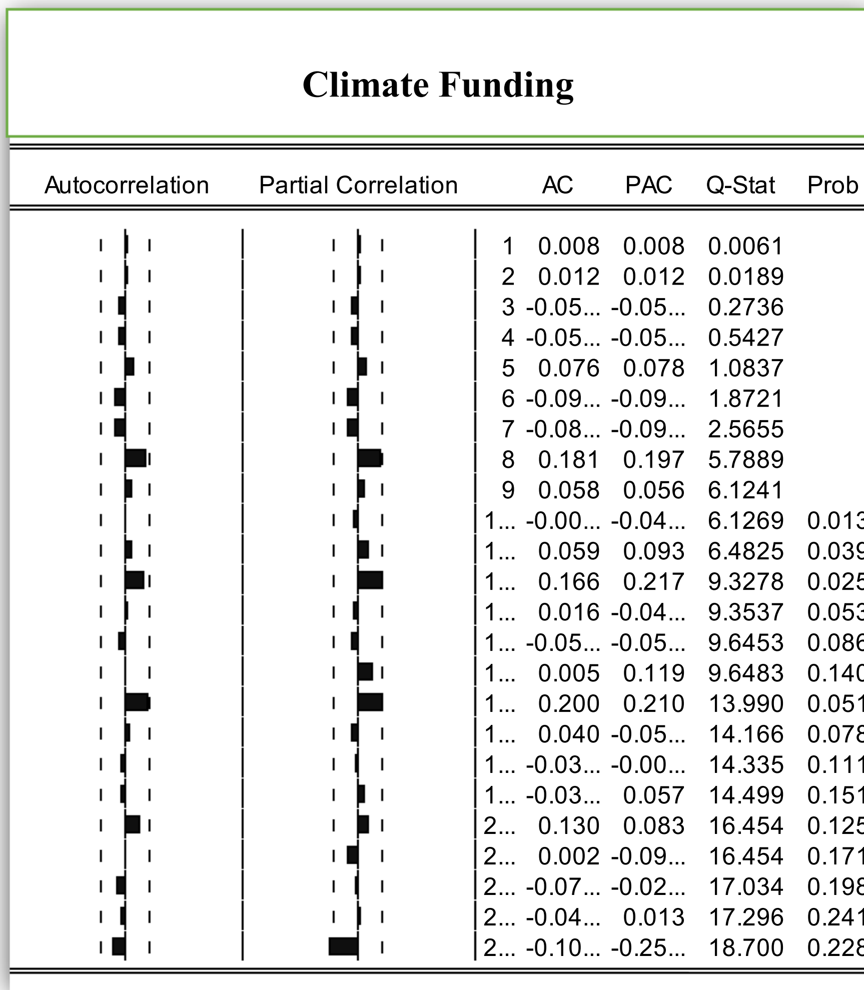
	ARIMA (1,1,1)	ARIMA (2,1,1)	ARIMA (1,1,2)	ARIMA (2,1,2)	ARIMA (2,1,3)	ARIMA (3,1,2)	ARIMA (3,1,3)	ARIMA (3,1,4)	ARIMA (4,1,3)	ARIMA (4,1,4)	ARIMA (5,1,4)	ARIMA (4,1,5)	ARIMA (5,1,5)
Significant coefficients	2	1	0	0	0	2	0	1	1	1	1	4	3
$Sigma^2$ (volatility)	1.72E+17	1.69E+17	1.7E+17	1.67E+17	1.67E+17	1.55E+17	1.47E+17	1.35E+17	1.34E+17	1.34E+17	1.33E+17	1.2E+17	1.23E+17
Adj. R^2	0.009426	0.013671	0.008674	0.011085	-0.000997	0.073199	0.11023	0.16948	178,220	0.169026	0.16092	0.240497	0.21657
AIC	42.61541	42.62282	42.62753	42.6363	42.65902	42.58639	42.59091	42.51448	42.4929	42.51428	42.53672	42.4608	42.53407

Table 4 Summary of the fitted models

Parameter	CF	
	Coefficient (B)	t-Statistic
C	58,766.00	1.2709
AR(1)	−0.6714	−2.5909**
AR(2)	−0.0002	−0.0007
AR(3)	−0.4586	−1.5467
AR(4)	−0.3504	−0.9852
MA(1)	0.6673	3.2630***
MA(2)	−0.1300	−0.5144
MA(3)	0.5363	2.1985**
MA(4)	−0.0689	−0.2103
MA(5)	−0.6370	−4.2811***
R-squared (R^2)	0.33	
Adjusted R-squared	0.24	

***Indicates significance at the 1% level

Fig. 3 Ljung–Box Q statistic


Climate Funding

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.008	0.008	0.0061	
		2	0.012	0.012	0.0189	
		3	-0.05...	-0.05...	0.2736	
		4	-0.05...	-0.05...	0.5427	
		5	0.076	0.078	1.0837	
		6	-0.09...	-0.09...	1.8721	
		7	-0.08...	-0.09...	2.5655	
		8	0.181	0.197	5.7889	
		9	0.058	0.056	6.1241	
		1...	-0.00...	-0.04...	6.1269	0.013
		1...	0.059	0.093	6.4825	0.039
		1...	0.166	0.217	9.3278	0.025
		1...	0.016	-0.04...	9.3537	0.053
		1...	-0.05...	-0.05...	9.6453	0.086
		1...	0.005	0.119	9.6483	0.140
		1...	0.200	0.210	13.990	0.051
		1...	0.040	-0.05...	14.166	0.078
		1...	-0.03...	-0.00...	14.335	0.111
		1...	-0.03...	0.057	14.499	0.151
		2...	0.130	0.083	16.454	0.125
		2...	0.002	-0.09...	16.454	0.171
		2...	-0.07...	-0.02...	17.034	0.198
		2...	-0.04...	0.013	17.296	0.241
		2...	-0.10...	-0.25...	18.700	0.228

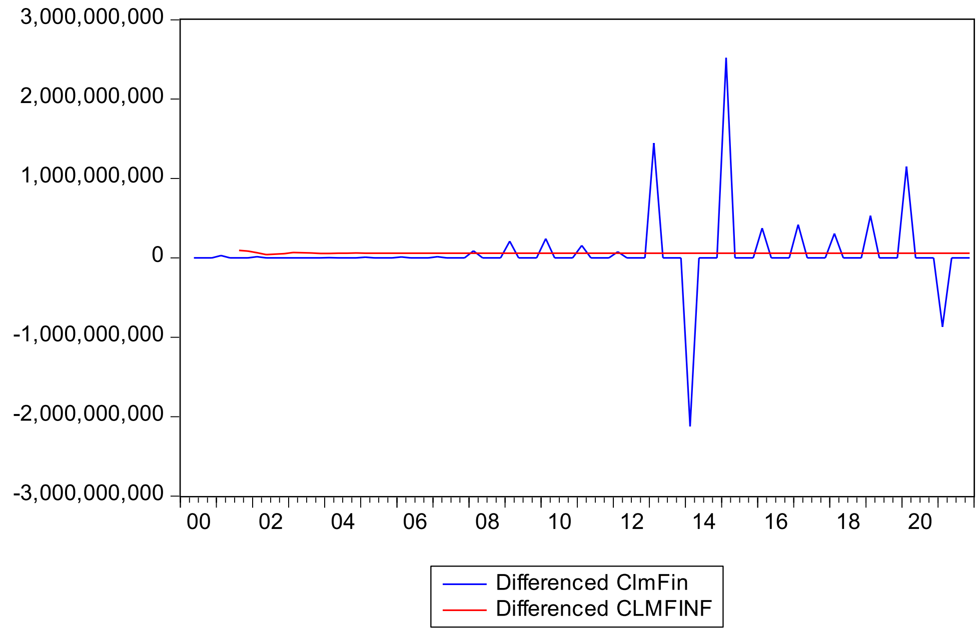


Fig. 4 Forecast comparison graph (all data; 2000q1:2021q4)

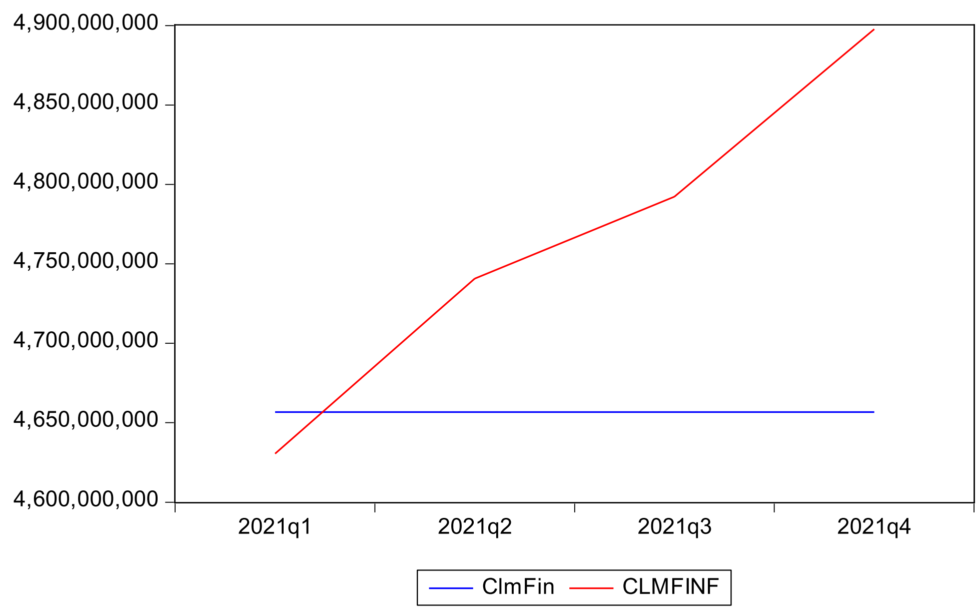


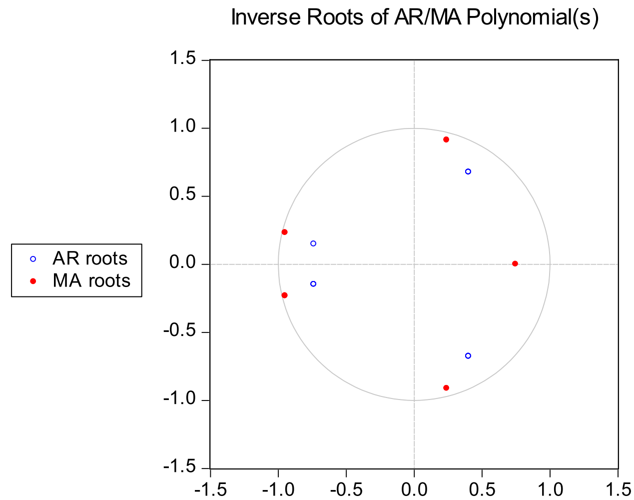
Fig. 5 Forecast comparison graph (2021q1:2021q4)

4.6.1 Is climate funding for LDCs predictable?

The unpredictability of climate finance for least developed countries (LDCs) presents a significant challenge in the global effort to combat climate change. The irregularity and nonstationary of funding, as indicated by ARIMA model analyses, reflect the complex dynamics influenced by shifting donor priorities, economic fluctuations, and political landscapes. These inconsistencies not only impair the ability of LDCs to forecast and strategize effectively but also undermine the execution of sustained climate action initiatives. Despite attempts to model these financial flows, the inherent volatility prevents reliable predictions, complicating the planning of long-term projects for mitigation and adaptation. This scenario stresses the need for a reformed approach that emphasizes stability and transparency in climate funding, as highlighted during the discussions at COP27 and COP28, where the focus increasingly shifted toward ensuring equitable financial support for vulnerable nations.

During the COP27 and COP28 conferences, the discourse frequently centered around enhancing the predictability and adequacy of climate finance, particularly in response to the challenges faced by LDCs. Comparatively, these discussions

Fig. 6 ARMA structure



underscore the importance of developing a more robust framework for climate finance that can withstand global economic and political perturbations. The emphasis was on creating mechanisms that ensure consistent and predictable funding streams, enabling LDCs to commit to more effective and resilient climate strategies. The contrast between the theoretical model limitations, such as those exhibited by ARIMA models in capturing the nuances of financial flows, and the practical discussions at international forums highlights a critical gap. The international community's focus on tailored, transparent, and accessible financial mechanisms at COP27 and COP28 reflects a collective acknowledgment of the need to bridge this gap, aiming to foster a more reliable support system for LDCs in their fight against climate change.

4.6.2 Is climate funding for LDCs adequate?

The adequacy of climate finance for least developed countries (LDCs) is a critical issue, underscored by a substantial discrepancy between the estimated financial requirements for effective climate action and the actual funds provided. The International Institute's estimation that LDCs require \$93.7 billion annually to implement their post-2020 climate action strategies starkly contrasts with the OECD's report of an average annual provision of merely \$14.8 billion since 2015. This significant funding gap not only highlights the inadequacy of current financial allocations but also raises concerns about the capacity of LDCs to pursue comprehensive mitigation and adaptation initiatives. This shortfall impacts the transparency and effectiveness of funding mechanisms, often leaving LDCs without the necessary resources to combat the adverse effects of climate change and to transition effectively toward sustainable development practices.

During the COP27 and COP28 conferences, the issue of climate finance adequacy was a focal point, reflecting an international acknowledgment of the funding disparities faced by LDCs. Discussions at these forums emphasized the need for developed nations to fulfill their financial commitments to support climate-vulnerable countries. Comparatively, the dialog at these conferences sought to bridge the gap highlighted by empirical data through pledges of increased financial support and the establishment of more robust funding mechanisms. However, despite these discussions, the persistent underfunding relative to the required amounts as outlined by the International Institute poses ongoing challenges. The conferences underscored the collective urgency of addressing these disparities but also illustrated the complexities involved in aligning international financial flows with the actual needs of LDCs, highlighting the critical need for a reevaluation of funding strategies to ensure that they meet the scale demanded by the global climate crisis.

4.7 Scenario analysis

In this study, scenario analysis plays a pivotal role in elucidating the multifaceted impacts of financial interventions under varying global economic and environmental conditions. By methodically delineating different plausible future scenarios—ranging from optimal to constrained financial inflows—this approach allows us to explore the resilience and vulnerability of the economies of LDCs to climate change. The scenarios are constructed based on key drivers such as international policy shifts, technological advancements in green technologies, and the geopolitical landscape of global finance. Through rigorous qualitative and quantitative assessments of these scenarios, our analysis offers critical insights into how different patterns of climate finance could influence sustainable development trajectories in LDCs. This not only aids policymakers in creating more robust and adaptive financial strategies but also enhances the global understanding of effective climate finance mechanisms tailored to the unique needs of LDCs.

The observed decline in climate funding allocated to least developed countries (LDCs) represents a critical barrier to their efforts in climate mitigation and adaptation. Despite the ostensibly stable commitment level of 93.70 between 2020 and 2021, the actual financial distribution to these nations decreased from 21.33 to 18.63, reflecting a notable erosion of trust in the efficacy and reliability of these allocations (see Table 5). This diminishing support not only underscores a growing disconnect between pledged aid and the actual fiscal requirements exacerbated by escalating climate challenges but also jeopardizes the ability of LDCs to pursue sustainable development and resilience. This trend poses a significant threat to global endeavors aimed at fostering a sustainable future, highlighting an urgent need for reassessment and reinforcement of international financial support mechanisms to ensure equitable and effective climate action.

4.7.1 Best case scenario

The fiscal landscape of climate finance for least developed countries (LDCs) is marked by profound challenges and a considerable funding gap, projected at approximately 60% by the year 2030. Although climate funding peaked in 2020 for these countries, the current trajectory of financial support is both insufficient and unpredictable. Estimates suggest that LDCs are likely to amass only approximately US$621.9 billion by 2030, which is significantly less than the US$1,030.7 billion deemed necessary to effectively address climate change and promote sustainable development (see Table 6). This financial shortfall not only indicates a pressing need for a strategic revision of financing mechanisms but also jeopardizes the capacity of LDCs to fulfill the United Nations Sustainable Development Goals and effectively tackle the myriad of challenges posed by climate change. This situation calls for an urgent global response to reassess and enhance financial support structures to ensure equitable and sustainable progress.

4.7.2 Worst case scenario

The stark disparity in climate financing for least developed countries (LDCs) underscores a critical shortfall in the global response to climate change. While climate funding has experienced a robust annual growth rate of 15.69% since 2015, LDCs are projected to receive a mere US$9.65 billion annually, falling approximately 80% short of the requisite funds by 2030. This funding gap starkly delineates the limitations faced by these nations, which need an estimated US$1,030.7 billion to effectively address climate change and promote sustainable development (see

Table 5 Climate funding for LDCs

Year	The estimated cost of LCDs climate action plans (US$ billion)	The funds received by LCDs (US$ billion)	Funding GAP (US$ billion)	Funding GAP (%)
2015		9.65		
2016		11.04		
2017		12.66		
2018		14.43		
2019		16.08		
2020	93.70	21.33	−72.37	−77.23
2021	93.70	18.63	−75.07	−80.12
2022	93.70			
2023	93.70			
2024	93.70			
2025	93.70			
2026	93.70			
2027	93.70			
2028	93.70			
2029	93.70			
2030	93.70			
Average climate funding	93.7	14.83		

Table 6 Best case scenario

Year	The estimated cost of LCDs climate action plans (US$ billion)	The funds received by LCDs (US$ billion)	Funding GAP (US$ billion)	Funding GAP (%)
2015		9.65		
2016		11.04		
2017		12.66		
2018		14.43		
2019		16.08		
2020	93.70	21.33	−72.37	−77.23
2021	93.70	18.63	−75.07	−80.12
2022	93.70	21.33	−72.37	−77.23
2023	93.70	24.68	−69.02	−73.66
2024	93.70	28.55	−65.15	−69.53
2025	93.70	33.04	−60.66	−64.74
2026	93.70	38.22	−55.48	−59.21
2027	93.70	44.21	−49.49	−52.81
2028	93.70	51.15	−42.55	−45.41
2029	93.70	59.18	−34.52	−36.84
2030	93.70	68.46	−25.24	−26.93
Average climate funding	93.7	29.54	−56.54	−60.34

Table 7). The current trajectory of climate financing not only highlights the need for a significant paradigm shift in funding attitudes and mechanisms but also poses a formidable challenge in enabling LDCs to meet their sustainable development goals and combat the adverse effects of climate change effectively.

Table 7 Worst case scenario

Year	The estimated cost of LCDs climate action plans (US$ billion)	The funds received by LCDs (US$ billion)	Funding GAP (US$ billion)	Funding GAP (%)
2015		9.65		
2016		11.04		
2017		12.66		
2018		14.43		
2019		16.08		
2020	93.70	21.33	−72.37	−77.23
2021	93.70	18.63	−75.07	−80.12
2022	93.70	9.65	−84.05	−89.71
2023	93.70	11.16	−82.54	−88.09
2024	93.70	12.91	−80.79	−86.22
2025	93.70	14.94	−78.76	−84.06
2026	93.70	17.28	−76.42	−81.56
2027	93.70	19.99	−73.71	−78.67
2028	93.70	23.13	−70.57	−75.32
2029	93.70	26.76	−66.94	−71.45
2030	93.70	30.95	−62.75	−66.97
Average climate funding	93.70	16.91	−74.91	−79.94

4.7.3 Average (normal) case scenario

The "Complex Landscape of Climate Finance" elucidates a pronounced climate funding chasm, projecting a 71% shortfall for least developed countries (LDCs) by 2030. Despite an average annual receipt of US$14.83 billion, LDCs are poised to garner only US$296.34 billion by the decade's close, a stark contrast to the US$1,030.7 billion deemed essential for efficacious climate change mitigation (see Table 8). This considerable deficit not only jeopardizes the attainment of sustainable development goals (SDGs) in these regions but also accentuates the imperative for a fundamental overhaul in climate finance strategies. Addressing this discrepancy requires not only an increase in funding but also a recalibration of financial flows to ensure that they meet the actual demands of climate-vulnerable nations, thereby fostering their sustainable development and resilience against climate adversities.

5 Discussion

The aim of this study is to investigate the complex landscape of climate finance and assess the adequacy, predictability, and implications for sustainable development in least developed countries (LDCs) using an econometric framework including the ARIMA model. This study highlights the significant gap between the required funding and the actual financial support provided to least developed countries (LDCs) in climate finance. Despite the urgent need for substantial and consistent funding, LDCs face unpredictable and inadequate funding. The study's scenario analysis shows that even in the best-case scenario, LDCs are projected to receive only a fraction of the required funds by 2030, exacerbating their vulnerability to climate impacts and jeopardizing their progress toward the Sustainable Development Goals. The unpredictability and insufficiency of climate funding, as well as disparities in annual allocations and limitations of forecasting models such as ARIMA, call for a fundamental overhaul in climate financing. A shift toward more predictable, adequate, and equitable financial support is crucial for empowering LDCs in their fight against climate change.

A study revealed that least developed countries (LDCs) receive significantly less climate financing than they need because of financial inadequacy and global inequality in addressing climate change. The estimated annual funding requirement for LDCs is $93.7 billion, but the actual average is $14.8 billion. This underfunding raises ethical and practical questions about the global commitment to sustainable development and climate justice. This study highlights the complex relationship between climate finance and the sustainable development of LDCs, with unpredictable planning and adequacy being influenced by donor priorities and global economic fluctuations. This calls for an urgent re-evaluation

Table 8 Average (normal) case scenario

Year	The estimated cost of LCDs climate action plans (US$ billion)	The funds received by LCDs (US$ billion)	Funding GAP (US$ billion)	Funding GAP (%)
2015		9.65		
2016		11.04		
2017		12.66		
2018		14.43		
2019		16.08		
2020	93.70	21.33	−72.37	−77.23
2021	93.70	18.63	−75.07	−80.12
2022	93.70	14.83	−78.87	−84.17
2023	93.70	17.16	−76.54	−81.69
2024	93.70	19.85	−73.85	−78.82
2025	93.70	22.96	−70.74	−75.49
2026	93.70	26.57	−67.13	−71.65
2027	93.70	30.73	−62.97	−67.20
2028	93.70	35.56	−58.14	−62.05
2029	93.70	41.14	−52.56	−56.10
2030	93.70	47.59	−46.11	−49.21
Average Climate Funding	93.7	22.51	−66.76	−71.25

of global climate finance mechanisms to ensure sufficient, stable, equitable, and strategically allocated funds to address the unique challenges of LDCs. The global climate crisis is a significant challenge, especially for least developed countries (LDCs), which are at the frontline of climate change impacts but are least equipped to cope. The International Institute for Environment and Development estimated that LDCs would require $93.7 billion annually to implement their post-2020 climate action plans. However, the actual funding received by these countries is only $14.8 billion per year, indicating a significant inadequacy in climate funding. The worst-case scenario could lead to an 80% climate budget shortfall by 2030, compared to 2015 when they received their lowest climate funding. This deficit highlights the need for a significant shift in attitudes and approaches toward climate financing for LDCs. Addressing the funding gap is not only financial necessity but also an ethical imperative. Developed nations, international organizations, and other stakeholders must mobilize resources that match the scale and urgency of the climate challenges faced by LDCs, ensuring that they are accessible, transparent, and aligned with their specific needs and priorities.

This study revealed that climate funding for least developed countries (LDCs) is unpredictable, posing challenges to their planning and execution. The ARIMA model reveals nonstationary, indicating potential volatility and unpredictability in climate funding. This volatility makes it difficult to plan long-term climate initiatives and forecast future financial support. The model's ability to capture historical patterns of climate funding also reveals challenges in predictability. External factors such as global economic conditions, policy changes, and international commitments to climate finance also contribute to the unpredictability of climate funding for LDCs. Climate change poses a significant threat to global stability, especially affecting the least developed countries (LDCs). Climate finance is crucial for sustainable development in LDCs, but the unpredictability of climate finance hinders their ability to plan and implement effective long-term climate strategies. The IIED estimated an annual requirement of $93.7 billion for LDCs, but the actual provision was only $14.8 billion. This inadequacy limits the capacity of LDCs to undertake climate change mitigation and adaptation measures. Bridging this funding gap is essential for their sustainable future. This study presents a scenario analysis for LDCs under varied funding landscapes, showing significant progress in climate resilience but a substantial shortfall in required funds.

This study's findings are in line with the literature, emphasizing the critical challenges faced by least developed countries (LDCs) in terms of the predictability and adequacy of climate funding. The unpredictability of climate finance, as identified in this study, echoes the concerns raised by [83], who pointed out the volatility in international climate finance and its impact on long-term strategic planning in LDCs. Similarly, the inadequate funding levels highlighted here are consistent with the observations of [10, 84], who noted a substantial gap between the climate finance needs of LDCs and the actual funds received, a gap also quantified by the International Institute for Environment and Development (IIED) (see, for instance [85–91]). Furthermore, the study's emphasis on the need for a strategic overhaul in climate finance aligns with the recommendations of [49, 92], who argued for a more robust, equitable, and needs-based approach to climate funding. Thus, this study not only corroborates existing research but also adds depth to the discourse on the challenges and necessary reforms in climate finance for LDCs, further emphasizing the urgent need for global action and policy adjustments to ensure sustainable development in these vulnerable regions.

The findings of this study underscore the persistent challenges in the predictability and adequacy of climate finance for least developed countries (LDCs), resonating with prior research. The volatility and insufficiency of climate funding, as revealed through ARIMA model analyses, align with the concerns raised by [93], who highlighted the unpredictability and political influences that hinder reliable climate finance [93]. Moreover, the significant gap between the estimated $93.7 billion needed annually for effective climate action and the average $14.8 billion provided, as reported by the OECD, echoes the conclusions of [94], who identified similar disparities in climate finance allocations. Despite the international community's pledges at COP27 and COP28 to enhance funding mechanisms, the consistency and adequacy of financial flows remain problematic, as also noted by [95, 96], who emphasized the importance of transparent and predictable funding [97]. Therefore, the current study supports previous findings that stress the need for reformed, stable, and transparent climate finance frameworks to effectively support LDCs in their climate action endeavors [98, 99].

In the realm of climate financing, it is imperative to acknowledge the multifaceted nature of the challenges faced by economies, particularly in the context of least developed countries (LDCs). Beyond purely quantitative assessments, a myriad of dynamic qualitative factors significantly shape the landscape of climate finance over the long term. These factors encompass socioeconomic conditions, political stability, demographic trends, humanitarian considerations, and cultural nuances. For instance, the socioeconomic context of an LDC, including its level of industrialization, income distribution, and access to financial services, can profoundly influence its capacity to mobilize and effectively utilize climate finance resources. Similarly, political factors such as governance structures, policy frameworks, and institutional capacities play a crucial role in determining the prioritization and implementation of climate-related initiatives within these economies. Moreover, demographic dynamics, such as population growth rates and urbanization trends, can impact the vulnerability of LDCs to climate risks and the allocation of financial resources for adaptation and resilience-building efforts. Humanitarian factors, including the prevalence of poverty, inequality, and displacement, further underscore the urgency of addressing climate change impacts in these vulnerable contexts, highlighting the interconnectedness between climate financing and broader development objectives.

In addressing the multifaceted challenges of climate finance in LDCs, the role of international organizations and global players, including the United Nations and multilateral financing institutions, is pivotal. These entities not only provide substantial financial support but also offer technical expertise, capacity-building initiatives, and policy guidance to enhance the resilience and adaptive capacities of LDCs in mitigating climate crises. Through their concessional lending mechanisms and grant programs, multilateral development banks and funding agencies play a crucial role in supporting climate-related projects and programs in LDCs, thereby facilitating sustainable development outcomes. Additionally, initiatives such as the Green Climate Fund, established under the United Nations Framework Convention on Climate Change, serve as vital channels for channeling climate finance to LDCs, prioritizing adaptation and resilience-building efforts. By leveraging their global networks, resources, and expertise, international organizations and multilateral financing institutions contribute to bridging the funding gap and fostering equitable access to climate finance in LDCs, thereby advancing collective efforts toward achieving global climate goals and promoting inclusive and sustainable development.

This study reveals a significant disparity in global environmental justice, with inadequate and unpredictable climate funding for least developed countries (LDCs). LDCs face difficulty in securing resources for mitigation and adaptation, in contrast to developed nations. This imbalance violates environmental justice principles, which demand equal access to resources for all nations. This study suggests a need for a recalibration of global climate finance mechanisms to address these inequities and ensure that LDCs are equipped to effectively confront and adapt to climate change, upholding their right to a safe, healthy, and sustainable environment. This study highlights dependency theory, which suggests that economic disparities between developed and developing nations can lead to dependence. The reliance of LDCs on insufficient climate funding from wealthier nations perpetuates this dependency, limiting their development prospects. The scenario analysis revealed significant shortfalls in climate funding and further entrenching dependency. This study calls for a restructuring of the international climate finance system, advocating for models that promote autonomy and self-reliance in LDCs, thereby breaking the dependency cycle and promoting equitable and sustainable development.

This study emphasizes the need for a reformed approach to climate finance, particularly for least developed countries (LDCs), to ensure predictability and adequacy. It advocates for a shift toward reliable, long-term funding mechanisms, increased transparency in fund allocation, and a paradigm shift in global climate finance policies. Implementing these recommendations would bridge the current funding gap and promote a more just and sustainable future for all, thereby reinforcing global efforts to achieve the United Nations Sustainable Development Goals. This study provides a comprehensive analysis of climate finance for least developed countries (LDCs) using advanced econometric models and global economic trends. This highlights the unpredictability and inadequacy of climate finance, urging systemic overhaul. The scenario analysis assesses future funding trajectories, identifying gaps between required and projected climate finance. This approach is valuable for policymakers, international funding agencies, and climate advocates and contributes to academic research and policy formulation in global climate change mitigation and adaptation. This study contributes significantly to the climate finance literature, particularly in the context of least developed countries (LDCs). Advanced forecasting techniques such as ARIMA models are used to analyze the predictability and adequacy of climate funding, revealing the inherent unpredictability of current mechanisms. The study also examines funding adequacy, contrasting IIED estimates with actual OECD data and highlighting the severe funding gap for LDCs. The scenario analysis provides a forward-looking perspective on potential future outcomes, enriching the discourse on climate finance and providing a reference point for policymakers, academics, and practitioners working toward more effective and equitable climate finance strategies.

6 Conclusion and policy suggestions

This study investigates the evident disparity in climate finance allocation, particularly focusing on the unmet financial needs of least developed countries (LDCs) in combating climate change impacts. Our analysis reveals a severe shortfall in funding, with LDCs requiring an estimated $93.7 billion annually to implement effective climate response strategies. However, the actual financial inflows are significantly lower, underscoring a critical gap that hampers sustainable development efforts in these vulnerable regions. Utilizing the Autoregressive Integrated Moving Average (ARIMA) model, our research highlights the volatility and unpredictability of climate finance, which is primarily influenced by fluctuating donor priorities and prevailing global economic conditions. This variability in funding not only complicates the financial planning required for long-term climate initiatives but also affects the stability and effectiveness of such interventions in LDCs. The findings of this study are situated within the frameworks of environmental justice and dependency theories, which argue that systemic inequities in global climate finance mechanisms contribute to and perpetuate the dependency of LDCs on developed countries. This dependency is exacerbated by the inequitable distribution of funds, which often fails to align with the most urgent needs of these countries, thereby undermining their efforts towards sustainable environmental management. Our analysis calls for a comprehensive reformation of the climate finance infrastructure. We advocate for the establishment of mechanisms that enhance the predictability and adequacy of funding. Key recommendations include improving transparency in the allocation processes, committing to sustained and adequate financial support, and ensuring that funding decisions are closely aligned with the specific needs and priorities of LDCs. By addressing these issues, it is possible to reduce the vulnerability of LDCs and support their transition towards sustainable development pathways. This reform is crucial not only for meeting global climate goals but also for advancing the principles of fairness and equity in international environmental governance.

6.1 Policy suggestions

To effectively confront the financing deficit in climate change mitigation and adaptation in least developed countries (LDCs), this paper proposes several strategic reforms aligned with the deliberations at recent Conference of the Parties (COP) sessions. The first and foremost reform is the escalation of financial commitments to match the substantial needs identified through climate vulnerability assessments. These assessments underscore the urgency and magnitude of required interventions, yet current funding levels remain insufficiently aligned with these identified necessities. Secondly, to assure the integrity and efficiency of climate finance, there is an imperative need for enhanced transparency. This can be achieved through the establishment of robust reporting and monitoring frameworks. Such mechanisms are essential to track the flow of funds and ensure they are effectively allocated to the intended projects and outcomes. These frameworks not only facilitate accountability but also foster trust among stakeholders, which is crucial for sustained financial support. Thirdly, the stabilization of funding streams is critical. Developing financial instruments that are less affected by the vicissitudes of political and economic climates can offer LDCs a more predictable source of finance. This stability is vital for long-term planning and implementation of climate resilience strategies, which often span multiple decades and require consistent funding. Lastly, it is paramount that climate finance mechanisms are meticulously aligned with the local needs of LDCs. Tailoring financial support to meet the specific environmental, social, and economic conditions of these countries ensures that funds are not only provided but utilized in a manner that maximizes impact. This approach necessitates a deep understanding of local contexts and a commitment to flexible, responsive funding strategies. These proposed reforms resonate with the global consensus on the need for equitable and adequate financial support, as emphasized in key discussions at COP27 and COP28. Implementing these strategies will be instrumental in enabling effective and sustainable climate action in the world's most vulnerable regions.

6.2 Limitations and future research directions

This investigation, while thorough, identifies several limitations that highlight essential directions for further scholarly inquiry. Primarily, the deployment of the Autoregressive Integrated Moving Average (ARIMA) model in analyzing climate finance may not sufficiently capture the complex and multifaceted impacts of global economic and political dynamics. This limitation suggests a potential oversimplification of intricate interactions, thus pointing to the need for models that can better encompass these complexities. Additionally, the study's reliance on existing data sources poses constraints, possibly overlooking emerging trends and issues within the realm of climate finance. This reliance underscores the necessity for research that integrates up-to-date data and explores innovative financing mechanisms that can adapt to shifting paradigms. Moreover, the analysis's focus on quantitative measures tends to marginalize the critical qualitative aspects of the issue. Aspects such as the socioeconomic conditions, political environments, and cultural dynamics of LDCs remain underrepresented. These dimensions are crucial for a comprehensive understanding of how climate finance affects these regions. Future research should aim to incorporate these qualitative elements, offering a more holistic view of the challenges and opportunities within climate finance for LDCs. Such studies would contribute significantly to the development of more stable and predictable financial support mechanisms, enhancing the efficacy of climate-related interventions in these vulnerable regions.

Author contributions Mohamed Ibrahim Nor: Conceptualization; study design; methodology; formal analysis; investigation; writing—original draft; project administration; acquiring the necessary funding for the project. Abdinur Ali Mohamed: Software; data curation; formal analysis; supervision; validation; writing—review and editing; visualization of data and results.

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Data availability The data will be made available upon reasonable request.

Declarations

Ethics approval and consent to participate This article does not contain any studies with human participants performed by any of the authors.

Consent for publication I hereby provide my permission for the publishing of this manuscript, which includes any associated images or data covered within the text.

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