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The spatial dynamics of climate shock impacts in SADC: a focus on selected economic sectors

Batsirai Mazviona,* Innocent Bayai† and Tafirei Mashamba‡

Abstract

Existing literature overlooks the spatial dynamics of localised climate shocks such as droughts, floods and extreme temperatures on key economic sectors within and across countries in the Southern African Development Community (SADC). Therefore, we analyse the direct and spillover effects of climate shocks on sector performance in the short and long run, considering the interdependencies of SADC countries. We use economic and climate shock datasets from 2010 to 2022. Specifically, we look at the agricultural, manufacturing, mining, energy, tourism and financial sectors. By using spatial Durbin and spatial autoregressive models, we test whether climate shocks in one SADC country can cause long-lasting effects on economic sector performance in neighbouring countries. We provide insights to inform policy development in the SADC region.

JEL classification

C31, O13, R15, Q54, Q56

Keywords

Climate shocks, economic sector performance, regional interdependence, SADC, spatial econometrics, spillover effects,

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1. Introduction

The Southern African Development Community (SADC) is increasingly vulnerable to recurring climate shocks, such as droughts, floods and extreme temperatures, which disrupt ecosystems, livelihoods and key economic sectors. The existing literature has primarily focused on the localised impacts of these shocks, often overlooking how shocks in one country can affect the same sectors in neighbouring countries, either directly or indirectly. Although there is a growing body of research on country-level climate vulnerabilities, there are limited studies examining the cross-border effects of climate shocks in Southern Africa. This study aims to address this gap by exploring how climate shocks in one country can trigger similar impacts in neighbouring countries, with significant implications for regional resilience and risk management.

This study draws on key theoretical frameworks to understand how climate shocks are transmitted across borders. Spatial dependence theory emphasises the interconnectedness of countries within a region, suggesting that climate events in one country can directly affect neighbouring countries. For example, droughts in South Africa may reduce agricultural productivity, with potential cascading effects in neighbouring countries due to shared environmental resources, trade routes or regional infrastructure (LeSage and Pace 2009; Schenker and Osberghaus 2025). Regional integration theory highlights the role of integrated economies and shared resources in amplifying the spread of climate shocks across borders. Cross-border infrastructure, for example in river basins and across trade networks, can either mitigate or exacerbate the impacts of climate events, especially in regions like Southern Africa (Blanchard, Brown and Johnson 2016; Simpson and Williams 2024). Furthermore, theories of externalities and risk transfer suggest that climate shocks can disrupt regional trade and shared resources, deepening vulnerabilities across neighbouring countries (Woetzel et al. 2020; Feng, Li and Wang 2025). Despite the existence of these theoretical frameworks, the propagation of climate shocks across national borders in Southern Africa has yet to be fully explored.

This study specifically investigates how climate shocks, such as droughts, floods, storms and extreme temperatures, that affect economic sectors in one country can affect the same sectors in neighbouring countries and the region. For instance, a drought that severely affects agricultural production in South Africa could disrupt agricultural activities in neighbouring countries that share trade routes, supply chains or market dependencies. Such sector-specific shocks have the potential to spread across borders, amplifying economic vulnerabilities throughout the region. These effects may unfold over both short and long periods, influencing national economies and regional stability.

By analysing spatial dynamics, this study seeks to show that climate shocks have varied impacts on key economic sectors and propagate across the region through various transmission channels. The findings can help strengthen SADC's climate policy – for example, the SADC Regional Resilience Framework 2020–2030, which aims to enable the region to withstand and recover from climate-related and socio-economic shocks. A better understanding of how climate shocks propagate can strengthen food security, disaster risk management and cooperation among member countries in addressing climate shocks.

Southern Africa faces many kinds of climate-related shocks, which worsen food insecurity, upend livelihoods, slow economic growth and reverse progress made in infrastructure development. Cyclones in Southern Africa often bring intense, localised rainfall, leading to flooding and the destruction of infrastructure such as hydropower plants, powerlines and water systems. For example, Cyclone Idai, which hit Mozambique, Zimbabwe and Malawi in 2019, caused more than 1 300 deaths and displaced more than 2.5 million people (UNICEF n.d.). Cyclone Idai swept away about 715 000 hectares of crops across the three countries (World Meteorological Organization 2020) and damaged or destroyed more than 1 200 kilometres of powerlines, plunging millions of people into darkness (Government of Mozambique 2019). More than 3 million people were estimated to need food assistance across the three countries.

Southern Africa is also heavily affected by prolonged droughts, with severe consequences for food security and water availability. A 2019 drought affected more than 45 million people in the region, causing crop failure, which worsened food shortages and inflation (Anyadike 2019). As temperatures rise and rainfall becomes more unpredictable, agricultural productivity declines, increasing countries' reliance on food imports. Droughts also exacerbate water scarcity, causing reservoirs to drop to dangerously low levels. This significantly affects hydroelectric power production, contributing to power shortages and rolling blackouts, which have a crippling effect on households and businesses. The economic cost of climate-related disasters in Southern Africa has been estimated at over US$10 billion annually, contributing to rising poverty and economic instability (African Development Bank 2021).

These facts suggest that the effects of climate shocks are transmitted among countries in the region, either directly or indirectly through trade linkages. And yet there are gaps in the literature on how spatial dependencies cause climate shocks to affect different economic sectors in Southern Africa.

2. Literature gaps in the Southern African context

2.1 Underexploration of spatial dynamics and interdependencies

The spatial dynamics of climate shocks in Southern Africa are underexplored, despite the region's high vulnerability to recurring climate events such as droughts, floods and extreme temperatures. Spatial dependence theory provides a valuable framework for understanding how climate shocks in one location can influence neighbouring areas through shared resources, trade networks or environmental linkages (LeSage and Pace 2009). For example, floods in Zambia may affect tourism and cascade into neighbouring countries due to shared river basins or regional infrastructure (Schenker and Osberghaus 2025). However, there has been limited application of this theory in the Southern African context.

2.2 Overrepresentation of evidence from developed economies

Much of the existing literature on the spatial dynamics of climate shocks focuses on developed economies (Dell, Jones and Olken 2012, 2014; Hsiang and Burke 2014; Burke, Hsiang and Miguel 2015), with limited attention paid to developing regions like Southern Africa. Regional integration theory highlights how interconnected economies and shared resources increase the likelihood of climate shocks spreading across borders (Baldwin, Freeman and Theodorakopoulos 2019). However, this theory has predominantly been applied in developed regions, where advanced infrastructure and governance systems mitigate cross-border risks. In contrast, Southern Africa's weak institutions and limited adaptive capacities exacerbate vulnerabilities, presenting a gap in understanding how spatial dependencies function in resource-constrained environments (Feng, Li and Wang 2025).

2.3 Overemphasis on localised effects with limited cross-border analysis

Existing studies on climate shocks in Southern Africa tend to focus on localised impacts within individual countries, often neglecting cross-border effects. Theories of externalities and risk transfer (Woetzel et al. 2020) suggest that climate shocks in one country can disrupt regional trade and shared resources, exacerbating vulnerabilities across neighbouring countries. For instance, disruptions in agricultural production due to droughts in South Africa can ripple into neighbouring countries that rely on cross-border food supply chains, exacerbating regional food insecurity (Dalin and Conway 2015). However, there has been limited application of these theories in Southern Africa, particularly to understand how localised shocks propagate across the region.

2.4 Focus on cross-sectoral effects with limited attention to sectoral propagation

While some studies have explored the cross-sectoral impacts of climate shocks, such as how droughts affect both the agricultural and energy sectors (Zappalà 2023), there is limited research on how shocks propagate within the same sector across borders. Network theory (Borgatti et al. 2009) offers insights into how sector-specific shocks can spread through interconnected systems, such as regional supply chains or shared infrastructure. For example, a drought affecting agriculture in South Africa could lead to similar disruptions in neighbouring countries that share trade routes or market dependencies. However, there has been little application of network theory to intrasectoral climate risks in Southern Africa.

2.5 Novel spatial dependency modelling approaches

We capitalise on recent advances in spatial dependency modelling to enhance understanding of the direct and indirect, as well as short- and long-term, effects of climate shocks. Spatial econometrics (LeSage and Pace 2009) provides a robust framework for quantifying spillover effects across regions, capturing both immediate and protracted impacts of shocks. These models are particularly useful for analysing the interconnected nature of climate risks in Southern Africa, where shared resources and regional trade networks create complex interdependencies (Schenker and Osberghaus 2025). According to our understanding, this study is the first to examine the spatial dependency of climate shocks in Southern Africa.

3. Data and methods

3.1 Data description and source

To understand the spatial dynamics of climate shocks, we examine the direct and indirect (spillover) effects of climate-related disasters, including droughts, floods, extreme temperatures and storms, on selected sectors' share of gross domestic product (GDP) in the SADC region. The SADC bloc is made up of 16 countries, namely Angola, Botswana, Comoros, Democratic Republic of Congo (DRC), Eswatini, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Tanzania, Zambia and Zimbabwe. We use data from these countries from 2010 to 2022 to investigate spatial dynamics and climate shocks in the agricultural, manufacturing, energy, tourism, mining and financial sectors. The analysis integrates data from SADC, EM-DAT (disasters) and the World Bank to comprehensively assess these extreme climate impacts.

Table 1 provides the data, source and measurement of variables used in the study. Each variable is compiled on an annual basis. The dependent variable is the contribution of each sector to total GDP, measured as a percentage share of GDP (SGDP). Key independent variables capture the regional climate disaster occurrence, such as drought, extreme heat, flood and storm. These occurrences are measured by a dummy variable of 1 to represent an event and 0 otherwise. Control variables include structural and economic factors: population growth, foreign direct investment (FDI), total external debt, broad money supply, annual headline inflation rate and current account balance. FDI, total external debt, broad money supply and current account balance are measured as a percentage of GDP. Population growth is measured as an annual percentage growth, and the annual headline inflation rate is based on a period average of the national consumer price index.

Table 1: Data and sources

Data	Description	Source	Measurement
Agriculture (AGRI)	Agriculture, forestry and fishing	SADC Data Portal	Percentage share of GDP
Mining (MINI)	Mining and quarrying	SADC Data Portal	Percentage share of GDP
Manufacturing (MANU)	Manufacturing	SADC Data Portal	Percentage share of GDP
Energy (ENER)	Electricity, gas and water supply	SADC Data Portal	Percentage share of GDP
Tourism (TOUR)	Hotels and restaurants	SADC Data Portal	Percentage share of GDP
Financial (FINA)	Financial intermediation	SADC Data Portal	Percentage share of GDP
Drought (DRT)	Drought	EM-DAT	Binary – presence and absence of an event
Extreme temperature (EXT)	Extreme temperature	EM-DAT	Binary – presence and absence of an event
Flood (FD)	Flood	EM-DAT	Binary – presence and absence of an event
Storm (STM)	Storm	EM-DAT	Binary – presence and absence of an event
Population growth (PG)	Population growth	World Bank	Annual percentage growth
Foreign direct investment (FDI)	Foreign direct investment and net inflows	World Bank	Percentage of GDP
Total external debt (TED)	Total external debt	SADC Data Portal	Percentage of GDP
Broad money supply (BMS)	Broad money supply:M2	SADC Data Portal	Percentage of GDP
Annual headline inflation rate (AHIR)	Annual headline inflation rate	SADC Data Portal	Period average
Current account balance (CAB)	Current account balance	SADC Data Portal	Percentage of GDP

Source: Authors' compilation

3.2 Spatial weight matrix

We employ an inverse distance spatial weight matrix to capture the spatial relationship among geographic units by assigning weights based on the inverse of the distance between units (Billé, Blasques and Catania 2020). The spatial dimension is defined at a country level to ensure spatial comparability. We use an inverse distance spatial weight matrix to reflect the intensity of spatial interactions among SADC countries. In the context of regional science, countries nearby are more likely to interact, thus necessitating a model that captures these regional dependencies (Franklin and van Leeuwen 2018). The simplicity and intuitiveness of inverse distance weighting provide a clear and straightforward means of quantifying spatial associations, facilitating an understanding of the spatialisation of economic and climate interactions without the need for overly intricate mathematical formulations (Barbulescu, Bautu and Bautu 2020; Massarelli, Campanale and Uricchio 2022). Using the definition of Krause and Kripfganz (2025), we construct the spatial weight matrix from:

$$\begin{cases} w_{ij} = \dfrac{1}{d_{ij}} \text{ for } i \neq j \\ w_{ij} = 0 \text{ for } i = j \end{cases}$$

where d_{ij} is the Euclidean distance between country i and country j.

3.3 Preliminary analysis of spatial data

Our exploratory analysis of spatial data begins by summarising the characteristics of the dependent and independent variables. We use the mean, standard deviation and minimum and maximum variance. Next, we test for spatial autocorrelation by applying Moran's I, which measures the degree of spatial dependence (and possible spillover effects) in the data. A positive and negative value of Moran's I illustrate spatial clustering and spatial dispersion, respectively (Quito et al. 2023). Finally, we conduct multicollinearity checks among the DRT, EXT, FD, STM, PG, FDI, TED, BMS, AHIR and CAB variables using the variance inflation factor (VIF) (Chavez-Chong, Hardouin and Fermin 2024). VIF values were computed using an ordinary least squares regression to assess multicollinearity before applying spatial models. This inspection was necessary to proactively address potential bias in parameter estimates that may arise due to highly correlated predictors. These preliminary analytical techniques provide a foundation for further spatial modelling.

3.4 Modelling motivation and specification

Given that the study is conceptualised in three dimensions: economic (economic sectors), environmental (climate shocks) and geographical (regional economies in SADC), we employ spatial econometric models, which offer several advantages. First, they provide a strong methodological approach to understand spatial dependencies in modelling economic sectoral performances within SADC (Mendes and Mendes 2015; LeSage and Pace 2021). Second, they can capture the spatial spillovers of climate shocks and their effect on sectoral outcomes. Third, by including spatial weights, they overcome the problem of spatial heterogeneity (Basile et al. 2014). Fourth, by incorporating a lagged dependent variable, spatial models control for any possible endogeneity (Huang, Dong and Zhao 2024). The spatial econometric models used in our analysis include the spatial Durbin model (SDM), the spatial autoregressive model (SAR), the spatial error model (SEM) and the spatial autoregressive model with spatially autocorrelated errors (SAC) (Belotti, Hughes and Mortari 2017; Elhorst 2022; Wang et al. 2023). These models are particularly relevant for our core tasks of quantifying spatial interdependencies and estimating the impact of spillovers of drought, extreme temperature, floods and storms in the short and long run in SADC.

The SDM is an extension of the SAR, developed by incorporating spatial lags of explanatory variables, which allows a flexible structure to assess spillover effects. This is specified as:

$$SGDP_{it} = \tau SGDP_{it-1} + \rho \sum_{j\neq i}^{N} w_{ij} SGDP_{jt-1} + \beta_1 DRT_{it} + \beta_2 EXT_{it} + \beta_3 FD_{it} + \beta_4 STM_{it} + \theta_1 \sum_{j\neq i}^{N} w_{ij} DRT_{jt} + \theta_2 \sum_{j\neq i}^{N} w_{ij} EXT_{jt} + \theta_3 \sum_{j\neq i}^{N} w_{ij} FD_{jt} + \theta_4 \sum_{j\neq i}^{N} w_{ij} STM_{jt} + \theta_5 PG_{it} + \theta_6 FDI_{it} + \theta_7 TED_{it} + \theta_8 BMS_{it} + \theta_9 AHIR_{it} + u_i + v_t + \varepsilon_{it} \quad (1a)$$

$$\varepsilon_{it} = \lambda \sum_{j\neq i}^{N} w_{ij} \varepsilon_{jt} + \psi \text{ and } \psi \sim \left(0, \sigma^2 I_j\right) \quad (1b)$$

$SGDP_{it}$ is the share of GDP by economic sector for country i in year t. τ and $SGDP_{it}$ measure the temporal and spatiotemporal effect of $SGDP_{it}$, respectively. The coefficients for drought, extreme temperature, flood and storm are depicted by β_1, β_2, β_3 and β_4, respectively. $\theta_1$is the coefficient measuring the contemporaneous or cross-country spillover effect of drought from neighbouring countries. Similarly, θ_2, θ_3 and θ_4 are estimates for extreme temperature, flood and storm, respectively. The coefficients for the control variables population growth, FDI, total external debt, broad money supply and annual headline inflation rate are represented by θ_5, θ_6, θ_7, θ_8 and θ_9, respectively. The country and time-fixed effects are denoted by u_i and v_t. ε_{it} is the composite error term for country i, corresponding to year t; it follows a Gaussian distribution with a mean of 0 and variance $\sigma^2_{\varepsilon_{it}}$. λ is the spatial autocorrelation coefficient, the intensity of the interaction effects among unobserved spatially correlated variables. ψ is the disturbance term that is independent and identically distributed. This has a mean of 0 and variance $\sigma^2 I_j$.

The SAR assumes that the spatial correlation exists in the dependent variable due to regional dependencies. The SAR is created by allowing $\theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$ and $\lambda = 0$ in 1(a) and 1(b), which results in the following specification:

$$SGDP_{it} = \tau SGDP_{it-1} + \rho \sum_{j\neq i}^{N} w_{ij} SGDP_{jt-1} + \beta_1 DRT_{it} + \beta_2 EXT_{it} + \beta_3 FD_{it} + \beta_4 STM_{it} + \theta_5 PG_{it} + \theta_6 FDI_{it} + \theta_7 TED_{it} + \theta_8 BMS_{it} + \theta_9 AHIR_{it} + u_i + v_t + \varepsilon_{it} \quad (2a)$$

$$\varepsilon_{it} = \psi \text{ and } \psi \sim (0, \sigma^2 I_j) \quad (2b)$$

By setting $\tau = 0$, $\rho = 0$, and $\theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$ in the SDM, we obtain the SEM specification:

$$SGDP_{it} = \beta_1 DRT_{it} + \beta_2 EXT_{it} + \beta_3 FD_{it} + \beta_4 STM_{it_1} + \theta_5 PG_{it} + \theta_6 FDI_{it} + \theta_7 TED_{it} + \theta_8 BMS_{it} + \theta_9 AHIR_{it} + u_i + v_t + \varepsilon_{it} \quad (3a)$$

$$\varepsilon_{it} = \lambda \sum_{j\neq i}^{N} w_{ij} \varepsilon_{jt} + \psi \text{ and } \psi \sim (0, \sigma^2 I_j) \quad (3b)$$

The SEM solves the spatial correlation found in the error structure, which can arise due to omitted spatially correlated variables or unobserved heterogeneity.

The SAC is derived by setting $\tau = 0$ and $\theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$ in 1(a). The SAC specification is as follows:

$$SGDP_{it} = \rho \sum_{j\neq i}^{N} w_{ij} SGDP_{jt-1} + \beta_1 DRT_{it} + \beta_2 EXT_{it} + \beta_3 FD_{it} + \beta_4 STM_{it_1} + \theta_5 PG_{it} + \theta_6 FDI_{it} + \theta_7 TED_{it} + \theta_8 BMS_{it} + \theta_9 AHIR_{it} + u_i + v_t + \varepsilon_{it} \quad (4a)$$

$$\varepsilon_{it} = \lambda \sum_{j\neq i}^{N} w_{ij} \varepsilon_{jt} + \psi \text{ and } \psi \sim (0, \sigma^2 I_j) \quad (4b)$$

The SAC specification is useful as it can combine the spatial lag and errors, resulting in a comprehensive assessment of the spatial interdependences. The most suitable model among the SDM, SAR, SEM and SAC is determined by the results of the selection criteria process.

3.5 Model selection criteria and estimation

In spatial econometric analysis, it is important to select a robust model that reflects the underlying data-generating process while prioritising simplicity. Our approach starts from a general spatial model and moves to a specific model (Mur and Angulo 2009). We apply a basket of model selection techniques: Lagrange multiplier (LM) spatial error, LM spatial lag, robust Lagrange multiplier (RLM) spatial error, RLM spatial lag, likelihood ratio (LR), Hausman test, chi-square tests and Akaike information criterion (AIC).

We test for the presence of spatial dependence in the dependent variable and spatial autocorrelation in the error terms by employing the LM spatial lag and LM spatial error tests, respectively. LM tests evaluate the presence of spatial dependence in regression models, with two common variants: the LM-lag test, which assesses whether a spatially lagged dependent variable should be included in the model, and the LM-error test, which detects spatial autocorrelation in the error terms, indicating the need for an SEM. The LM statistic follows a chi-square distribution and is computed using a transformation matrix, a spatial weight matrix and the residuals.

The AIC seeks to balance model fit and complexity, penalising excessive parameters to mitigate overfitting. Its value is derived from the log-likelihood and the number of estimated parameters. A model with the lowest AIC value is the most preferred, signalling the best balance between goodness-of-fit and model complexity (Akaike 1973). We used the AIC to compare non-nested spatial models and choose the best model. Spatial models are said to be non-nested when parameters in one model are not contained in the other model. Conversely, for nested models, one model's parameters are derived from the other's by setting restrictions on parameters.

Another model selection criterion uses the Hausman test to evaluate the null hypothesis that the random effects model is consistent and efficient against the alternative hypothesis that the fixed-effects model provides unbiased estimates (Wu et al. 2022). A significant result indicates support for including fixed effects in the spatial modelling. Further, we employed the LR test to assess the null hypothesis that either individual or time effects are appropriate compared to the alternative that individual-time effects are preferred (Xie et al. 2021). The double or individual-time fixed effects are appropriate if the LR test results are significant. Both the Hausman and LR tests are based on the chi-square statistic.

Although the SAR and SEM can be obtained from the SDM, it is necessary to assess whether the former models are embedded in the general model (LeSage and Pace 2009; Elhorst 2010). To do so, we first compare an SDM and an SAR. A chi-square test is used to investigate the null hypothesis that $\theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$ and $\rho \neq 0$ (that is, the model is an SAR). A rejection of the null hypothesis proves that the SDM is favoured over the SAR. We also test whether to choose the SEM or SDM, and this is done via the chi-square, which aims to verify the null hypothesis that $\theta_1 = -\beta_1\rho, \theta_2 = -\beta_2\rho, \theta_3 = -\beta_3\rho,$ and $\theta_4 = -\beta_4\rho$ (that is, SEM). The significance of the chi-square demonstrates that the SDM is more appropriate than the SEM.

When the SDM is preferred over the SAR and the SEM, the next procedure compares the SDM and the SAC. Since these are non-nested, the AIC is applied to select a model with a lower AIC value. When the tests show that the SAR or the SEM is preferred over the SDM, the appropriate model is chosen based on the AIC technique (Mur and Angulo 2009).

The spatial models are implemented in Stata 18 and estimation is via the quasi-maximum likelihood estimator (Yu, de Jong and Lee 2008). The xsmle package is used in our spatial panel analysis (Belotti, Hughes and Mortari 2017). To check for the robustness of the coefficients, we re-estimate the selected spatial model with an additional control variable, current account balance. This is done to assess whether the results of the climate shock impacts on economic sector performance are sensitive to omitted variables. If the results of climate shock impacts change substantially when the current account balance is included, it suggests instability and the need to interpret findings with caution.

4. Results and analysis

4.1 Statistical description of variables and multicollinearity inspection

Table 2 presents the descriptive statistics for the variables used in the study, summarising their distribution, dispersion and central tendency to highlight data patterns and trends. The table also includes VIF values to assess multicollinearity among the variables.

Table 2: Descriptive statistics and multicollinearity

Independent variables										
	DRT	EXT	FD	STM	PG	FDI	TED	BMS	AHIR	CAB
Mean	0.34	0.18	0.64	0.38	2.07	4.30	28.49	38.20	12.33	-5.92
SD	0.36	0.24	0.37	0.38	1.06	7.45	17.11	25.51	44.50	9.38
Min	0	0	0	0	-2.62	-10.73	3.52	8.71	-2.40	-40.29
Max	1	1	1	1	3.75	56.28	118.82	159.94	557.20	13.12
VIF	1.25	1.30	1.47	1.41	1.29	1.15	1.23	1.31	1.08	1.28

Dependent variables							
		AGRI	MINI	MANU	ENER	TOUR	FINA
SGDP	**Mean**	13.34	9.16	12.17	1.65	4	7.41
	SD	11.09	9.89	6.04	1.06	4.59	4.07
	Min	0.77	0	4.47	-0.05	0	1.49
	Max	38.10	47	33.39	4.22	19.39	19.14

Note: SD is the standard deviation. Min and max are minimum and maximum values, respectively. VIF is the variance inflation factor. DRT: drought; EXT: extreme temperature; FD: flood; STM: storm; PG: population growth; FDI: foreign direct investment; TED: total external debt; BMS: broad money supply; AHIR: annual headline inflation rate; CAB: current account balance; AGRI: agriculture; MINI: mining; MANU: manufacturing; ENER: energy; TOUR: tourism; FINA: financial intermediation.

The mean values show that floods are the most frequently occurring climate impact in SADC, accounting for 64% of observations. This corroborates the analysis of climate change in SADC between 1970 and 2020 by Chesterman, Neely and Gosling (2020), who identified cyclones as the most recurrent climate hazard. This high frequency suggests that flooding is a persistent issue in the SADC region. On the other hand, droughts and storms (mean = 0.34 and 0.38, respectively) show moderate occurrence, while extreme temperature has the lowest occurrence during the sampling period, accounting for only 18% of observations. Although extreme temperatures have a low frequency, they can have devastating effects on humans and crops through heatwaves. On the other hand, droughts, floods and storms exhibit moderate variability (SD = 0.36, 0.37 and 0.38, respectively), suggesting that although these impacts are widespread, they are not uniformly distributed. Some countries or periods experience more frequent events than others. Likewise, extreme temperature also shows low variability (SD = 0.24), suggesting that this event is rare but potentially severe.

The statistics on GDP contribution indicate that agriculture has the highest contribution (mean = 13.34) but with wide variability (SD = 11.09). This suggests that some sampled countries largely depend on agriculture (for instance, Zimbabwe and Zambia), while others have minimal dependence. Mining has high variability (range: from min = 0 to max = 47), showing that some SADC countries are highly dependent on it (such as South Africa and the DRC) while others have limited mining activities (such as Mauritius and the Seychelles, which rely more on tourism). Manufacturing is the third contributor, varying across countries (SD = 6.04). Finance and tourism are also important contributors but vary across countries, suggesting that their economic importance is significant in some countries but weak in others. Energy contributes the least, suggesting that the region has an underdeveloped energy sector.

4.2 Determining the spatial econometric model for each sector

We applied Moran's I test to assess spatial patterns across the economic sectors. Table 3 presents the results, which are discussed below.

Table 3: Moran's I test of spatial autocorrelation for the dependent variable

	Sector					
Year	AGRI	MINI	MANU	ENER	TOUR	FINA
2010	0.080***	0.058***	-0.041	-0.106	-0.026	0.007*
2011	0.089***	0.049***	-0.043	-0.025	-0.035	0.036**
2012	0.084***	0.059***	-0.070	-0.070	-0.028	0.026**
2013	0.087***	0.061***	-0.063	-0.081	-0.032	0.023**
2014	0.087***	0.049***	-0.052	-0.066	-0.037	0.038**
2015	0.085***	0.051***	-0.024	-0.074	-0.036	0.031**
2016	0.084***	0.038**	-0.011	-0.082	-0.037	0.036**
2017	0.075***	0.045**	-0.007	-0.059	-0.024	0.021**
2018	0.072***	0.051***	0.015**	-0.052	-0.022	0.010**
2019	0.070***	0.058***	0.013**	-0.080	-0.024	-0.017
2020	0.064***	0.060***	-0.001	-0.041	-0.033	-0.030
2021	0.059***	0.055***	0.011**	-0.057	-0.046	-0.022
2022	0.062***	0.049***	0.017**	-0.070	-0.030	-0.022

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

The results in Table 3 reveal strong spatial clustering in agriculture, indicating that agriculture-dependent economies such as Zimbabwe and Zambia are geographically close, likely due to shared climate and soil conditions. Mining also shows high clustering, reflecting the natural concentration of mineral deposits across the region. In contrast, manufacturing exhibits weak spatial correlation, though a shift from negative to positive in 2018 suggests emerging spatial dependence in industrial activity, which supports prospects for regional integration. Energy records negative Moran's I values throughout, indicating fragmented regional infrastructure and limited cross-border integration, consistent with ongoing power supply challenges in many SADC countries. Tourism displays negative and insignificant values, indicating limited spillover effects and the dominance of destination-specific attractions like cultural heritage and wildlife. Financial intermediation showed positive spatial correlation from 2010 to 2018 but turned negative from 2019, suggesting that financial activity, once clustered in regional hubs such as South Africa and Mauritius, has become more dispersed, possibly due to the rise of pan-African financial institutions and broader access to financial services across the region.

Next, Table 4 shows the results for the criteria used to select the most suitable spatial model from among the SAR, SEM, SDM and SAC. The statistical tools used include the LM test, the LR test, the Hausman test, the chi-square test and the AIC values.

Table 4: Model selection tests and criteria

	Sector					
Test/criteria	**AGRI**	**MINI**	**MANU**	**ENER**	**TOUR**	**FINA**
LM spatial error	64.610***	7.899***	46.749***	11.025***	26.524***	2.515
RLM spatial error	56.070***	1.384	50.800***	17.378***	2.464	0.761
LM spatial lag	8.543***	13.994***	0.088	5.398**	56.386***	6.129**
RLM spatial lag	0.003	7.479***	4.140**	11.751***	32.327***	4.375**
LR (ind vs both)	24.52**	25.15**	33.72***	33.16***	21.28*	56.89***
LR (time vs both)	64.25***	27.67**	57.12***	73.45***	58.72***	61.05***
Hausman	94.64***	440.09***	335.44***	270.71***	79.59***	346.65***
Chi-square (SDM vs SAR)	2 065.43***	8.93*	5.52	18.49***	1.06	25.22***
Chi-square (SDM vs SEM)	966.50***	8.20*	6.44	17.75***	1.04	24.34***
AIC-SAR	-	-	482.024	-	486.7751	-
AIC-SDM	522.4567	839.0301	-	149.034	-	338.3178
AIC-SAC	893.3269	1082.215	628.215	331.435	576.8665	596.6841
Decision	**SDM**	**SDM**	**SAR**	**SDM**	**SAR**	**SDM**

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

The results in Table 4 provide the basis for choosing the most appropriate spatial model for each economic sector – agriculture, mining, manufacturing, energy, tourism and finance. The results show that the SDM is the preferred estimator for agriculture, mining, energy and finance as these sectors are influenced by both spatial lag and spatial error. For these sectors, policies in one country can have spillover effects in neighbouring countries. Meanwhile, the SAR is best suited for the manufacturing and tourism sectors, where spatial lag effects dominate, reflecting regional interdependencies. The Hausman test is statistically significant in all sectors, indicating the presence of unobserved heterogeneity that should be controlled for. Lastly, there is strong evidence of spatial dependence (error or lag) across all sectors, highlighting the need to account for spatial interactions in the analysis.

4.3 Short- and long-run effects for each sector

4.3.1 Agriculture

The results in Table 5 show a positive and significant coefficient for SGDP.L1 (0.77, significant at the 1% level), indicating strong path dependence in the agricultural sector. This implies that the past contribution of agriculture to GDP strongly influences current performance – countries that performed well in the past are likely to sustain their growth trajectories. In contrast, the significantly negative coefficient for the spatiotemporal term W*SGDP.L1 (-0.99) points to negative spillover effects, where high past agricultural performance in neighbouring countries suppresses the focal country's performance. This may reflect regional interdependencies and competition over shared resources, particularly water and climate conditions. Agriculture in the SADC region is predominantly rainfed and heavily dependent on shared ecosystems. Roughly 70% of water resources in Southern Africa are transboundary, with the Zambezi River basin spanning eight countries (Boroto 2006). In this context, climate shocks such as droughts can trigger regional ripple effects. For instance, the 2015/16 and 2018/20 droughts led to widespread crop failures, with estimated losses exceeding US$286.9 billion (Chesterman, Neely and Gosling 2020), explaining the observed negative spatiotemporal effect.

Table 5: Estimated parameters of the SDM for the agricultural sector

Variable	Coefficient	Std. err
SGDP.L1	0.770985***	0.041516
W*SGDP.L1	-0.98785**	0.408091
DRT	3.009343***	0.235774
EXT	7.548806***	0.432523
FD	3.755051***	0.256649
STM	4.386779***	0.255855
PG	1.625396***	0.211344
FDI	0.057802***	0.015381
TED	0.046816***	0.00817
BMS	-0.05113***	0.010969
AHIR	-0.0083***	0.001642
W*DRT	26.78681***	1.521932
W*EXT	82.5011***	2.843129
W*FD	41.0842***	1.481473
W*STM	33.02643***	1.3904
ρ	1.66077***	0.287288
R^2	0.6466	
LL	-5148.4417	

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

Turning to climate variables, all four shocks – drought, extreme temperature, floods and storms – strongly affect agricultural GDP. Although counterintuitive, this likely reflects the impact of widespread adaptation measures rather than productivity gains. Farmers and governments in the region have adopted climate-resilient practices, including drought-tolerant crop varieties, improved irrigation systems and early warning mechanisms (Arslan et al. 2014; Thornton et al. 2014). These adaptive responses may spur short-term investments and activity in agriculture, boosting the sector's GDP contribution despite adverse conditions. Walker (2011) emphasises the role of accurate climate forecasting and community participation in reducing vulnerability, although such strategies often require significant funding.

Among the control variables, population growth, FDI and total external debt show positive and significant effects on agricultural GDP. The positive coefficient for population growth (1.63) suggests increased labour availability and food demand, supporting sectoral expansion (Barrett, Ortiz-Bobea and Pham 2021). Similarly, FDI and total external debt indicate that external financial flows, when effectively used, can enhance agricultural productivity and infrastructure (OECD 2018; Collier and Dercon 2014). Conversely, broad money supply (-0.05) and inflation (-0.01) exert weak negative effects, underscoring the sensitivity of agriculture to macroeconomic instability and the erosion of purchasing power.

The spatially lagged climate variables, W*DRT, W*EXT, W*FD, and W*STM, are all significantly positive, with the strongest effect observed from extreme temperature (82.50), followed by floods (41.08), storms (33.03) and drought (26.79). These findings highlight strong cross-border climate spillovers in agriculture, which may be attributed to interconnected supply chains, shared water systems and similar climatic zones (Dell, Jones and Olken 2014; Conway et al. 2015). Regional shocks, especially extreme weather events, can disrupt not only production but also trade, labour movement and investment across SADC countries, making collaborative climate strategies essential.

4.3.1.1 Decomposition of impacts in the agricultural sector

We further decompose the impacts into direct and indirect in both the short and long run (Table 6).

Table 6: Decomposition of impacts in the agricultural sector

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	1.069234***	10.33487***	11.4041***	10.84176	-0.16694	10.67482***
EXT	1.274957	32.83767***	34.11262***	32.96082	-1.19603	31.76479***
FD	0.630168	16.45096***	17.08113***	16.7064	-0.79829	15.90811***
STM	2.102***	12.11873***	14.22072***	13.04761	0.328757	13.37636***
PG	1.874388***	-1.24048***	0.633904***	-0.16777	0.914714	0.746945***
FDI	0.066099***	-0.04385***	0.022249***	0.006597	0.019766	0.026363***
TED	0.054656***	-0.03611***	0.01855***	0.01763	0.004496	0.022126***
BMS	-0.05837***	0.038705***	-0.01966***	0.027233	-0.05014	-0.02291***
AHIR	-0.0096***	0.006335***	-0.00327***	0.001967	-0.0058	-0.00384***

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

Table 6 shows that, in the short run, all four climate shocks – drought, extreme temperature, floods and storms – have a strong positive effect on agricultural GDP, primarily driven by indirect (spillover) effects. Extreme temperatures have the largest impact (34.11), followed by floods (17.08), storms (14.22) and drought (11.40). This suggests that climate shocks in one SADC country are closely linked to changes in agricultural outcomes in neighbouring countries. The magnitude of these spillovers reflects the region's interconnected agricultural systems and shared exposure to climate risks (Conway et al. 2015). These positive short-term effects may be driven by increased aid, adaptive investments and trade re-routing, which buffer the immediate impact of climate disruptions (Arslan et al. 2014).

Population growth positively affects domestic agriculture, likely through rising food demand and increased labour availability (Barrett, Ortiz-Bobea and Pham 2021). However, its negative indirect effect suggests that regional demographic pressure, combined with shared vulnerability to climate shocks, may suppress agricultural growth in neighbouring countries. FDI and total external debt show small but positive direct effects on agricultural GDP, implying a role in financing short-term recovery and productivity-enhancing inputs (Collier and Dercon 2014; OECD 2018). Yet their negative spillover effects may reflect regional capital concentration or trade imbalances, especially under environmental stress. Furthermore, broad money supply and inflation show negative total effects, highlighting how macroeconomic instability, through rising costs and eroded purchasing power, can undermine agricultural output.

In the long run, climate shocks continue to have positive total effects, but the spatial spillovers weaken. The indirect effects of drought, extreme temperature and floods become negative or insignificant, indicating that while short-term adaptation stimulates activity, persistent exposure without deep resilience erodes long-term benefits. The diminishing influence of population growth also suggests resource constraints and land pressure over time, although the total effect remains mildly positive, reflecting its potential when supported by effective planning and infrastructure (United Nations Department of Economic and Social Affairs 2022). FDI and total external debt retain modest positive effects, pointing to their longer-term development potential if used effectively. In contrast, money supply and inflation remain negative, reaffirming that sound macroeconomic management is essential for sustaining agricultural growth.

4.3.2 Mining

Table 7 presents the parameter estimation results of the SDM for the mining sector.

Table 7: Estimated parameters of the SDM for the mining sector

Variable	Coefficient	Std. err
SGDP.L1	1.05036***	0.053822
W*SGDP.L1	0.466515	0.408709
DRT	-0.73122	0.543939
EXT	0.515216	0.988428
FD	-0.57055	0.555153
STM	0.087301	0.577425
PG	0.015501	0.467997
FDI	-0.06252*	0.034547
TED	0.005902	0.017106
BMS	-0.02971	0.02451
AHIR	-0.00027	0.003734
W*DRT	-6.78467*	3.483617
W*EXT	-3.66455	6.474453
W*FD	2.9383	3.446576
W*STM	-1.22891	3.144316
ρ	0.703147**	0.282573
R^2	0.9340	
LL	-465.3264	

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

The results in Table 7 reveal strong path dependence in the mining sector, with a significant coefficient for SGDP.L1 (1.05), indicating that current mining output is primarily driven by past performance. This aligns with the long investment horizons and capital-intensive nature of the industry, where production is often locked into multi-year operational cycles (Tilton and Guzmán 2016). However, the spatial spillover term (W*SGDP.L1 = 0.47) is statistically insignificant ($p > 0.05$), suggesting that mining activities in one country have minimal influence on neighbouring countries. This localised behaviour contrasts with sectors like agriculture, where cross-border interdependencies are more prominent due to shared environmental systems (Conway et al. 2015).

Direct climate variables, namely drought, extreme temperature, floods and storms, show no statistically significant effect on mining output. This points to the relative climate resilience of the sector in the short term, likely because mining operations are often equipped with infrastructure that buffers immediate environmental changes (United Nations Environment Programme 2024). However, the spatially lagged drought variable (W*DRT = -6.78, $p < 0.10$) is negative and significant, indicating that drought conditions in one country can disrupt mining activities in neighbouring states. This may reflect regional competition over shared water resources, as mining processes, particularly ore processing and dust suppression, are water-intensive (Garner et al. 2012; Morgan and Dobson 2020). For instance, prolonged droughts in Southern Africa have constrained mine operations, particularly in Zimbabwe and Zambia along the Zambezi.

Regarding macroeconomic controls, most variables are statistically insignificant. FDI is the only significant factor, with a small negative coefficient (-0.06, $p < 0.10$). This suggests that capital inflows do not immediately lead to production gains, likely due to long project development timelines and regulatory hurdles (Gochero and Boopen 2020). Other financial indicators, such as total external debt and broad money supply, show no significant effects, reinforcing the idea that mining output is more structurally determined and less sensitive to short-term financial fluctuations.

The results in Table 8 indicate that most climate-related and macroeconomic variables have no statistically significant impact on mining GDP in either the short or long run. This suggests that the mining sector in the SADC region is relatively insulated from short-term climate shocks and economic fluctuations. The finding aligns with literature highlighting the sector's structural rigidity, long investment cycles and reliance on pre-established extraction infrastructure, which together reduce its responsiveness to immediate environmental and financial changes (Tilton and Guzmán 2016; Garner et al. 2012). The exception in this analysis is FDI, which shows a weak but statistically significant negative relationship with mining GDP in the short run, both directly (-0.07) and in total (-0.04). This outcome implies that while foreign investment is flowing into the sector, it may be geared more towards extraction and capital repatriation than towards production-enhancing investments. Such behaviour is consistent with concerns raised in resource-rich developing countries, where FDI may prioritise resource exploitation over long-term sectoral development. Overall, the findings reinforce the notion that mining in SADC is driven more by long-term operational factors than by external shocks.

Table 8: Decomposition of impacts in the mining sector

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	-0.41699	-3.89132	-4.3083	1.496683	-12.5179	-11.0212
EXT	0.686049	-2.96529	-2.27924	-10.8039	7.907744	-2.89614
FD	-0.71075	2.386673	1.675921	13.45725	-3.03071	10.42654
STM	0.189143	-0.84515	-0.656	-5.5049	1.232493	-4.27241
PG	0.021026	-0.00275	0.01828	-0.03213	-2.5122	-2.54434
FDI	-0.0659*	0.02737	-0.03853*	0.963015	-0.92457	0.038447
TED	0.007837	-0.00327	0.004565	-0.20176	0.121015	-0.08075
BMS	-0.02968	0.012747	-0.01694	0.453956	-0.36572	0.088239
AHIR	-0.00039	0.000192	-0.0002	0.04912	-0.04868	0.000445

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

4.3.3 Manufacturing

The results in Table 9 show an insignificant positive coefficient for SGDP.L1 (0.76; $p > 0.05$), indicating no clear temporal dependence in the regional manufacturing sector. This suggests that past manufacturing output does not significantly influence current performance across SADC countries. One plausible explanation is the persistent infrastructural challenges that undermine industrial continuity, such as unstable electricity supply, poor transport infrastructure and supply chain disruptions (SADC and SARDC[1] 2018). These bottlenecks may suppress the benefits of past investments and interrupt production cycles, leading to weak path dependence.

With respect to climate variables, the results show generally negative but statistically insignificant effects, except for storms, which show a weak but significant negative coefficient (-0.38; $p < 0.10$). This implies that storm-related events may temporarily disrupt manufacturing activities, for instance through flooding, road damage or electricity outages, all of which interfere with production and logistics. The absence of

1 Southern African Research and Documentation Centre.

significant effects from droughts, floods and extreme temperature suggests that manufacturing activities in the region are relatively sheltered from direct climate shocks, possibly due to being concentrated in urban areas with more climate-resilient infrastructure.

Table 9: Estimated parameters of the SAR model for the manufacturing sector

Variable	Coefficient	Std. err
SGDP.L1	0.757904	0.056255
DRT	-0.03941	0.176526
EXT	-0.28894	0.324084
FD	-0.18093	0.205508
STM	-0.37935*	0.212065
PG	-0.07811	0.188763
FDI	-0.01328	0.0139
TED	0.015638**	0.00698
BMS	0.014613	0.009593
AHIR	0.00215	0.001484
ρ	-0.66009***	0.231867
R^2	0.9043	
LL	-270.4848	

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

Among macroeconomic controls, external debt is the only variable with a statistically significant positive impact (0.016; $p < 0.05$), suggesting that when effectively allocated, borrowed funds can enhance manufacturing productivity through investment in equipment, technology or infrastructure. The insignificance of other variables such as population growth, inflation, money supply and FDI indicates limited responsiveness of the sector to broader economic changes in the short term, reinforcing the idea that structural and logistical barriers may dampen the impact of external economic conditions.

The decomposed impact results presented in Table 10 show that storms are the only climate variable with a statistically significant impact on manufacturing GDP, though only in the short run. Specifically, storms have a negative direct effect (-0.3954; $p < 0.10$) and a positive but smaller indirect effect (0.1599), yielding a net negative total impact (-0.2355). This suggests that storm events disrupt manufacturing activity within countries. For instance, Typhoon Yagi caused severe floods in Vietnam, damaging factories and warehouses (Coonan 2024). The insignificant effects of other climate shocks indicate limited or diffuse transmission of such shocks to manufacturing activities, possibly due to unlinked manufacturing activities in the region.

Table 10: Decomposition of impacts in the manufacturing sector

	Short run			Long run		
Variable	Direct	Indirect	Total	Direct	Indirect	Total
DRT	-0.04795	0.018441	-0.02951	-0.30712	0.244207	-0.06291
EXT	-0.26375	0.111829	-0.15192	-1.2795	0.974741	-0.30475
FD	-0.19265	0.07688	-0.11577	-2.00827	1.766733	-0.24153
STM	-0.3954*	0.159874*	-0.23552*	-3.75216	3.265688	-0.48647
PG	-0.07111	0.026751	-0.04436	-0.94099	0.846152	-0.09484
FDI	-0.01371	0.005643	-0.00806	-0.12484	0.10831	-0.01653
TED	0.015946**	-0.00649**	0.009452**	0.141607	-0.1222	0.019411*
BMS	0.015878	-0.00652	0.009356	0.185327	-0.16619	0.019136
AHIR	0.002288	-0.00094	0.001352	0.02253	-0.01976	0.002768

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

Among macroeconomic indicators, total external debt is the only variable with a statistically significant effect in both the short and long run. While the total effect remains positive, it is relatively small in magnitude, highlighting a modest role of debt-financed investment in driving manufacturing output in SADC. This finding aligns with the notion that external borrowing can support capital formation (Almeida and Wolfenzon 2005), but the returns depend on how efficiently resources are allocated.

4.3.4 Energy

The results in Table 11 show a positive and statistically significant coefficient for the lagged sectoral GDP for energy (0.62; $p < 0.01$), indicating temporal dependence. This means past energy performance has a significant effect on current energy output. Similarly, the spatial lag of the dependent variable (W*SGDP.L1 = 0.82) is positive and statistically significant, indicating that energy sector growth in one country has a positive spillover effect on neighbouring countries. This suggests that the energy sector in SADC is regionally interconnected, and performance improvements in one country can stimulate energy activity across borders, likely through shared power infrastructure.

Table 11: Estimated parameters of the SDM for the energy sector

Variable	Coefficient	Std. err
SGDP.L1	0.6213167***	0.048945
W*SGDP.L1	0.821076**	0.380732
DRT	-0.1519*	0.089903
EXT	0.062664	0.165032
FD	-0.10881	0.093235
STM	0.044211	0.095262
PG	-0.0285	0.078476
FDI	-0.00031	0.00581
TED	-0.00441	0.002831
BMS	0.002441	0.003974
AHIR	-0.00096	0.00061
W*DRT	-2.13708***	0.573824
W*EXT	0.365244	1.087258
W*FD	0.268131	0.562442
W*STM	0.354328	0.519476
ρ	0.54275**	0.269981
R^2	0.7555	
LL	-115.7072	

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

As for the climate variables, only drought and its spatial lag have a significant effect on energy GDP. The negative coefficient (0.15) indicates that local droughts dampen energy output (Qiu et al. 2023), likely due to depressed hydropower generation. Likewise, the strong negative coefficient on the spatial lag (W*DRT = -2.14) shows that drought in one country affects power generation in neighbouring economies, possibly due to shared water systems. A clear example is the Kariba Dam, which supplies hydroelectric power to both Zimbabwe and Zambia. In recent years, low rainfall and reduced water levels in the Zambezi River have forced both countries to cut electricity generation, leading to widespread power shortages (Dube and Nhamo 2023). This shows how drought conditions in one part of the region can disrupt energy security across borders, reinforcing the evidence of significant regional spillover effects.

All the macroeconomic control variables – population growth, FDI, external debt, money supply and inflation – have statistically insignificant coefficients, indicating that they exert minimal influence on energy GDP in the region. This limited responsiveness may be explained by structural challenges in the energy sector such as ageing infrastructure, inadequate maintenance, limited grid coverage and high technical losses (Eberhard et al. 2016), which constrain the sector's ability to translate macroeconomic gains into actual output growth. As a result, these underlying constraints would need to be addressed to improve the long-term performance of the energy sector.

The decomposition of impacts in the energy sector (Table 12) shows that drought is the only statistically significant factor in the analysis. It has a negative short-run regional spillover effect, indicating that drought in one country reduces energy output in neighbouring countries.

Table 12: Decomposition of impacts in the energy sector

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	-0.07096	-1.43722***	-1.50819***	1.13433	16.56368	17.69801
EXT	0.046985	0.185046	0.232032	-0.33041	-6.03195	-6.36236
FD	-0.11886	0.264588	0.145728	-0.34839	-0.4381	-0.78649
STM	0.039305	0.236862	0.276167	0.025576	-0.70188	-0.67631
PG	-0.0288	0.010105	-0.01869	-0.08379	-0.17092	-0.25471
FDI	-0.00048	0.000161	-0.00031	-0.00252	-0.01886	-0.02137
TED	-0.00426	0.001471	-0.00279	-0.00876	0.026043	0.017281
BMS	0.002683	-0.00092	0.00176	0.005091	-0.02238	-0.01729
AHIR	-0.00099	0.000334	-0.00066	-0.0024	0.001079	-0.00132

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

As noted earlier, this is linked to the shared use of water resources for power generation in the region. For example, the Kariba Dam is highly affected by rainfall levels. The regional energy sector is thus vulnerable to drought conditions. All other variables, both climatic and macroeconomic, have insignificant short- and long-term effects. This reinforces the view that energy production in the region is shaped more by structural constraints, such as outdated infrastructure, limited generation capacity and poor maintenance, rather than by climatic events or short-term economic changes

4.3.5 Tourism

In Table 13, the spatial spillover coefficient (W*SGDP.L1) for tourism shows a strong and significant negative effect (-1.93), indicating an adverse spillover across borders. This suggests that when one country experiences tourism growth, it may reduce tourist arrivals in neighbouring countries. This pattern aligns with regional trends where smaller SADC countries such as Eswatini, Lesotho, Malawi and Zambia have struggled to attract high tourist spending compared to more established destinations (Lehloenya 2017). These smaller countries' limited competitiveness, which is often linked to poor connectivity, geographic remoteness and underdeveloped tourism offerings, means that neighbouring countries absorb the bulk of regional tourism.

Table 13: Estimated parameters of the SAR model for the tourism sector

Variable	Coefficient	Std. err
W*SGDP.L1	-1.93388***	0.565236
DRT	-0.05993	0.181987
EXT	-0.3009	0.330488
FD	-0.57811***	0.209259
STM	-0.18127	0.218455
PG	-0.18631	0.193644
FDI	0.018239	0.014291
TED	-0.00378	0.007248
BMS	-0.03577***	0.009689
AHIR	-0.0022	0.001521
ρ	-0.26972	0.266434
R^2	0.2047	
LL	-352.1597	

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

As for climate variables, floods are the only significant factor, showing a negative effect on tourism GDP. Flood events disrupt travel, damage key infrastructure and reduce the overall appeal of affected destinations, leading to a decline in tourism activity. This finding aligns with that of Southon and van der Merwe (2018), who found that floods in the Limpopo Province of South Africa severely impacted tourist accommodation businesses – disrupting bookings, shortening tourist stays and causing economic losses during peak seasons. Their study also noted a lack of adequate adaptation plans and flood management strategies, making tourism operations more vulnerable to flooding events.

On the macroeconomic side, money supply is the only significant variable, with a small but negative coefficient (-0.04). This suggests that increases in money supply may contribute to domestic inflation, making the destination more expensive for visitors by raising the cost of travel, accommodation and services, and in turn reducing its attractiveness to tourists. This view aligns with the finding of Athari et al. (2020), who established that high inflation reduces international tourism in a sample of 76 tourism destinations. Their findings support the result here, where an increase in money supply, linked to inflationary pressures, negatively affects tourism GDP by raising the cost of travel and services, making destinations less attractive to visitors.

The impact decomposition results (Table 14) confirm that floods remain the most damaging climate shock to tourism, with significant negative effects in both the short and long term. This supports earlier findings that floods diminish destination appeal by disrupting travel, damaging infrastructure and deterring visitors. Although the positive indirect effect (0.55) suggests some level of regional recovery, the overall impact remains negative, indicating that flood-affected destinations experience prolonged recovery periods and a decline in competitiveness. In addition, the positive long-run indirect coefficient may indicate a substitution effect, where tourists shift their travel to unaffected neighbouring countries due to disruptions in flood-hit destinations. For example, floods in Mozambique might divert tourists to South Africa or Zimbabwe. Similarly, broad money supply shows a consistently negative effect on tourism GDP, both directly and in total. This highlights the importance of inflation control and price stability, as rising costs for travel, accommodation and services reduce the attractiveness of destinations to both domestic and international tourists.

Table 14: Decomposition of impacts in the tourism sector

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	-0.06754	0.013311	-0.05423	-0.08517	0.063515	-0.02165
EXT	-0.26859	0.060326	-0.20826	-0.3403	0.254983	-0.08532
FD	-0.58948***	0.112602	-0.47688**	-0.74191***	0.552303***	-0.18961***
STM	-0.1863	0.034093	-0.15221	-0.23421	0.174181	-0.06003
PG	-0.17792	0.033554	-0.14436	-0.2234	0.165942	-0.05745
FDI	0.018397	-0.00357	0.01483	0.023158	-0.01724	0.005918
TED	-0.00401	0.000672	-0.00334	-0.00502	0.003718	-0.0013
BMS	-0.03547***	0.006838	-0.02863***	-0.04465***	0.033242***	-0.0114***
AHIR	-0.00215	0.000403	-0.00175	-0.00271	0.002012	-0.00069

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

4.3.6 Finance

The results in Table 15 show a significant positive coefficient for the lagged dependent variable (SGDP.L1), indicating strong temporal persistence in the financial sector. This means past performance in financial intermediation has a strong influence on current outcomes. Similarly, the positive and significant spatial dependence coefficient (0.64) suggests regional spillovers, where growth in one country's financial sector supports growth in neighbouring countries. This likely reflects cross-border banking links and shared market dynamics in the SADC region. The existence and operation of the SADC-Real Time Gross Settlement system enables real-time settlement of payments across participating countries, facilitating smooth cross-border financial transactions, thereby reinforcing the interconnectedness of the region's banking system.

Drought and its spatial lag (coefficients = 0.37 and 1.86, respectively) are both positive and significant, suggesting that drought conditions increase the financial sector's share of GDP both locally and regionally. This may be driven by higher demand for credit, insurance and other financial services in response to climate-related shocks. In contrast, extreme temperatures show negative and significant effects both locally (-0.54) and regionally (-6.42), suggesting that heat stress undermines financial intermediation.

Table 15: Estimated parameters of the SDM for the financial sector

Variable	Coefficient	Std. err
SGDP.L1	0.887362***	0.04182
W*SGDP.L1	0.638702**	0.279263
DRT	0.371346***	0.143104
EXT	-0.54172**	0.260596
FD	0.171905	0.147544
STM	0.071522	0.153363
PG	0.052065	0.126828
FDI	-0.00953	0.009193
TED	-0.00541	0.004552
BMS	0.01895***	0.006594
AHIR	0.001098	0.000975
W*DRT	1.864183**	0.919466
W*EXT	-6.42101***	1.739018
W*FD	-1.91553**	0.888042
W*STM	0.159546	0.842309
ρ	1.184107***	0.293935
R^2	0.9307	
LL	-298.4567	

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

Zeidy (2023) notes that climate-related events, such as heatwaves and severe weather, can damage payment system infrastructure, disrupt the settlement of financial obligations and weaken the flow of capital in the financial system. Zeidy further notes that climate-induced uncertainty can lead to capital flight and liquidity shortages as investors withdraw funds or demand higher premiums in risk-prone areas. These disruptions can hamper efficient financial intermediation, destabilising the sector and undermining its contribution to GDP. Floods have an insignificant direct effect (0.17), but the spatial lag is significantly negative (-1.92), implying that flooding in one country negatively affects financial activity in neighbouring economies. This may be due to cross-border credit exposure or shared economic conditions. Storms show no significant effect, suggesting no measurable impact on financial intermediation. Among the macroeconomic variables, broad money supply is the only one with a significant effect. The positive coefficient (0.02) indicates that increased liquidity supports financial sector growth, though the impact is small. This shows the importance of stable monetary conditions for financial development in the region.

The decomposed impact results in Table 16 show that in the short run, drought, extreme temperature, floods and broad money supply have a significant effect on financial intermediation, both directly and through spillovers. However, these effects do not persist in the long run. This implies that climate shocks and monetary changes trigger immediate responses in the financial sector, but their impact fades as conditions stabilise or as the sector adapts. Overall, the results point to the transient nature of climate- and liquidity-driven shocks in the financial intermediation sector across SADC.

Table 16: Decomposition of impacts in the financial sector

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	0.283034**	0.815692*	1.098726**	3.156843	1.117236	4.274079
EXT	-0.15777	-3.19069***	-3.34846***	-0.45105	-12.382	-12.833
FD	0.317469**	-1.09989**	-0.78242	3.302961	-6.35054	-3.04757
STM	0.07919	0.029438	0.108628	1.354129	-1.06765	0.286481
PG	0.058263	-0.03465	0.023612	-0.31994	0.426018	0.106073
FDI	-0.01062	0.006037	-0.00458	-0.19998	0.182623	-0.01736
TED	-0.00546	0.003087	-0.00238	-0.05606	0.046279	-0.00978
BMS	0.020796***	-0.01176***	0.009033***	0.239259	-0.20323	0.036031
AHIR	0.001166	-0.00066	0.000507	0.02062	-0.0182	0.00242

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

5. Robustness tests

We check the robustness of our empirical findings using an additional control variable – current account balance. The results in Table 17 confirm the reliability of the short-run findings reported in Table 6. Climate variables – drought, extreme temperature, floods and storms – remain positive and statistically significant across both models, supporting the conclusion that climate shocks drive short-term responses in the agricultural sector. Likewise, broad money supply and inflation maintain their negative and significant effects, while population growth, FDI and external debt continue to show positive but modest impacts. In contrast, the long-run results display greater variability in coefficient magnitudes, especially for climate-related variables, suggesting that these estimates are sensitive to model specification. Although the direction of most long-run effects remains consistent, the fluctuations in size highlight the need for cautious interpretation. Notably, the inclusion of the current account balance in the robustness test reveals a positive and significant association with agricultural GDP – an insight not captured in the original model but relevant for policy. Overall, the short-run results are robust, while the long-run estimates call for a more nuanced reading.

Table 17: Robustness of the agricultural sector results

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	1.183366***	13.12882***	14.31219***	-130.294	165.8811	35.58721
EXT	3.284218***	40.65239***	43.93661***	-388.544	497.5	108.9564
FD	1.02878**	20.02932***	21.0581***	-206.995	259.787	52.79213
STM	2.368899***	15.32832***	17.69722***	-116.269	160.0911	43.82171
PG	1.582336***	-0.89283***	0.689505***	50.44825	-48.6085	1.839728
FDI	0.084942***	-0.04802***	0.036921***	3.391583	-3.29293	0.098658
TED	0.080655***	-0.04546***	0.035196***	2.907989	-2.81553	0.092462
BMS	-0.05421***	0.030669***	-0.02354***	-1.66737	1.603056	-0.06431
AHIR	-0.0093***	0.005232***	-0.00407***	-0.27356	0.262538	-0.01102
CAB	0.104809***	-0.05901***	0.045804***	3.604157	-3.48107	0.123089

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

The robustness results in Table 18 largely confirm the short-run findings in Table 8. Drought remains a significant negative influence, while floods show a consistent short-run positive effect, possibly reflecting post-disaster demand. FDI maintains a weak but consistent negative impact. Extreme temperature becomes insignificant in the robustness model, showing sensitivity to specification. However, long-run results are less stable, with notable shifts in magnitude and sign, particularly for climate variables. The current account balance, not included in the main model, emerges as significant and positive – highlighting the influence of external balances on mining GDP. In summary, short-run effects are robust, but long-run outcomes are variable and should be interpreted cautiously.

Table 18: Robustness of the mining sector results

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	-0.40463	-3.91293*	-4.31756*	-27.943	18.06706	-9.87597
EXT	0.988552	-0.87365	0.114899	-106.903	103.1135	-3.78994
FD	-0.73687	2.519681	1.782811	58.04799	-56.5093	1.538697
STM	0.003812	-0.70157	-0.69775	10.71227	-10.4584	0.253862
PG	0.038369	-0.00614	0.032229	15.33692	-15.2446	0.092309
FDI	-0.05157	0.020804	-0.03077	1.826625	-1.86514	-0.03851
TED	0.009959	-0.00399	0.005966	-0.0292	0.025615	-0.00359
BMS	-0.02078	0.008428	-0.01235	0.346632	-0.38531	-0.03867
AHIR	-0.00184	0.000773	-0.00107	0.413696	-0.41461	-0.00091
CAB	0.091254***	-0.03551**	0.055747**	-6.71523	6.834638	0.119407

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

The robustness results in Table 19 confirm the original short-run findings in Table 10. Storms continue to have a negative impact, while external debt shows a positive effect, likely supporting investment. Drought, extreme temperature and floods remain insignificant, with a limited short-term role. In the long run, effects are generally stable but mostly small and insignificant, indicating a minimal lasting impact of climate and macroeconomic shocks on manufacturing. The current account balance also shows no significant influence. Overall, the findings suggest that SADC's manufacturing sector is relatively resilient to both short- and long-term shocks.

Table 19: Robustness of the manufacturing sector results

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	-0.03252	0.011284	-0.02123	-0.19583	0.146261	-0.04957
EXT	-0.31399	0.131472	-0.18252	-1.35612	0.980474	-0.37564
FD	-0.18954	0.075479	-0.11406	-0.82271	0.578712	-0.244
STM	-0.38242*	0.153253	-0.22917*	-1.97464	1.487689	-0.48695
PG	-0.07787	0.031557	-0.04631	-0.16036	0.061665	-0.09869
FDI	-0.01486	0.006135	-0.00872	-0.0712	0.053032	-0.01817
TED	0.01516**	-0.00614*	0.009021**	0.099181	-0.08024	0.018945
BMS	0.014329	-0.00581	0.008519	0.070061	-0.05224	0.01782
AHIR	0.002516	-0.00102	0.001494	0.013512	-0.01037	0.003139
CAB	-0.01224	0.005132	-0.0071	-0.04936	0.034775	-0.01459

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

The robustness results in Table 20 confirm the key short-run findings in Table 12. Drought remains the only significant climate variable, with a strong negative regional spillover on energy output. This underlines the role of shared water systems in cross-border power disruptions. Other climate and macroeconomic variables remain insignificant, indicating limited short-run influence on energy GDP. In the long run, the effects vary in size and direction, suggesting model instability. The current account balance shows no meaningful impact. Overall, short-run findings are stable, but long-run results remain inconclusive.

Table 20: Robustness of the energy sector results

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	-0.08527	-1.56453***	-1.6498***	0.401215	7.1674	7.568615
EXT	0.083881	0.423227	0.507108	0.376591	2.74894	3.12553
FD	-0.11773	0.253333	0.135599	-0.34312	-0.50572	-0.84884
STM	0.036576	0.307411	0.343987	-0.15398	-3.15631	-3.3103
PG	-0.02608	0.009018	-0.01707	-0.06258	0.032751	-0.02983
FDI	0.000321	-3.5E-05	0.000286	0.000713	-0.00111	-0.0004
TED	-0.00386	0.001189	-0.00267	-0.00859	0.01417	0.005576
BMS	0.00361	-0.00115	0.002456	0.00797	-0.0142	-0.00622
AHIR	-0.00113	0.000345	-0.00078	-0.0025	0.004364	0.001865
CAB	0.006697	-0.00199	0.004705	0.015636	-0.01442	0.001216

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

The robustness results in Table 21 confirm the main findings in Table 14, particularly the strong short-run impact of floods and broad money supply on tourism. Floods consistently emerge as the most damaging climate shock, with significant negative total effects across both models, underscoring their role in disrupting travel and infrastructure. Broad money supply maintains a stable negative effect, reflecting the continued influence of inflation on tourism competitiveness. The drought, extreme temperature and storm variables retain their signs but remain statistically insignificant. The inclusion of the current account balance shows a small but significant short-run negative effect, possibly reflecting trade or exchange rate factors. Overall, the short-run results are robust, highlighting tourism's vulnerability to floods and monetary conditions, while long-term effects remain relatively modest and stable.

Table 21: Robustness of the tourism sector results

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	-0.04687	0.00556	-0.04131	-0.05693	0.040978	-0.01595
EXT	-0.32028	0.04881	-0.27147	-0.39033	0.282208	-0.10812
FD	-0.58203***	0.084299	-0.49773**	-0.70831***	0.510993***	-0.19732***
STM	-0.16947	0.021672	-0.1478	-0.20552	0.147699	-0.05782
PG	-0.18139	0.031031	-0.15036	-0.22163	0.160576	-0.06105
FDI	0.017182	-0.00254	0.014643	0.020901	-0.01506	0.005838
TED	-0.00513	0.00067	-0.00446	-0.00622	0.00447	-0.00175
BMS	-0.03794***	0.005571	-0.03237**	-0.04619***	0.033342***	-0.01285***
AHIR	-0.00193	0.00031	-0.00162	-0.00235	0.001697	-0.00065
CAB	-0.01318***	0.001417	-0.01176	-0.01595	0.01144	-0.00451

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

The robustness results in Table 22 confirm the short-run findings in Table 16. Drought continues to show a significant positive effect, while extreme temperature maintains a strong negative spillover, highlighting the financial sector's exposure to climate extremes. Floods remain mixed, positive locally but negative regionally, with a net negative total impact. Broad money supply is again the only macroeconomic variable with a consistent short-run influence, reinforcing the importance of liquidity conditions. Long-run effects vary slightly in size and direction, but overall trends remain stable. The inclusion of the current account balance does not change the results. These findings confirm that short-run climate and monetary shocks significantly affect financial intermediation, while long-run effects are more uncertain.

Table 22: Robustness of the financial sector results

	Short run			Long run		
Variable	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
DRT	0.305094**	0.774427*	1.079521**	3.269046	0.723981	3.993027
EXT	-0.2208	-3.15756***	-3.37837***	-9.5437	-3.02651	-12.5702
FD	0.334482**	-1.16849***	-0.83401**	-1.64977	-1.60936	-3.25912
STM	0.092619	-0.01771	0.074905	-0.38757	0.483696	0.096128
PG	0.053159	-0.03143	0.021726	1.953168	-1.85901	0.094157
FDI	-0.012	0.006879	-0.00512	-0.05499	0.036748	-0.01824
TED	-0.00623	0.00353	-0.0027	0.00312	-0.01492	-0.0118
BMS	0.018761**	-0.01068**	0.008081**	0.005599	0.025753	0.031351
AHIR	0.001397	-0.00079	0.000607	-0.00484	0.007498	0.002662
CAB	-0.01065	0.006074	-0.00457	0.026541	-0.0464	-0.01986

Note: *, ** and *** denote 10%, 5% and 1% significance level, respectively.

6. Conclusion and policy implications

This study has examined the spatial dynamics of climate shocks in SADC and how they affect economies. We have analysed data from 2010 to 2022 for all 16 countries, focusing on six sectors: agriculture, manufacturing, energy, tourism, mining and finance. The climate variables considered were drought, extreme temperature, floods and storms. Moran's I and LM tests were used to guide model selection. The SDM and SAR were used to examine short- and long-run effects.

The findings reveal strong spatial dependence in the agricultural sector, where climate shocks in one country cause significant spillovers in neighbouring states. This highlights the urgent need for regional coordination on climate adaptation. Policy efforts should prioritise joint investments in cross-border irrigation infrastructure, early warning systems and food security programmes to build resilience at both national and regional levels.

In the mining sector, spatial interdependence is moderate. While direct climate effects are generally weak and mixed, spillovers – especially from drought – do occur. Addressing this vulnerability requires localised climate risk management, supported by harmonised cross-border environmental standards and disaster response protocols to safeguard the region's extractive industries.

The manufacturing sector shows low spatial dependence. Although climate shocks have negative effects, these are mostly contained within national borders. This points to the need for country-specific adaptation strategies, including investment in climate-resilient infrastructure and adoption of robust production technologies.

For the energy sector, the results indicate moderate spatial dependence, particularly in response to drought. Strong indirect effects are due to cross-border energy links across the region. To enhance resilience, policy should focus on strengthening the Southern African Power Pool, scaling up regional renewable energy investments and upgrading infrastructure to withstand climate shocks.

Tourism displays minimal spatial effects. Climate shocks tend to affect countries individually, with little evidence of regional spillovers. As such, adaptation efforts should target national infrastructure resilience and promote diversification in tourism offerings to reduce exposure to specific climate risks.

The financial sector exhibits high spatial dependence, with droughts and floods causing immediate and long-term impacts across borders. This underlines the need for SADC-wide frameworks for climate risk disclosure, expansion of green finance initiatives, and development of regional models to assess and manage financial risks linked to climate change.

In conclusion, this study shows that climate shocks in SADC frequently extend beyond national boundaries. Agriculture, energy and finance are the most interconnected sectors and require coordinated regional responses. For sectors like manufacturing and tourism, national-level adaptation remains critical. An effective response to climate-related economic risks demands a dual strategy – strengthening regional collaboration while tailoring resilience plans to sector-specific vulnerabilities.

7. Areas for further research

While this study provides important insights into the spatial and temporal impacts of climate shocks on sectoral GDP in SADC, several areas merit further investigation, as outlined below.

1. Future research could examine the dynamic interactions between sectors, exploring how shocks in one area cascade through others over time.
2. There is a need to evaluate the effectiveness of specific adaptation measures – such as insurance mechanisms, infrastructure development and climate-smart technologies – in reducing the vulnerability of certain sectors.
3. Using more granular data, such as subnational or firm-level information, could offer a deeper understanding of local resilience and exposure. Studies could also consider how institutional quality, governance and policy frameworks influence a country's capacity to manage climate risks.
4. Despite our study using climate shocks from the EM-DAT disaster

database, other measures of climate shocks could be explored to understand their impacts on the SADC region. For instance, although we used a drought variable in our analysis, we recognise the need to use variables (meteorological, hydrological and agricultural) that capture other drought types, which may have differing impacts.

5. While the inverse distance spatial weighting is considered a standard for measuring spatial decay (Li et al. 2020), future studies can enhance robustness by incorporating alternative spatial weighting, such as economic distance and contiguity-based weights.
6. Given the sensitivity of drought impacts in the mining sector under the current account balance, further studies are needed to improve understanding of the spatial dynamics of climate shock impacts on the sector’s performance.
7. Finally, the uncertainty observed in long-run outcomes points to the need for further work on modelling persistent climate shocks and long-term structural adjustments under varying climate scenarios.

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