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# Measuring climate-related financial market volatility in the Southern African Development Community

Moinak Maiti* and Chimwemwe Chipeta†

## Abstract

This study shows that different climate factors induce asymmetric stock market volatility across the Southern African Development Community (SADC). The transfer entropy estimates confirm that the impact of different climate variables on SADC nations' financial markets is heterogeneous, segmented and influenced by local factors. Further, the wavelet coherence results confirm the presence of asymmetric lag/lead effects over different time horizons across SADC nations' financial markets. Overall, the results show the importance of both short- and long-term climate-finance risk assessment and management measures. Moreover, they highlight the need for prudential policies, regulations, disclosure requirements and stress testing specific to the SADC region.

## JEL classification

G11, Q54

## Keywords

Climate risk, financial markets, volatility, asset pricing, financial stability

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## 1. Introduction

Climate change represents an unprecedented global challenge, demanding comprehensive and innovative solutions to facilitate the transition towards a low-carbon and climate-resilient future. The urgency of this transition is underscored by the World Meteorological Organization's prediction that there is a 66% probability of global temperatures surpassing 1.5°C above pre-industrial levels between 2023 and 2027.[1] The organisation further reports that climate-related disasters led to the loss of more than 2 million lives and triggered economic losses of US$3.64 trillion over the period 1970 to 2019.[2]

Recent studies, such as those by Battiston, Dafermos and Monasterolo (2021), DeMenno (2023) and Fabris (2020), highlight the increasing risks posed by climate-induced extreme weather events to various economic sectors. There is thus a critical need for a nuanced understanding of the complexities involved in climate change. Extreme weather events are becoming more frequent and severe, and a comprehensive examination is needed to unravel the intricate interplay between climate-related risks and financial resilience, particularly in the understudied region of the Southern African Development Community (SADC).

Macroprudential policy has emerged as a pivotal tool with the potential to mitigate the adverse impacts of climate change on financial stability (Dikau and Volz 2021). Akinci and Olmstead-Rumsey (2018) have observed that macroprudential policies have been used more actively in emerging and developed markets since the 2008 global financial crisis. Incorporating climate-related considerations into macroprudential frameworks is a proactive way to enhance the resilience of financial institutions and foster a sustainable and adaptive financial system.

Furthermore, understanding how climate change influences financial stability within SADC is crucial for designing region-specific adaptation and mitigation strategies. The unique challenges faced by SADC nations in the face of climate change require tailored solutions. Examining the relationship between climate change and financial stability in

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1 This report is available at: https://library.wmo.int/idurl/4/66224

2 This report is available at: https://library.wmo.int/idurl/4/57564

the SADC region can shed light on potential economic ramifications, inform policy decisions and contribute to the development of resilient financial systems.

A considerable body of literature has yielded valuable insights on how the risks posed by climate change  affect the stability of financial markets (Battiston, Dafermos and Monasterolo 2021; D'Orazio 2021; Liu et al. 2024). Another body of literature underscores the pivotal role of macroprudential policy in bolstering financial stability (Akinci and Olmstead-Rumsey 2018; Apergis, Aysan and Bakkar 2021). Notwithstanding these notable contributions, we address several critical research gaps. First, while the existing literature on sustainable finance acknowledges the importance of climate change (Battiston, Dafermos and Monasterolo 2021; DeMenno 2023; Fabris 2020), there is a lack of comprehensive empirical investigations into the specific pathways through which climate change influences the stability of financial markets, particularly in the SADC region. Given the unique socio-economic and environmental dynamics of this region, we aim to fill this gap by conducting empirical analyses that uncover the nuanced relationships between climate change and the volatility of financial markets in the region. Second, studies have shown that macroprudential policies are important and SADC central banks need to be more engaged in framing and deploying these policies effectively to mitigate the adverse effects of climate change on the stability of financial markets. We attempt to address this gap by offering tailored policy recommendations for SADC policymakers and central banks.

The rest of the paper is structured as follows. Section 2 discusses the theoretical context and formulates the hypothesis. Section 3 details data and methodology. Section 4 discusses the findings and section 5 concludes the paper and outlines key policy implications and directions for future studies.

## 2. Theoretical context and hypothesis development

Our hypothesis is formulated based on the nexus between climate change and the stability of financial markets. We conjecture that climate risks can influence the financial stability of financial markets through several interconnected channels. First, climate-induced weather-related events such as floods, cyclones, wildfires and extreme temperatures can lead to substantial asset devaluation, particularly for firms in high-risk sectors such as real estate and agriculture (Maiti and Kayal 2024). Second, transition risks arising from shifts towards a low-carbon or green economy could negatively affect the performance of firms, particularly those that are heavily dependent on fossil fuels (Basel Committee on Banking Supervision 2021). Third, climate-related risks can amplify credit, market and operational risks, consequently increasing volatility in asset prices and disrupting business operations. Together, these risks can cause systemic instability in financial markets, especially if they are unanticipated or inadequately managed (Basel Committee on Banking Supervision 2021; Albanese et al. 2025). Interestingly, Pisor et al. (2023) highlight the importance of examining climate variability to enhance climate change adaptation strategies.

Previous studies have made considerable progress in documenting the impact of climate change on financial markets. There is a substantial body of literature that confirms the above propositions by documenting the negative effects of climate risk on firms. For instance, Naseer et al. (2024) show that there is a positive association between climate risk and stock market volatility, indicating that firms more exposed to climate change risk tend to exhibit higher stock market volatility. Mao, Wei and Ren (2023) show the pervasive nature of climate risks across financial markets. They find that climate risk not only affects a single financial market but also induces risk co-movement, which aggravates potential systemic financial risks. Their study shows that bond and stock markets are the primary transmitters of climate shocks, while forex and commodity markets appear to be more sensitive to climate-related information. Various weather and climate variables have been used as a proxy for climate change in financial studies (see Table 1).

**Table 1: Variables used as a proxy for climate change in financial studies**

| Proxy climate variables | Study |
|---|---|
| Temperature (Temp) and dew | Keef and Roush (2007); Yan et al. (2022); Entezari and Fuinhas (2024) |
| Water resources: Humidity (HUM) | Lu and Chou (2012); Ahmed et al (2024) |
| Feel like (FL) | Yan et al. (2022) |
| Visibility (VIS), wind direction (WD), wind gust (WG) and wind speed (WS) | Keef and Roush (2007); Lu and Chou (2012) |
| Solar cycle: solar energy (SE) and solar radiation (SR) | Kam and Tong (2025) |
| Lunar cycle: moon phase (MP) | Yuan, Zheng and Zhu (2006) |

Based on the above arguments, we formulate and test the following hypothesis:

*H1: Climate-related risks have a significant impact on the volatility of stock markets in the SADC region.*

Macroprudential policy plays an important role in alleviating the adverse impacts of climate change on the stability of financial markets. In the face of climate risk, macroprudential policies are an effective way to bolster the resilience of financial institutions and mitigate the transmission of financial risk across institutions, industries and markets (Chenet, Ryan-Collins and van Lerven 2021). According to Mester (2017), macroprudential policy can support financial stability by influencing the asset composition of financial institutions through regulating risk weights and imposing additional capital requirements.

Altunbas, Binici and Gambacorta (2018) demonstrate that macroprudential policies, particularly those aimed at enhancing the resilience of the banking sector and those targeting the moderation of the business cycle, have a substantial positive impact on the risk profile of banks. Furthermore, macroprudential tools, such as taxes or subsidies on the assets of banks, can alleviate the transition risks associated with ambitious climate policies.[3] These tools help manage the financial sector's exposure to climate risks, thus preventing abrupt market disruptions. By addressing the interconnectedness of financial markets, macroprudential policies can reduce systemic risks that arise from climate-related shocks. This helps stabilise the overall financial system, including the stock market (Chen, Zhang and Weng 2023). Consequently, the implementation of macroprudential policies is deemed vital for sustaining the health and stability of the financial system in the face of climate shocks.

Empirical evidence suggests that macroprudential policies can effectively maintain financial stability in the face of climate shocks. For example, countries with robust macroprudential frameworks have shown better financial stability despite climate-

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[3] For example, if a country introduces a carbon tax, high-emitting industries may face sudden losses and loan defaults. In such case, a macroprudential tool such as a higher capital buffer for banks with large carbon-intensive exposures can help to absorb potential credit losses and maintain financial stability.

related shocks (Liu et al. 2024). Macroprudential policies increase the resilience of financial institutions by improving governance, enhancing supervision and implementing stricter regulatory frameworks (Liu et al. 2024; Ayele and Fisseha 2024). Policies that integrate climate risk assessments, such as stress tests and scenario analyses, enable financial institutions to better prepare for and respond to climate-related shocks, thereby reducing volatility (Ayele and Fisseha 2024; Chenet, Ryan-Collins and van Lerven 2021). Studies have shown that macroprudential policies can reduce the volume and volatility of bank flows, which in turn stabilises the financial system during climate-related extreme weather events (Maran 2023; Chari, Dilts-Stedman and Forbes 2022). Evidence suggests that macroprudential frameworks that align with climate goals, such as green-enhanced capital requirements and climate-related large exposure limits, can further mitigate the financial risks posed by climate change (D'Orazio 2021; D'Orazio and Popoyan 2019).

## 3. Data and methodology

### 3.1 Data

In this section, we collect data from eight SADC countries, namely South Africa, Botswana, Malawi, Mauritius, Namibia, Tanzania, Zambia and Zimbabwe. We consider equity indices and exchange rate data of SADC nations[4] as proxies for financial assets. We use 11 different proxies for the climate variables: temperature, humidity, visibility, dew, feel like, wind direction, wind gust, wind speed, solar energy, solar radiation and moon phase. The data period is 3 September 2018 to 30 August 2024, with a daily frequency to maintain uniformity for comparison.[5] The details are summarised in Table 2.[6]

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4 Except Zimbabwe.

5 Only active market periods were considered.

6 First difference is used for all EI and ER estimates (represented as DEI and DER). Malawi uses VIS (as DVIS) for first difference to make it stationary.

**Table 2: Summary of variables**

| Country | Variable | Data source |
|---|---|---|
| **SADC region:**<br>South Africa (SA)<br>Botswana (BWA)<br>Malawi (MWI)<br>Mauritius (MUS)<br>Namibia (NAM)<br>Tanzania (TZA)<br>Zambia (ZMB)<br>Zimbabwe (ZWE) | **Equity indices (EI):**<br>South Africa (JSE 40)<br>Botswana (DOMCOIN_BW)<br>Malawi (MSEALSHIN_MW)<br>Mauritius (SEMDEX_MU)<br>Namibia (N098_NA)<br>Tanzania (DSESHIN_TZ)<br>Zambia (ALLSHIN_ZM)<br>Zimbabwe (ALSHIN_ZW)<br><br>**Exchange rates (ER):**<br>South Africa (ZAR_USD)<br>Botswana (BWP_USD)<br>Malawi (MWK_USD)<br>Mauritius (MUR_USD)<br>Namibia (NAD_USD)<br>Tanzania (TZS_USD)<br>Zambia (ZMW_USD) | EquityRT |
| | **Climate variables:**<br>Temperature (Temp), humidity (HUM), visibility (VIS), dew, feel like (FL), wind direction (WD), wind gust (WG), wind speed (WS), solar energy (SE), solar radiation (SR) and moon phase (MP) | Visual Crossing |

## 3.2 Methodology

We deploy the Spearman correlation test at the initial level of analysis to understand the relationships among the variables. The stock markets are usually not linearly related to the climate variables and often deviate from the normal distributions (Peillex et al. 2021). To capture such monotonic or nonlinear relationships, the Spearman correlation test is more efficient than Pearson's correlation. Thereafter, we use both the Shannon and Rényi transfer entropy functions to examine if there is any statistically significant information flow between the study variables. We use the transfer entropy approach because it is an efficient way to detect causal information flow, capturing asymmetric and nonlinear dependencies, and is a model-free approach. The idea is to examine if there is any statistically significant flow of asymmetric information and causality between the variables. If there is, it means that the respective variable is responsible for inducing volatility on the other variable, and vice versa. For robustness checks, the study uses both the Shannon and Rényi transfer entropy function, as the latter is more efficient in capturing the tail risk associated with the datasets or series.

The Shannon transfer entropy function is defined in equation (1) under the assumption that the process follows a Markov chain (Schreiber 2000):

$$S_{J \to I}(k,l) = \sum_{i,j} p\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right) . \log\left(\frac{p\left(i_{t+1} | \, i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1} | \, i_t^{(k)}\right)}\right) \qquad (1)$$

where $S_{J \to I}$ measures the Shannon transfer entropy from information *J* to *I*. The marginal probability distribution of the two random discrete variables *(I* and *J)* is represented by *p(i)* and *p(j)* respectively. The joint probability distribution between the two random discrete variables is represented by *p (i, j)*. The order of the stationary Markov process for *I* and *J* is represented by *k* and *l* respectively. The information flow from *J* to *I* can be quantified by measuring the deviation from the generalised Markov property $p\left(i_{t+1} | \, i_t^{(k)}\right) = \; p\left(i_{t+1} | \, i_t^{(k)}, j_t^{(l)}\right)$ using the Kullback-Leibler distance, as proposed by Kullback and Leibler (1951). This is a non-parametric method for measuring causal information transfer between systems in the bidirectional flow (Schreiber 2000).

Similarly, the derived Rényi transfer entropy function incorporates a weighting parameter denoted by *q* that controls the sensitivity of the entropy measure to different probability distributions (Jizba, Kleinert and Shefaat 2012), as shown in equation (2):

$$R_{J \to I}(k,l) = \frac{1}{1-q} \log\left(\frac{\sum_i \emptyset_q (i_t^{(k)}) \, p^q\left(i_{t+1} | \, i_t^{(k)}\right)}{\sum_{i,j} \emptyset_q (i_t^{(k)}, j_t^{(l)}) \, p^q\left(i_{t+1} | \, i_t^{(k)}, j_t^{(l)}\right)}\right) \qquad (2)$$

where $R_{J \to I}$ measures the transfer entropy or information flow from *J* to *I*. The escort distribution (Beck and Schögl 1993) is represented by $\emptyset_q (i_t^{(k)})$ and weighting parameters by *q*. The value of weighting parameter *q* is important to the tail events. In the case of a lower *q* value (between 0 and 1), it will give more weights in an extreme event and an event of low probability will receive more weight. In the case of *q* being bigger than 1, the weights prefer outcomes with higher initial probabilities. Accordingly, we follow the overall guidelines by Behrendt et al. (2019) for estimations of the Shannon and Rényi transfer entropy function.

Lastly, we deploy wavelet coherence analysis to examine the time series in both time frequency domains using multiscale analysis (Maiti et al. 2020; Maiti 2021).

$$R^2(u,s) = \frac{\left|S(s^{-1}W_{xy}(u,s))\right|^2}{S(s^{-1}|W_x(u,s)|^2)S(s^{-1}\left|W_y(u,s)\right|^2)} \tag{3}$$

where $W_{xy}(u,\ s)$ represents the cross-wavelet function; $S$ is the smoothing operator; $u$ represents the position index; and $s$ represents the scale.

## 4. Findings and discussion

### 4.1 Descriptive statistics

The descriptive statistics for all the variables under consideration are presented in Table 3. Most of the series have a standard deviation above 1 and high kurtosis. This indicates the presence of fat tails, deviations from the normal distributions and demands for sophisticated modelling to further explore the insights among the variables (Giglio, Kelly and Stroebel 2021). The Jarque-Bera test statistics confirms that all series do not follow normal distribution. A few series show high values for skewness, indicating possible tail risks, and thus require further examination.

**Table 3: Descriptive statistics**

| | DEI | DER | Temp | FL | DEW | HUM | WG | WS | WD | VIS | SR | SE | MP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **SA** | | | | | | | | | | | | | |
| Mean | 15.946 | 0.000 | 18.229 | 18.041 | 7.891 | 56.375 | 35.875 | 18.579 | 166.675 | 13.379 | 171.888 | 14.847 | 0.482 |
| Std. dev. | 715.929 | 0.001 | 4.500 | 4.613 | 6.661 | 16.073 | 12.278 | 7.091 | 119.042 | 1.879 | 64.969 | 5.624 | 0.290 |
| Skewness | -0.184 | -0.407 | -0.287 | -0.413 | -0.515 | -0.212 | 1.293 | 2.500 | 0.203 | 0.246 | 0.392 | 0.393 | 0.006 |
| Kurtosis | 5.453 | 15.870 | 2.285 | 2.583 | 2.388 | 2.430 | 7.210 | 24.167 | 1.492 | 2.828 | 2.655 | 2.653 | 1.786 |
| **BWA** | | | | | | | | | | | | | |
| Mean | 1.005 | 0.000 | 20.855 | 20.532 | 8.001 | 50.612 | 35.144 | 20.960 | 115.302 | 10.553 | 239.222 | 20.664 | 0.481 |
| Std. dev. | 15.803 | 0.011 | 5.185 | 5.141 | 7.673 | 18.106 | 11.669 | 9.049 | 85.150 | 1.461 | 64.911 | 5.604 | 0.289 |
| Skewness | -6.038 | 0.017 | -0.254 | -0.389 | -0.504 | 0.006 | 2.216 | 7.675 | 1.194 | 5.082 | -0.154 | -0.155 | 0.016 |
| Kurtosis | 162.184 | 61.657 | 2.188 | 2.270 | 2.422 | 2.466 | 15.683 | 130.062 | 3.339 | 39.681 | 2.597 | 2.600 | 1.794 |
| **MWI** | | | | | | | | | | | | | |
| Mean | 73.291 | 0.000 | 20.590 | 20.545 | 13.639 | 68.111 | 34.090 | 24.496 | 118.443 | 0.007 | 230.769 | 19.931 | 0.483 |
| Std. dev. | 400.741 | 0.000 | 2.835 | 2.796 | 4.157 | 14.133 | 8.238 | 7.527 | 58.355 | 1.735 | 56.526 | 4.889 | 0.289 |
| Skewness | 3.217 | -25.820 | -0.104 | -0.205 | -0.281 | -0.301 | 0.429 | 5.496 | 2.125 | -0.031 | -0.321 | -0.318 | 0.000 |
| Kurtosis | 27.795 | 690.231 | 2.554 | 2.512 | 2.081 | 2.071 | 2.960 | 79.742 | 8.469 | 9.586 | 3.053 | 3.045 | 1.797 |
| **MUS** | | | | | | | | | | | | | |
| Mean | 0.011 | 0.000 | 23.952 | 24.566 | 19.889 | 78.865 | 42.783 | 24.742 | 106.928 | 13.308 | 219.690 | 18.985 | 0.485 |
| Std. dev. | 12.554 | 0.001 | 2.141 | 2.896 | 2.876 | 6.624 | 10.624 | 6.000 | 49.222 | 3.374 | 61.938 | 5.351 | 0.286 |
| Skewness | -2.354 | -0.028 | -0.048 | 0.414 | -0.212 | -0.166 | 0.788 | 0.559 | 1.729 | 0.851 | -0.128 | -0.130 | -0.019 |
| Kurtosis | 74.041 | 725.662 | 1.851 | 2.290 | 2.175 | 2.851 | 5.982 | 4.441 | 9.384 | 3.470 | 2.631 | 2.643 | 1.806 |
| **NAM** | | | | | | | | | | | | | |
| Mean | 0.351 | 0.000 | 20.614 | 20.169 | 0.275 | 31.867 | 41.723 | 19.131 | 151.444 | 19.622 | 241.955 | 20.899 | 0.482 |
| Std. dev. | 170.541 | 0.001 | 4.434 | 4.363 | 8.294 | 17.708 | 9.018 | 5.523 | 97.131 | 3.318 | 57.507 | 4.970 | 0.290 |
| Skewness | 0.293 | -0.123 | -0.456 | -0.717 | 0.117 | 1.063 | 0.309 | 3.359 | 0.580 | -1.584 | 0.222 | 0.221 | 0.004 |
| Kurtosis | 725.688 | 41.116 | 2.723 | 3.253 | 2.290 | 3.576 | 3.754 | 41.719 | 1.992 | 11.100 | 2.500 | 2.501 | 1.784 |
| **TZA** | | | | | | | | | | | | | |
| Mean | -0.078 | 0.000 | 23.042 | 23.017 | 15.168 | 64.421 | 36.004 | 28.256 | 104.943 | 17.970 | 254.848 | 22.014 | 0.483 |
| Std. dev. | 14.000 | 0.000 | 1.659 | 1.645 | 2.916 | 9.929 | 7.451 | 11.763 | 51.070 | 2.814 | 49.784 | 4.315 | 0.290 |
| Skewness | 3.817 | -0.074 | 0.077 | -0.005 | -0.184 | 0.378 | -0.335 | 9.476 | 2.952 | 1.879 | -0.843 | -0.833 | -0.003 |
| Kurtosis | 94.757 | 8.045 | 2.601 | 2.435 | 1.924 | 2.416 | 2.487 | 162.114 | 11.077 | 8.197 | 3.854 | 3.825 | 1.782 |

| ZMB | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 6.691 | 0.000 | 21.539 | 21.430 | 12.238 | 60.475 | 41.434 | 21.956 | 110.242 | 18.077 | 241.394 | 20.850 | 0.480 |
| Std. dev. | 52.077 | 0.000 | 3.378 | 3.297 | 5.542 | 17.641 | 7.755 | 9.096 | 62.724 | 5.828 | 55.614 | 4.809 | 0.289 |
| Skewness | 2.119 | 2.333 | -0.171 | -0.284 | -0.301 | -0.188 | 0.827 | 7.290 | 2.588 | 0.220 | -0.438 | -0.434 | 0.011 |
| Kurtosis | 30.892 | 24.029 | 2.570 | 2.537 | 1.983 | 1.998 | 7.930 | 101.742 | 9.434 | 1.992 | 3.038 | 3.033 | 1.796 |
| **ZWE** | | | | | | | | | | | | | |
| Mean | 0.137 | --- | 19.509 | 19.365 | 10.605 | 61.707 | 33.633 | 18.595 | 97.431 | 13.565 | 241.501 | 20.858 | 0.482 |
| Std. dev. | 0.794 | --- | 3.273 | 3.286 | 5.285 | 15.347 | 7.965 | 5.345 | 60.717 | 5.220 | 57.701 | 4.990 | 0.290 |
| Skewness | 5.154 | --- | -0.333 | -0.502 | -0.385 | -0.159 | 0.567 | 0.966 | 2.141 | -0.558 | -0.372 | -0.375 | -0.004 |
| Kurtosis | 45.436 | --- | 2.616 | 2.749 | 2.343 | 2.288 | 3.167 | 5.128 | 8.880 | 4.888 | 3.370 | 3.374 | 1.780 |

**Table 4: Spearman correlations between financial assets and climate variables**

| | Temp | FL | DEW | HUM | WG | WS | WD | VIS | SR | SE |
|---|---|---|---|---|---|---|---|---|---|---|
| DEI | (MWI) | (MWI) | ZWE | MWI, ZWE | (MWI) | BWA | (BWA), MWI, ZWE | BWA, ZMB, ZWE | (MWI), (ZWE) | (MWI), (ZWE) |
| DER | (ZMB) | (ZMB) | (ZMB) | --- | --- | --- | ZMB | MUS | (ZMB) | (ZMB) |

Note: 1. () represents a negative sign; 2. Only statistically significant associations at 5% are represented here.

## 4.2 Correlation analysis

Since all the variables under consideration do not follow a normal distribution, we rely on the Spearman correlations among the variables over the Pearson's correlations estimates (see Table 4). The Spearman correlations use a non-parametric measure to assess the strength and direction of associations among the two variables. This technique is efficient in dealing with the outliers and non-normal distributions. Table 4 estimates show that the equity indices and exchange rates of South Africa, Namibia and Tanzania are resilient to the climate variables under consideration (at the 5% significant level). It is therefore likely that these markets are not pricing climate risks, are more influenced by short-term macroeconomic factors and have sector-specific effects. This may also point to the non-linear nature of climate risks, insofar as they do not affect sectors uniformly; lag effects, as markets adjust only after shocks occur; and methodological limitations, as studies indicate that traditional models are less efficient in capturing long-term and sector-specific climate exposures (Peillex et al. 2021).

In line with Yan et al. (2022 and Keef and Roush (2007), the equity index of Malawi shows a negative association with temperature, which is indicative of the pervasive effects of global warming on the financial markets. A similar negative association is observed between the climate variables feel like, wind gust, solar radiation and solar energy. In contrast, there is a positive association with humidity and wind direction. This suggests that extreme heat, solar intensity and wind gusts are the possible climate risk factors for Malawi, while a moderate level of humidity and wind patterns can impact market stability.

The equity index of Botswana shows a positive correlation with wind speed and visibility, and a negative correlation with wind direction, whereas the equity index of Zambia shows a positive association with the visibility variables. However, the exchange rate of Zambia shows a negative association with temperature, feel like, dew, solar radiation and solar energy, and a positive association with wind direction. This indicates that Botswana is weather sensitive and good climate conditions may improve its overall performance. Similarly, better visibility favours Zambia, while adverse climate conditions may lead to currency depreciations.

The equity index of Zimbabwe shows a positive association with dew, humidity, wind direction and visibility, and a negative association with solar radiation and solar energy. This suggests that high solar radiations or excessive heat pose potential systematic risk and market instability for Zimbabwe (Dube 2023). In the case of Mauritius, the equity index is not associated with any of the climate variables under consideration. However, its exchange rate shows a positive relationship with visibility. This indicates that Mauritius's exchange rates can benefit from clear climate conditions. Lastly, no statistically significant association was found between financial assets and the lunar cycle (moon phase). At the initial level, correlation analysis suggests that the SADC region is climate sensitive and diverse, requiring further analysis.

### 4.3 Transfer entropy analysis

In this section, we use two different transfer entropy measures to examine the non-linear causal relationship between climate factors and financial assets (see Tables 5 and 6). We find no statistically significant information flow from climate variables to the equity indices of Botswana, Mauritius and Namibia. This finding indicates that these economies are less sensitive to climate risks, have well-developed infrastructures or lack a pricing mechanism for climate-induced risk factors. However, the Shannon or Rényi transfer entropy estimates confirm the asymmetric and statistically significant flow of information from the climate variables to the equity indices of SADC nations in a few specific cases, as discussed here (Table 5). Consistent with Kam and Tong (2025), we find a statistically significant flow of information from solar radiation and solar energy to South Africa's equity index, indicating that these two climate variables influence market movements. In line with Hassan et al. (2024), we therefore conclude that investors in South Africa are sensitive to renewable energy trends and energy-intensive sectors specifically.

Similarly, a statistically significant information flow is observed from dew and visibility factors to the equity indices of Malawi and Zimbabwe. Both these SADC nations are heavily dependent on agriculture and are sensitive to changes in weather such as dew formation and visibility issues. While in Tanzania, wind patterns are crucial due to renewable energy production, maritime and transportation, agriculture and tourism (Shimba, Pauline and Luhende 2024). Interestingly, a statistically significant information flow is detected from the moon phase to the equity index of Zambia, suggesting that trading behaviour may be linked to lunar cycles. The findings are in line with Yuan, Zheng and Zhu (2006).

The estimates in Table 6 highlight the link between climate variables and exchange rates in SADC nations. There is no statistically significant information flow from climate variables to the exchange rate regimes of Mauritius and Namibia, suggesting less sensitivity to climate-driven exchange rate effects, dominance of other macroeconomic factors or lack of pricing mechanisms for climate-induced risks.

**Table 5: Transfer entropy estimates for equity indices**

| | SA | Temp | FL | DEW | HUM | WG | WS | WD | VIS | SR | SE | MP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shannon | TE | 0.0054 | 0.0057 | 0.0064 | 0.0086 | 0.0053 | 0.0044 | 0.0042 | 0.0052 | **0.009** | **0.0091** | 0.0082 |
| | Prob. | 0.44 | 0.3967 | 0.23 | 0.06 | 0.4533 | 0.69 | 0.76 | 0.46 | 0.0433* | 0.0467* | 0.1067 |
| Rényi | TE | 0.0524 | 0.0624 | 0.0659 | 0.1035 | 0.0898 | 0.0788 | 0.0841 | 0.1072 | **0.1042** | 0.1002 | 0.0619 |
| | Prob. | 0.69 | 0.5367 | 0.4633 | 0.09 | 0.1833 | 0.3233 | 0.2467 | 0.07 | 0.0367* | 0.0667 | 0.57 |
| **BWA** | | | | | | | | | | | | |
| Shannon | TE | 0.0035 | 0.0035 | 0.0026 | 0.0034 | 0.0096 | 0.0086 | 0.0043 | 0.0071 | 0.0033 | 0.0038 | 0.0068 |
| | Prob. | 0.8267 | 0.81 | 0.9233 | 0.8333 | 0.07 | 0.12 | 0.6233 | 0.19 | 0.8633 | 0.77 | 0.21 |
| Rényi | TE | 0.0639 | 0.0618 | 0.0442 | 0.0181 | 0.0655 | 0.0653 | 0.1079 | 0.0988 | 0.0538 | 0.0502 | 0.0889 |
| | Prob. | 0.4 | 0.4967 | 0.74 | 0.9633 | 0.45 | 0.3967 | 0.0567 | 0.1133 | 0.6367 | 0.6767 | 0.1633 |
| **MWI** | | | | | | | | | | | | |
| Shannon | TE | 0.0029 | 0.0034 | **0.0092** | 0.0054 | 0.0074 | 0.0067 | 0.0053 | **0.0108** | 0.0031 | 0.0031 | 0.003 |
| | Prob. | 0.91 | 0.8 | 0.0467* | 0.41 | 0.1433 | 0.25 | 0.3733 | 0.02* | 0.83 | 0.8633 | 0.8633 |
| Rényi | TE | 0.0841 | 0.0631 | 0.026 | 0.0888 | 0.0046 | 0.0111 | 0.0486 | 0.0428 | 0.0791 | 0.0782 | 0.0758 |
| | Prob. | 0.2167 | 0.4733 | 0.9333 | 0.1233 | 0.9867 | 1 | 0.6933 | 0.8 | 0.2533 | 0.2433 | 0.3467 |
| **MUS** | | | | | | | | | | | | |
| Shannon | TE | 0.0029 | 0.004 | 0.008 | 0.003 | 0.0031 | 0.0032 | 0.0052 | 0.0028 | 0.002 | 0.0019 | 0.0042 |
| | Prob. | 0.89 | 0.7667 | 0.1333 | 0.91 | 0.8667 | 0.8733 | 0.5433 | 0.9367 | 0.98 | 0.9833 | 0.77 |
| Rényi | TE | 0.0706 | 0.0534 | 0.0501 | 0.0496 | 0.0754 | 0.033 | 0.0001 | 0.0542 | 0.0449 | 0.0451 | 0.0212 |
| | Prob. | 0.3333 | 0.6667 | 0.64 | 0.6967 | 0.3067 | 0.85 | 0.1831 | 0.5467 | 0.72 | 0.72 | 0.9367 |
| **NAM** | | | | | | | | | | | | |
| Shannon | TE | 0.0049 | 0.0025 | 0.0052 | 0.0057 | 0.0042 | 0.0036 | 0.0027 | 0.0048 | 0.0051 | 0.0051 | 0.0081 |
| | Prob. | 0.5867 | 0.97 | 0.53 | 0.3867 | 0.7067 | 0.8667 | 0.9567 | 0.61 | 0.5233 | 0.49 | 0.1467 |
| Rényi | TE | 0.0388 | 0.0242 | 0.0569 | 0.0681 | 0.03 | 0.0518 | 0.0784 | 0.0609 | 0.0719 | 0.0733 | 0.0671 |
| | Prob. | 0.79 | 0.93 | 0.6233 | 0.3933 | 0.9033 | 0.63 | 0.2933 | 0.6567 | 0.3867 | 0.3733 | 0.44 |
| **TZA** | | | | | | | | | | | | |
| Shannon | TE | 0.0054 | 0.0053 | 0.005 | 0.0037 | 0.0041 | 0.0092 | 0.0076 | 0.0078 | 0.0082 | 0.0082 | 0.0053 |
| | Prob. | 0.55 | 0.5933 | 0.5933 | 0.8767 | 0.7967 | 0.0533 | 0.2467 | 0.15 | 0.18 | 0.14 | 0.6033 |
| Rényi | TE | 0.0597 | 0.0686 | 0.0685 | 0.1054 | 0.003 | 0.123 | **0.1236** | 0.0182 | 0.0668 | 0.0799 | 0.0615 |
| | Prob. | 0.5733 | 0.4533 | 0.4833 | 0.1167 | 0.16 | 0.08 | 0.02* | 0.9633 | 0.51 | 0.3533 | 0.5767 |
| | | | | | | | | | | | | |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **ZMB** | | | | | | | | | | | | |
| Shannon | TE | 0.0042 | 0.0049 | 0.0064 | 0.0064 | 0.004 | 0.0084 | 0.0057 | 0.0093 | 0.0073 | 0.0071 | 0.0084 |
| | Prob. | 0.7633 | 0.6233 | 0.37 | 0.3433 | 0.77 | 0.1033 | 0.4733 | 0.0533 | 0.2067 | 0.2167 | 0.13 |
| Rényi | TE | 0.0779 | 0.0763 | 0.0587 | 0.0633 | 0.0562 | 0.0301 | 0.0539 | 0.1074 | 0.0784 | 0.0772 | **0.1264** |
| | Prob. | 0.3033 | 0.3867 | 0.5967 | 0.5733 | 0.6333 | 0.9333 | 0.65 | 0.12 | 0.29 | 0.3467 | 0.03* |
| **ZWE** | | | | | | | | | | | | |
| Shannon | TE | 0.0028 | 0.003 | **0.012** | 0.0084 | 0.0075 | 0.0075 | 0.0055 | 0.0064 | 0.0062 | 0.0063 | 0.008 |
| | Prob. | 0.9567 | 0.9367 | 0.0067* | 0.1067 | 0.2233 | 0.16 | 0.63 | 0.4067 | 0.4533 | 0.4033 | 0.16 |
| Rényi | TE | 0.0736 | 0.0734 | 0.0066 | 0.0714 | 0.1096 | 0.0883 | 0.1031 | **0.1565** | 0.1 | 0.1004 | 0.0942 |
| | Prob. | 0.5633 | 0.6333 | 0.9833 | 0.6233 | 0.2567 | 0.45 | 0.28 | 0.0233* | 0.3033 | 0.3267 | 0.39 |

Note: * Significant at 5%.

**Table 6: Transfer entropy estimates for exchange rates**

| | SA | Temp | FL | DEW | HUM | WG | WS | WD | VIS | SR | SE | MP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shannon | TE | 0.0055 | 0.0055 | 0.0072 | 0.0058 | 0.0068 | 0.0056 | 0.0064 | 0.0073 | 0.0088 | 0.0089 | 0.0076 |
| | Prob. | 0.4467 | 0.4333 | 0.1833 | 0.4167 | 0.2633 | 0.4567 | 0.37 | 0.18 | 0.08 | 0.0833 | 0.1633 |
| Rényi | TE | 0.0765 | 0.0765 | 0.0567 | 0.0968 | **0.1274** | 0.0234 | 0.0515 | 0.0782 | 0.0707 | 0.0695 | 0.0493 |
| | Prob. | 0.34 | 0.3267 | 0.6467 | 0.1567 | 0.03* | 0.9533 | 0.67 | 0.2733 | 0.42 | 0.3867 | 0.7367 |
| **BWA** | | | | | | | | | | | | |
| Shannon | TE | 0.0036 | 0.0029 | 0.0037 | 0.0037 | 0.0054 | 0.0073 | 0.0069 | 0.0052 | 0.0014 | 0.0021 | 0.0043 |
| | Prob. | 0.7167 | 0.8733 | 0.68 | 0.72 | 0.4233 | 0.15 | 0.23 | 0.4167 | 0.9967 | 0.96 | 0.5733 |
| Rényi | TE | 0.0768 | 0.0625 | 0.0453 | 0.0453 | 0.0825 | 0.0694 | **0.1254** | 0.1017 | 0.0441 | 0.0641 | 0.0438 |
| | Prob. | 0.24 | 0.41 | 0.7 | 0.67 | 0.1633 | 0.2967 | 0.0033* | 0.0667 | 0.6933 | 0.3933 | 0.6567 |
| **MWI** | | | | | | | | | | | | |
| Shannon | TE | 0.0096 | **0.012** | 0.0051 | 0.0078 | 0.0081 | 0.0079 | 0.0067 | **0.012** | 0.0065 | 0.0064 | 0.0048 |
| | Prob. | 0.0667 | 0.0267* | 0.5533 | 0.21 | 0.1667 | 0.14 | 0.3233 | 0.0233* | 0.3767 | 0.3533 | 0.7167 |
| Rényi | TE | 0.0596 | 0.0597 | 0.061 | 0.1065 | 0.0407 | 0.0777 | 0.0592 | **0.1796** | 0.1239 | **0.123** | 0.0798 |
| | Prob. | 0.59 | 0.57 | 0.63 | 0.0633 | 0.7833 | 0.3267 | 0.5967 | 0* | 0.05 | 0.0233* | 0.3233 |
| **MUS** | | | | | | | | | | | | |
| Shannon | TE | 0.0025 | 0.0032 | 0.0058 | 0.0041 | 0.0074 | 0.0064 | 0.0031 | 0.0045 | 0.0085 | 0.0085 | 0.0057 |
| | Prob. | 0.9767 | 0.86 | 0.36 | 0.7133 | 0.1333 | 0.2733 | 0.9233 | 0.6767 | 0.09 | 0.1133 | 0.4567 |
| Rényi | TE | 0.0668 | 0.0449 | 0.0599 | 0.0343 | 0.1087 | 0.0195 | 0.0528 | 0.0396 | 0.0752 | 0.0757 | 0.0626 |
| | Prob. | 0.4733 | 0.75 | 0.58 | 0.8533 | 0.09 | 0.9733 | 0.6533 | 0.8333 | 0.3667 | 0.33 | 0.48 |
| **NAM** | | | | | | | | | | | | |
| Shannon | TE | 0.0063 | 0.0081 | 0.0033 | 0.005 | 0.0075 | 0.0058 | 0.0026 | 0.003 | 0.0039 | 0.0041 | 0.0055 |
| | Prob. | 0.2233 | 0.0533 | 0.7233 | 0.3867 | 0.0933 | 0.2767 | 0.8433 | 0.75 | 0.5733 | 0.5467 | 0.3 |
| Rényi | TE | 0.0263 | 0.0205 | 0.0375 | 0.066 | 0.0307 | 0.075 | 0.0405 | 0.0532 | 0.095 | 0.0963 | 0.0617 |
| | Prob. | 0.8333 | 0.8433 | 0.6867 | 0.31 | 0.7867 | 0.2633 | 0.6667 | 0.49 | 0.0667 | 0.0533 | 0.33 |
| **TZA** | | | | | | | | | | | | |
| Shannon | TE | 0.0029 | 0.004 | 0.0052 | **0.0067** | **0.0108** | 0.0049 | **0.014** | 0.0053 | 0.0062 | 0.0061 | 0.0017 |
| | Prob. | 0.52 | 0.27 | 0.1533 | 0.0467* | 0* | 0.1467 | 0* | 0.13 | 0.0833 | 0.07 | 0.7867 |
| Rényi | TE | 0.0149 | 0.0297 | 0.0583 | 0.0436 | -0.0082 | 0.0329 | -0.0117 | 0.0268 | 0.0335 | 0.0323 | 0.0194 |
| | Prob. | 0.8367 | 0.6433 | 0.1967 | 0.3867 | 0.9667 | 0.6033 | 0.98 | 0.6633 | 0.5767 | 0.54 | 0.7467 |
| | | | | | | | | | | | | |

| **ZMB** | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shannon | TE | 0.0038 | 0.0038 | 0.0037 | 0.0065 | 0.0014 | 0.0053 | 0.0033 | 0.0098 | 0.0044 | 0.0045 | 0.0087 |
| | Prob. | 0.7633 | 0.7867 | 0.8033 | 0.3433 | 0.9933 | 0.53 | 0.8367 | 0.06 | 0.6967 | 0.67 | 0.0933 |
| Rényi | TE | 0.0776 | 0.0775 | 0.097 | 0.1046 | 0.0452 | 0.0157 | 0.0448 | **0.1419** | 0.0873 | 0.0878 | **0.1343** |
| | Prob. | 0.3467 | 0.3167 | 0.2267 | 0.1233 | 0.7367 | 0.96 | 0.6867 | 0.01* | 0.3067 | 0.2233 | 0.0367* |

Note: * Significant at 5%.

A statistically significant asymmetric information flow from wind gust to South Africa (ZAR_USD), or from wind direction to Botswana (BWP_USD), implies the impact of climate variables on currency movements. Similarly, evidence of information flow between climate variables such as feel like, visibility, solar energy, humidity and moon phase and the exchange rates of Malawi, Tanzania and Zambia implies local climate sensitivity and/or sectoral influences.

In summary, the climate variables dew, wind direction, visibility, solar radiation, solar energy and moon phase influence SADC nations' equity indices. Similarly, the climate variables feel like, humidity, wind gust, wind direction, visibility, solar energy and moon phase show causal information flow with the exchange rates of SADC nations. In line with Venturini (2022) and Campiglio et al. (2023), our findings reflect the role of climate factors in shaping economic activity and stock market performance. Overall, our results (see Table 7) support our hypothesis that *"climate-related risks have a significant impact on the volatility of stock markets in the SADC region".*

**Table 7: Summary of transfer entropy analysis**

| Climate variables | EI | ER |
|---|---|---|
| Temp | x | x |
| FL | x | MWI |
| DEW | MWI, ZWE | x |
| HUM | x | TZA |
| WG | x | SA, TZA |
| WS | x | x |
| WD | TZA | BWA, TZA |
| VIS | MWI, ZWE | MWI, ZMB |
| SR | SA | x |
| SE | SA | MWI |
| MP | ZMB | ZMB |

Note: x represents no statistically significant information flow or causal relationship.

## 4.4 Wavelet coherence analysis

In this section, we use wavelet coherence analysis to examine the time-varying impact of the climate variables on different financial assets. The estimates obtained from the analysis are shown in Figures 1 to 8. The red, yellow and blue colours indicate high, moderate and low coherence, respectively, among the two time series under consideration. The horizontal axis shows how the relationship between the two time series evolves over time. Similarly, the vertical axis shows this relationship in frequency domains, such as short- and long-term dynamics. The arrows in the coherence diagram represent the lead or lag phase difference. If the arrow direction points towards the right, this means the time series are in positive coherence, while arrows to the left represent a negative coherence.

Figures 1 to 8 suggest dynamic co-movements and lead/lag effects between the climate variables and financial assets of SADC nations in time frequency domain. The relationship between the two time series changes across time and different scales. Clear evidence of coherence is observed in the wavelet coherence diagram ranges from short to longer durations.

Figure 1(a) indicates strong and long coherence between the Johannesburg Stock Exchange (JSE) 40 index and climate variables (feel like, humidity and temperature) during the COVID-19 period. Figures 1(a) and (b) also suggest multiple and dynamic coherence between South Africa's financial assets and climate variables that last for short to moderate durations. The Climate Change Bill was introduced in 2018 in South Africa and became a formal act in 2024, affecting the coherence level. In addition to the legislation, the South African Reserve Bank (SARB) acknowledged climate risks as systematic in 2022. Looking at Figure 1(a), especially for temperature, humidity, solar and feel like after 2022 at the higher scales (256), it can be observed that the overall coherence level between these climate variables and the JSE 40 index diminishes towards 2024.[7] This could be in response to the SARB initiating climate-related stress testing after 2022. As a result, overall transition risks arising from these climate variables (temperature, humidity, solar radiation and energy, and feel like) decline over a period.[8]

In line with D'Orazio and Popoyan (2019), our findings indicate that macroprudential policies may mitigate the negative impact of climate risks on the stock market's volatility. Our results reinforce the notion that policies that integrate climate risk assessments, such as stress tests and scenario analyses, enable financial institutions

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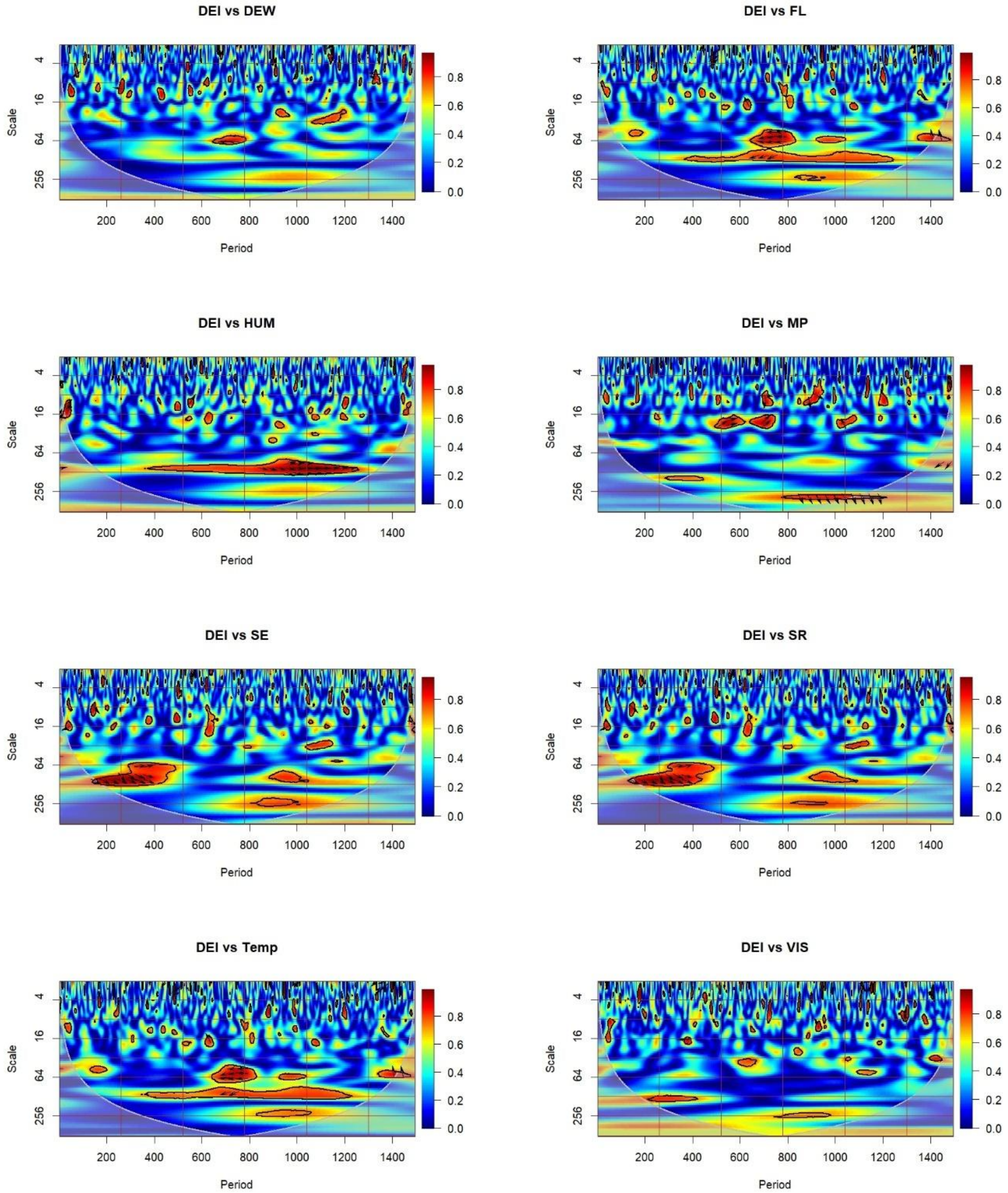
7 Generally, the coherence level diminishes from red to yellow.

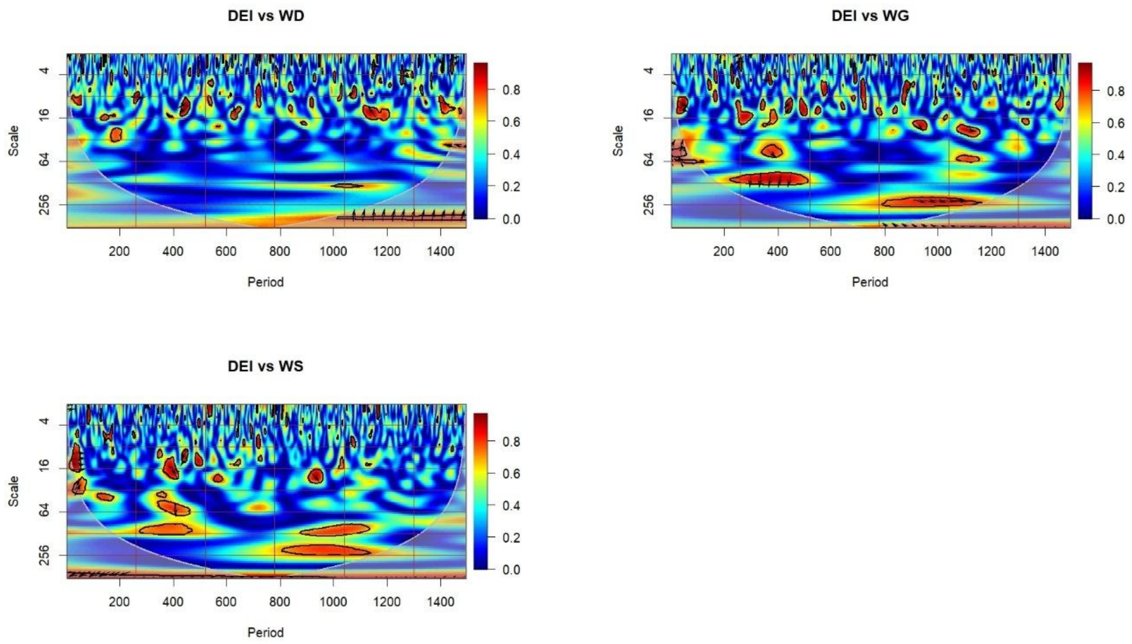
8 See Anvari et al. 2022; SARB 2024; SARB 2025.

to better prepare for and respond to climate-related shocks (Ayele and Fisseha 2024; Chenet, Ryan-Collins and van Lerven 2021).

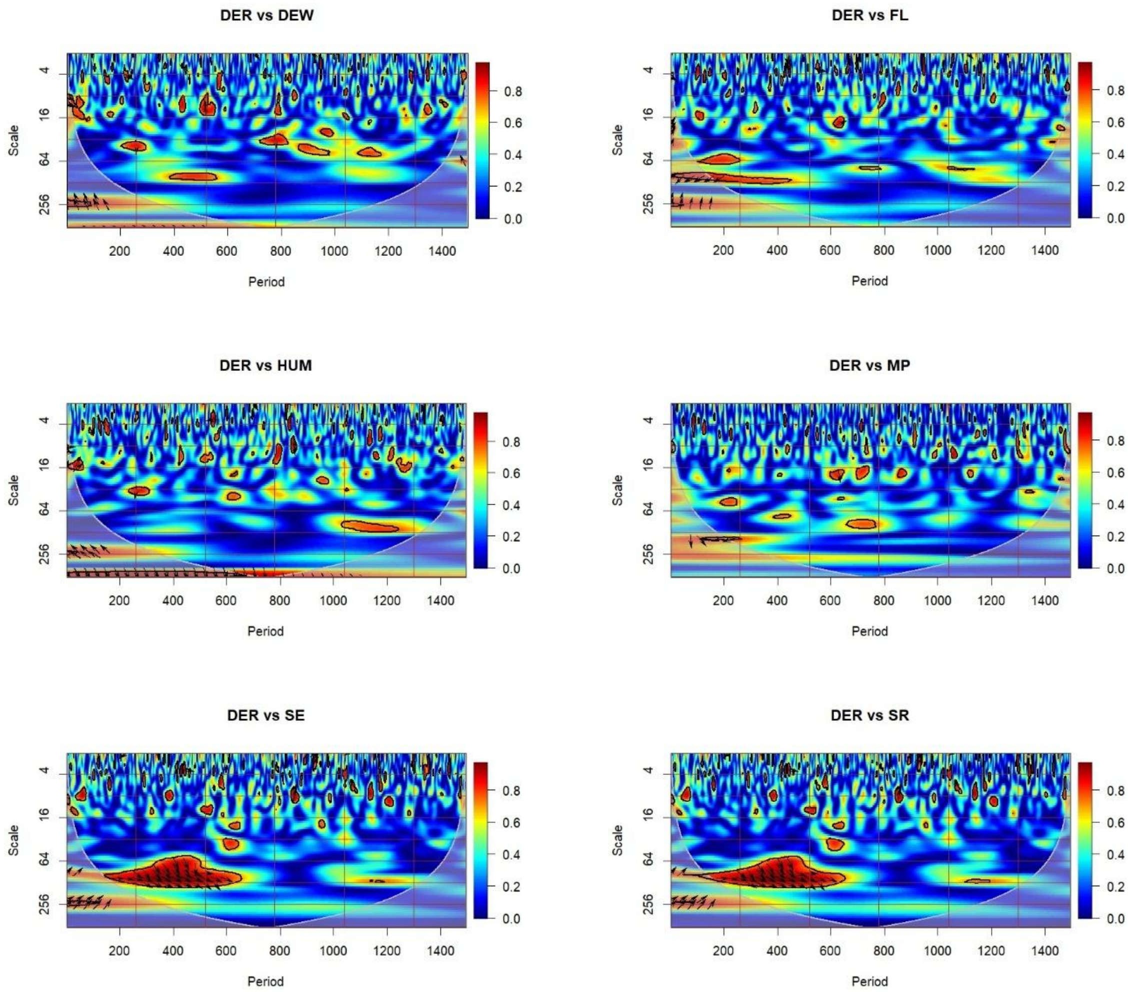
**Figure 1(a) and (b): Wavelet analysis for South Africa**

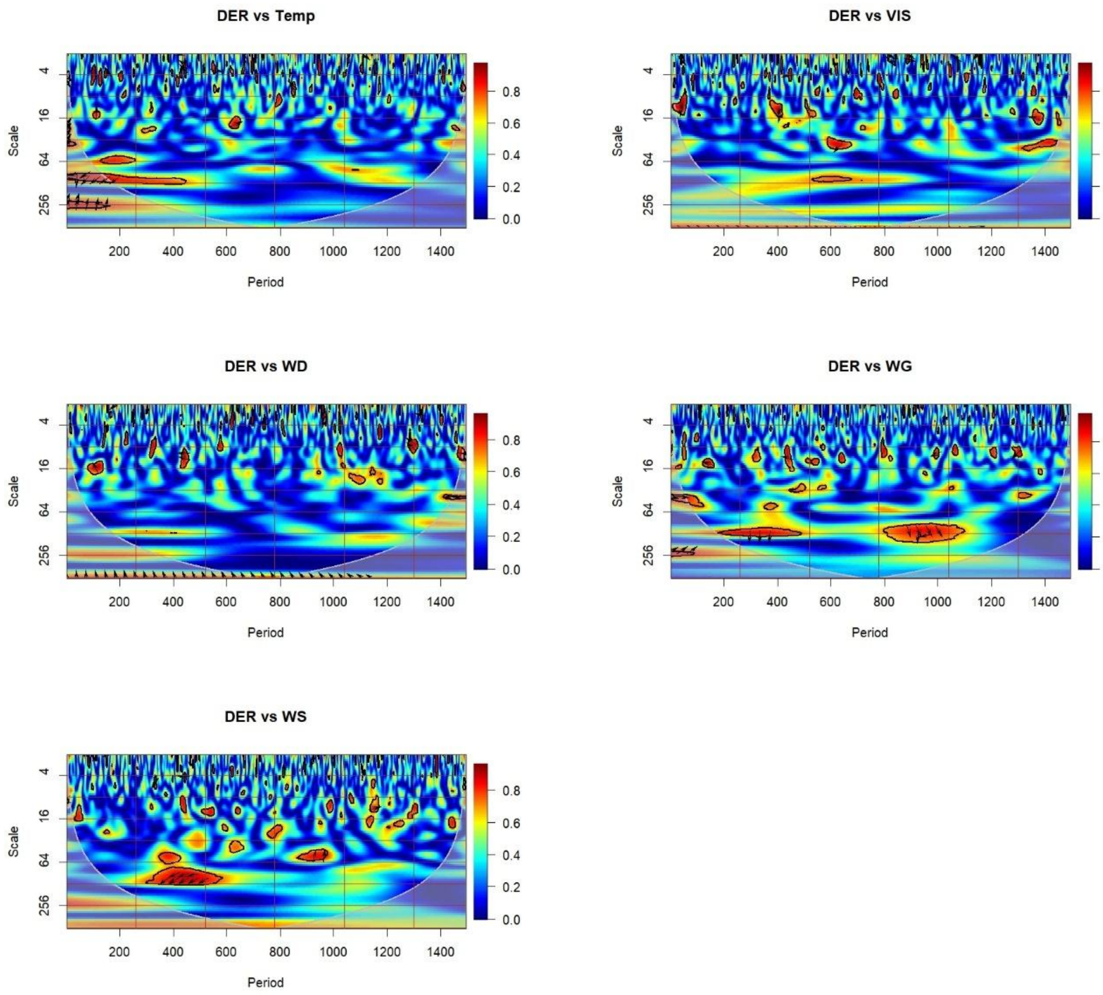
**1(a)**




DEI vs WD
DEI vs WG
DEI vs WS
Scale
Period

1(b)

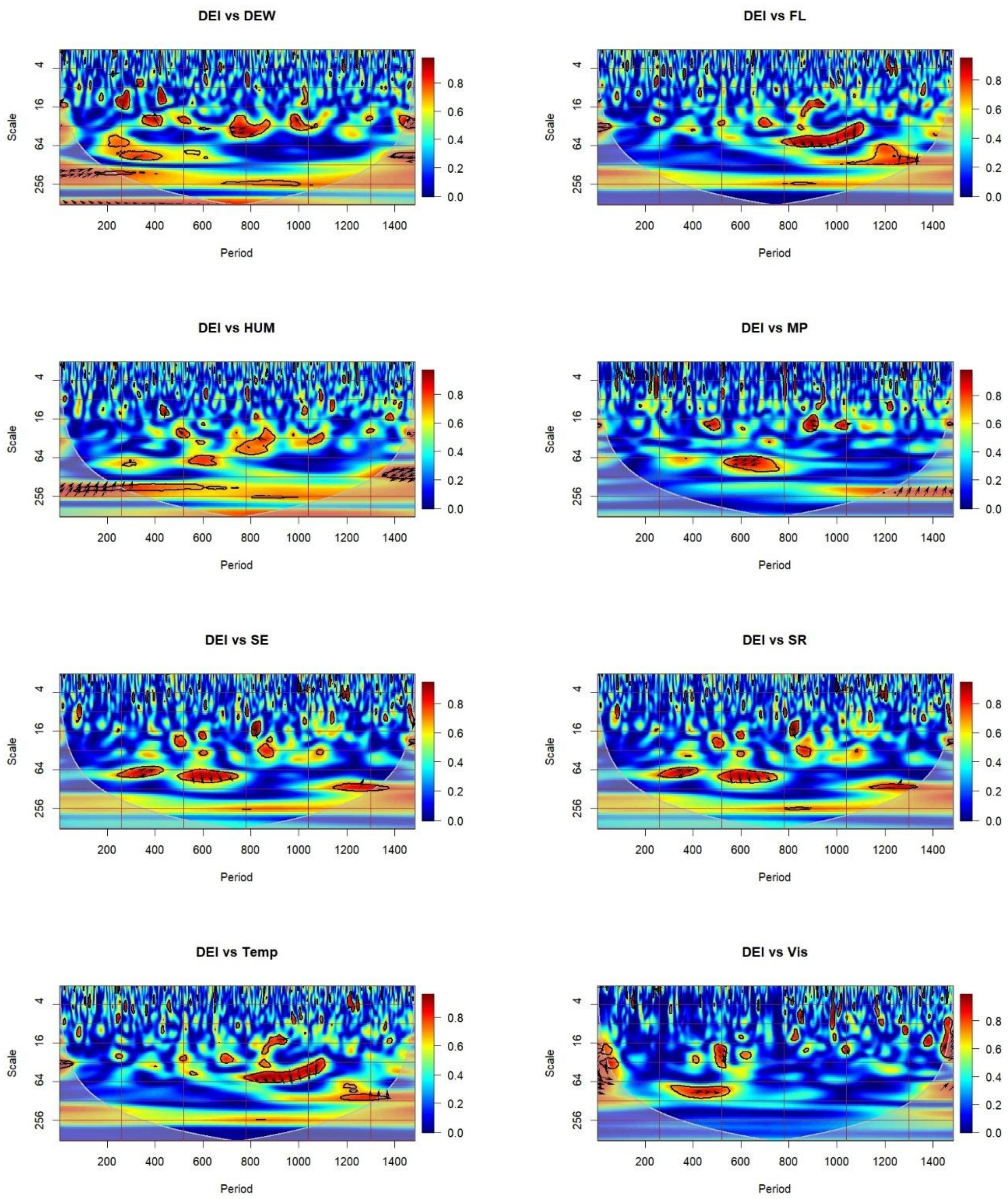

DER vs DEW
DER vs FL
DER vs HUM
DER vs MP
DER vs SE
DER vs SR
Scale
Period

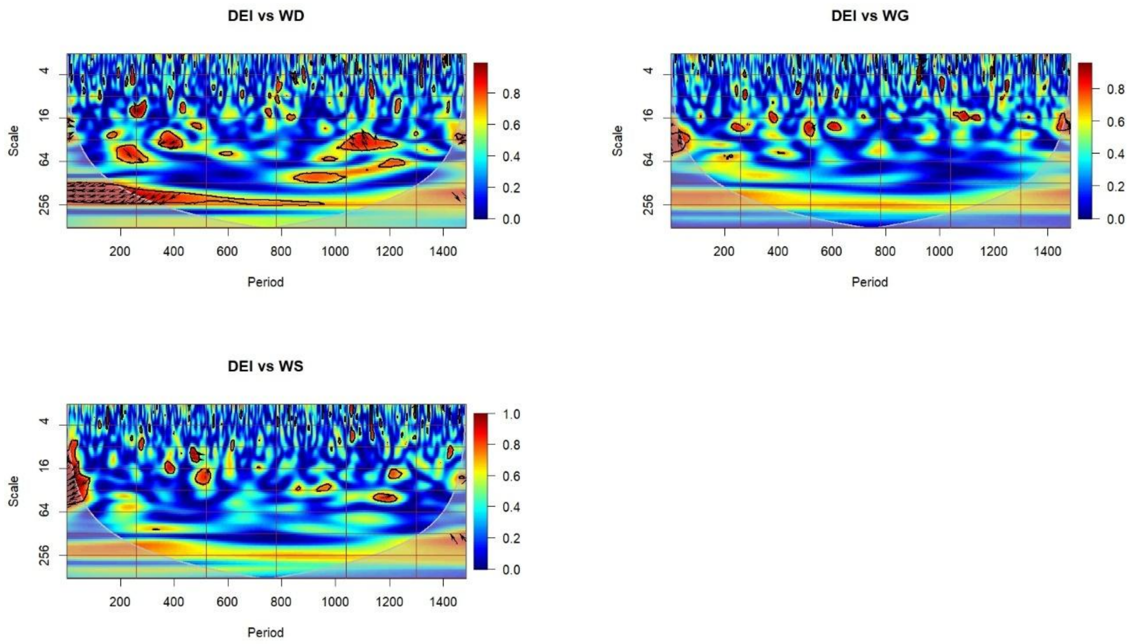

DER vs Temp
DER vs VIS
DER vs WD
DER vs WG
DER vs WS
Scale
Period
4
16
64
256
200
400
600
800
1000
1200
1400
0.0
0.2
0.4
0.6
0.8

Multiple and dynamic coherence is observed between Botswana's financial assets and climate variables that last for short to moderate durations (Figure 2). Botswana introduced the Climate Change Policy in 2021. Figures 2(a) and (b) show that since 2022 the overall coherence level between Botswana's equity index and the climate variables dew, wind and humidity becomes weaker at the higher scales (256).

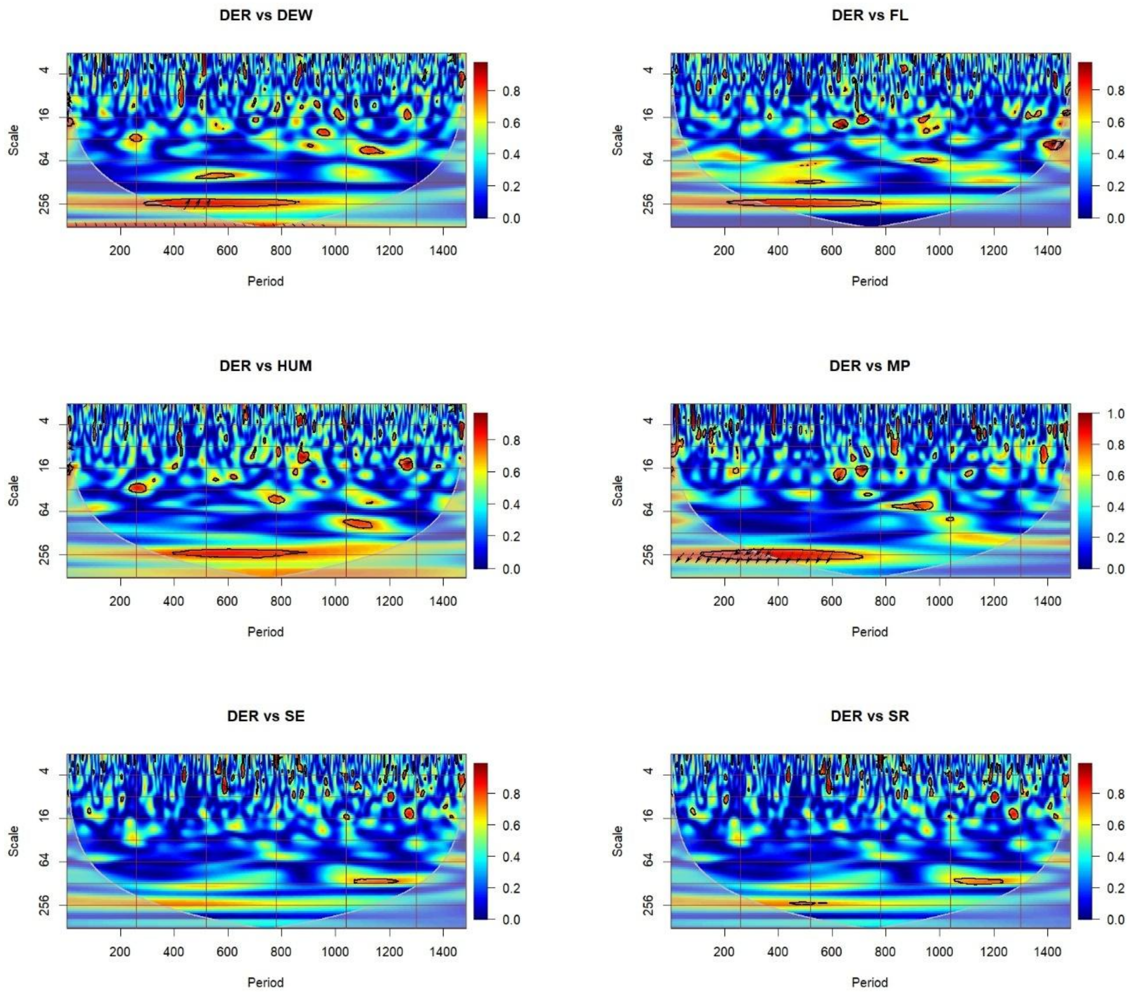
**Figure 2(a) and (b): Wavelet analysis for Botswana**

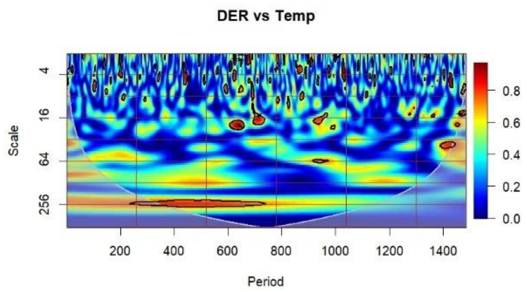
**2(a)**

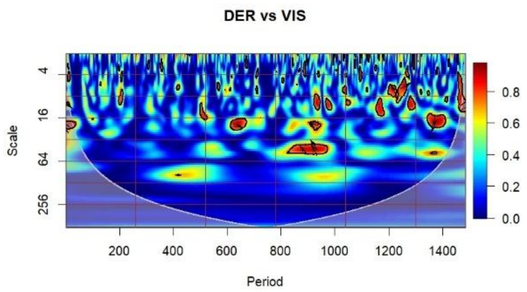


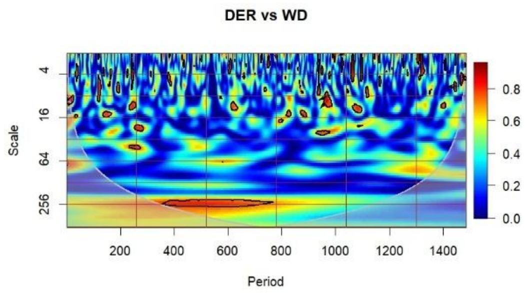

DEI vs WD
DEI vs WG
DEI vs WS
Scale
Period
4
16
64
256
200
400
600
800
1000
1200
1400
0.0
0.2
0.4
0.6
0.8
1.0

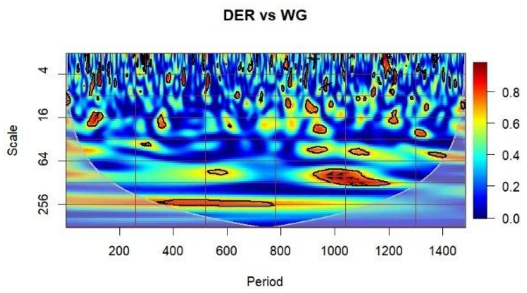
**2(b)**

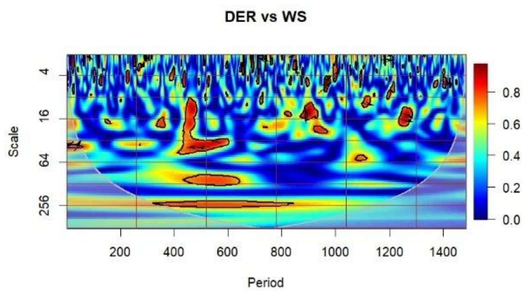

DER vs DEW
DER vs FL
DER vs HUM
DER vs MP
DER vs SE
DER vs SR
Scale
Period
4
16
64
256
200
400
600
800
1000
1200
1400
0.0
0.2
0.4
0.6
0.8
1.0


DER vs Temp
Scale
4
16
64
256
200
400
600
800
1000
1200
1400
Period
0.0
0.2
0.4
0.6
0.8


DER vs VIS
Scale
4
16
64
256
200
400
600
800
1000
1200
1400
Period
0.0
0.2
0.4
0.6
0.8


DER vs WD
Scale
4
16
64
256
200
400
600
800
1000
1200
1400
Period
0.0
0.2
0.4
0.6
0.8

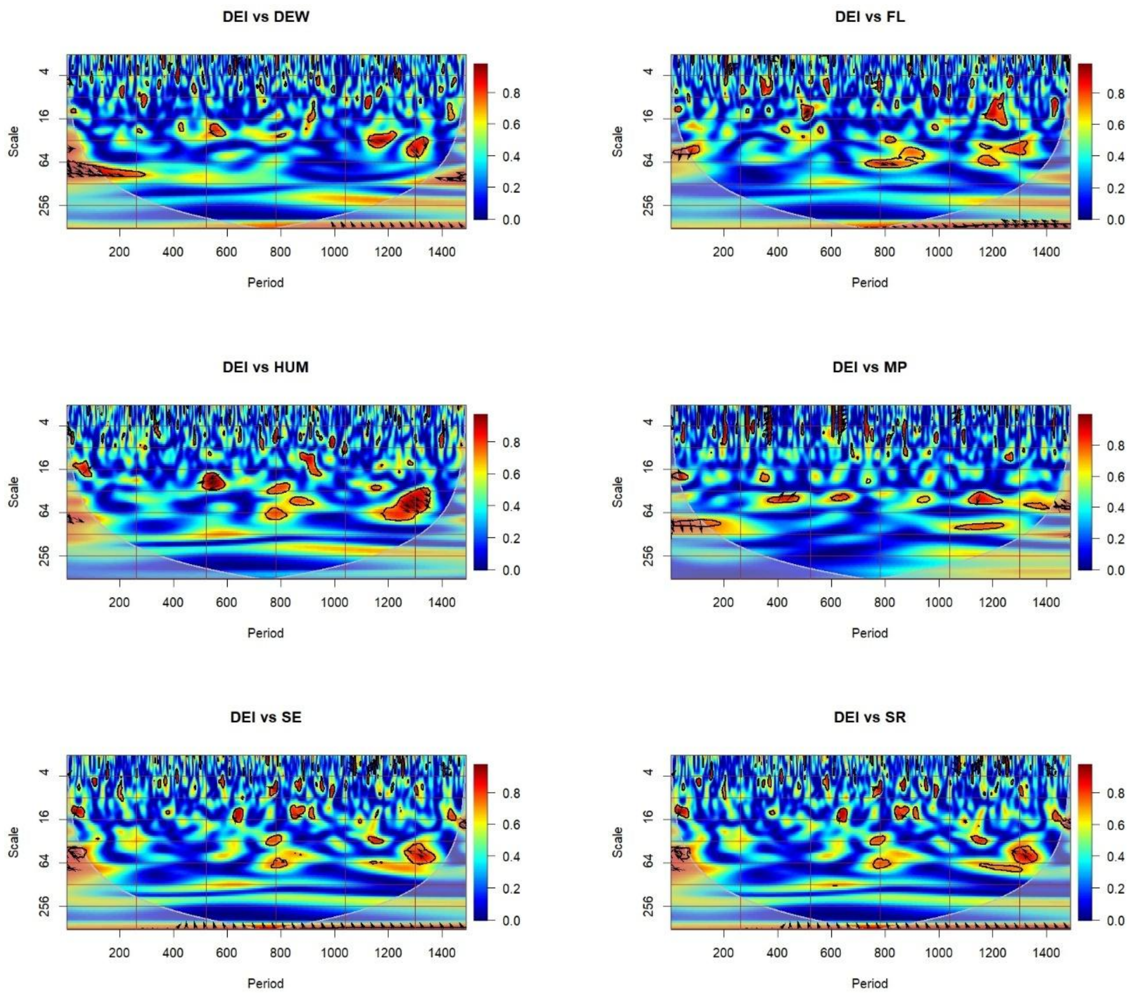

DER vs WG
Scale
4
16
64
256
200
400
600
800
1000
1200
1400
Period
0.0
0.2
0.4
0.6
0.8

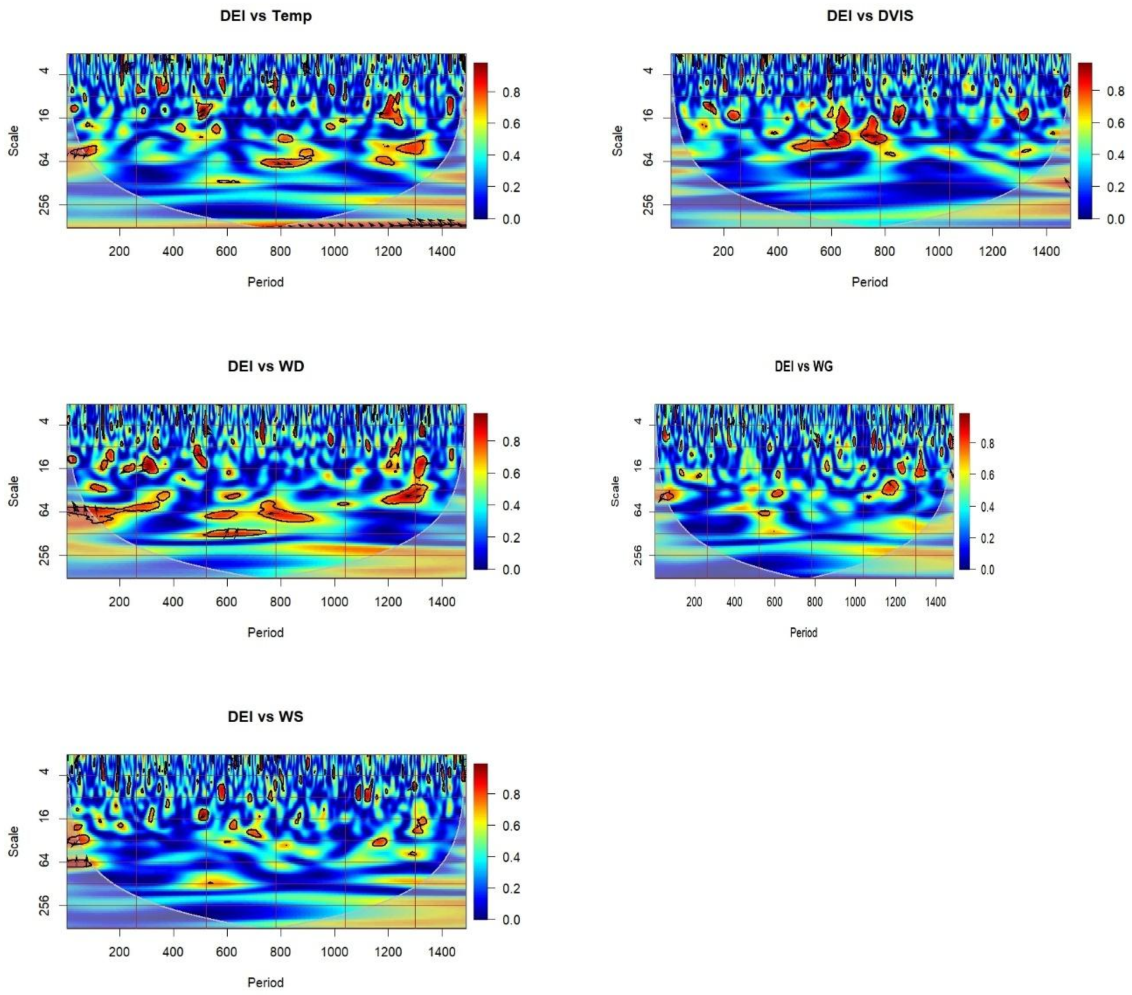

DER vs WS
Scale
4
16
64
256
200
400
600
800
1000
1200
1400
Period
0.0
0.2
0.4
0.6
0.8

Similar patterns are observed for Malawi following the introduction of the National Climate Change Management Policy in 2016 (see Figure 3(a)). These results suggest that carefully designed macroprudential policies have an important role to play in mitigating the potential negative effects of climate risks on the stability of financial markets in the SADC region. Figure 3(b) shows strong and long coherence between Malawi (MWK_USD) and visibility at higher scales of 256. It indicates the need for macroprudential policies that support climate adaptation financing to address the long-term volatility of the exchange rate.

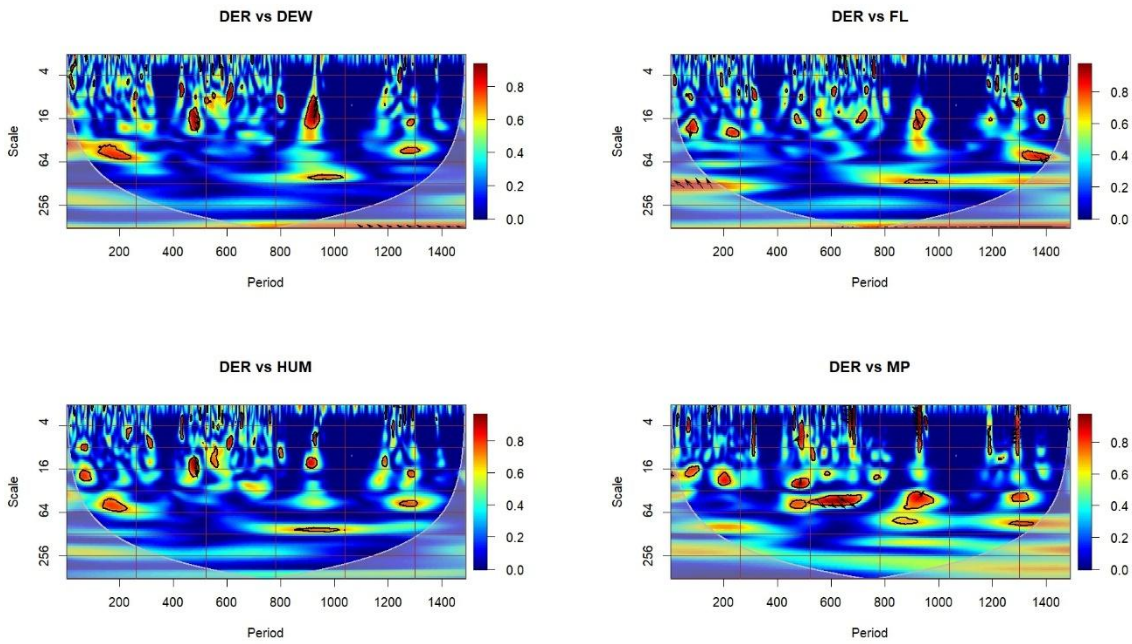
**Figure 3(a) and (b): Wavelet analysis for Malawi**

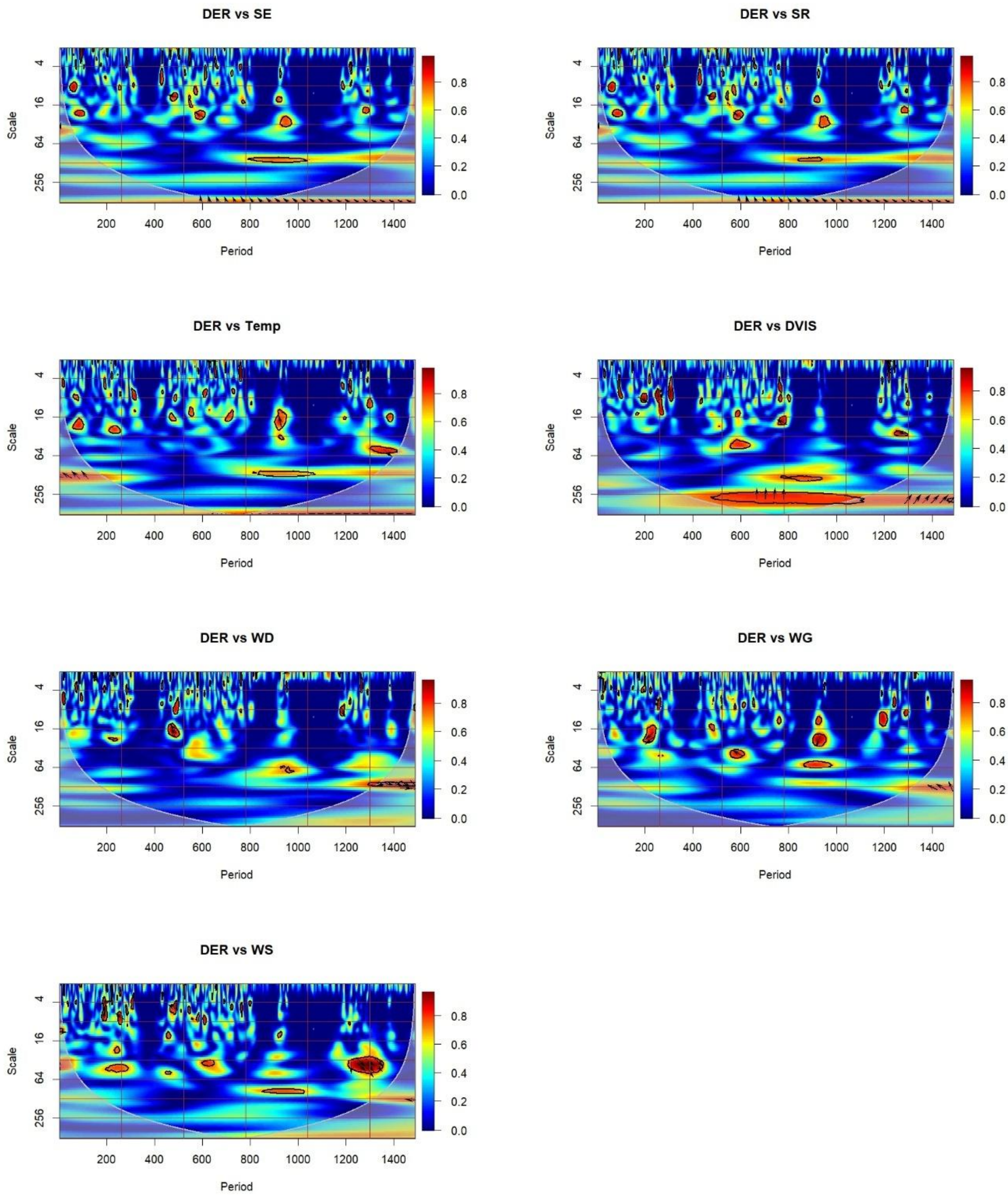
**3(a)**




DEI vs Temp
DEI vs DVIS
DEI vs WD
DEI vs WG
DEI vs WS
Scale
Period

**3(b)**

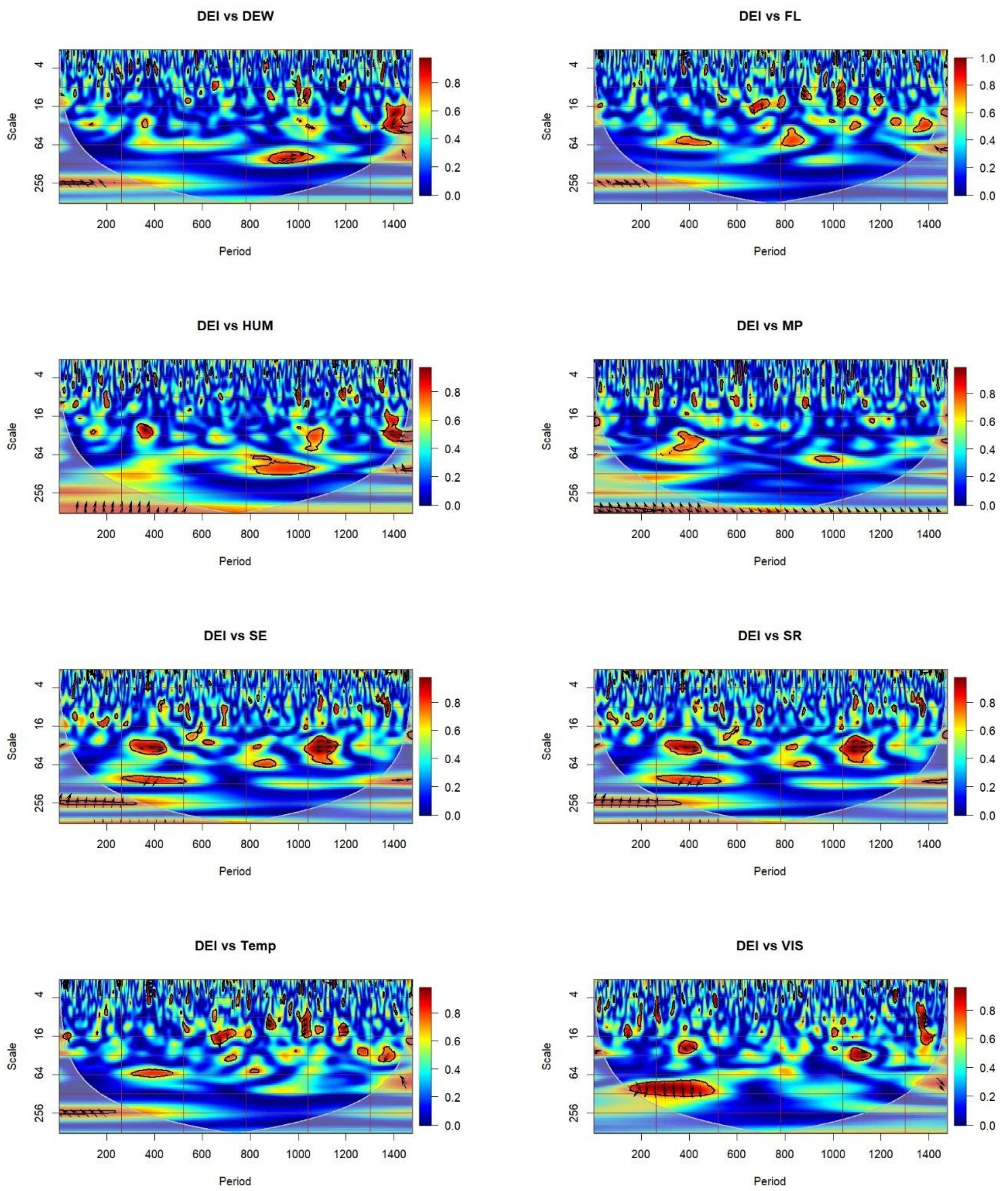

DER vs DEW
DER vs FL
DER vs HUM
DER vs MP
Scale
Period

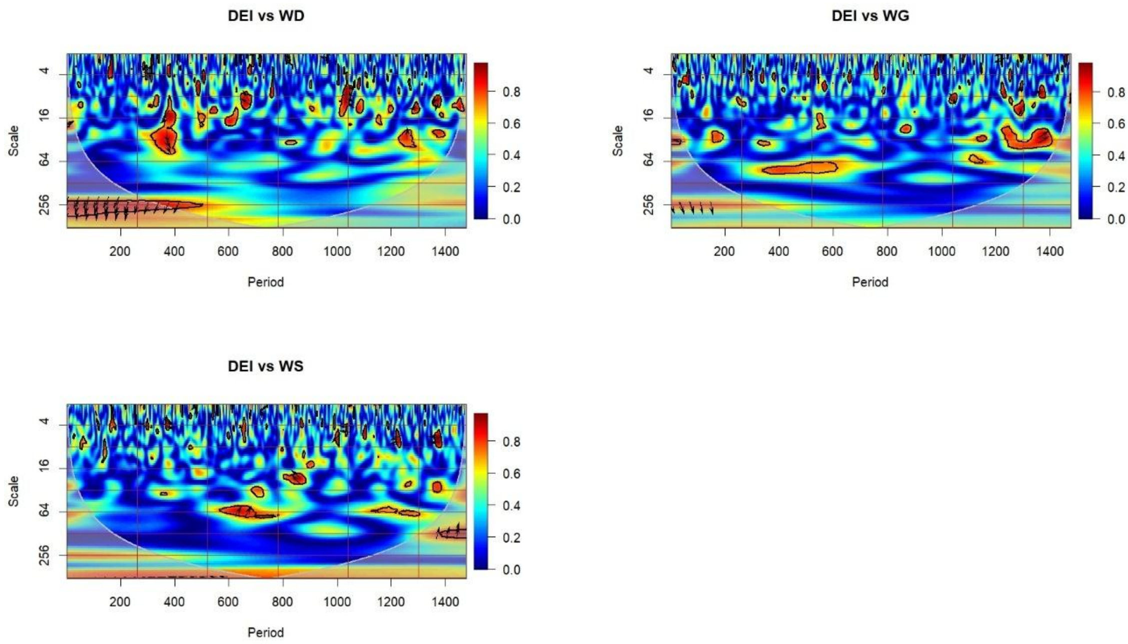

DER vs SE
DER vs SR
DER vs Temp
DER vs DVIS
DER vs WD
DER vs WG
DER vs WS
Scale
Period
4
16
64
256
200
400
600
800
1000
1200
1400
0.0
0.2
0.4
0.6
0.8

Multiple and dynamic coherence is also observed between Mauritius's financial assets and climate variables that last for short to moderate durations (Figure 4). Mauritius introduced the Climate Change Act in 2020. Its effect can possibly be observed in the decrease in coherence strength (at a higher scale of 256) over time among the climate variables and financial assets in most cases.

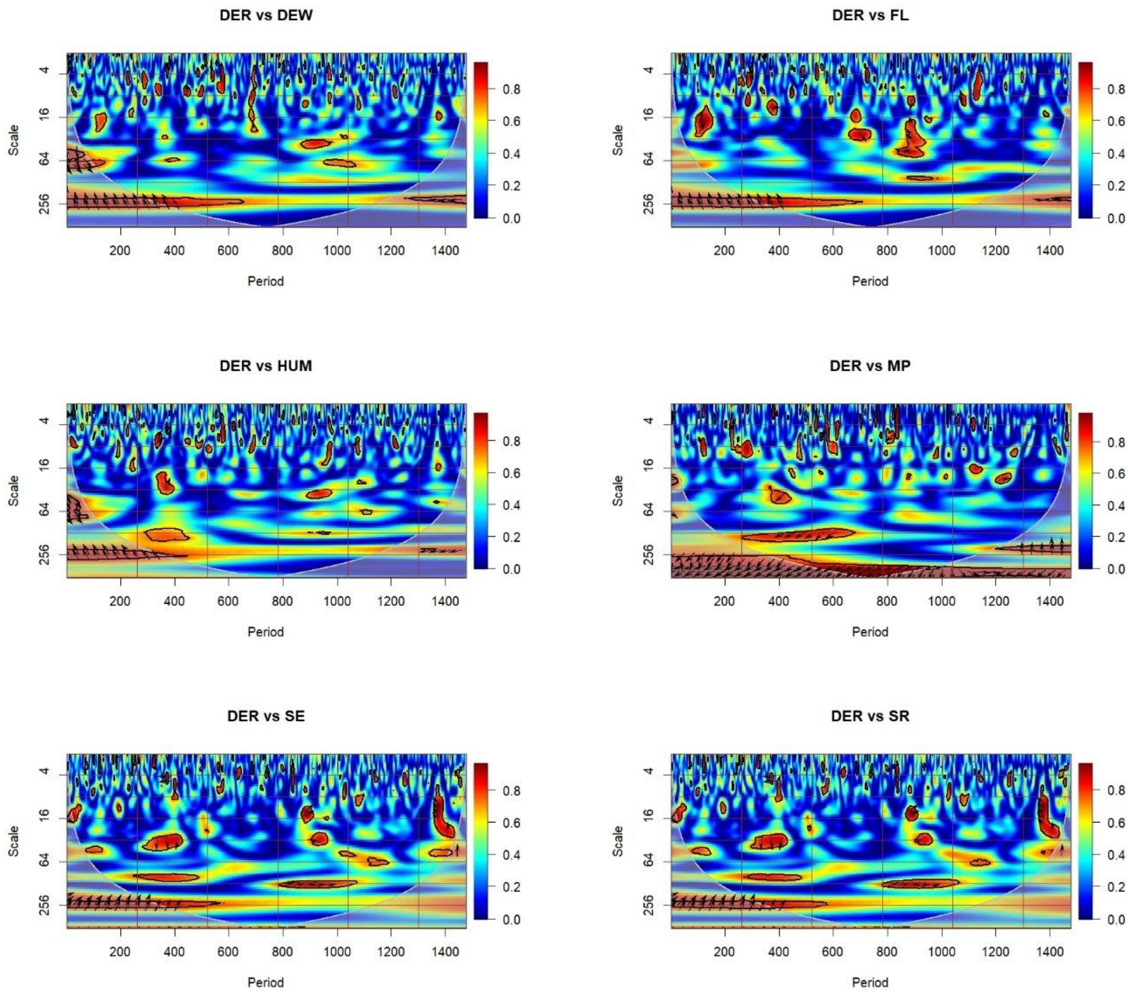
**Figure 4(a) and (b): Wavelet analysis for Mauritius**

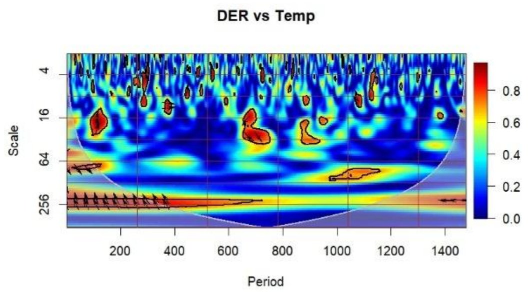
**4(a)**




DEI vs WD
DEI vs WG
DEI vs WS
Scale
Period

**4(b)**


DER vs DEW
DER vs FL
DER vs HUM
DER vs MP
DER vs SE
DER vs SR
Scale
Period


DER vs Temp
Scale
4
16
64
256
200
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Period
0.8
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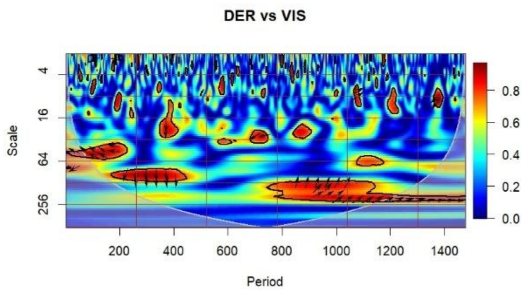
0.0


DER vs VIS
Scale
4
16
64
256
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400
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800
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1200
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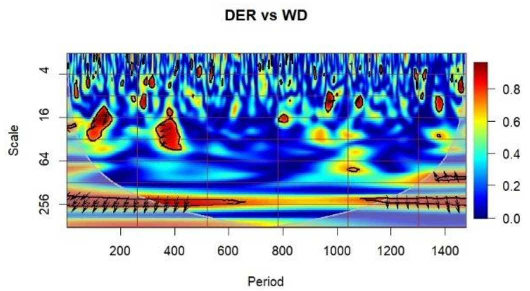
Period
0.8
0.6
0.4
0.2
0.0


DER vs WD
Scale
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200
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1200
1400
Period
0.8
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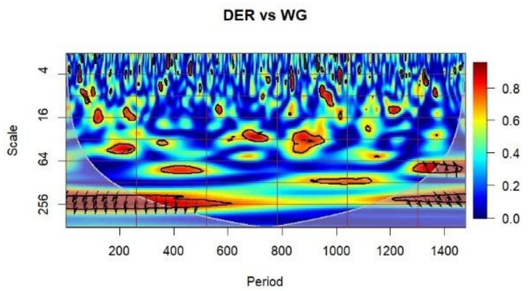
0.0


DER vs WG
Scale
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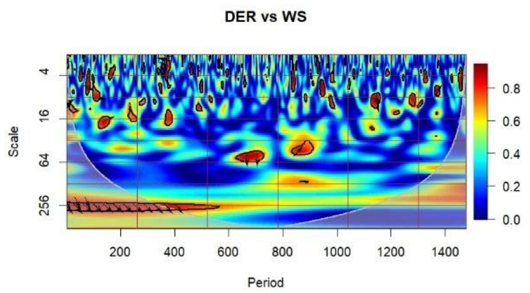
DER vs WS
Scale
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64
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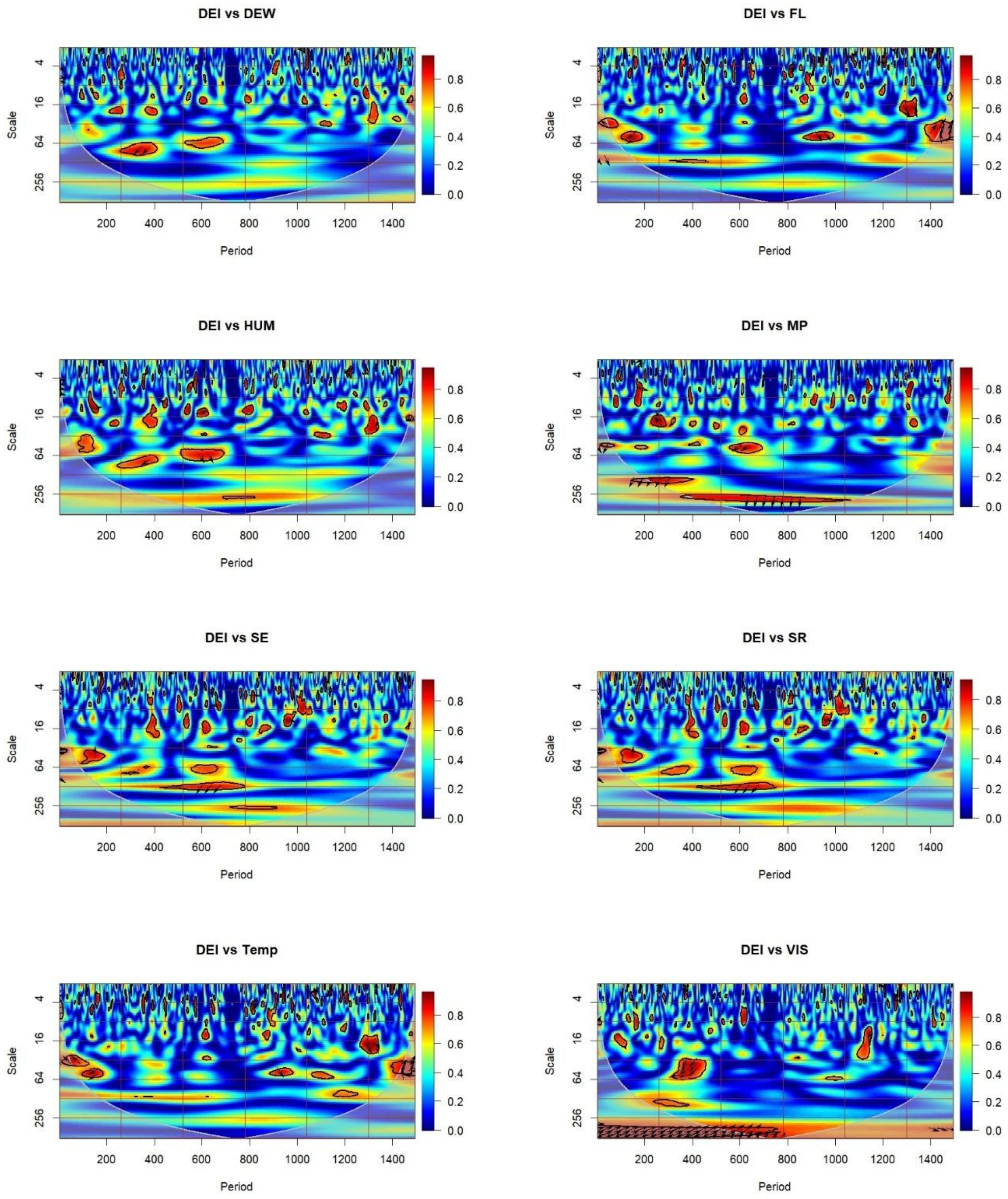
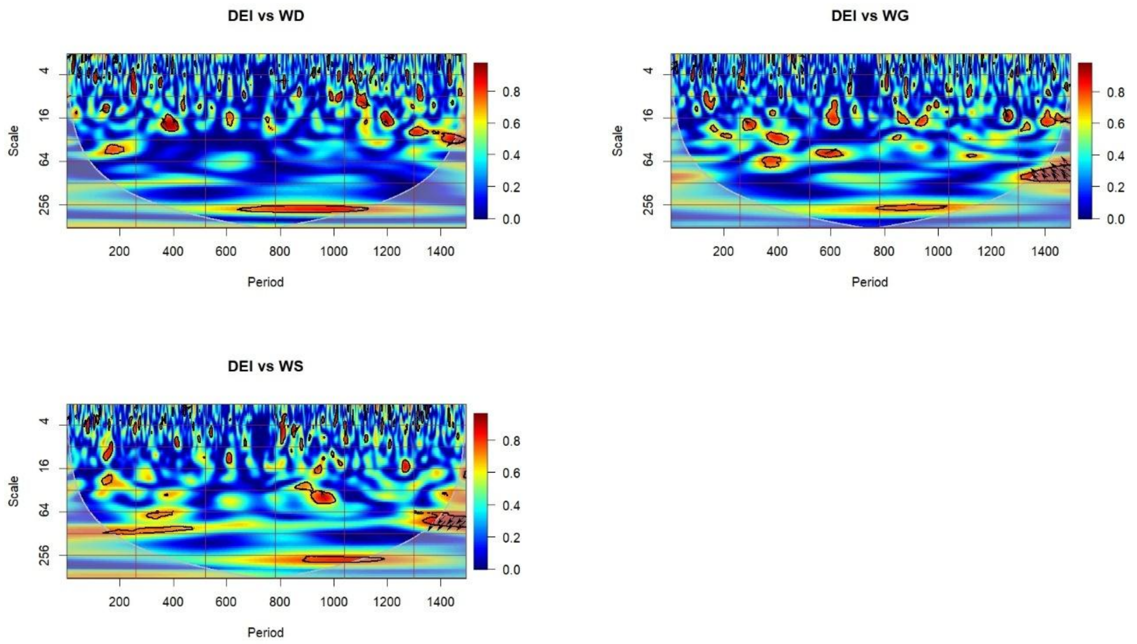
200
400
600
800
1000
1200
1400
Period
0.8
0.6
0.4
0.2
0.0

Figure 5(a) indicates strong and comparatively longer coherence between Namibia's equity index and the climate variables moon phase, visibility and wind direction at higher scales of 256 days. Similar effects are observed between Namibia (NAD_USD) and visibility at a scale of 128 days (See Figure 5(b)).

**Figure 5(a) and (b): Wavelet analysis for Namibia**

**5(a)**




DEI vs WD
DEI vs WG
DEI vs WS
Scale
Period
4
16
64
256
200
400
600
800
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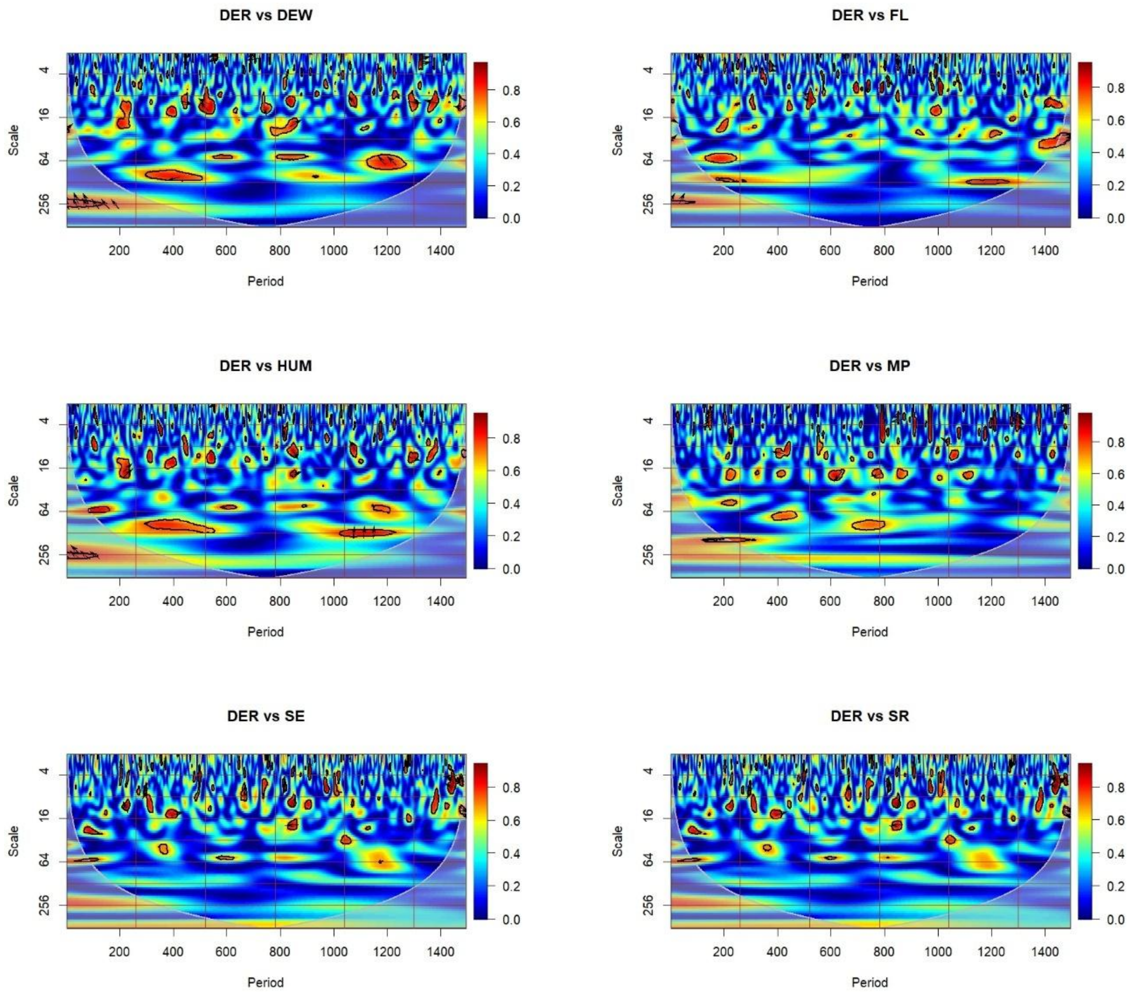
1200
1400
0.0
0.2
0.4
0.6
0.8

**5(b)**


DER vs DEW
DER vs FL
DER vs HUM
DER vs MP
DER vs SE
DER vs SR
Scale
Period
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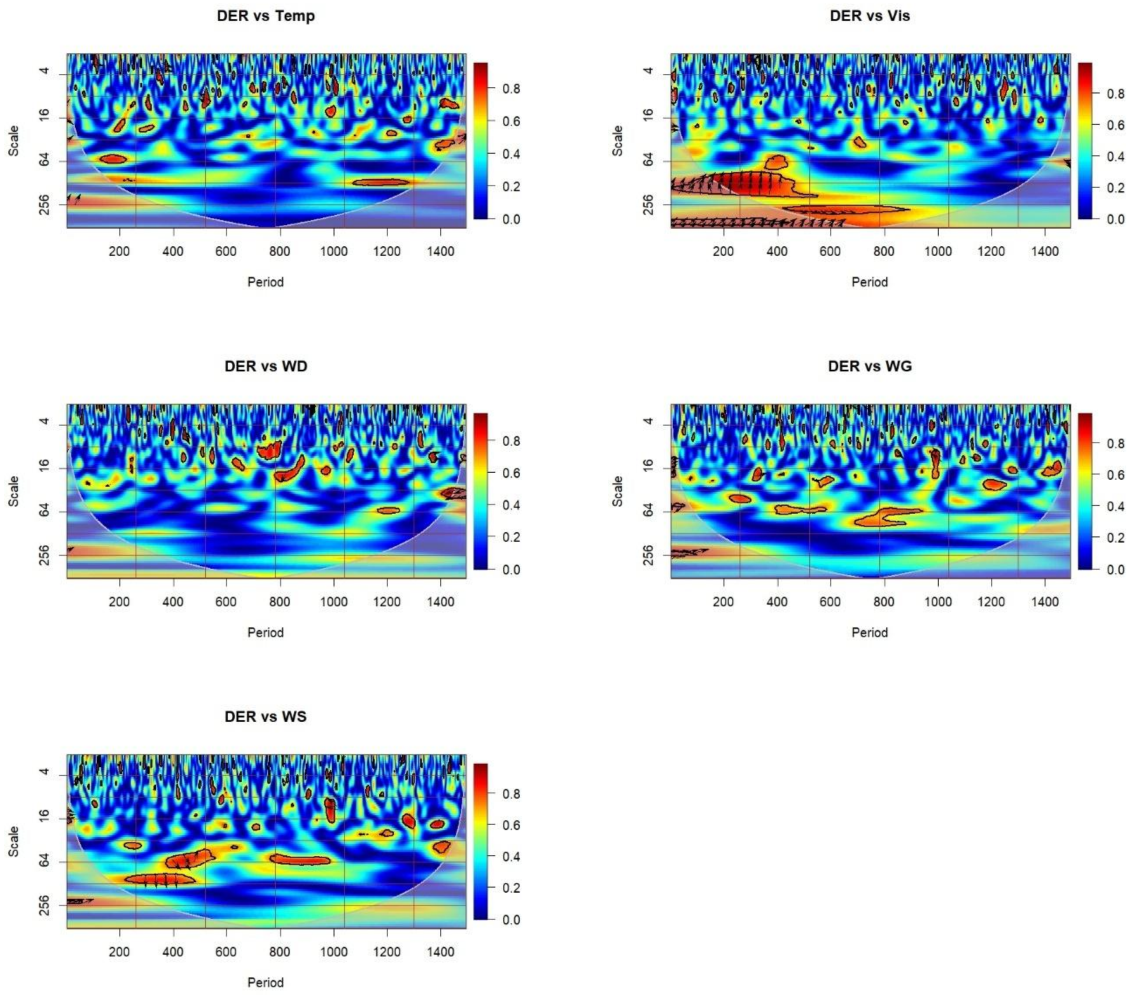
1000
1200
1400
0.0
0.2
0.4
0.6
0.8




This prolonged coherence between the Namibian financial markets and climate factors is evidence of the heightened exposure of the financial sector to prolonged climate-related risks. In such cases, it is imperative for there to be early macroprudential interventions. Namibia does not have any formal national policy on climate change but relies on guidelines laid down in 2011. Thus, framing macroprudential policies covering the climate variables moon phase, visibility, solar and wind would mitigate the overall physical risks.

Multiple and dynamic coherence is observed between Tanzania's financial assets and climate variables that last for short to longer durations (Figure 6).[9] Similar effects are observed for Zambia (see Figure 7). Figure 7(b) indicates moderate to strong and

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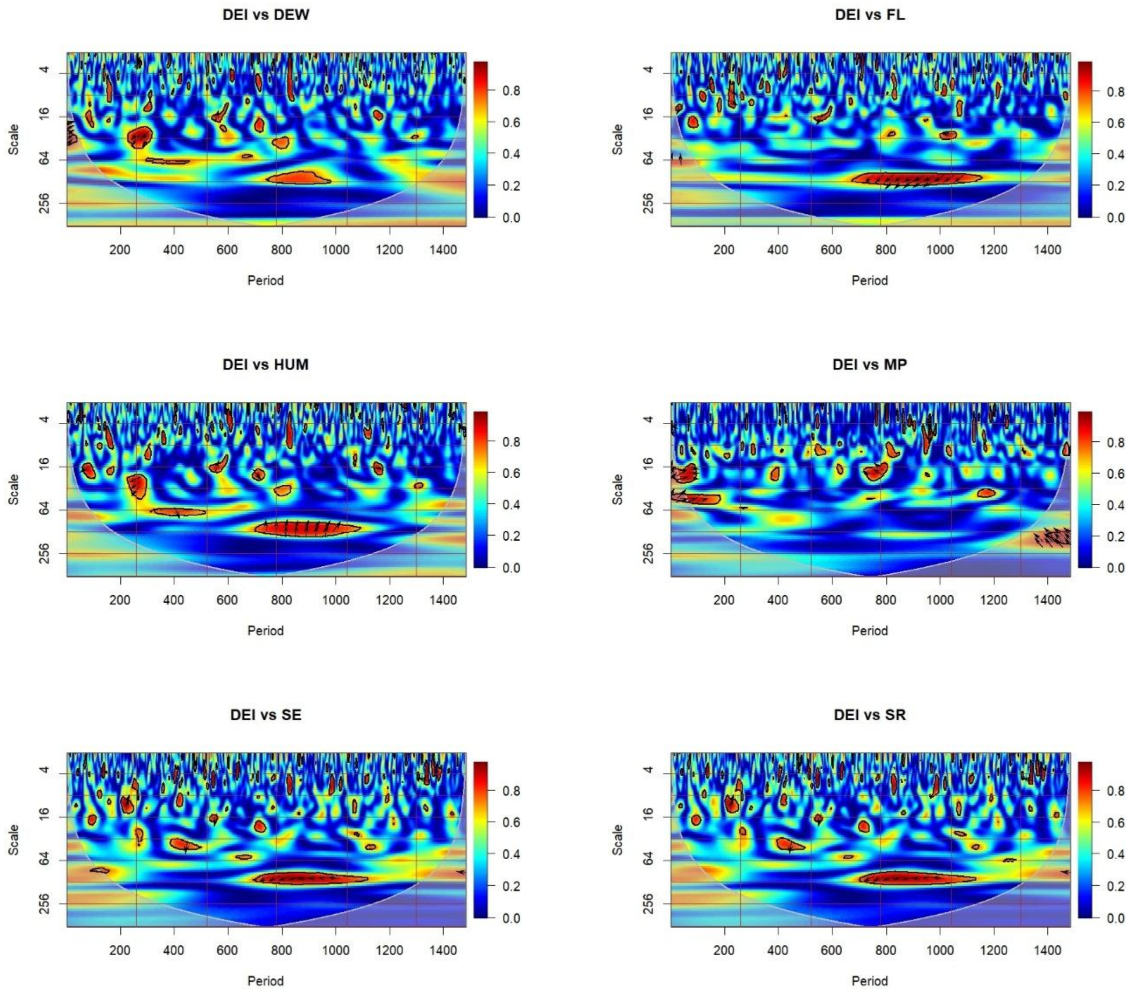
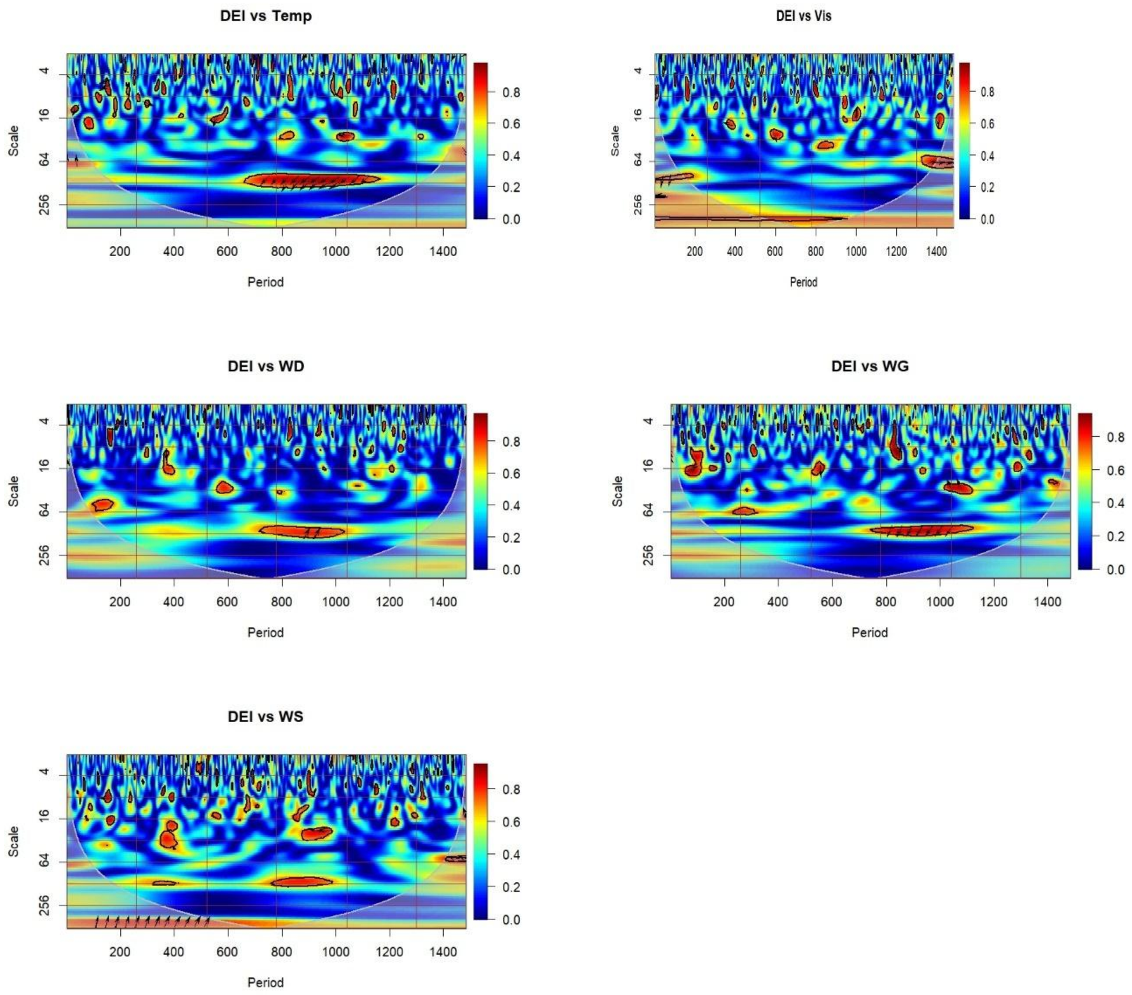
9 Essentially, shifts in coherence levels reveal whether a policy is amplifying or dampening interactions between economic or financial variables.

comparatively long coherence periods between Zambia (ZMW_USD) and the climate variables dew, humidity, temperature, wind speed, wind direction, wind gust, solar radiation, solar energy and feel like. Given this undesirable association, it is imperative for macroprudential authorities in Zambia to implement proactive measures such as climate-related stress testing and sectoral exposure limits. Stress tests reveal which sectors and firms are most vulnerable to climate shocks, and sectoral exposure limits can then prevent banks from over-concentrating in high-risk sectors, lowering the chance that losses in a few firms amplify market volatility. These measures improve risk awareness and dampen spillovers, even when non-financial firms' trade and climate risks are uneven across sectors. This can help alleviate risks before they lead to broader financial instability.

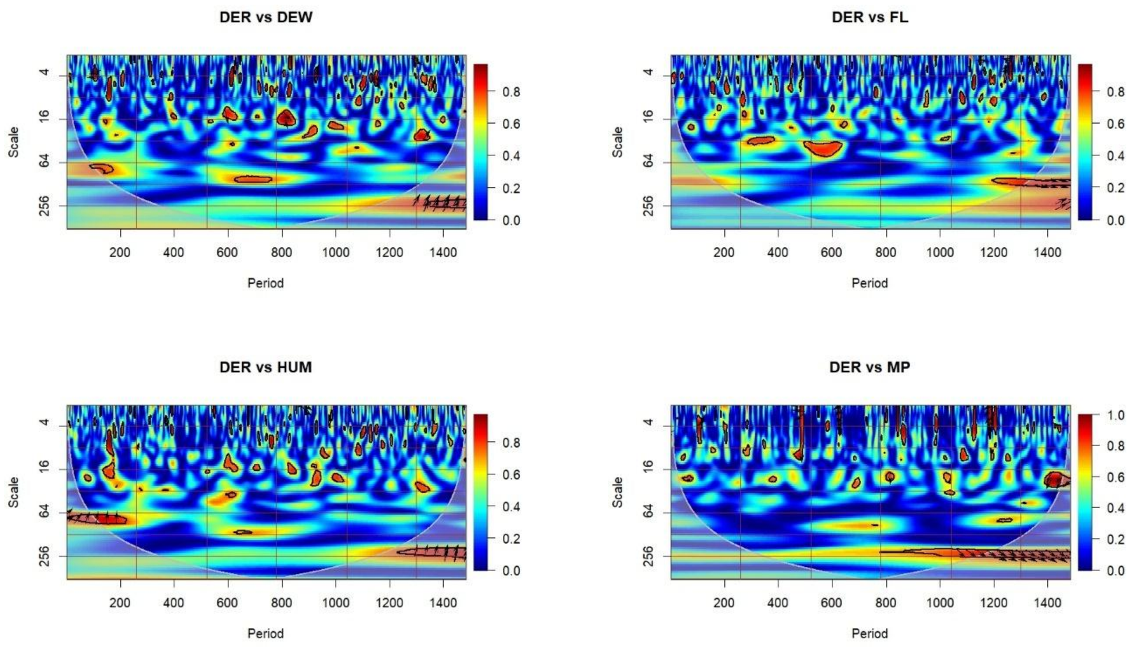
**Figure 6(a) and (b): Wavelet analysis for Tanzania**

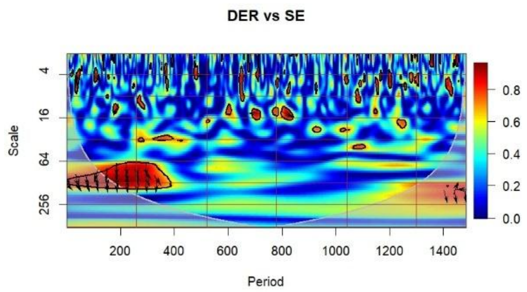
**6(a)**




DEI vs Temp
DEI vs Vis
DEI vs WD
DEI vs WG
DEI vs WS
Scale
Period

**6(b)**


DER vs DEW
DER vs FL
DER vs HUM
DER vs MP
Scale
Period


DER vs SE
Scale
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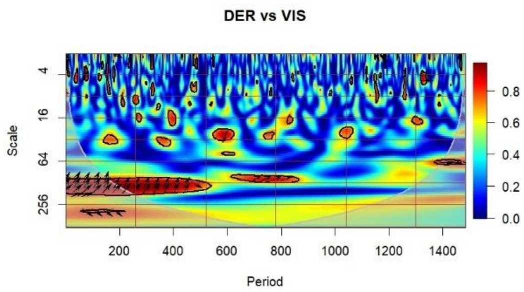
Period
200 400 600 800 1000 1200 1400
0.0 0.2 0.4 0.6 0.8


DER vs VIS
Scale
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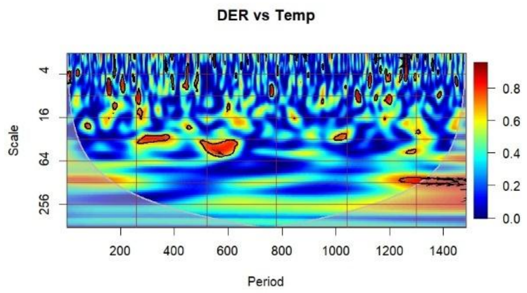
Period
200 400 600 800 1000 1200 1400
0.0 0.2 0.4 0.6 0.8


DER vs Temp
Scale
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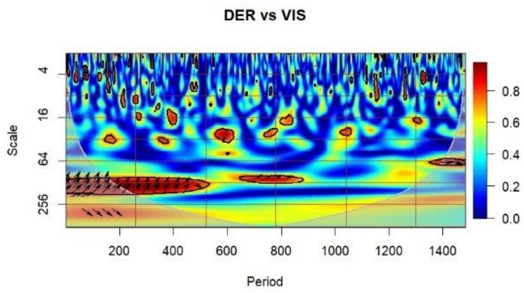
256
Period
200 400 600 800 1000 1200 1400
0.0 0.2 0.4 0.6 0.8


DER vs VIS
Scale
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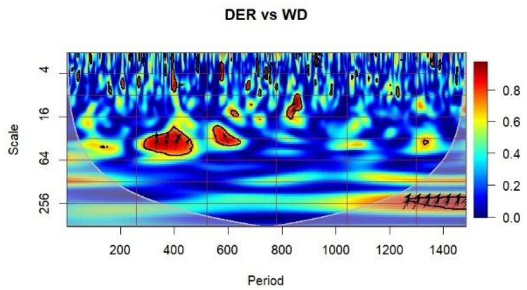
256
Period
200 400 600 800 1000 1200 1400
0.0 0.2 0.4 0.6 0.8


DER vs WD
Scale
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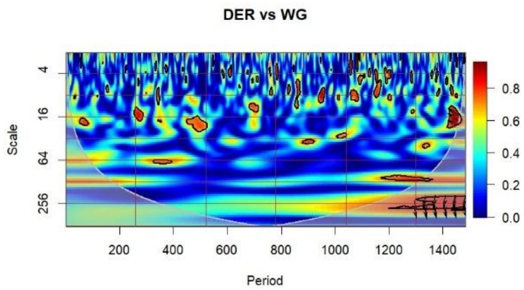
Period
200 400 600 800 1000 1200 1400
0.0 0.2 0.4 0.6 0.8


DER vs WG
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Period
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0.0 0.2 0.4 0.6 0.8

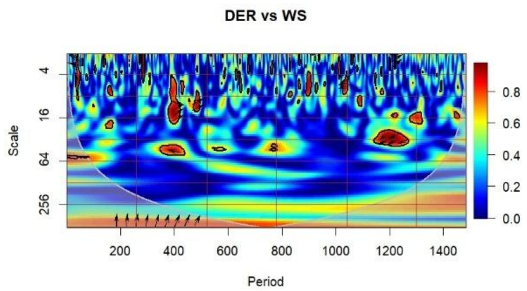
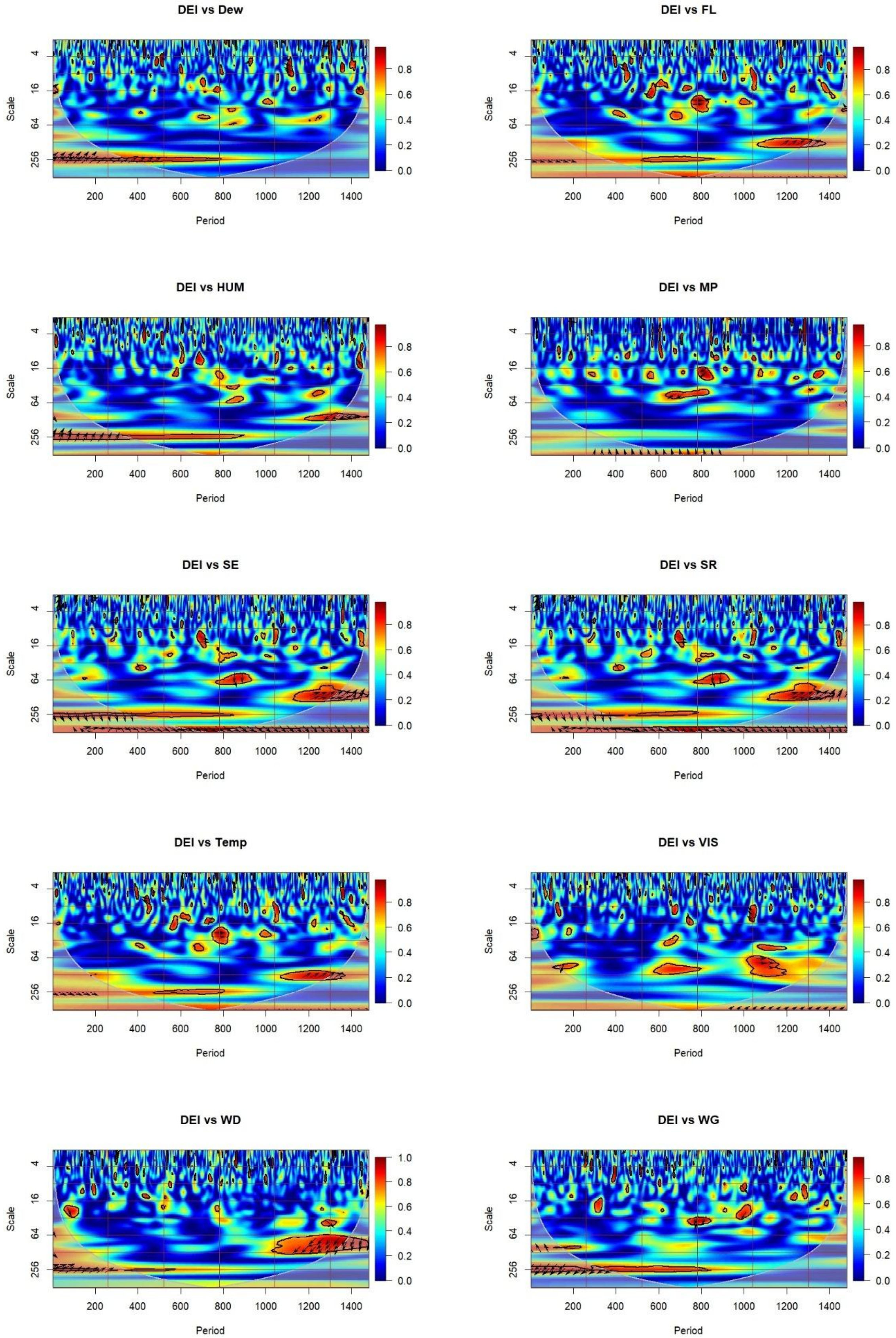
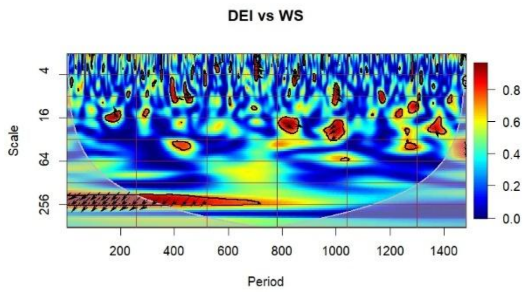

DER vs WS
Scale
4
16
64
256
Period
200 400 600 800 1000 1200 1400
0.0 0.2 0.4 0.6 0.8

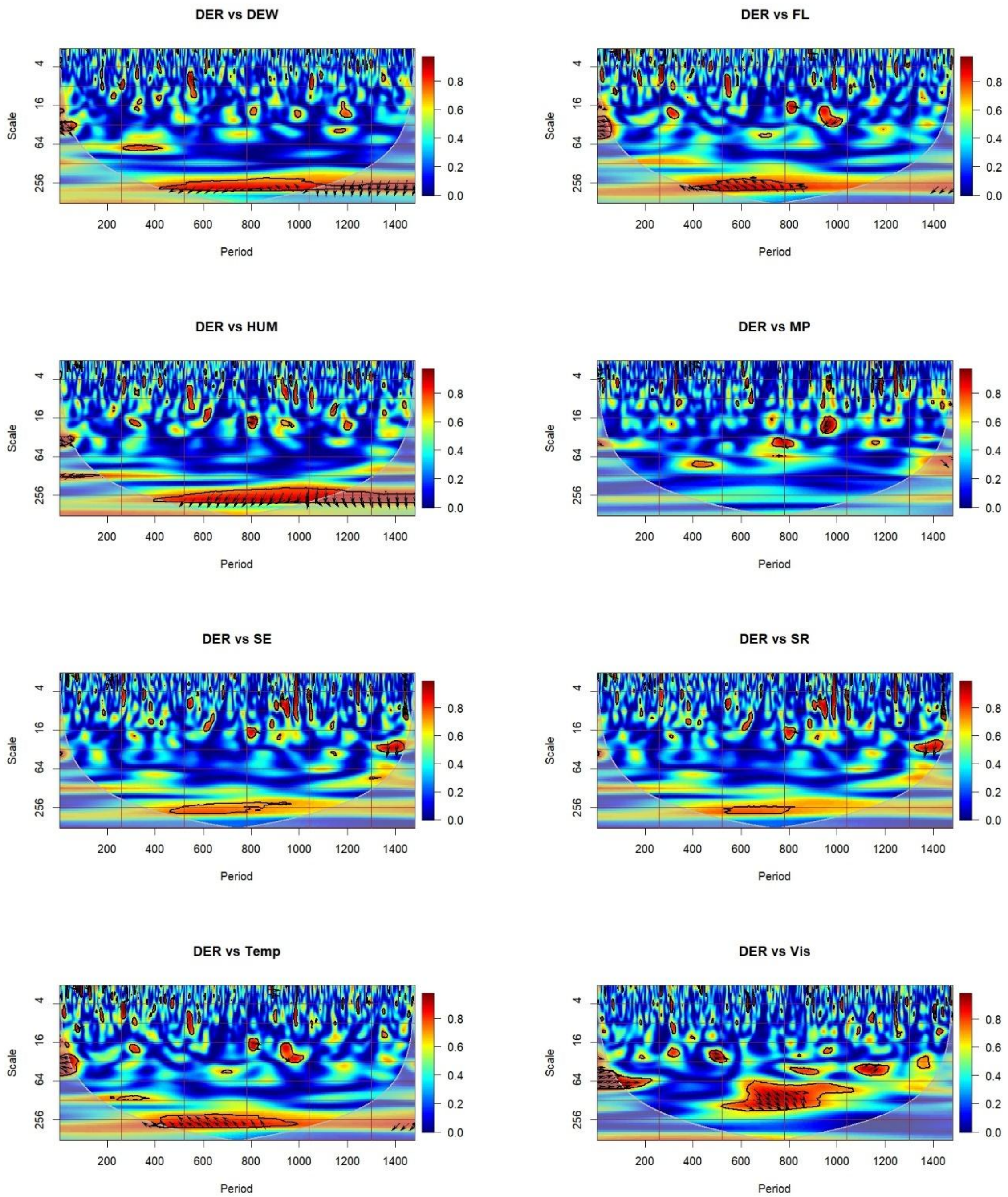
**Figure 7(a) and (b): Wavelet analysis for Zambia**

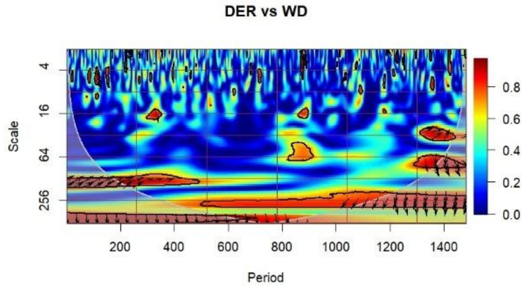
**7(a)**

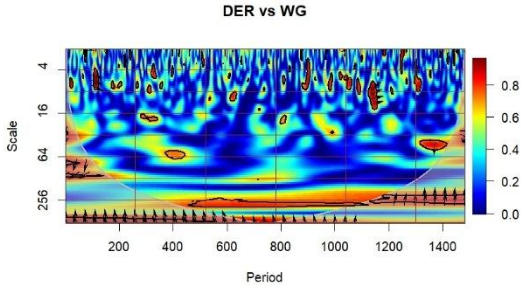


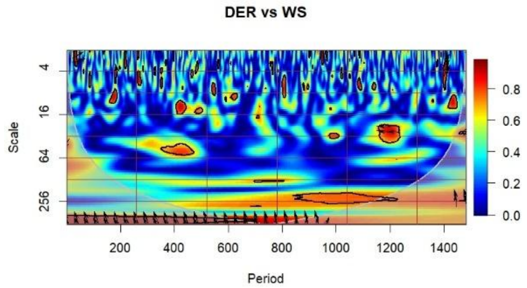

DEI vs WS
Scale
Period

**7(b)**


DER vs DEW
DER vs FL
DER vs HUM
DER vs MP
DER vs SE
DER vs SR
DER vs Temp
DER vs Vis
Scale
Period

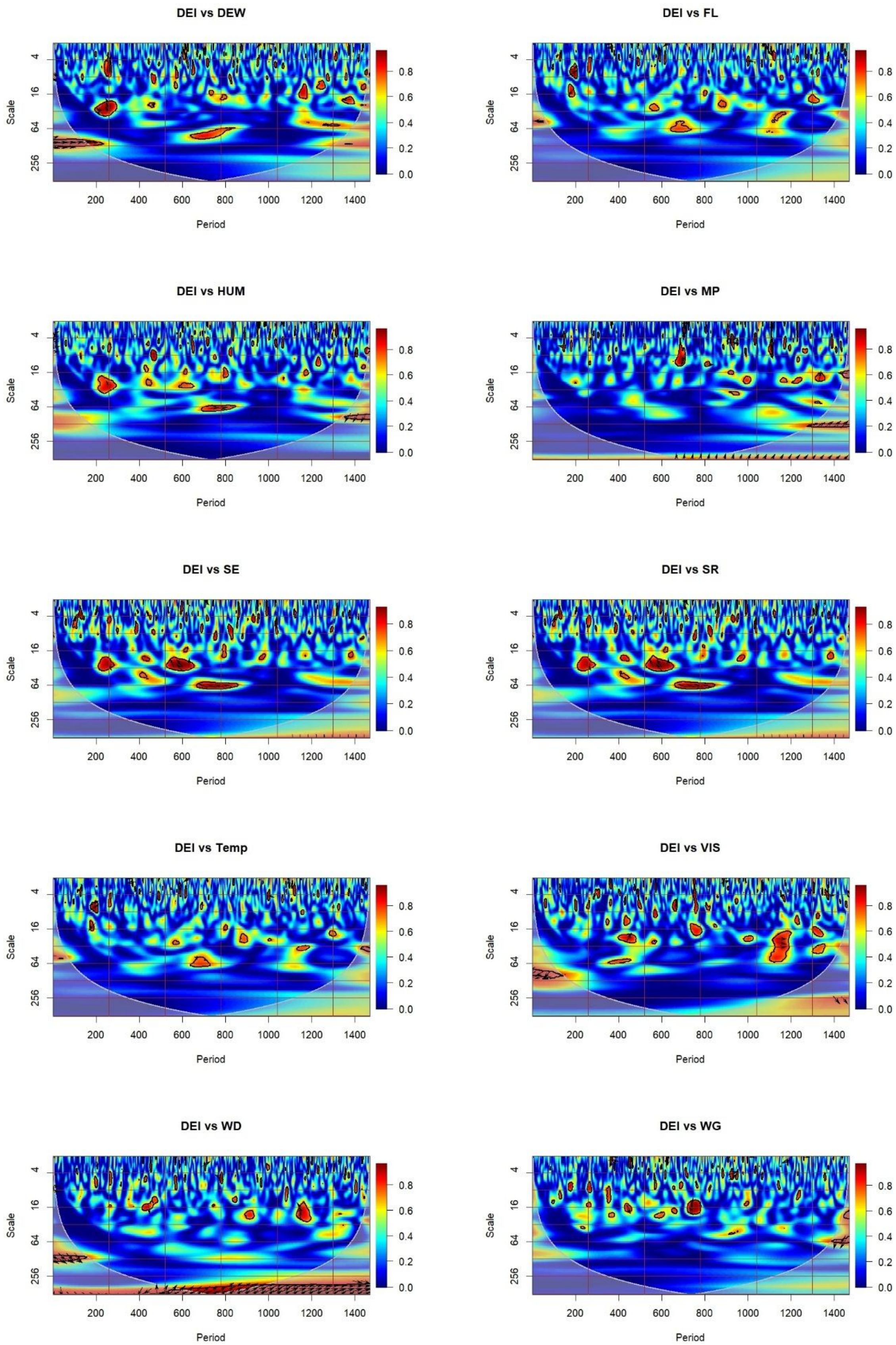


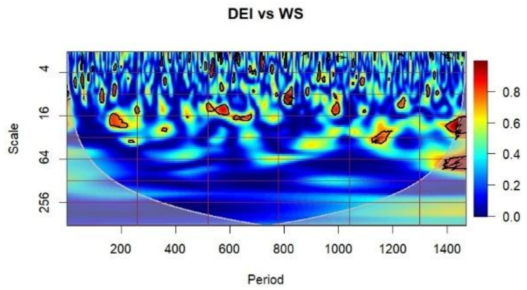




Multiple and dynamic coherence is observed between Zimbabwe's equity index and climate variables that last for short to moderate durations (Figure 8). Zimbabwe adopted its climate change national adaptation plan in 2023. The wavelet coherence estimates suggest that Zimbabwe can reduce its climate-related risks by integrating climate variables into systemic risk models, promoting green finance and developing climate-resilient infrastructure. Overall, the wavelet coherence analysis suggests that risks arising from the different climate variables are time varying and deviate from the behaviour of traditional risk factors. The presence of persistent coherence between the different climate variables and SADC nations' financial assets implies that informational inefficiencies and climate signals are moderately priced. It might also indicate possible links between climate conditions and investors' emotions and risk perceptions (Goetzmann et al. 2015).

**Figure 8: Wavelet analysis for Zimbabwe**






The above findings have several key implications for investors in the SADC region. In the short term, investors can use lead/lag indicators for tactical asset allocations for short-term trading and hedging. Climate-related shocks can induce volatility in the financial system for short to long durations, so investors should adjust risk exposures in such climate-sensitive sectors (Antoniuk and Leirvik 2024). It is also essential to price the climate-induced behavioural pattern in investment models. In the long term, climate integrated risk management models are desirable for valuations, especially for climate-sensitive sectors such as agriculture, energy, real estate, mining and tourism (Dolan et al. 2018). It is also important to shift the investment portfolio composition towards more climate-resilient assets or sectors (Antoniuk and Leirvik 2024). Lastly, climate-related prudential policies and disclosures are needed for financial stability (Hidalgo-Oñate, Fuertes-Fuertes and Cabedo 2024). This finding supports current central bank efforts to increase the resilience of the financial system to climate-related shocks through various instruments such as disclosure requirements and climate stress testing.

## 5. Conclusion

This paper has examined the impact of 11 climate factors on the financial markets of SADC nations over the period 3 September 2018 to 30 August 2024. The explanatory analysis reveals that all the variables under consideration deviate from a normal distribution and are volatile. Accordingly, we deploy the Spearman technique to examine the correlations among the variables. This approach is more efficient for dealing with the non-normal and non-linear characteristics of the data variables. Overall, we provide evidence of a significant association between the different climate variables and financial assets of SADC nations. The Spearman technique is efficient in capturing the monotonic relationship. However, it has limitations, such as the inability to detect asymmetric directional dependencies, lead or lag effects, and time frequency properties. To capture such characteristics, we deploy transfer entropy estimates and wavelet coherence techniques to test the study hypotheses.

The transfer entropy estimates yield mix results. There is some evidence of a statistically significant asymmetric information flow from the climate variables feel like, dew, humidity, wind gust, wind direction, visibility, solar radiation, solar energy and moon phase to the financial assets of SADC nations. However, the transfer entropy directional dependencies from climate variables to financial assets are not uniform for SADC nations. We document several findings of empirical and practical significance. First, we show that the impact of different climate variables on the financial markets of SADC nations is heterogeneous. Second, we find that SADC financial markets are segmented as the impact of climate variables on financial assets is not uniform. Lastly, we document evidence of the impact of local culture, beliefs and knowledge on investment decisions, suggesting the need for tailored financial models (Van Nieuwkerk 2014). In terms of prudential policies, our study highlights the need for SADC-specific prudential policies, regulations, disclosure requirements and stress testing.

The results of the wavelet coherence analysis highlight three main issues. First, we show that time-varying co-movements among the climate variables and financial assets across SADC nations last for short to longer durations. Second, we confirm the presence of asymmetric lag/lead effects over different time horizons. Lastly, we highlight the multiscale behaviour between the climate variables and financial assets across SADC nations.

Our findings have several implications for macroprudential policies. First, our paper emphasises the importance of both short- and long-term risk assessment and management measures. Short-term coherence with high frequency indicates immediate climate shocks (physical risks). Similarly, moderate to long-term coherence with moderate or low frequency suggests market adjustment to the policies or structural shifts (transition risks). This approach enables a nuanced evaluation of the effectiveness of policies and supports the formulation of evidence-based climate risk management strategies. Second, central banks should refine region-specific macroprudential policies and conduct climate stress testing from time to time, by targeting weather-sensitive sectors that account for specific climate risk factors (Acharya et al. 2023). Lastly, policymakers should improve the framework for understanding climate-induced risks along with macroeconomic variables, and design an appropriate policy statement regarding these risks (Feyen et al. 2020). Overall, the study findings suggest that central banks in the region need to scale up their efforts to tackle climate change.

Future studies could include more climate variables to analyse the impact on different financial markets globally and within Africa's regional blocs. Instead of analysing stock indices, future studies could analyse sectoral and individual stocks.

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