

THE IMPACT OF DISAGGREGATED PHYSICAL CLIMATE RISK ON THE VOLATILITY OF PROPERTY INDICES: EVIDENCE FROM SOUTH AFRICA

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ARTICLE INFO	ABSTRACT
Keywords: physical climate risk, property market, volatility JEL Classification: G12, G17, Q54, R30	Climate change increasingly affects real estate markets because property assets are location-specific and directly exposed to environmental conditions. This study examines whether physical climate risks influence volatility in South African listed property markets. Using a GARCH–MIDAS framework, daily returns from five property indices are linked to monthly indicators of drought, extreme precipitation, and temperature extremes derived from the Actuarial Society of South Africa Climate Index. Results show that physical climate conditions contribute to persistent market volatility. Short-run volatility persistence is strong across all indices. Drought consistently increases long-run volatility, particularly in segmented indices, while broader indices show weaker effects. Temperature extremes exert the greatest influence, with minimum temperatures affecting most indices. Precipitation effects vary with flood exposure and infrastructure resilience, reducing volatility where rainfall alleviates drought stress and increasing it where flood risk dominates. These findings highlight the importance of incorporating physical climate risks into portfolio risk assessment, volatility forecasting, and long-term investment decisions in climate-exposed real estate markets.
Citation: Ahead of Print	Mtunzi Merana, S., Tinotenda Muguto, H. & Muguto, L. (2026). The impact of disaggregated physical climate risk on the volatility of property indices: Evidence from South Africa. <i>Real Estate Management and Valuation</i> , [Ahead of print]. https://doi.org/10.2478/remav-2026-0034

1. Introduction

Climate change has become a material source of financial risk across global asset markets (Battiston et al., 2021). Property markets are particularly exposed because real estate assets are immobile and vulnerable to environmental conditions such as droughts, extreme temperatures, and changing rainfall patterns (Shahid et al., 2017). These events can damage buildings, disrupt rental income, increase insurance and maintenance costs, and weaken long-term asset values (Hirsch et al., 2015). For property investors and fund managers, an important question is whether such climate shocks alter the risk profile of property investments and require adjustments to portfolio allocation and risk management.

Most climate–finance research focuses on developed markets and emphasizes transition risks

associated with carbon regulation and decarbonization policies (Semieniuk et al., 2021). This provides limited insight into emerging economies, where physical climate events are more frequent and harder to mitigate due to infrastructure and adaptation constraints (Bradshaw et al., 2022). South Africa illustrates this challenge, having experienced recurrent droughts, heatwaves, and uneven rainfall patterns that affect economic activity and infrastructure (Bradshaw et al., 2022; Thomas et al., 2022). Yet it remains unclear whether these physical climate exposures are reflected in financial markets, particularly listed property markets.

Another limitation is the reliance on aggregate climate indicators, which can obscure the effects of specific risks such as drought, rainfall variability, and temperature shocks (Balcilar et al., 2023). Moreover, much of the evidence focuses on broad equity markets

rather than property securities, providing limited insight into how climate risks affect real estate investments (Battiston et al., 2021; Feng et al., 2025). This leaves an important gap in understanding whether investors respond differently to specific climate exposures and whether these risks are reflected in property market volatility. The present study addresses this gap by examining whether disaggregated physical climate risks influence volatility in South African listed property markets.

Using a mixed-frequency framework, the analysis combines high-frequency property market data with slowly evolving climate indicators to isolate the persistent effects of specific climate shocks on property market volatility. By moving beyond broad climate proxies, the study provides evidence on whether disaggregated climate risks translate into measurable financial risk in property securities. This contributes to the property investment literature while offering practical insights into how climate exposure may affect portfolio risk, asset pricing, and the resilience of property investment strategies in climate-exposed markets.

2. Theoretical framework

The theoretical foundation of this study rests on two interrelated frameworks: asset-pricing and information-efficiency theories. Together, they explain how physical climate risks transmit to listed property market volatility and motivate the adopted empirical

approach. Asset pricing theory posits that investors require compensation for bearing systematic risk (Sharpe, 1964). Physical climate risks are increasingly recognized as systematic because they affect asset performance in ways that cannot be diversified away (Engle et al., 2013; Giglio et al., 2021). For property assets, climate exposure increases uncertainty around expected cash flows and long-term performance, raising the risk premium demanded by investors and contributing to higher and more persistent volatility.

Information efficiency theory further explains how climate risk is priced (Fama, 1970). Physical climate risks are slow-moving and difficult to quantify, meaning markets may not price them immediately (Hong et al., 2023). Risk information is therefore assimilated gradually, contributing to volatility as market expectations are updated. These frameworks connect to distinct transmission channels. Drought acts through a cash flow channel, precipitation through a damage-and-insurance channel, and temperature extremes through an energy-and-operational-efficiency channel. In South Africa, infrastructure constraints amplify each channel, producing persistent uncertainty that manifests as long-run property market volatility (Naidoo et al., 2025).

Figure 1 highlights both theories' complementary roles in explaining how physical climate risks are transmitted to listed property market volatility through risk-premium adjustments and the gradual assimilation of information.

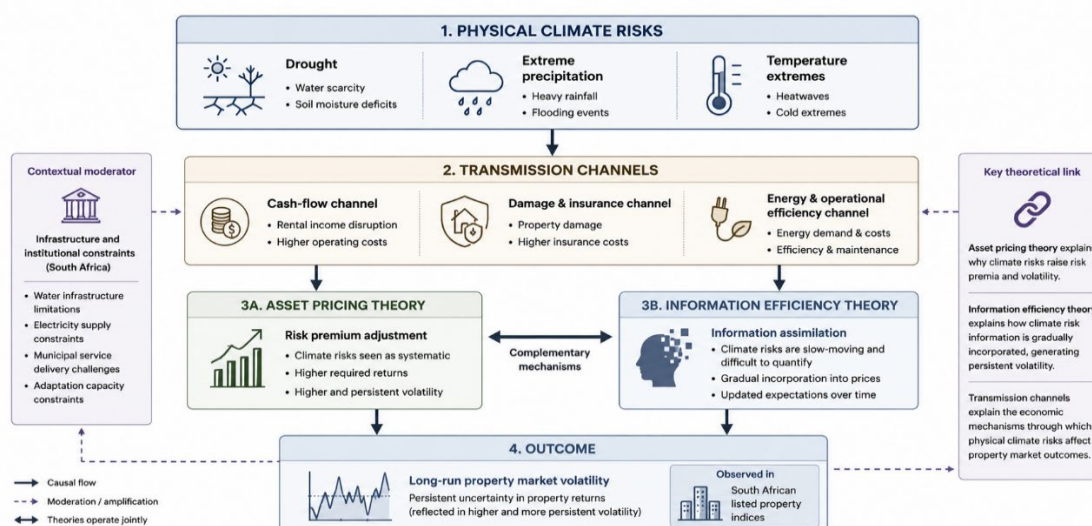


Fig. 1. Theoretical transmission channels linking physical climate risks to property market volatility. Source: Author (2026).

3. Literature review

Climate change is increasingly recognized as a material risk for real estate markets because property assets are

location-specific and directly exposed to environmental conditions. Physical climate shocks can damage buildings, increase insurance and maintenance costs,

disrupt rental income, and alter long-term property values (Clayton et al., 2021; Warren-Myers & Hurlimann, 2022). These risks affect both expected cash flows and discount rates, even when prices do not fully reflect future climate exposure (Sayce et al., 2022).

Empirical evidence shows that climate exposure influences financial outcomes in property-related securities. Greater climate risk exposure is associated with weaker REIT cash flows, lower firm values, and reduced returns, suggesting that climate risk operates as a persistent rather than temporary factor in property markets (Ling et al., 2024; Feng et al., 2025). However, the magnitude and timing of these effects vary across markets and sectors, indicating that climate risk is only partially incorporated into property asset pricing.

One explanation is that climate risk pricing remains incomplete and heterogeneous. Balcilar et al. (2023) show that climate-risk pricing depends on investor awareness, disclosure standards, and information availability, implying gradual or imperfect incorporation in some markets. Similarly, Alahouel (2025) finds that volatility responses differ across REIT sectors, with some segments displaying resilience despite heightened climate exposure. These findings suggest that climate risk is recognized unevenly across real estate markets.

Recent climate–finance research suggests that climate risk affects markets primarily through volatility rather than immediate price adjustments. Climate risk indices and climate-related sentiment improve volatility forecasts in equity markets by capturing uncertainty surrounding future cash flows and policy responses (Ben Ameer et al., 2025; Bua et al., 2024). Similarly, climate-related risks forecast realized volatility in commodity-exporting economies, including South Africa (Bonato et al., 2023). This highlights uncertainty as a key transmission channel.

This channel is particularly relevant for property markets because real estate assets are long-lived and sensitive to local environmental conditions. Climate shocks can affect asset durability, operating costs, and long-term income expectations, causing changes in risk perceptions to emerge first through volatility rather than prices. Supporting evidence from South Africa shows that temperature anomalies improve forecasts of aggregate stock market volatility (Wu et al., 2024). However, whether similar dynamics apply to property securities remains unclear.

Differences in climate-risk pricing also emerge across regions. Adediran et al. (2024) show that climate risk is more consistently priced in advanced than

emerging economies, while Xu et al. (2025) find that climate-risk pricing depends on investor attention and nonlinear dynamics. These findings suggest that climate risks may be priced more weakly or, with a delay in emerging markets due to information and disclosure constraints, while investor attention influences the timing and intensity of climate-risk pricing.

Property assets may also respond differently because their exposure is primarily physical rather than policy-driven. Flood risks, for example, are often not fully reflected in property prices, resulting in persistent overvaluation in exposed areas (Gourevitch et al., 2023). When risks are imperfectly priced, market reactions may occur through uncertainty and investor sentiment rather than immediate price adjustments. Consistent with this, Muzindutsi et al. (2023) show that investor sentiment significantly influences volatility in South African property stocks.

Overall, the literature recognizes climate change as an emerging financial risk, yet the channels through which it affects property markets remain poorly understood. Existing evidence shows that climate risk is priced unevenly and often manifests through volatility rather than immediate price changes. However, most studies focus on aggregate climate indicators or broad equity markets, providing limited insight into how specific physical climate shocks affect property-related securities.

Two limitations remain. First, aggregate climate indicators obscure the distinct effects of droughts, rainfall variability, and temperature extremes (Albanese et al., 2025; Bua et al., 2024). Second, conventional models struggle to align high-frequency financial data with lower-frequency climate indicators, limiting their ability to capture persistent climate-driven volatility. Although mixed-frequency frameworks address this mismatch, they are rarely applied in real estate finance, leaving it unclear which physical climate risks materially affect property market volatility.

4. Materials and methods

4.1. Data description

The analysis is conducted separately for five major property indices listed on the Johannesburg Stock Exchange (JSE), obtained from Bloomberg: the Tradable Property Index (J800), All-Property Index (J803), SA REIT Index (J805), SA Listed Property Index (J253), and Capped Property Index (J254). Together, these indices provide broad and segmented coverage of the South African listed property market, enabling comparisons of volatility responses across market segments. Daily

index prices are used to construct continuously compounded returns over the period 30 June 2004 to 31 October 2025, reflecting the common availability period across indices. Returns are calculated as logarithmic differences of index levels. Daily data enable the model to capture short-run volatility dynamics driven by trading activity and market-specific information.

Physical climate risk is proxied using the Actuarial Society of South Africa (ASSA) Climate Index, a monthly indicator constructed from observed meteorological data to capture persistent climate conditions rather than short-term weather fluctuations. The analysis employs four disaggregated climate measures: a drought index (DROU), an extreme precipitation index (EXPT), and indices of extreme minimum (EXMI) and maximum temperatures (EXMA). DROU captures prolonged rainfall deficits associated with water scarcity and rising operating costs, while EXPT reflects unusually heavy rainfall linked to flooding and infrastructure damage. EXMI and EXMA measure temperature extremes that affect building efficiency, energy demand, and maintenance costs. Collectively, these indicators capture distinct climate-risk channels relevant to property market dynamics.

4.2. Model specification

This study investigates the impact of disaggregated physical climate risk on the volatility of South African listed property indices using the GARCH-MIDAS framework (Engle et al., 2013). The approach accommodates mixed-frequency data by jointly modelling daily property returns and monthly climate indicators. Unlike traditional GARCH models, GARCH-MIDAS preserves short-run volatility dynamics while capturing the long-run influence of climate risk through a separate low-frequency volatility component, allowing clearer economic interpretation without interpolation (Chen et al., 2023; Ghani et al., 2024; Naidoo et al., 2025). The framework resolves the frequency mismatch by assigning each monthly climate observation to the corresponding trading days. The MIDAS polynomial then aggregates lagged climate information into the long-run volatility component. Letting $r_{i,t}$ denote the daily log return of property index i on day t , returns are modelled as:

$$r_{i,t} = \mu_i + \varepsilon_{i,t} \quad (1)$$

where μ_i is the conditional mean and $\varepsilon_{i,t}$ is the error term. The error is assumed to follow:

$$\varepsilon_{i,t} = \sqrt{h_{i,t}} z_{i,t} \quad (2)$$

where $z_{i,t} \sim \mathcal{N}(0,1)$ and $h_{i,t}$ is the conditional variance. In the GARCH-MIDAS framework, the conditional variance is decomposed into a short-run and a long-run component:

$$h_{i,t} = \tau_{i,t} \cdot g_{i,t} \quad (3)$$

where $g_{i,t}$ captures high-frequency, short-run volatility dynamics and $\tau_{i,t}$ represents the slowly moving long-run volatility component driven by monthly climate risk variables. The short-run component follows a standard GARCH (1,1) process scaled by the long-run component as:

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{\varepsilon_{i,t-1}^2}{\tau_{i,t-1}} + \beta_i g_{i,t-1} \quad (4)$$

where $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\alpha_i + \beta_i < 1$ to ensure covariance stationarity. This captures volatility clustering arising from market-specific shocks in the returns. The long-run component $\tau_{i,t}$ evolves at the monthly frequency and is specified as a function of lagged physical climate risk indicators. Letting X_m denote a monthly climate risk variable observed at month m , where $m(t)$ maps each trading day t to its corresponding month, the MIDAS component is defined as:

$$\log(\tau_{i,t}) = m_i + \theta_i \sum_{k=1}^K \phi_k(\omega_1, \omega_2) X_{m(t)-k} \quad (5)$$

where m_i is a constant, θ_i measures the impact of climate risk on long-run volatility, and K is the number of monthly lags included. Per Liu et al. (2021) and Msomi and Kunjal (2024), the optimal lag range is between 12 and 36. Thus, this study chooses a model that minimizes the Bayesian Information Criterion (BIC) and maximizes the log-likelihood function (LLF) for 12, 24, and 36 lags. In line with Salisu and Gupta (2021) and Kunjal et al. (2022), the weights $\phi_k(\omega)$ follow a normalized beta polynomial defined as:

$$\phi_k(\omega) = \frac{\left(\frac{k}{K}\right)^{\omega_1-1} \left(1 - \frac{k}{K}\right)^{\omega_2-1}}{\sum_{j=1}^K \left(\frac{j}{K}\right)^{\omega_1-1} \left(1 - \frac{j}{K}\right)^{\omega_2-1}}, \omega > 0 \quad (6)$$

This weighting scheme allows both recent and more distant climate conditions to influence long-run volatility in a flexible, data-driven manner (Conrad and Kleen, 2020; Liu et al., 2021). To identify the channels through which physical climate risk affects property market volatility, the model is estimated separately using DROU, EXPT, EXMI, and EXMA as alternative climate indicators. This disaggregated approach enables assessment of whether specific climate risks

exert stronger effects on volatility in South African listed property markets. Following Engle et al. (2013) and Conrad and Kleen (2020), the parameters are estimated using quasi-maximum likelihood estimation, which is robust to non-normality in financial returns. Interpretation focuses on the MIDAS coefficient, θ_i , where a significant positive (negative) coefficient indicates that increases (decreases) in climate risk raise (reduce) long-run volatility, while an insignificant coefficient suggests limited sensitivity. Robustness checks using alternative lag lengths and comparisons across property indices and climate indicators ensure that results are not specification- or segment-driven.

5. Results

5.1. Descriptive statistics and stationarity results

Table 1 reports descriptive statistics and stationarity tests for South African listed property indices and disaggregated climate indicators. Average daily returns for the J253, J254, J800, J803, and J805 indices are close to zero, consistent with financial return series and indicating that property market performance fluctuates around a stable long-run mean. The standard deviations, however, show noticeable day-to-day variation, reflecting the sensitivity of listed property markets to changing investor risk perceptions. In contrast, climate indicators exhibit substantially greater dispersion, particularly drought intensity (DROU) and extreme temperature measures (EXMA and EXMI). This pattern reflects the episodic nature of climate shocks, where periods of relative stability are interrupted by extreme events. For property investors, such shocks can

increase uncertainty surrounding asset values, insurance costs, and operational risks in climate-exposed regions.

The return distributions of all property indices are negatively skewed and highly leptokurtic, suggesting a greater likelihood of extreme downside movements. In property securities, such tail risks are often associated with abrupt repricing during periods of market stress. The presence of heavy tails, therefore, supports the use of volatility models to capture these risk dynamics and assess how external shocks, including climate events, influence market uncertainty. Stationarity tests confirm that all variables are stationary in levels, indicating stable long-run volatility and risk patterns rather than persistent trends. The climate indicators are likewise stationary, suggesting that climate shocks occur as episodic deviations rather than continuously evolving processes. Consequently, both financial and climate variables can be incorporated directly into the volatility models without additional transformation.

Diagnostic tests further reveal significant ARCH effects and volatility clustering in the property return series, indicating that periods of high volatility tend to persist rather than dissipate quickly. For investors, this persistence implies that shocks may have prolonged effects on property market risk. Although climate shocks occur episodically, their interaction with persistent market volatility may amplify uncertainty and risk perceptions. The coexistence of volatile climate indicators and clustered market volatility, therefore, provides a strong motivation for examining whether specific climate risks systematically influence listed property market volatility.

Table 1

Descriptive statistics and stationarity results									
	J253	J254	J800	J803	J805	DROU	EXPT	EXMA	EXMI
Mean	0.0005	0.0003	-5.00E-05	6.43E-05	6.84E-05	0.0246	-0.01981	0.1343	-0.0544
Maximum	0.1101	0.1419	0.1119	0.10272	0.0981	2.4800	2.1100	3.7200	2.8700
Minimum	-0.1807	-0.1739	-0.1848	-0.1704	-0.1740	-0.2700	-0.6200	-0.3300	-0.4100
Std. Dev.	0.0108	0.0110	0.0144	0.0135	0.0146	0.4688	0.4845	0.6484	0.5223
Skewness	-1.8583	-1.6449	-2.0235	-2.2024	-1.3225	2.6232	1.2398	2.4055	2.6120
Kurtosis	46.5701	50.2841	40.4448	40.2817	30.1566	10.8814	4.7862	9.8259	10.4943
Jarque-Bera	441312.1*	480118.1*	122049.5*	121001.9*	64056.2*	952.4*	99.2*	741.0*	886.7*
Observations	5539	5129	2065	2065	2065	255	255	255	255
ARCH-LM	182.50*	244.42*	44.71*	58.34*	76.85*	-	-	-	-
Ljung-Box	205.89*	189.72*	178.75*	186.01*	165.54*	-	-	-	-
ADF Test	-2.8210**	-29.7371*	-18.9407*	-18.7265*	-18.3234*	-3.7801*	14.6606*	-6.4634*	-14.6245*
Breakpoint Test	-3.2048	-65.3364*	-41.4730*	-41.5747*	-44.8278*	-4.4472**	-15.1461*	-10.6626*	-15.7312*
Integration	I (0)	I (0)	I (0)	I (0)	I (0)	I (0)	I (0)	I (0)	I (0)

Note: * $p < 0.01$; ** $p < 0.05$; *** $p < 0.1$

Source: own study.

5.2. Lag length selection

Table 2 reports optimal lag-length selections based on the Bayesian Information Criterion and log-likelihood function. Across most property indices and climate segments, the preferred specification uses 36 lags, indicating persistent transmission of climate shocks to listed property markets. The predominance of longer lag structures suggests that climate risks are incorporated gradually, reflecting the slow adjustment of rents, insurance costs, operating expenses, and asset valuations that characterize real estate markets.

Differences across climate segments are limited, although shorter lag structures occasionally emerge for extreme precipitation (EXPT) and, to a lesser extent, drought (DROU). This indicates that some climate shocks may affect property markets more rapidly when

they disrupt infrastructure, accessibility, or building operations. Nevertheless, the dominance of longer lag structures shows that climate risks generally influence property market volatility through extended adjustment processes rather than abrupt price responses.

Variation across indices is also modest, indicating that climate-risk transmission operates broadly across listed property market segments rather than specific portfolios. In the South African context, where drought and temperature extremes often interact with infrastructure and energy constraints, climate stress appears to influence market risk over prolonged periods. For investors, this persistence implies that climate shocks are more likely to generate sustained volatility than short-lived disturbances.

Table 2

Lag length selection											
Seg- ment	Lags	J253		J254		J800		J803		J805	
DROU	12	6.6908	[-17648.1]	6.6879	[-17125.40]	6.2608	[-6441.40]	6.3800	[-6564.22]	6.1680	[-6345.60]
	24	6.5747	[-16232.52]	6.6809	[-16750.26]	6.2650	[-6445.75]	5.8036	[-5969.37]	6.1453	[-6322.09]
	36	6.5630	[-15597.84]	6.6635	[-15837.14]	5.5807	[-5739.15]	6.3766	[-6560.89]	6.1644	[-6341.82]
EXPT	12	5.4998	[-14502.01]	6.6639	[-17063.95]	6.2631	[6443.78]	6.3807	[-6565.22]	6.1688	[-6346.40]
	24	5.6420	[-14141.47]	6.6275	[16616.14]	6.2630	[6443.66]	6.3802	[-6564.67]	5.0661	[-5207.80]
	36	5.3185	[-12635.31]	6.2556	[-14866.14]	6.2641	[-6444.75]	6.3875	[-6567.89]	6.1648	[-6342.22]
EXMA	12	6.4626	[-17045.33]	6.6716	[-17083.70]	6.2633	[-6443.99]	6.3804	[-6564.91]	6.1708	[-6348.22]
	24	6.6484	[-16668.58]	6.6589	[-16694.84]	5.0708	[-5212.71]	6.3811	[-6565.57]	6.1700	[-6347.61]
	36	5.4687	[-13012.23]	5.9544	[-14149.03]	4.0887	[-4198.65]	4.7581	[-4889.86]	4.5757	[-4701.50]
EXMI	12	6.2554	[-16497.93]	6.6634	[-17062.51]	6.2614	[-6441.95]	6.3795	[-6563.94]	6.1470	[-6323.93]
	24	6.6057	[-16561.28]	6.6434	[-16656.08]	6.2620	[-6442.63]	6.3775	[-6561.87]	-6.1654	[-6342.93]
	36	3.7875	[-8990.78]	5.7482	[-13658.18]	6.2525	[6343.16]	6.4392	[-6625.60]	6.4826	[-6637.889]

Note: the BIC and LLF values are in brackets. The optimal model selected by LLF and BIC appears in bold.

Source: own study.

5.3. Discussion

Table 3 reports GARCH–MIDAS estimates linking daily volatility in South African listed property indices to low-frequency physical climate indicators. Across all specifications, the short-run volatility parameters are highly significant, indicating strong volatility persistence. This suggests that shocks dissipate slowly and that changes in risk conditions can influence market volatility over extended periods. Such dynamics are consistent with the gradual adjustment of asset values, contractual arrangements, operating costs, and rental structures in real estate markets (Ling et al., 2024). Consequently, slow-moving environmental risks

appear to contribute to long-run volatility rather than short-lived market fluctuations.

Drought conditions exhibit the most consistent relationship with long-run volatility. Positive and significant MIDAS coefficients for J253 (4.35) and J254 (1.07) indicate that sustained drought conditions increase volatility, while the negative coefficient for J800 (-5.41) suggests that broader market diversification may partially offset drought-related risk. Economically, drought raises uncertainty by increasing water costs, putting pressure on municipal services, and constraining infrastructure, affecting property operations and tenant activity. These findings are consistent with evidence that environmental stress

disrupts operating conditions and long-term asset viability (Clayton et al., 2021; Warren-Myers & Hurlimann, 2022).

The effects of extreme precipitation are more heterogeneous. Negative coefficients for J253 (-16.93) and J805 (-1.40) suggest that sustained rainfall may reduce volatility by alleviating drought-related pressures. In contrast, the positive, marginally significant coefficient for J803 (0.90) indicates that heavy rainfall can increase uncertainty through property damage, insurance costs, and infrastructure vulnerability. These mixed responses are consistent with evidence that flood risk can destabilize property markets where risk disclosure and adaptation remain incomplete (Gourevitch et al., 2023). The results, therefore, suggest that precipitation effects depend on physical exposure and infrastructure resilience.

Temperature extremes generate the most widespread volatility effects. Extreme maximum temperatures increase long-run volatility in J253 (2.30) and J800 (1.92), while extreme minimum temperatures affect J253 (11.05), J254 (2.82), and J805 (2.02). In South Africa, where electricity constraints and energy costs

amplify temperature-related pressures, extreme temperatures increase uncertainty surrounding building efficiency, operating costs, and infrastructure reliability. This supports evidence that climate exposure acts as a persistent risk factor in real estate securities through its effects on asset performance, operating costs, and building resilience (Feng et al., 2025).

Overall, the results indicate that physical climate risks influence listed property markets primarily through volatility rather than immediate price adjustments. Drought and temperature extremes exert the most consistent effects on long-run volatility, suggesting that sustained environmental stress represents a more important source of market risk than short-lived weather events. This pattern aligns with broader climate–finance evidence showing that climate risks are transmitted through uncertainty and volatility rather than contemporaneous price changes (Ben Ameer et al., 2025; Bonato et al., 2023). For investors, these findings highlight the importance of incorporating climate exposure into long-term risk assessments of property portfolios.

Table 3

Estimated GARCH-MIDAS Models							
Segment	Index	μ	α	β	m	θ	ω
DROU	J253	0.1230*	0.3885*	0.6115*	0.8076	4.3505*	0.0025
	J254	0.0061*	0.7249*	0.2751*	0.3950*	1.0730*	0.9498*
	J800	0.0084	0.4169*	0.5831*	0.4690	-5.4098***	2.4434
	J803	0.0068	0.4169*	0.5831*	0.4003	-4.2629	1.1360
	J805	0.0012	0.4169*	0.5831*	-0.6050	1.1529	1.0660
EXPT	J253	0.7183*	0.3935*	0.6070*	0.8551*	-16.9300*	2.0089*
	J254	0.0055	0.7247*	0.2752*	0.1893	-4.9695	0.6787
	J800	0.0023	0.4172*	0.5828*	-1.1086	0.5442	0.3513
	J803	0.0002	0.4773*	0.5827*	-1.2843*	0.9014***	0.9267
	J805	0.0014	0.6299*	0.3701*	0.9187*	-1.3957*	1.8932***
EXMA	J253	0.0436*	0.3907*	0.6093*	0.6320	2.2977*	15.8713
	J254	0.0083	0.6880*	0.3120*	-0.0023	0.3427	0.8043
	J800	0.0283*	0.6075*	0.3925*	1.0136*	1.9208**	1.1687*
	J803	0.0190	0.6070*	0.3930*	1.0558	1.6864	1.0393
	J805	0.0255	0.6074*	0.3925*	0.9902	1.8636	1.0530
EXMI	J253	0.0340*	0.4480*	0.5520*	0.8884**	11.4460*	5.0055
	J254	0.0102*	0.3465*	0.6535*	0.3911*	2.8198*	1.5833*
	J800	0.0002	0.4180*	0.5819*	-2.0950*	0.0001*	0.9237*
	J803	0.0003	0.4169*	0.5831*	-1.3361*	0.3575***	0.7261
	J805	0.0012*	0.4169*	0.5831*	1.1889*	2.0198*	2.2563*

Note: * $p < 0.01$; ** $p < 0.05$; *** $p < 0.1$.

Source: own study.

6. Conclusions

This study examines whether physical climate risks

influence volatility in South African listed property markets using a GARCH–MIDAS framework. The results provide clear evidence that climate conditions

contribute to long-run property market volatility. Drought increases volatility through water scarcity and rising operating costs, precipitation exerts mixed effects linked to drought relief and flood risk, while temperature extremes have the most pervasive influence. Collectively, the findings indicate that climate exposure functions as a persistent source of operational and financial uncertainty rather than an immediate pricing shock.

For property investors, these findings demonstrate that climate exposure constitutes a measurable source of portfolio risk even when asset prices appear stable. Because physical climate risks are transmitted primarily through volatility and uncertainty, investors may underestimate exposure when focusing solely on returns or valuations. The results further show that different climate shocks operate through distinct channels, including water scarcity, flood exposure, and temperature-related operating costs, underscoring the need to incorporate climate risk into portfolio diversification, asset resilience assessments, and long-term risk management.

From a broader market perspective, the findings suggest that climate risks are likely to play an increasingly important role in shaping volatility dynamics within climate-exposed property sectors. In emerging economies such as South Africa, environmental pressures often interact with infrastructure limitations, energy constraints, and municipal service challenges, amplifying the economic consequences of climate shocks. Improving disclosure of property-level climate exposure and environmental vulnerabilities would therefore help investors identify risk concentrations and reduce the potential for climate-related mispricing.

Although the GARCH-MIDAS framework captures persistent low-frequency climate effects, it does not explicitly account for seasonal patterns embedded in climate data. Future research could extend this analysis by incorporating firm-level exposure measures, seasonal climate indicators, and nonlinear or regime-dependent specifications to better capture differences in vulnerability across property portfolios and market conditions. As climate variability intensifies, integrating physical climate risk into property investment analysis will become increasingly important for effective portfolio risk management and the resilience of climate-exposed real estate markets.

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