Journal of Transport and Supply Chain Management
ISSN: (Online) 1995-5235, (Print) 2310-8789

Trends in weather-related marine cargo insurance claims: A South African perspective

Authors:
Francois du Plessis[1]
Leila Goedhals-Gerber[1]
Joubert van Eeden[2]

Affiliations:
[1]Department of Logistics, Faculty of Economic and Management Sciences, Stellenbosch University, Stellenbosch, South Africa

[2]Department of Industrial Engineering, Faculty of Engineering, Stellenbosch University, Stellenbosch, South Africa

Research Project Registration:
Project Number: 24735

Corresponding author:
Francois du Plessis,
fransdup@sun.ac.za

Dates:
Received: 16 May 2023
Accepted: 07 June 2023
Published: 31 July 2023

How to cite this article:
Du Plessis, F., Goedhals-Gerber, L. & Van Eeden, J., 2023, 'Trends in weather-related marine cargo insurance claims: A South African perspective', *Journal of Transport and Supply Chain Management* 17(0), a954. https://doi.org/10.4102/jtscm.v17i0.954

Background: Marine cargo insurance covers the loss or damage to goods while in transit. It is an important supply chain risk management tool for organisations involved in international trade, especially in regions where cargo insurance penetration is low, and protection gaps are high. However, marine cargo insurance faces new challenges because of increasing frequency and severity of extreme weather events. This study focuses on the case of South Africa: a developing country with a strategic role in connecting Africa with the global market.

Objectives: The research analyses the trends, differences, and seasonality of weather-related marine cargo insurance claims in South Africa from 2013 to 2022.

Method: Statistical and general claims analysis was performed on a master dataset of 17 727 claims to answer the three research questions related to the research objectives.

Results: The results show that weather-related marine cargo insurance claims have been increasing over the past decade, creating challenges and disruptions to the supply chain network in South Africa. Furthermore, this research shows that weather-related claims have higher average values and follow a seasonal pattern compared with non-weather-related events on supply chains in South Africa.

Conclusion: This research reveals the growing impact of weather-related events in South Africa.

Contribution: It provides practical and theoretical implications for supply chain managers and insurers to manage weather-related risks more effectively and proactively contributes to the literature by offering empirical insights from a developing country perspective, and provides considerations for future work.

Keywords: claims; developing country; marine cargo insurance; supply chain risk management; weather events.

Introduction

In November 2020, the 14 000 TEU ONE Apus containership experienced harsh weather conditions about 1600 nautical miles northwest of Hawaii, resulting in the loss of an estimated 1900 containers overboard (Sheldrick 2020). Global marine claims consultancy WK Webster approximated that the total cargo loss for this event could exceed US$200 million (WK Webster 2020). By contrast, Mccord (2021) estimated that only 10% of cargo shipped globally is insured, exposing organisations to severe financial losses in case of a risk event (Mccord 2021).

This situation is especially acute in Africa, where Kwalar (2023) identified the main challenges for cargo insurance market penetration as: (1) a lack of awareness and trust among potential customers, who perceive it as an unnecessary expense; (2) limited availability of tailored insurance products that suit the needs and preferences of different segments; and (3) high premiums driven by claims related to fraud and corruption (Kwalar 2023). The low insurance coverage also contributes to a large protection gap in the continent, which measures the difference between total economic and insured losses. For example, Swiss Re Group (2023), a leading reinsurance company, estimated that the protection gap in South Africa during natural hazards from 2013–2022 was $5 billion (or 67%) (Swiss Re Group 2023).

This gap can be widened by unforeseen or unprecedented events that increase the risk and uncertainty for insurers. One such event is extreme weather, which has become more frequent and severe because of climate change. Weather-related claims are common in the marine insurance industry; however, extreme weather as a result of climate change in South Africa has been identified as a new threat, potentially costing the industry millions (Orlek 2015). The province of KwaZulu-Natal (KZN) in South Africa has experienced several devastating storms in recent years, causing widespread damage and losses to homes, businesses, infrastructure, and lives. These storms have also significantly impacted the insurance industry, as claims for weather-related damages have soared (KPMG 2019).

Globally, supply chains are becoming more complex because of innovative outsourcing strategies, shorter product lifecycles, high demand, and globalisation (Pfohl, Gallus & Thomas 2011). These strategies create more complicated supply chains by increasing the number of stakeholders involved, which increases exposure to potential risks (Tang & Nurmaya Musa 2011). According to Manners Bell (2014), these complicated supply chains are more exposed to external events such as climate and weather-related risks, which are increasing worldwide (IPCC 2023; Manners-Bell 2014; Mpungose 2021). Companies (or supply chain risk managers) may not fully understand their risk exposure because of the unique risks created by the strategies mentioned here.

This lack of understanding can have significant financial consequences. According to an article published in Inbound Logistics in 2004, many supply chain managers fail to account for all the factors of cargo loss that affect their profitability (Inbound Logistics 2004). These costs can include supply chain disruptions, expedited replacement freight, storage and disposal of damaged cargo, and labour costs related to filing insurance claims. Other intangible costs, such as damage to customer loyalty and business reputation, loss of customers to competitors, and revenue loss, are all critical factors to consider when assessing the true cost of cargo loss (Inbound Logistics 2004; Kotenko et al. 2022). Given these factors' importance, supply chain risk management plays a vital role in organisational performance and competitiveness (Abolghasemi, Khodakarami & Tehranifard 2015; Vanany, Zailani & Pujawan 2009).

To fulfil this role effectively, supply chain risk managers have various options for mitigating risk. Some mechanisms include transferring risk to marine cargo insurance companies (Barthel & Neumayer 2012; Blecker & Kersten 2006). However, even with the expertise of insurers in adjusting policy premiums based on changes in risk exposure, weather-related risks are changing in a non-linear trend causing high claim ratios (Epstein & Mills 2005). To manage and transfer these risks, insurers use strategies such as insurance policy exclusions and premium increases (Orlek 2015).

The remainder of the article is structured as follows: the Literature review provides a background on marine cargo insurance, the effects of South African weather events on logistical networks, and the theoretical aspects of supply chain risk management (and where the focus of this research fits into the existing theory). The Research, methods and design section outlines the methods and data control framework the research followed. The Analysis and results section presents the results from the data analysis, followed by a discussion in the Discussion and conclusions and management considerations in the Conclusion section. Finally, the authors present suggestions for future research in Section 7.

Literature review

Through a brief literature overview, this section provides the reader with a general background on this article's main topics, including marine cargo insurance, impacts of weather on South African logistical networks, and theoretical considerations of supply chain risk management.

Marine cargo insurance

Marine insurance is the oldest practiced form of insurance and can be traced back to ancient Greece, where it became highly developed during the 15th century. During that time, it was a well-known insurance contract among maritime nations trading commercially with Greece (Encyclopaedia Britannica 2019). The earliest marine insurance policies in English were recorded in 1555, and in 1613, a Lloyd's cargo insurance policy insured goods shipped on the vessel *Tiger* on terms that would exist in some form until 1982 (Dunt 2009).

During the 19th century, the global increase in trade led to the creation of the *Marine Insurance Act* (MIA) in 1906, and in 1912, the Institute of London Underwriters developed standardized clauses for cargo insurance called the Institute Cargo Clauses (ICC) (LMA 2009). Most companies worldwide took to underwriting risks subject to the ICC or a variation thereof. The core focus of the ICC is insurance against physical loss of or damage to the cargo, not financial losses or expenses following an insured event. *Marine Insurance Act* 1906 defines 'marine insurance' as:

> A contract of marine insurance is a contract whereby the insurer undertakes to indemnify the assured, in a manner and to the extent thereby agreed, against marine losses, that is to say, the losses incident to marine adventure. (Dunt 2009:9)

The start and end of risk attachment are essential aspects of marine cargo insurance that need a clear definition. The ICC have a complex and comprehensive scheme that specifies the duration of the insurance and its continuation in case of events that affect the transit or alter the voyage. This scheme consists of three main clauses, but this article will only cover some key points from clause 8, the Transit Clause, that relate to the start and end of risk attachment. According to sub-clause 8.1, the risk starts 'from the time the subject-matter insured is first moved ... for the purpose of the immediate loading...', and according to sub-clause 8.1.1, the risk ends at 'unloading at final warehouse or place of storage named in the insurance' (Dunt 2009; LMA 2009).

As is typical with other forms of property insurance following the principle of indemnity, it is a requirement for the insured to be able to substantiate that he or she has suffered a loss in the event of a claim. *Marine Insurance Act* 1906 stipulates: 'The assured must be interested in the subject-matter insured at the time of the loss though he or she need not be interested when the insurance is effected…' The principle of indemnity is also echoed in the ICC under clause 11, creating an express contractual requirement: 'In order to recover under this insurance, the Assured must have an insurable interest in the subject-matter insured at the time of the loss' (Dunt 2009:425).

Although research exists on cargo accumulation risks in maritime supply chains (Freichel et al. 2022), value loss in cargo transportation on water (Kotenko et al. 2022), cargo loss in logistics systems (Wu, Chen & Tsau 2017), and marine insurance claims analysis for accidents (Ching & Yip 2022), to the authors' knowledge, there is no known research investigating weather-related marine cargo insurance claims in South Africa (or in general) (Du Plessis, Goedhals-Gerber & Van Eeden 2023).

Weather affecting South African logistical networks

South Africa is a critical player in the global logistics network, as it hosts several major ports that connect Africa with other continents. However, the country's logistics network is vulnerable to disruptions caused by extreme weather events, such as floods, storms, droughts, and wildfires (Mutumbo 2017). On average, South African ports record one weather-related incident per day (Danladi 2020; Freight News 2014). These incidents are considered one of the main drivers of congestion at these ports (Nze & Onyemechi 2018; Potgieter, Goedhals-Gerber & Havenga 2020).

Weather-related effects that could impact South African logistics infrastructure include rising atmospheric and water temperatures, strong winds, strong waves, rising sea levels, strong ocean currents, and heavy rainfall (Phelp, Rossouw & Theron 2013). These events can damage infrastructure, disrupt operations, delay shipments, increase costs, and affect customer satisfaction. Furthermore, the likelihood and occurrence of these severe weather conditions are expected to rise, which will present significant challenges to various logistics infrastructure (Muyambo et al. 2023).

For instance, devastating floods hit the coastal city of Durban in 2017 and again in 2022. Experts have attributed the 2022 storm to climate change, which brought nearly a year's worth of rain in 2 days (The Guardian 2022). At the Port of Durban and Cape Town, terminal equipment (cranes and gantries) cannot be operated safely in wind speeds of over 70 kph –100 kph. Adverse weather conditions and powerful winds affect the Port of Cape Town year-round, leading to substantial delays in marine and cargo handling operations (Potgieter et al. 2020). Nearly 15% of lost time in the Port of Cape Town is because of extreme weather conditions (Rosario 2019,2020). In general, wind velocity is expected to increase year-round in South Africa as an effect of climate change (Theron & Rossouw 2008).

This trend is further supported by the Annual State of the Climate of South Africa 2022 report. The South African weather service (SAWS) highlighted eight extreme climate events during 2022 in their report, ranging between January (2 events), April (1 event), November (4 events), and December (1 event) (SAWS 2022). Furthermore, the report highlighted that 2022 was hotter than usual for South Africa, especially in the middle of the country. The data from 26 weather stations show that the average yearly temperature was about 0.4 degrees Celsius higher than the average from 1991 to 2020, which makes 2022 one of the four warmest years since 1951. According to SAWS, the country has been warmer by 0.16 degrees Celsius every 10 years from 1951 to 2022 (SAWS 2022).

The increasing frequency and intensity of extreme weather events in South Africa have been observed by other studies as well. The Long-Term Adaptation Scenarios Flagship Research Programme (LTAS) specified that South African infrastructure is more at risk from the impacts of floods and storms (see Table 1) (Munzhedzi et al. 2016). They observed that floods in KwaZulu-Natal destroyed thousands of kilometres of roads and 14 bridges, blocked all the roads, and left 68 000 people homeless and 388 people dead back in 1987. Furthermore, the Western Cape had floods in March 2003 and April 2005, caused by cut-off lows, that cost up to R260m in damages. Storm surges have threatened the coastal provinces of South Africa many times and caused massive damage to infrastructure such as sea walls, railway lines, harbours, and coastal properties. Moreover, weather experts state that the frequency and intensity of extreme weather events in South Africa are increasing (Mpungose 2021; Munzhedzi et al. 2016).

As discussed here, weather-related incidents are becoming more frequent in South Africa, causing disruptions to the logistics network. These disruptions can significantly impact supply chains, leading to shipment delays and increased costs. By focusing on weather-related risks and taking appropriate measures to address them, companies can ensure that their operations continue running smoothly despite the challenges of changing weather conditions.

Supply chain risk management

In 2015, Ho et al. (2015) defined supply chain risk management (SCRM) as:

> [*A*]n inter-organizational collaborative endeavour utilizing quantitative and qualitative risk management methodologies to

TABLE 1: Climate risks affecting South African infrastructure.

Climate Risks	Examples
Drought	Extreme precipitation events have detrimental effects on public and private infrastructure, resulting in high maintenance costs, transportation disruptions, reduced or disrupted access to electricity, and malfunctioning of sewage and storm water systems.
Low	
Wildfires	
Moderate	
Floods	
High	
Storm surges	
High	

Source: Adapted from Munzhedzi, S., Khavhagali, V., Midley, G., De Abreu, P., Scorgie, S., Braun, M. et al., 2016, *Climate information and early warning systems*, viewed 19 July 2022, from https://www.dffe.gov.za/sites/default/files/reports/ltasbook2of7_climateinformationandearlywarningsystemsforsupportingtheDRR.pdf

> identify, evaluate, mitigate and monitor unexpected macro and micro level events or conditions, which might adversely impact any part of a supply chain. (p. 5036)

This definition considers the impact and frequency of potential risks and includes concepts from the risk management process (Ho et al. 2015).

The key steps to managing supply chain risks are: (1) risk identification, (2) risk assessment, (3) risk mitigation, and (4) risk monitoring (Grant, Wong & Trautrims 2017; Ho et al. 2015). The mechanisms for mitigating risks include prevention of risk (e.g., stopping activities), reduction of risk (e.g., training and education), transfer of risk (e.g., insurance), or bearing the risk by the company itself (Blecker & Kersten 2006; Tarei, Thakkar & Nag 2020).

With reference to a recent publication by Tarei et al. (2020), where they examined the relationship between supply chain risk mitigation strategies and practices, most research has focused on identifying and evaluating potential risks and very few mitigating them. Therefore, the explicit focus of this research is to evaluate the 'Transfer of risk' strategy, specifically concerning marine cargo insurance (see Figure 1) as it relates to the research questions (RQs) of this research. In addition to risk transfer, it is also important to consider the supply chain's resilience to certain impacts.

While there is a lack of consensus on the definition of supply chain resilience (SCR), Yang, Tian and Gao (2023) proposed the following framework: (1) the absorptive capacity – refers to the preparedness for crises and/or catastrophes; (2) the adaptive capacity – indicates the response to crises and/or catastrophes, and; (3) the restorative capacity (the ability to restore) determines the recovery from the crises and/or catastrophes and the competitive advantage achieved afterward. The three capacities correspond to temporal aspects before, during, and after an emergency and/or disaster, respectively, and form a valuable framework for assessing SCR (Yang et al. 2023). Shekarian and Mellat Parast (2021) emphasized the holistic way of managing SCRM and SCR regarding supply chain disruptions (Shekarian & Mellat Parast 2021). They further observed that by finding ways to respond to and recover from a disruption, either by restoring or improving its original function, a supply chain could enhance its resilience and reduce the adverse effects of the disruption, which is in line with Step 3 of the SCRM framework.

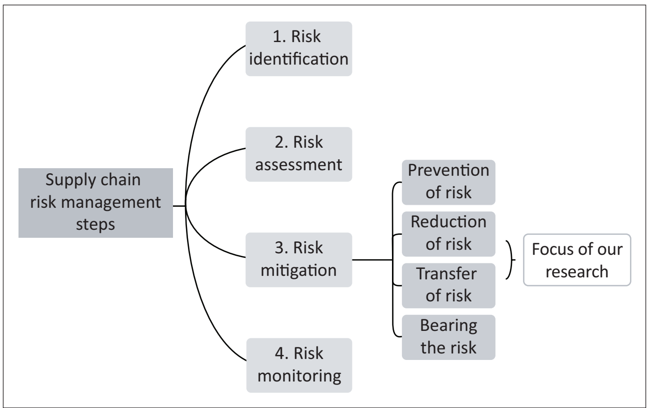


FIGURE 1: The focus of this article within the supply chain risk management framework.

Therefore, according to Yang et al. (2023), measuring the SCR could be defined as quantifying the three capacities of SCR. For instance, the absorptive capacity could be quantified by diversification of suppliers, various sourcing strategies, inventory positioning, and multiple logistic networks; the adaptive capacity could be quantified based on the ability of reserve suppliers, rerouting strategies, communication, and input replacement; and the restorative capacity could be quantified by the suppliers' reinstatement budgets (insurance) and technology reinstatement sources (Wedawatta, Ingirige & Amaratunga 2010; Yang et al. 2023). One can, therefore, conclude that marine cargo insurance is not only a risk transfer strategy through the SCRM framework but also presents a restorative capacity through the SCR definition.

Research methods and design

To the best of the authors' knowledge, no literature currently exists on weather-related marine cargo insurance claims that: (1) evaluates whether there is an observable trend, (2) a difference in claim values compared with non-weather-related claims, and (3) research on seasonality and type of weather impacts. As a result, this research aims to address the following RQs:

- RQ1. Is there an observable trend in South African weather-related marine cargo insurance claims?
- RQ2. Is there a difference in the average claim values between weather-related and non-weather-related marine cargo insurance claims in South Africa?
- RQ3. Is there seasonality in the dataset, and do specific weather events have a bigger impact than others?

The Saunders, Lewis & Thornhill (2007) created the adapted research onion model used for this research (Goodson & Phillimore 2004). This model was explored based on the work by Kivunja and Kuyini (2017). The onion comprises six layers, each representing a different onion layer (OL) of research. These layers allow the user to systematically peel away each layer until the core is reached, starting with OL1, the research philosophy. This research followed the realism philosophical stance, which believes that social reality and the researcher(s) are independent, thus enabling unbiased results. Realism explains that scientific methods are imperfect and that all theories can be modified. This philosophy is grounded on the notion of a scientific method for the creation of knowledge (Dudovskiy 2016).

In OL2, the research approach of the study is examined. This research followed an inductive approach, starting with a research question and leading to a theory. The OL3 details the research strategy followed, referring to how the researchers did the necessary work. The researchers used archival research to obtain secondary quantitative data (OL4). The fifth layer, OL5, details the time horizon of the study, which is longitudinal (multiple points in time; sample type is the same; results provide details of changes over time). Finally, the sixth layer (OL6) represents the data collection techniques, which are discussed in more detail in the next section.

Data processing method

In their article on data-driven analytics for cargo loss, Wu et al. (2017) proposed a 'business analytics for cargo loss severity' framework for processing claims data. This framework was adapted to explore the RQs of this study (see Figure 2).

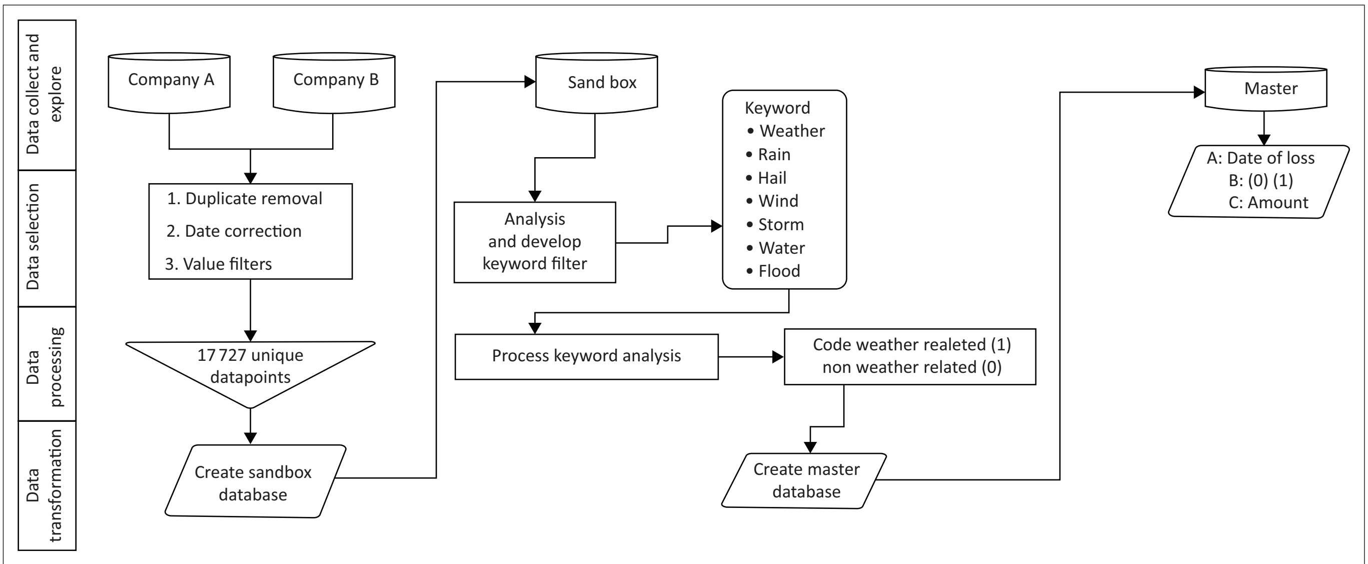
This research analysed claims statistics from Companies A & B (which are among the top five marine insurers in South Africa, accounting for ±35% of the non-life insurance sector). The datasets pertain to the marine insurance portfolios of these two companies (as a case study) and did not include specific locations of the loss, so it is possible that some of the identified claims occurred outside the borders of South Africa, although it still impacts the company as a claim. The combined dataset covers 17 727 unique claims over 10 years from 2013 to 2022 and offers a comprehensive market view. The data are specific to marine cargo insurance products (owner of the goods) and does not include claims that would normally be found under marine liability products (third party services). The first objective was to create a master dataset for investigation. The datasets received contained: (1) the date of loss, (2) a description of the loss, and (3) the gross claim amount.

Initially, datasets were cleaned by removing duplicates, correcting the date format, and applying value filters. The next step was to analyse the description of the claims to identify weather and non-weather-related claims. As a result of inconsistencies in the descriptions of claims (open text field where each claims handler has textual claim description freedom), a set of keywords was developed to filter the dataset with a keyword formula. Weather-related claims and non-weather-related claims were coded as 1 and 0, respectively. Finally, a master dataset was obtained and used for further analysis. A sample dataset is presented in Table 2.

The master dataset was analysed using Excel® to answer RQ2 and RQ3, and, with the assistance of Stellenbosch University's Centre for Statistical Consultation, Statistica 14® was used to explore RQ1. The master dataset was further processed for the RQ1 analysis to include a percentage (%) weather-related column to provide a ratio. This ratio is obtained by dividing the weather-related claims by the total number of recorded claims for the month. *It is worth noting that the datasets from both Company A and B were reviewed separately, and the results were comparable, which provided reliability and validity for a combined master dataset.*

Ethical considerations

Ethical clearance to conduct this study was obtained from the Stellenbosch University Social, Behavioural and Education Research Ethics Committee (REC: SBE).



Source: Adapted from Wu, P.J., Chen, M.C. & Tsau, C.K., 2017, 'The data-driven analytics for investigating cargo loss in logistics systems', *International Journal of Physical Distribution and Logistics Management* 47(1), 68–83. https://doi.org/10.1108/IJPDLM-02-2016-0061

FIGURE 2: Data processing framework.

TABLE 2: Sample master dataset.

Date of loss	Year	Month	Month number	Gross	Weather	Rain	Hail	Wind	Storm	Water	Flood	Weather related
2018-06-02	2018	Jun	6	123.00	0	0	0	0	0	0	0	0
2018-06-30	2018	Jun	6	456.00	0	0	0	0	1	0	0	1
2018-07-01	2018	Jul	7	789.00	0	0	0	0	0	0	0	0

Analysis and results

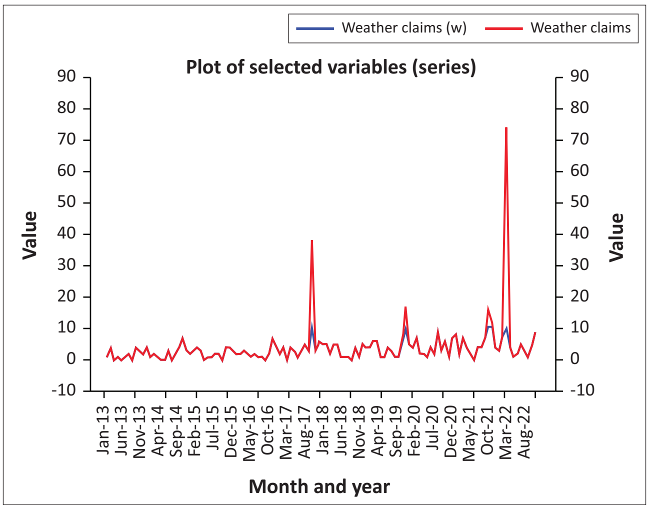
This section discusses the analysis and results linked to each RQ noticed.

Research question 1: Is there a trend in South African weather-related marine cargo insurance claims?

The number of claims was plotted for 2013 until 2022 (see 'Weather claims' in Figure 3 and 'Non-weather claims' in Figure 4). As a result of the significant size of the outliers in weather claims (compared with the rest of the data), the situation will distort the subsequent analysis of trends. As a result, the data have undergone a winsorisation procedure to eliminate the impact of significant outliers. Winsorisation is a general approach to constructing robust statistics (Cheng & Young 2023). This procedure involves altering statistics by restricting extreme variation in the data to minimize the influence of outliers, as is detailed in the procedure below.

The ten percent winsorisation procedure

The sample is reduced by removing all values that are outliers or extremes, and then the *maximum*, *minimum*, and interquartile range (*IQR*) of the reduced sample are calculated. All upper outliers and extremes in the original sample are assigned the value: *maximum +10%*IQR*. Likewise, all lower outliers and extremes in the original sample are assigned the value: *minimum –10%*IQR*. The original sample with the outliers and extremes interchanged by these values is called the 10% winsorisation sample.



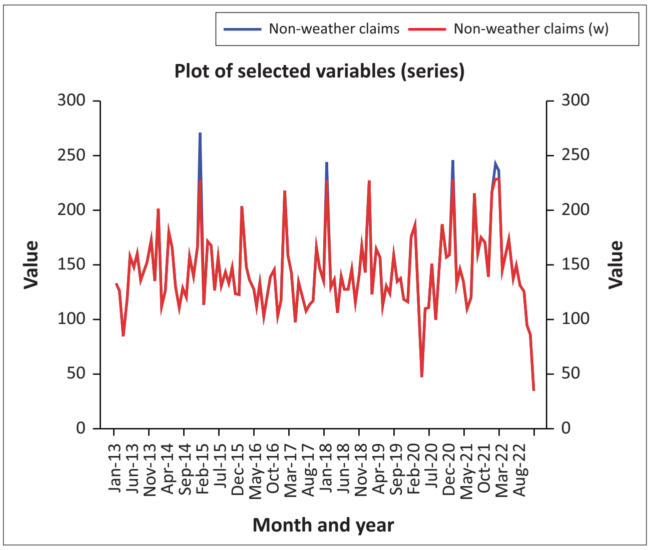
w, % weather related.

FIGURE 3: Weather-related claims.

The descriptive statistics for the dataset are presented in Table 3. The effect after the winsorisation procedure is shown in Figure 3 and Figure 4 with the line designated as (w). The combined effect is shown in the percent of Weather related' plot of variables (see Figure 5), and this is the plot of variables that are used for most of the upcoming statistical analysis as it provides the ratio of weather-related claims compared with the total number of claims per month. In doing so, percentages eliminate data points based on potential changes in weather-related claims because of, for instance, fluctuations in the portfolio size of the insurance company. The box plot in Figure 6 confirms that the dataset now excludes any outliers or extremes and can be used for statistics.

The authors used Levene's test to confirm whether the variances of a response variable are equal across groups. It is a statistical test commonly used to test the assumption of homogeneity of variances before performing a parametric statistical test such as a *t*-test or analysis of variance (ANOVA). This assumption is important for many parametric statistical tests, and if violated, the results may not be reliable. Levene's test provides a way to test this assumption and determine if the variances of the groups being compared are equal. The results from Levene's test are presented in Table 4.

MS effect and MS error represent the mean squares for the effect and error, respectively. The F-value of 1.44 is calculated from the mean squares for the effect and error. The *p*-value of



w, % weather related.

FIGURE 4: Non-weather-related claims.

TABLE 3: Descriptive statistics.

Variable	Valid N	Mean	Median	Minimum	Maximum	Lower quartile	Upper quartile	SD
Weather claims	120	4.1667	3.0000	0.00000	74.0000	1.0000	4.0000	7.71807
Weather claims (w)	120	3.2964	3.0000	0.00000	10.5133	1.0000	4.0000	2.61172
Non-weather claims	120	143.5583	137.5000	35.00000	269.0000	121.5000	159.0000	37.05975
Non-weather claims (w)	120	142.7473	137.5000	35.00000	228.3341	121.5000	159.0000	34.82742
% Weather related	120	2.7801	1.8693	0.00000	31.6239	0.8696	3.3841	3.97294
% Weather related (w)	120	2.2919	1.8693	0.00000	7.0444	0.8696	3.3841	1.80621

SD, standard deviation; w, % weather related.

0.182 represents the probability of observing a test statistic as extreme as 1.44 or higher if the null hypothesis of equal variances were true. As the *p*-value is greater than 0.05, one cannot reject the null hypothesis of equal variances, and this suggests that there is not enough evidence to conclude that the variances of the groups being compared are significantly different. Therefore, it would be appropriate to continue with further statistical analysis, as the assumption of homogeneity of variances has not been violated.

Next, the authors used a one-way ANOVA with least squares means (LS-means) to compare the groups. Least squares means are: (1) based on a linear model such as ANOVA that assumes equal variances and (2) estimates of the means in a balanced population. The results are presented in Figure 7.

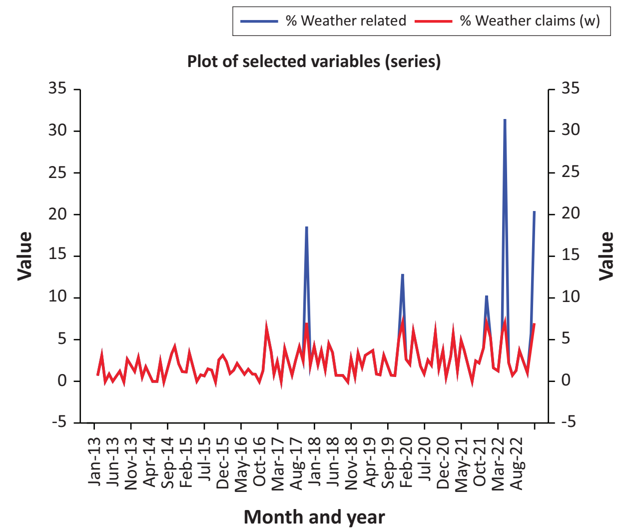
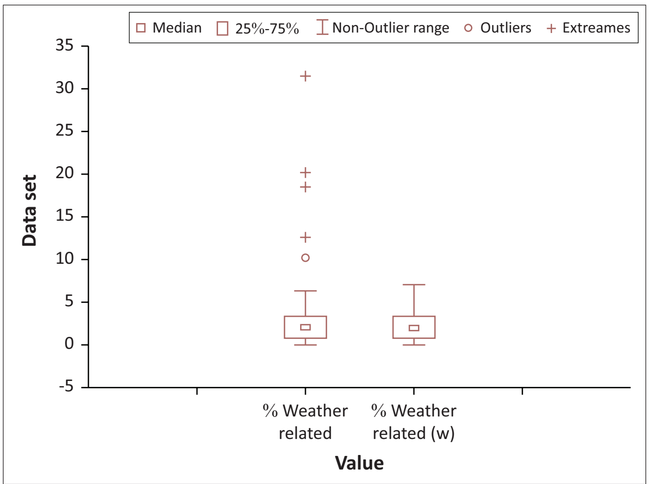


FIGURE 5: Weather-related claims in percentage.



Note: Median; box 25%–75%; whisker: Non-outlier range.

FIGURE 6: Box plot after winsorisation.

TABLE 4: Levene's test for homogeneity of variances effect: year.

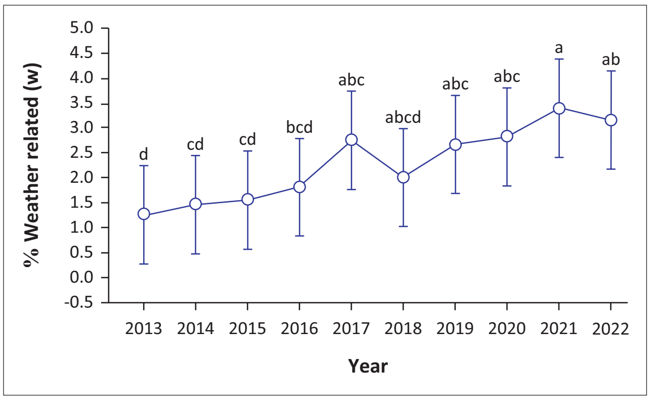
Variable	MS effect	MS error	*F*	*P*
% Weather related (w)	1.32	0.92	1.44	0.182

MS, mean square

Based on these results, the null hypothesis can be rejected as the *p*-value = 0.019. In hypothesis testing, a *p*-value is the probability of obtaining results as extreme as the observed results of a statistical hypothesis test, assuming that the null hypothesis is true. A small *p*-value (typically less than 0.05) indicates strong evidence against the null hypothesis, so one can reject the null hypothesis. In this case, the F-value of 2.3397 and *p*-value of 0.019 suggest a statistically significant difference between the means of the groups being compared. The *p*-value is less than the commonly used significance level of 0.05, indicating that the probability of observing the data, if the null hypothesis were true, is less than 5%, and this means that if there were no difference between the groups, there would be less than a 5% chance of observing an *F*-value as large as 2.3397. The probability plot of the residuals after the ANOVA is presented in Figure 8. In a normal probability plot, the points lie close (or as close as possible) to a straight line, indicating that the data are consistent with a sample from a normal distribution.

Following LS-means, the least significant difference (LSD) multiple comparisons test was performed. It is a statistical method used in the context of the ANOVA when the F-ratio suggests rejection of the null hypothesis, that is, when the difference between the population means is significant. This test helps to identify the populations whose means are statistically different. The LSD multiple comparisons test results are included in Figure 7, and the data for this test are presented in Table 5. Post hoc groups in the table are based on the letters assigned to each year. Years that share a letter have similar means, while years that do not share a letter have significantly different means.

Lastly, a Kruskal–Wallis test was performed. This test is a non-parametric test used to determine if there are statistically significant differences between two or more groups, if the assumption of normality of the residuals is invalid. The Kruskal–Wallis *p*-value = 0.032, also less than 0.05, confirms the conclusion from the ANOVA that the yearly means differ significantly, even if the residuals are not normally distributed.



Note: current effect: $F(9, 110) = 2.3397$, $p = 0.019$ kruskal-Wallis $p = 0.032$ effective hypothesis decomposition vertical bars denote 0.95 confidence intervals.

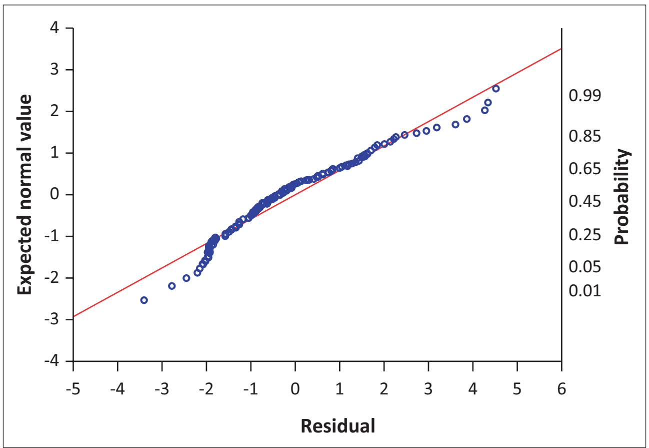
FIGURE 7: Least squares means and least significant difference test.

This section concludes that there is a statistical observable upward trend in weather-related marine cargo insurance claims in South Africa over the years 2013 to 2022.

Research question 2: Is there a difference in the average claim values between weather-related and non-weather-related marine cargo insurance claims in South Africa?

The master dataset was analysed by filtering weather and non-weather-related claims per year, including: (1) the gross value related to each claim and (2) the corresponding number of claims. It is important to note that the dataset for this analysis was not winsorised and outliers (as shown in Figure 5) will impact the overall statistics. The authors and consulting statistician agreed with this approach as the four extremes identified in 2017, 2019, 2021 and 2022 are crucial for presenting the actual state. The results from this analysis are shown in Table 6. Averages over 10 years were also calculated and are used in the discussion.

This section concludes that there was a considerable statistical difference between the average value of weather-related and non-weather-related claims in South Africa for the period investigated.



Note: Normal prob. plot; raw residuals dependent variable: % Weather realted (w) (Analysis sample).

FIGURE 8: Normal probability plot.

Research question 3: Is there seasonality in the dataset, and does specific weather events have a bigger impact than others?

Firstly, the master dataset was analysed by filtering weather-related claims by month and keyword (keywords noted in Figure 2), including the corresponding number of claims (see Figure 9). It is important to notice that: (1) some claims trigger more than one keyword and (2) that the authors decided not to winsorise the dataset for the analysis of RQ3, despite the presence of outliers (as depicted in Figure 5) that could affect the overall statistics. This decision was made because the extreme values identified are considered essential for accurately representing the current situation, showing that these outlier events are happening more often. Secondly, the gross value related to each keyword was analysed (see Figure 10).

Lastly, the dataset was filtered by annual weather-related claims per month to identify whether the cargo is more prone to loss during certain months of the year (see Figure 11 and Figure 12). The years 2017 and 2022 were excluded as extreme outliers. The discussion of this analysis is in the next Discussion section. This section concludes that there is statistical seasonality in the dataset and specific events have a more significant gross impact than others for the years 2013–2022.

Discussion

As outsourcing, product lifecycles, demand, and globalisation advance, supply chains become more complex and involve more stakeholders, and this increases the exposure to various risks, especially external ones such as climate and weather events, which are intensifying globally. South Africa's logistics network connects Africa with the world, but it is vulnerable to weather disruptions that can harm trade and the economy. By applying the SCRM framework, supply chain managers can transfer risks to marine cargo insurance providers.

Through three RQs, this research analysed whether there is a trend, difference in average claims value, and seasonality present in South African weather-related marine cargo insurance claims data. By analysing 17 727 individual claim

TABLE 5: Least significant difference multiple comparisons.

Cell number	Year	Group	(1) 1.2631	(2) 1.4637	(3) 1.5543	(4) 1.8249	(5) 2.7529	(6) 2.0107	(7) 2.6719	(8) 2.8182	(9) 3.3975	(10) 3.1616
1	2013	d	-	0.776	0.679	0.426	0.036	0.290	0.047	0.029	0.003	0.008
2	2014	cd	0.776	-	0.898	0.608	0.069	0.438	0.088	0.056	0.007	0.017
3	2015	cd	0.679	0.898	-	0.701	0.091	0.517	0.115	0.075	0.010	0.024
4	2016	bcd	0.426	0.608	0.701	-	0.189	0.792	0.231	0.160	0.027	0.060
5	2017	abc	0.036	0.069	0.091	0.189	-	0.293	0.908	0.926	0.361	0.562
6	2018	abcd	0.290	0.438	0.517	0.792	0.293	-	0.349	0.253	0.051	0.104
7	2019	abc	0.047	0.088	0.115	0.231	0.908	0.349	-	0.835	0.304	0.487
8	2020	abc	0.029	0.056	0.075	0.160	0.926	0.253	0.835	-	0.411	0.626
9	2021	a	0.003	0.007	0.010	0.027	0.361	0.051	0.304	0.411	-	0.738
10	2022	ab	0.008	0.017	0.024	0.060	0.562	0.104	0.487	0.626	0.738	-

Note: (Data 20230411) probabilities for post hoc tests Error: Between MS = 2.9623, df = 110.00.
w, % weather related.

TABLE 6: Average claims values.

Year	Non weather related				Weather related				Totals	
	Gross†	Gross (% of total)	Claim count	Number of claims (% of total)	Gross	Gross (% of total)	Claim count	Number of claims (% of total)	Gross	Number of claims
2013	123 658 838	98,98	1671	98,70	1 279 065	1,02	22	1,30	124 937 904	1693
2014	143 224 485	96,80	1737	98,58	4 736 261	3,20	25	1,42	147 960 746	1762
2015	164 334 144	86,59	1809	98,53	25 453 909	13,41	27	1,47	189 788 053	1836
2016	140 862 339	97,94	1594	98,27	2 962 431	2,06	28	1,73	143 824 771	1622
2017	347 848 232	85,46	1657	95,84	59 193 177	14,54	72	4,16	407 041 409	1729
2018	201 395 875	98,48	1724	98,01	3 105 500	1,52	35	1,99	204 501 375	1759
2019	220 118 695	93,94	1705	96,93	14 189 343	6,06	54	3,07	234 308 038	1759
2020	256 397 837	98,59	1640	97,27	3 671 581	1,41	46	2,73	260 069 417	1686
2021	286 224 967	98,14	1969	96,43	5 410 235	1,86	73	3,57	291 635 202	2042
2022	382 249 728	49,48	1721	93,58	390 276 245	50,52	118	6,42	772 525 974	1839
Grand Total	2 266 315 141	81,62	17227	97,18	510 277 747	18,38	500	2,82	2 776 592 888	17727
Average	226 631 514	90,44	1 723	97,21	51 027 775	9,56	50	2,79	277 659 289	1 773
					1 020 555					

Note: †, 1 x claim = 131 556.

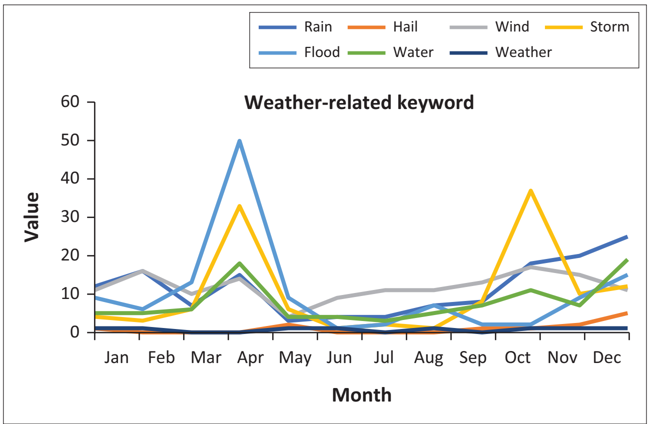


FIGURE 9: Weather-related (gross).

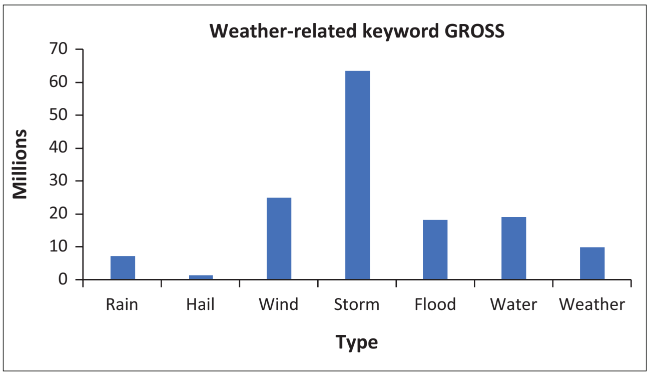


FIGURE 10: Weather-related keyword (Number claims).

data points from companies A and B (which accounts for roughly 35% of the non-life insurance sector in South Africa) between 2013 and 2022, this research identified through RQ1 (and the statistical one-way ANOVA LS-means test) a positive trend (increase) in the mean weather-related marine cargo insurance claims over the observed period. The null hypothesis (that there is no significant difference between the group means) was rejected with a p-value = 0.019, thus concluding that there is a statistically observable trend.

Based on the results from the LSD test, in the context of percent of Weather-related claims, the LSD post hoc results

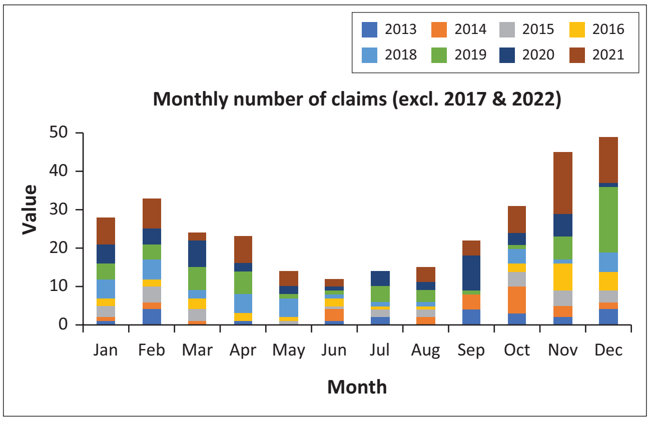


FIGURE 11: Average monthly claims.

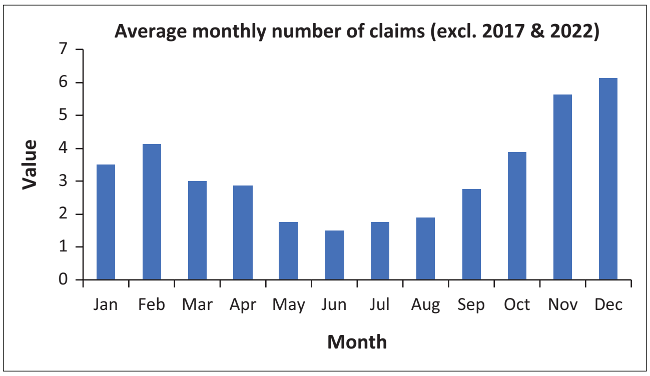


FIGURE 12: Monthly number of claims.

indicated that: (1) the mean percent of Weather-related claims in 2021 and 2022 was significantly higher than the mean percent of Weather-related claims in all other years ($p < 0.01$), (2) the mean percent of Weather-related claims in 2013 and 2014 was significantly lower than the mean percent of Weather-related claims in all other years except 2015 and 2016 ($p < 0.05$), and (3) there were no significant differences in the mean percent of Weather related claims between 2015 and 2016, or between 2017, 2018, 2019, and 2020 ($p > 0.05$). It is important to note that the data for the analysis of RQ1 was winsorised, which removed all outliers, and the results still indicated a statistically significant difference in mean weather-related claims over 10 years.

The second research question explored the difference in the mean values of weather-related and non-weather-related claims. The results showed weather-related claims over the last 10 years: (1) accounted for 2.79% of the total number of claims but 9.56% of the total gross claims paid and (2) had an average value that was 7.76 times higher than that of non-weather-related claims. For the overall dataset, weather-related claims represented 2.82% of the total number of claims but 18.38% of the total gross claims paid – a substantial disproportion. This indicates that insurers have to pay much more for weather-related claims than for non-weather-related claims, even though they are less frequent. Weather-related claims are a significant risk factor for insurers and can affect their profitability and solvency.

The third research question explored the seasonality and impact of various weather-related claims. The results showed that: (1) the most costly weather-related claims were caused by storms, wind, and water, followed by floods, rain, and hail; (2) the number of weather-related claims was highest in October, November, and December, and lowest in May, June, and July; (3) the frequency of weather-related claims rose over the years, with notable spikes in 2017, 2019, 2021 and 2022; (4) the frequency of weather-related claims statistically varied seasonally according to the weather conditions of South Africa. This suggests that weather-related claims impose a considerably higher financial burden on insurers than non-weather-related claims, despite their lower frequency.

Conclusions and management considerations

This research has shown that weather-related marine cargo insurance claims in South Africa have increased over the last decade, and this suggests that supply chain stakeholders are facing more challenges and disruptions because of weather-related events. In addition, it also found a difference in the average claims value between weather-related and non-weather-related claims, with the former being significantly higher. In addition, the research revealed a seasonal pattern in weather-related claims.

These findings have implications for both supply chain managers and marine cargo insurance companies, as they must adopt effective strategies to mitigate and transfer the risks associated with weather-related events. The research has demonstrated the significant impact of weather-related claims on South African supply chains and the marine cargo insurance industry through the identified RQs. The research also contributes to the SCRM and marine cargo insurance literature by providing empirical evidence from a developing country context. Furthermore, the findings suggest that supply chain managers and insurers must adopt a more comprehensive and proactive approach to managing weather-related risks. This approach should include:

- assessing and mitigating the potential effects of weather-related events on cargo and operations (as identified through Steps 2 and 3 of the SCRM framework in Figure 1);
- ensuring adequate and appropriate insurance coverage, premium computation, and underwriting considerations (as discussed in the Introduction, and Step 3 of the SCRM framework in Figure 1);
- enhancing the communication and coordination of claims processes between insurers and other stakeholders
- leveraging data and analytics to inform decision making and planning (as this research highlighted).

By implementing these recommendations, supply chain managers and insurers can potentially improve their performance and competitiveness in the face of increasing weather-related challenges (Vanany et al. 2009; Abolghasemi et al. 2015). Furthermore, these recommendations can also enable them to anticipate and adapt to the changing climate and weather patterns, which are likely to pose more challenges in the future. In conclusion, this study encourages supply chain managers and insurers to adopt a more holistic and proactive SCRM approach incorporating marine cargo insurance as a critical risk transfer mechanism.

Future work

There is little research that investigates the perceptions of marine cargo insurers on the impacts of weather-related claims on their portfolios, and to the best of the authors' knowledge, no research exists on models that forecast future situations. Therefore, the following future work is proposed by the authors:

- Gather primary data to determine the perceptions of marine cargo insurers and supply chain logistics operators through survey questions linked to the SCRM framework.
- Create a model to forecast the effects of changing weather-related events on claims. This model should provide data to assist stakeholders (marine cargo insurers and supply chain logistics operators) in making strategic decisions.

Acknowledgements

The authors would like to thank the following people: members of the International Union of Marine Insurance (IUMI) for their valuable discussions and ongoing support; companies A and B for sharing their data for analysis; Prof Daan Nel from the Centre for Statistical Analysis at Stellenbosch University for his assistance with the statistical analysis.

Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Authors' contributions

F.d.P. was responsible for the conceptualisation, methodology, validation, formal analysis, investigation, writing of the original draft and visualisation.

L.G-G. and J.v.E. was responsible for the validation, writing, review and editing, and supervision.

Funding information

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

Data availability

Data sharing is not applicable to this article, as no new data were created or analysed in this study.

Disclaimer

The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of any affiliated agency of the authors, and the publisher.

References

Abolghasemi, M., Khodakarami, V. & Tehranifard, H., 2015, 'A new approach for supply chain risk management: Mapping SCOR into Bayesian network', *Journal of Industrial Engineering and Management* 8(1):280–302. https://doi.org/10.3926/jiem.1281

Barthel, F. & Neumayer, E., 2012, 'A trend analysis of normalized insured damage from natural disasters', *Climatic Change* 113(2), 215–237. https://doi.org/10.1007/s10584-011-0331-2

Blecker, T. & Kersten, W., 2006, Managing risks in supply chains: How to build reliable collaboration in logistics, vol. 1, Erich Schmidt Verlag GmbH & Co KG, Berlin.

Cheng, K. & Young, D.S., 2023, 'An approach for specifying trimming and Winsorization Cutoffs', *Journal of Agricultural, Biological and Environmental Statistics* 28, 299–323. https://doi.org/10.1007/s13253-023-00527-4

Ching, R.H.F. & Yip, T.L., 2022, 'Marine insurance claims analysis using the Weibull and log-normal models: Compensation for oil spill pollution due to tanker accidents', *Maritime Transport Research* 3, 100056. https://doi.org/10.1016/j.martra.2022.100056

Danladi, C., 2020, *Evaluating the impact of extreme weather-related events on port safety resilience : A case study of the African Continent,* University of Plymouth, Plymouth.

Dudovskiy, J., 2016, 'Realism research philosohy', *Research Methodology* 04, 11–13, viewed 19 July 2022, from http://research-methodology.net/research-philosophy/realism/.

Dunt, J., 2009, *Marine cargo insurance*, 1st edn., Informa Law, New York, NY.

Du Plessis, F., Goedhals-Gerber, L.L. & Van Eeden, J., 2023, 'A systematic literature review and bibliometric analysis on the impacts of climate change on marine cargo insurance of cold chains', *Transportation Research Interdisciplinary Perspectives*. Currently under review.

Encyclopaedia Britannica, 2019, viewed 20 June 2020, from https://www.britannica.com/topic/insurance/Historical-development-of-insurance.

Epstein, P. & Mills, E., 2005, *Climate change futures: Health, ecological and economic dimensions*, viewed 03 April 2023, from http://ccsl.iccip.net/ccf_report_oct_06.pdf.

Freichel, S.L.K., Wörtge, J.K., Haas, A. & Veer, L., 2022, 'Cargo accumulation risks in maritime supply chains: A new perspective towards risk management for theory, and recommendations for the insurance industry and cargo shippers', *Logistics Research*. https://www.doi.org/10.23773/2022_4

Freight News, 2014, *Survey reveals extent of delays facing Africa's shippers*, viewed 20 June 2020, from https://www.freightnews.co.za/article/survey-reveals-extent-delays-facing-africas-shippers.

Goodson, L. & Phillimore, J., 2004, *Qualitative research in tourism: Ontologies, epistemologies and methodologies*, pp. 1–333, Routledge, London.

Grant, D.B., Wong, C.Y. & Trautrims, A., 2017, Sustainable logistics and supply chain management: principles and practices for sustainable operations and management, Kogan Page Publishers, London.

Ho, W., Zheng, T., Yildiz, H. & Talluri, S., 2015, 'Supply chain risk management: A literature review', *International Journal of Production Research* 53(16), 5031–5069. https://doi.org/10.1080/00207543.2015.1030467

Inbound Logistics, 2004, The full cost of cargo losses viewed 20 April 2023, from https://www.inboundlogistics.com/articles/the-full-cost-of-cargo-losses/.

IPCC, 2023, 'AR6 synthesis report: Summary for policymakers', in *Intergovernmental panel on climate change*, viewed 15 April 2023, from https://www.ipcc.ch/report/sixth-assessment-report-cycle/.

Kivunja, C. & Kuyini, A.B., 2017, 'Understanding and applying research paradigms in educational contexts', *International Journal of Higher Education* 6(5), 26. https://doi.org/10.5430/ijhe.v6n5p26

Kotenko, S., Ilchenko, S., Kasianova, V., Diakov, V., Mashkantseva, S. & Nitsenko, V., 2022, 'Determination of the expected value of losses caused by the cargo transportation insurance risks by water transport', *Inventions* 7(3), 1–13. https://doi.org/10.3390/inventions7030081

KPMG, 2019, *The South African insurance industry survey*, viewed 19 July 2022, from http://www.kpmg.com/NA/en/IssuesAndInsights/ArticlesPublications/General-interest/Documents/KPMG South African Insurance Industry Survey 2011.pdf.

Kwalar, K., 2023, *Cargo insurance penetration in Africa: The role of technology and subrogration recovery*, Amazon Digital Services, viewed 15 April 2023, from https://www.amazon.com/dp/B0C2JC19GC?ref_=cm_sw_r_cp_ud_dp_KK34VM76VGS8KEJQXHT3.

LMA, 2009, *Institute cargo clauses (A)*, viewed 19 July 2022, from https://www.lmalloyds.com/lma/underwriting/marine/JCC/JCC_Clauses_Project/Revised_Clauses/ICC_A_CL382.aspx.

Manners-Bell, J., 2014, *Supply chain risk: Understanding emerging threats to global supply chains*, Kogan Page Publishers, London.

Mccord, J., 2021, *The true cost of unrecovered cargo loss*, viewed 17 April 2023, from https://www.loadsure.net/latest/article/the-true-cost-of-unrecovered-cargo-loss/.

Mpungose, N., 2021, *An analysis of extreme weather events over the 1981 – 2018 period : A South African-based study*, viewed 11 April 2023, from https://globalhistory.org.uk/2021/11/an-analysis-of-extreme-weather-events-over-the-1981-2018-period-a-south-african-based-study/.

Munzhedzi, S., Khavhagali, V., Midley, G., De Abreu, P., Scorgie, S., Braun, M. et al., 2016, *Climate information and early warning systems*, viewed 19 July 2022, from https://www.dffe.gov.za/sites/default/files/reports/ltasbook2of7_climateinformationandearlywarningsystemsforsupportingtheDRR.pdf.

Mutumbo, K.N.P., 2017, *The maritime commons : Digital repository of the World a holistic risk-oriented framework for port infrastructure adaption to climate change,* World Maritime University, Malmo.

Muyambo, F., Belle, J., Nyam, Y.S. & Orimoloye, I.R., 2023, 'Climate-change-induced weather events and implications for urban water resource management in the free state province of South Africa', *Environmental Management* 71(1), 40–54. https://doi.org/10.1007/s00267-022-01726-4

Nze, I.C. & Onyemechi, C., 2018, 'Port congestion determinants and impacts on logistics and supply chain network of five African ports', *Journal of Sustainable Development of Transport and Logistics* 3(1), 70–82. https://doi.org/10.14254/jsdtl.2018.3-1.7

Orlek, J., 2015, *Climate change could cost marine insurance industry millions*, viewed 19 July 2022, from https://www.freightnews.co.za/article/ftw-pick-climate-change-could-cost-marine-insurance-industry-millions.

Pfohl, H.C., Gallus, P. & Thomas, D., 2011, 'Interpretive structural modeling of supply chain risks', *International Journal of Physical Distribution and Logistics Management* 41(9), 839–859. https://doi.org/10.1108/09600031111175816

Phelp, D., Rossouw, M. & Theron, A., 2013, *Potential impacts of climate change on Southern African ports and coast,* CSIR, Stellenbosch.

Potgieter, L., Goedhals-Gerber, L.L. & Havenga, J., 2020, Risk profile of weather and system-related port congestion for the Cape Town container terminal', *Southern African Business Review* 24, 26. https://doi.org/10.25159/1998-8125/6149

Rosario, I., 2019, *How the port of CT could avoid weather-related delays*, viewed 04 June 2020, from https://www.ftwonline.co.za/article/how-port-ct-could-avoid-weather-related-delays.

Rosario, I., 2020, *Congestion at Durban – A technical evaluation*, viewed 04 June 2020, from https://www.freightnews.co.za/article/congestion-durban-technical-evaluation.

Saunders, M., Lewis, P. & Thornhill, A., 2007, *Research methods for business students*, 6th edn., Pearson, London. Saunders, M.,

SAWS, 2022, *Annual state of the climate of South Africa*, viewed 03 April 2023 from https://www.weathersa.co.za/Documents/Corporate/Annual State of the Climate 2022_21042023120105.pdf.

Shekarian, M. & Mellat Parast, M., 2021, 'An integrative approach to supply chain disruption risk and resilience management: A literature review', *International Journal of Logistics Research and Applications* 24(5), 427–455. https://doi.org/10.1080/13675567.2020.1763935

Sheldrick, A., 2020, *Container ship loses nearly 2,000 cargo carriers in Pacific storm*, viewed 17 April 2023, from https://www.reuters.com/article/us-china-shipping-container-accident-idUSKBN28E0T7.

Swiss Re Group, 2023, *How big is the protection gap from natural catastrophes where you are?*, viewed 11 April 2023, from https://www.swissre.com/risk-knowledge/mitigating-climate-risk/natcat-2019.html.

Tang, O. & Nurmaya Musa, S., 2011, 'Identifying risk issues and research advancements in supply chain risk management', *International Journal of Production Economics* 133(1), 25–34. https://doi.org/10.1016/j.ijpe.2010.06.013

Tarei, P.K., Thakkar, J.J. & Nag, B., 2020, 'Benchmarking the relationship between supply chain risk mitigation strategies and practices: An integrated approach', *Benchmarking: An International Journal* 27(5), 1683–1715. https://doi.org/10.1108/BIJ-12-2019-0523

The Guardian, 2022, After the relentless rain, South Africa sounds the alarm on the climate crisis, pp. 1–12, viewed from https://www.theguardian.com/world/2022/apr/24/south-africa-floods-rain-climate-crisis-extreme-weather.

Theron, A.K. & Rossouw, M., 2008, Analysis of potential coastal zone climate change impacts and possible response options in the southern African region, viewed 19 July 2022, from http://hdl.handle.net/10204/2561.

Vanany, I., Zailani, S. & Pujawan, N., 2009, 'Supply chain risk management: Literature review and future research', *International Journal of Information Systems and Supply Chain Management* 2(1), 16–33. https://doi.org/10.4018/jisscm.2009010102

Wedawatta, G., Ingirige, B. & Amaratunga, D., 2010, 'Building up resilienc e of construction sector SMEs and their supply chains to extreme weather events', *International Journal of Strategic Property Management* 14(4), 362–375. https://doi.org/10.3846/ijspm.2010.27

WK Webster, 2020, *One Apus*, viewed 17 April 2023, from https://www.wkwebster.com/casualty-details/158/one-apus.

Wu, P.J., Chen, M.C. & Tsau, C.K., 2017, 'The data-driven analytics for investigating cargo loss in logistics systems', *International Journal of Physical Distribution and Logistics Management* 47(1), 68–83. https://doi.org/10.1108/IJPDLM-02-2016-0061

Yang, C., Tian, K. & Gao, X., 2023, 'Supply chain resilience: Measure, risk assessment and strategies', *Fundamental Research*. https://doi.org/10.1016/j.fmre.2023.03.011