Applying predictive analytics to account for climate change in insurance risk management - A case study of Santam

Student name: Asithandile Malote

Student number: 566087

Student email: 566087@students.wits.ac.za

Mobile number: 0762871236

Supervisor: Dr Roselyne Cheruiyot

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ABSTRACT

Weather-related disasters have become more frequent and severe in the past decade. Insurance companies continuously face increased insurance claims pay outs for property and infrastructure damage, business interruption, and other weather-related insurance claims. This surge in weather-related insurance claims strains the financial resources of insurers, leading to rising premiums for policyholders and potentially reduced coverage in high-risk areas. Moreover, the unpredictability of weather patterns makes it challenging for insurers to accurately assess and price risk, leading to uncertainty in underwriting practices. To mitigate these challenges, insurers are increasingly investing in advanced analytics and data modelling techniques and risk management strategies. However, the long-term sustainability of the insurance industry depends on collaborative efforts to address the underlying causes of climate change.

This case study explores the relationship between weather change-related occurrences and insurance claims, examining the correlation between these events and the financial ramifications experienced by the South African insurance industry. Additionally, the study investigates the specific impact of weather-related events on Santam as well as Santam's property insurance business unit, particularly focusing on the escalation of property and infrastructure damages attributable to such occurrences. Three multivariate linear regression models were developed to assess the relationships between the independent variables (number of weather-related events, average rainfall, minimum and maximum temperatures) and dependent variables (insurance claims incurred, Santam’s net underwriting margin and Santam’s property net underwriting result) . The results of the study show that there is a statistically significant relationship between financial state of the non-life insurance industry and weather-related factors such as temperature, precipitation, and natural catastrophe events. These variables were also found to be key factors in the financial losses incurred by Santam as the results show a significant positive correlation between weather change-related events and weather-related insurance claims. This implies that the higher the frequency of weather-related catastrophes, the higher the number of weather-related claims. This outcome is similar to the previous studies which assessed the impact of climate change on weather-related damages and insurance claims.

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AI	**Artificial Intelligence**
CCRAF	**Climate Change Risk Assessment Framework**
CCRM	**Climate Change Risk Management**
COP27	**Conference of the Parties**
CSIR	**Council for Scientific and Industrial Research**
ERM	**Enterprise Risk Management**
ESG	**Environmental, Social and Governance**
IPCC	**Intergovernmental Panel on Climate Change**
IoT	**Internet of Things**
ISO	**International Organisation for Standardisation**
KZN	**KwaZulu Natal**
ML	**Machine Learning**
PA	**Paris Agreement**
SAIA	**South African Insurance Association**
SARB	**South African Reserve Bank**
SAWS	**South African Weather Service**
Stats SA	**Statistics South Africa**
TCFD	**Taskforce on Climate related Financial Disclosures**
UNFCCC	**United Nations Framework on Convention on Climate Change**
WMO	**World Meteorological Organization**

CHAPTER 1. INTRODUCTION

1.1 Introduction to the study

There is a wide innovation gap in mitigating the impact of weather-related disasters in the non-life insurance industry; this is more observable in incumbents such as Santam compared to younger firms such as Discovery Insure, which was launched in 2011 (Santam, n.d.; Discovery Integrated Report, 2018). This study explores how non-life insurance organisations in South Africa could reduce insured losses due to catastrophe claims by implementing climate change adaptation models using predictive analytics. Chapter 1.2 introduces the background and describes the context of this study. The research problem is discussed in Chapter 1.3, followed by the aim of the study (Chapter 1.4) and the research questions that will be used as a guide for the study (Chapter 1.5). The rationale and delimitations of the study in Chapters 1.6 and 1.7, respectively, followed by a brief introduction of the terms and concepts that were used in conceptualising this study (Chapter 1.8). The structure of this document is provided in Chapter 1.9.

1.2 Background and context of the study

The United Nations Framework Convention on Climate Change (UNFCCC) focuses on analysing the impacts of climate change in Africa and highlights the key roles that every stakeholder plays in addressing climate risk (UNFCCC, 2022). Climate change is a complex and evolving phenomenon that poses serious risks to the stability and quality of human society and global economy. The 2022 Intergovernmental Panel on Climate Change (IPCC) Working Group II Report confirms that natural disasters are becoming more intense and frequent owing to climate change, and there is an urgent need to transition to a low-carbon economy to reduce the impact of climate change (IPCC, 2022; Ziervogel et al., 2022).

The world is on course to reach 1.5 degrees Celsius of warming within the next two decades; this increase could happen quicker under a high-emissions and may lead to extreme weather conditions that will have devastating impact in the livelihoods, agriculture, water systems, and ecosystems (Odebiri et al., 2023; Liu et al., 2023). Every fraction of warming has dangerous and costly impacts. These studies also show that all regions are affected by the impacts of climate change, with enormous human and economic costs far outweighing the costs of action. One of the recommendations is to incorporate risk management and insurance-related development strategies to create development pathways that are resilient to climate change and disasters, both public and private sectors must participate in a larger social conversation about the insurance business in its entirety (IPCC, 2022; Ziervogel et al., 2022). According to the South African Reserve Bank (2022), the claims ratio for non-life insurers and reinsurers has increased from 60.7% in 2021 to 68.2% in 2022 and from 62.9% in 2021 to 75.3% in 2022, respectively. Insurers have cited a higher frequency and severity of drought, flooding, storms, and wildfires (South African Reserve Bank, 2022). Santam has been experiencing an increase in catastrophe claims since the early 2000s, largely driven by hail, floods, and wildfires (Santam, n.d.).

Over the past five years, South Africa has faced extreme weather events that have generated the most expensive losses, accounting for more than 60% of non-life insurance claims, and more than 30% of corporate insurance claims in South Africa are the result of losses due to flood damage (Phibbs, 2022). Non-life insurance claims have been increasing exponentially, because insurers are not adequately prepared for climate change adaptation (Phibbs, 2022). This was mainly due to the uncertain nature of these weather-related catastrophes. Based on studies by Frost et al. (2018) and Quiroz et al. (2023), the Knysna fires in June 2017 were the worst wildfire disasters in South African history.

The AON's Weather, Climate, and Catastrophe Insight reported a total economic loss of $343 billion in 2021, 96% of which was attributable to weather-related disasters (AON, 2021; Masters, 2022). As a result, 2021 was the third most expensive year on record (Masters, 2022). Although the number of major disaster events has declined since 2020, the number of losses has increased, highlighting the increased severity and expense of these events (AON, 2021; WMO, 2021). Only 38% of losses in 2021 had insurance coverage (AON, 2021).

President Cyril Ramaphosa of South Africa proclaimed a nationwide state of disaster in April 2022 because of the damage and loss caused by extreme weather-related catastrophes that hit several parts of the country, particularly the floods in the KZN province (Ramaphosa, 2022). According to the KZN provincial government, the estimated cost of the damage caused by floods in the KZN province alone was R17 billion (Ngobeni, 2022). This declaration enabled the government to allocate the resources necessary to provide relief in the affected regions

(Disaster Management Act, 2002). According to the Weather, Climate, and Catastrophe Insight report, South Africa and Australia recorded their costliest insurance claims in 2022 (AON, 2022). Additionally, 2022 had the fifth most expensive loss on record for insurers, as climate change continues to drive extreme weather records (AON, 2022).

This was also highlighted by Tavaziva Madzinga (Santam CEO), who described the KZN floods as the largest natural catastrophe Santam experienced in 105 years of its existence; Santam was expected to pay R4 billion in insurance claims (Santam, n.d.; Mabaso, 2022). This also shows that natural disasters can result in catastrophic losses to the insurance industry. For instance, Hurricane Katrina severely impacted the profitability of the National Flood Insurance Program (NFIP), as flood insurance pay outs have increased 20-folds since 1998 (Horn and Brown, 2018). These losses reflect the global trend of rising costs incurred by insurers owing to weather-related catastrophes (Bevere and Holzheu, 2021).

Existing climate change adaptation models should consider the increasing frequency and severity of disruptive natural disasters (White et al., 2020). Climate data serves as the foundation for insights that can help business leaders and analysts measure the rate and magnitude of climate change-related risks (Dessai and Sluijs, 2007; Christ et al., 2022). Additionally, climate data is necessary for climate change risk modelling; however, the availability of real-time satellite and radar data from the South African Weather Services (SAWS) is limited (Dessai and Sluijs, 2007; Ayob, 2019). These data limitations and inaccuracies invalidate the output of the artificial intelligence (AI) and machine learning (ML) predictive models (White et al., 2020). Climate change has contributed significantly to global damage to infrastructure, businesses, and agriculture (White et al., 2020; Bevere and Holzheu, 2021).

1.3 Research problem

The South African insurance industry is grappling with how to respond to the increasing effects of climate change (UNFCCC, 2022; Ziervogel et al., 2022). The 2022 IPCC Working Group II Report compiled the most recent data on the impacts, vulnerabilities, and adaptation to climate change as well as what this means for the establishment of climate-resilient communities (IPCC, 2022). This report focuses on knowledge and capacity building related to climate change, these include climate change literacy, climate finance as well as pathways for climate-resilient development (IPCC, 2022; Ziervogel et al., 2022).

Extreme weather events, such as floods, heatwaves, and droughts, have had an increasing negative impact on several countries including South Africa (UNFCCC, 2022; Meque et al., 2022). Natural catastrophes have increased in frequency and severity (Bevere and Holzheu, 2021). Consequently, there is increasing demand for action on climate change is being felt across all financial service providers, including the insurance industry. Regulators require insurers to embed climate-related risks within their risk management frameworks, and investors are increasingly considering Environmental, Social and Governance (ESG) principles in investment decisions (ClimateWise, 2021).

The natural catastrophe events such as damage to infrastructure, damage to businesses, environmental degradation and socioeconomic risks are likely to increase in future. This has resulted in an increase in insurance claims due to extreme weather events. In the past two years, Santam has experienced a difficult underwriting and claims environment due to unexpected adverse weather coupled with local and international factors that have emerged, such as Covid-19, which has resulted in a tough global economic climate (Santam, n.d.; Santam Integrated Report, 2022). The high volume of claims due to the KZN floods has further dampened the overall performance of the business (Santam Integrated Report, 2022). Thus, in June 2022, Santam recorded a lower net underwriting margin of 2.3% compared to 6.7% in June 2021 (Santam Integrated Report, 2022). This was far below the company's target range of 5%–10%, as the company had to dig into its reserves (Santam Integrated Report, 2022). Although re-insurance provided a protection measure for KZN floods, the company still experienced a net impact of more than R560 million (Santam Integrated Report, 2022). This natural catastrophe negatively impacted the company's net underwriting margin, economic capital coverage ratio as well as the headline earnings, showing a significant downward shift from 2021 to 2022 (Santam Integrated Report, 2022).

This raises the question of how short-term insurers can adopt and implement predictive modelling regarding climate change risk analytics as a loss-prevention strategy to mitigate future risks of climate change in the non-life insurance industry. According to Wagner (2022), the cost impact of weather-related catastrophes has put a spotlight on existing policy solutions as climate risks have become more frequent and disastrous compared to historical records.

Innovative insurance policies that involve the development of underwriting policies that cover emerging risks such as climate change risks and adopting the use of artificial intelligence or blockchain to automate underwriting, claims processing and risk management (White et al., 2020).

Various probabilistic and statistical methodologies have been applied to quantify changes in the likelihood of natural catastrophe events to rising global temperatures, for instance Botzen et al., 2019, Krikken et al., 2021, Meque et al., 2022, Smith et al. 2022 and Liu et al., 2023 have developed models to predict the likelihood of extreme weather conditions. Although these earlier studies provide valuable insights, there are some potential gaps that could be addressed. For instance, these studies have mainly focused on overseas countries. This is not representative of the climate change impact experienced by insurers in South Africa. Adapting these models to a South African context could help to better understand the overall climate change impacts in South Africa and help insurers in their decision-making processes regarding climate change adaptation. Some insurers cease to insure disaster-prone areas because of the disconnection between climate-change risks and insurance underwriting (Kunreuther and Michel-Kerjan, 2019).

Another potential gap is the reliance on country-specific data. While this data can be valuable, it is subject to potential biases and overgeneralisation. This could be a result of various aspects such as different regions in the country may be using different types of instruments to measure meteorological variables. The accuracy, calibration and maintenance of these instruments can vary leading to differences in the recorded data. These measurements can be affected due to weather stations being in different environments such as urban and rural areas. Additionally, using multiple data sources could help triangulate the findings and provide a more complete understanding of climate change adaptation. Incorporating other sources of data, such as historical records or on-the-ground observations, could provide a more comprehensive understanding of the relationship between climate change and natural catastrophe event insurance claims. Examining the potential cost of these impacts could inform how insurers structure their premiums as well as highlight the importance of integrating climate change in insurance risk management. This research aims to assess the relationship between weather-related events and the financial losses incurred by Santam due to increased weather-related claims with an additional focus on infrastructure and property damage claims.

1.4 Research purpose

This study seeks to explore how predictive analytics can be applied in insurance risk management to account for climate change-related losses in Santam, an organisation that is 105 years old - with limited development and adoption of AI and ML technologies (Santam, n.d.). Very little research has been conducted on climate change risk management in the insurance industry. This study will look at integrating multiple data sources and evaluating the potential climate change related risks that insurers carry. This includes assessing the impact of climate change-related events on weather-related insurance claims and how this relates to property and infrastructure damage. It will also examine how insurers can quantify potential risks using predictive analytics (quantitative risk models) to determine the financial losses incurred by insurers. This research will also investigate key internal and external factors that contribute to climate change risk assessment predictive analytics models using the proposed Climate Change Risk Assessment Framework (CCRAF). This will help better understand the relationship between climate change-related events and insurance losses.

The aim of the research is to determine whether predictive analytics be used to minimise the financial impact of weather-related events and claims in the insurance industry. This will be done by assessing the relationship between weather-related events and insurance claims; financial losses incurred by insurers, as well as how property damage insurance claims are related to weather-related events.

1.5 Research objectives

This research will be guided by the following questions:

1.5.1 Is there a relationship between weather-related events and weather insurance claims?

H_0: There is no relationship between climate change-related events and weather-related insurance claims.

H_a: There is a relationship between climate change-related events and weather-related insurance claims.

1.5.2 Is there a relationship between the financial losses incurred by insurers and weather-related events?

H_0: There is no relationship between the financial losses incurred by insurers and climate change-related events.

H_a: There is a relationship between the financial losses incurred by insurers and climate change-related events.

1.5.3 Has there been an increase in property damages as a result of weather-related events?

H_0: There has been no increase in property damages as a result of climate change-related events.

H_a: There has been an increase in property damages as a result of climate change-related events.

1.6 Rationale

The global trend of increasing weather-related catastrophes has pushed climate change adaptation to the forefront of organisations such as SAIA and COP27 (SAIA, 2022). The increasing costs incurred by insurance companies will result in solvency problems if the risk is not accurately calculated (SAIA, 2022). The research gap is that insurance models often underestimate the frequency and magnitude of weather-related catastrophes. There is also a lag in updating insurance premiums to correlate with the disastrous impacts of climate change experienced by policyholders (Portner et al., 2022; SAIA, 2022).

Santam has 22% market share in the South African non-life insurance industry, serving more than one million policyholders (Santam, n.d.; Santam Integrated Report, 2022). The KZN floods resulted in Santam paying more than R4 billion for claims (Santam, n.d.). Weather-related catastrophes are becoming increasingly frequent and severe (White et al., 2020). This provides an opportunity for Santam to evaluate climate change risks and mitigate future losses. This research will contribute to the development of a Climate Change Risk Analysis

Framework (CCRAF) for Santam (Smith et al., 2022). Evaluating and managing climate change risks are becoming increasingly crucial to support planning for climate change adaptation (Tonmoy et al., 2019; Smith et al., 2022). Failure to plan and manage future risks can negatively affect the insurer's bottom line (Tonmoy et al., 2019).

1.7 Delimitations of the study

This study focuses on Santam (a non-life insurer) and how climate change risks can be mitigated by adopting CCRAF and incorporating this into catastrophe modelling for organisational climate change adaptation. The scope of the research does not cover climate change policies or partnerships with the government or climate change institutions. This study focuses on the South African insurance industry. It will also examine insurance losses incurred by Santam over a period of two decades, from 2001 to 2022. The variables that will be used in this study will be identified from literature.

1.8 Definition of terms

The following definitions are based on the non-life insurance industry from the perspective of the organisation:

Short-term insurance: Short-term insurance, also known as temporary or non-life insurance, is designed to meet immediate and temporary needs by providing temporary coverage to individuals and businesses to protect themselves from specific risks and unexpected events. This allows policyholders to obtain insurance for a limited period of time without committing to long-term contracts. Short-term insurance policies are flexible, can be customised to meet specific requirements, and provide quick and targeted coverage when needed. These policies offer a wide range of coverage options across various assets, such as property and vehicles amongst others. According to the KPMG (2022) report, there are currently 34 non-life insurance companies in South Africa.

Climate change: refers to severe weather patterns and due to increased average temperatures globally (World Bank, n.d.; Jindrová and Pacáková, 2019). Quantitative assessment of such risks is crucial to adequately price insurance products and develop proactive interventions to mitigate financial losses (Jindrová and Pacáková, 2019). For insurers, the complexity of climate risks (due to the uncertainty of natural catastrophe events) eliminates the suitability of generic industry-focused approaches (Taszarek et al., 2021; Lepore et al., 2021).

Insurance risk management: Dessai and Sluijs (2007) define risk management as tools and processes that are put in place to measure and analyse and proactively mitigate risks. In the case of the short-term insurance industry, risk management techniques are used to estimate future financial losses using previous data on insured losses from unexpected events (White et al., 2020). For analysts and risk managers, these estimates are crucial because they serve as a foundation for determining and modifying the premiums for policies that cover these types of risks (Taszarek et al., 2021; Lepore et al., 2021). Current risk management strategies estimate premiums to cover financial risks using the available information (Cohen and Fischhendler, 2022). This study investigates the integration of predictive analytics into the insurance risk-management process using various data sources.

Predictive analytics: Predictive analytics is a subset of data analytics that employs statistical models and algorithms to examine historical data and identify patterns that can be used to forecast future events or actions (Provost and Fawcett, 2013). These statistical models aid in identifying patterns and trends in climate data to identify the factors and interconnected processes that drive climate change (Jindrová and Pacáková, 2019; Cohen and Fischhendler, 2022). The output of these predictive models informs and directs proactive actions to mitigate and adapt to the impacts of climate change (Cohen and Fischhendler, 2022). According to a study conducted by White et al. (2020), AI technologies can be adopted in various risk management use cases, such as risk assessment for underwriters, computer vision for remote sensing, and determination of flood danger in the agriculture industry. The successful application of these predictive models requires accurate and reliable projections of climate change risks, which require both historical and real-time data (White et al., 2020; Cohen and Fischhendler, 2022). This study seeks to identify relevant data (from internal and external sources) that can be used to train predictive statistical models.

Catastrophe modelling: is a risk management concept that involves the development of various computerised statistical models used to assess potential losses from natural hazards due to climate change (Botzen et al., 2019; Lepore et al., 2021). For instance, the Climate Change Risk Analysis Framework (CCRAF) is an analytical framework for predicting climate change events (Leggett et al., 2003; Stolpman, 2012). Catastrophe modelling also involves the assessment of atmospheric variables and climate data to aid in quantifying the impact of climate change and identifying factors that are highly likely to contribute to natural catastrophic events (Pacáková & Gogola, 2013; Hermans et al., 2021; Lepore et al., 2021). However, these models are usually trained based on historical observations of natural catastrophic events, which may reduce the prediction accuracy (Jindrová and Pacáková, 2019; Cohen and Fischhendler, 2022). Therefore, this study will explore predictive big data analytics using AI and ML to aid in improving the performance of natural catastrophe models (White et al., 2020).

1.9 Structure of the paper

Chapter 1 outlines the statement of purpose and provides the background and context of the study, the research problem, and the primary and sub questions that the study expounds on. This is followed by the rationale, delimitations and the definitions of the keywords used in the study. Chapter 2 provides a critical review of the literature. The literature review will identify research gaps and justify the rationale of the study as well as the theoretical framework that will be adopted in this study. This is followed by Chapter 3, which details the research methodology that will be followed to address the proposed research questions. This includes research approach, design, data collection, and analyses. The results of this study are presented in Chapter 4. This is followed by recommendations and conclusions in Chapters 5 and 6, respectively.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

This section explores the literature on how predictive analytics can be applied to insurance risk management, as well as the various climate change-related impacts in the short-term insurance industry. Historical studies were critically reviewed to identify research gaps and relevant conceptual frameworks that will be adopted in this study. The first part of this chapter provides the background context of the study, followed by an analysis of the existing literature and reflection on research gaps that need to be filled in the process of mitigating climate change risks in the insurance industry. This is followed by a critical review of the models to justify the undertaking of the theoretical framework.

2.1.1 Climate change-related events in South Africa

In the past five years, South Africa has experienced extreme weather events. These recent climate change related events included severe drought, heavy rainfall, flash floods and an earthquake (recently experienced in June 2023). For instance, in 2017 Knysna and surrounding areas were engulfed by fires – this resulted in over R7 billion in insurance claims. The 2018 drought led to the Cape Town being declared a disaster area due to severe water shortage – which led to the Western Cape province preparing for 'day zero'. This involved a mandated reduction of water usage as well as the implementation of desalination plants to increase the production of water. This increased the insurance losses due to fires. In 2019, KZN was hit by floods which resulted in over R1 billion in insurance claims. This was followed by tropical cyclone Eloise which caused calamitous flooding leading to property, infrastructure and business insurance losses which saw Santam paying out R4.4 billion in claims. Santam paid out a record of R14 billion in insurance claims in the first half of 2022 (Santam, n.d.). According to the 2022 World Economic Forum Global Risks Perception Survey, extreme weather' is the second most severe risk on a global scale during the next ten years (World Economic Forum, 2022). South Africa has been hit hard by this forecast, with severe rains causing flooding and extensive property damage in recent weeks in huge portions of the country. Climate change events have a direct impact on the short-term insurance industry. The insurance costs incurred due to damages caused by extreme weather events such as flooding, heavy rainfalls, drought, and hailstorms may adversely impact the overall company financial performance leading to further risks manifesting.

2.1.2 Weather related insurance claims

According to KPMG's latest South African Insurance Industry Survey 2022, weather-related disaster losses surpassed all previous records for the 2011-20 period, totalling US$135 billion, the highest figure ever recorded (KPMG, 2022). The new decade began with 2021 being the world's second most expensive year for insurers. The claims experience over the last few years has demonstrated that South Africa is not immune to disaster events, and that changing weather patterns are a fact. Drought, flooding, storms, and wildfires seemed to be becoming more frequent and severe in South Africa. Net claims incurred in the non-life industry climbed by 11.5%, while net earned premiums increased by 4.7% (South African Reserve Bank, 2022). As a result, the non-life industry bore the burden of many of these claims, contributing to the worsening of the net claims incurred ratio.

2.1.3 Predictive Analytics

Predictive analytics is a subset of data analysis that employs statistical models and ML algorithms to forecast future events based on historical data (Provost and Fawcett, 2013). This entails identifying trends and generating insights by extracting significant patterns and correlations from a multitude of datasets. It is a multistep process that includes data collection, pre-processing, model selection, training, and evaluation (Provost and Fawcett, 2013). The objective is to develop models that are sufficiently accurate and dependable to predict outcomes with a high degree of confidence. Predictive analytics are used in a variety of industries, including insurance, marketing, healthcare, and manufacturing. Predictive models can help businesses optimise their operations, identify risks, detect abnormalities, improve decision making, and increase overall efficiency (Provost and Fawcett, 2013).

2.1.4 Adaptation of insurance risk management considering climate change

Risk management in the insurance industry has evolved from not only focusing on policy frameworks and legislation but also incorporating statistical impact models and scenario analysis of the potential risks posed by climate change (Hightower, 2012; Fronzek et al., 2022). Studies on this topic are still premature because the rate and magnitude of natural catastrophes are challenging to predict with certainty (Dessai et al., 2022; Cohen and Fischhendler, 2022).

This process involves the assessment and quantification of potential financial losses from claims submitted by policyholders (Jindrová and Pacáková, 2019). It also explores the development of scenario analysis and statistical modelling to determine the probability of events to quantify the value of premiums as well as the insurance risk that the company has to hold or distribute to reinsurers (Pacáková and Gogola, 2013; Ioannides, 2020). In the past decade, the concept of risk management in insurance has evolved to consider the financial impact of natural catastrophes on insurance portfolios (Dionne, 2013). The purpose of risk management is to minimise the company's exposure to risk, maximise reserves and improve the capital structure by reducing costs associated with various risks (Cohen and Fischhendler, 2022). Insurers require an integrated risk management strategy with decisions that enable proactive interventions (Cohen and Fischhendler, 2022).

A study conducted by Lyubchich et al. (2019) shows that in recent years, localised natural catastrophes have caused more financial losses to insurers than other types of claims. The method of execution was a time-series analysis using secondary data (weather and insurance claim records) and weather-related damages (Lyubchich et al., 2019). However, this study has limitations because it used historical data to assess and analyse climate change risks (Lyubchich et al., 2019). The results of the study show that this approach underestimates the likelihood of risk, insurance premiums underwritten for natural catastrophes as well as potential financial losses (Lyubchich et al., 2019). The increasing insurance claims are largely due to climate change events and insurers globally are facing increased climate change effects (World Meteorological Organization, 2021; World Economic Forum, 2022). The Global Risks Report produced by the World Economic Forum identified climate action failure, extreme weather impacts and biodiversity loss as the top three risks for insurers (World Economic Forum, 2022). This study was conducted through a survey to ascertain the perceptions of climate change experts and leaders in the insurance industry (World Economic Forum, 2022).

Climate change is defined as a significant shift in average weather conditions, such as changes in weather patterns, rising temperatures, and a high frequency of natural catastrophes

(Hightower, 2012). Climate change has led to several transitions, such as ESG ratings, carbon pricing, enforced regulation and policy mandates, net zero, and changing customer behaviour and stakeholder preferences (World Economic Forum, 2022).

Regulators and policymakers expect insurers to integrate the assessment of climate risks as part of their ERM process to meet the required ESG scores (World Economic Forum, 2022). This includes adopting scenario analysis to predict potential financial losses under various climate change events (Doff, 2015). According to Doff (2015), scenario analysis explores possible desired outcomes by evaluating possible future uncertainties, which results in a number of proactive interventions that a company can act on to reduce their overall risk and exposure. The main limitation of scenario analysis is that it uses historical data trends and past observations; thus, it does not reduce uncertainty and has limited predictive capabilities (Doff, 2015).

Phibbs (2022) categorises the impact of climate change into physical and transition risks. Physical risks are caused by extreme weather events and changing average weather conditions, whereas transition risks include policies, legislation, technologies, and consumer markets (Phibbs, 2022). Taszarek et al. (2021) and Lepore et al. (2021) identified key natural catastrophe events in Southern African region for insurers to lookout for, these include: severe storms and hail, flash floods, wildfires, drought and tropical cyclones. These are acute extreme weather events attributed to climate change (Phibbs, 2022).

2.1.5 Development and adoption of predictive analytics in insurance risk management

In recent years, insurers have developed various statistical risk management models to account for the potential impacts of climate change (Jindrová and Pacáková, 2019). Cohen and Fischhendler (2022) argue that there is a lack of studies that incorporate natural disasters in the insurance risk assessment framework. Their study focuses on the impact of climate change on the agricultural sector. Gatzert et al. (2020) and Fronzek et al. (2022) suggest that the lack of data, computational capacity constraints and a limited selection of climate projection models are some of the challenging factors that contribute to the lack of implementation and adoption of statistical climate change impact models. These limiting factors result in inaccurate and unreliable model outputs (Esfandiari et al., 2020; Fronzek et al., 2022).

Current statistical natural catastrophe models are trained on historical climate data, which depict less frequent natural catastrophe events with minimal devastating impacts (Fronzek et al., 2022). This is a concern for insurance companies because these models underestimate the frequency and magnitude of the impact thus resulting in higher financial losses for the companies (Lyubchich et al., 2019; Fronzek et al., 2022).

2.2 Empirical review of literature

Insurance risk management mitigates financial losses by enhancing the underwriting process to determine appropriate insurance premiums and unforeseen catastrophic events (White et al., 2020; Oluwaleye et al., 2022). In the past, insurance companies assessed risks for pricing and hedging reasons by relying on the effectiveness of the sector's present risk management frameworks as well as statistical modelling of technical regulatory frameworks (White et al., 2020). Several natural catastrophe models have been developed in the last five years in line with the International Organisation for Standardisation (ISO) standard 14091 which speaks to climate change adaptation (International Organisation for Standardisation, 2021). These standards also include guiding principles for Climate Change Risk Management (CCRM) to assess and quantify the impact (International Organisation for Standardisation, 2021).

The CCRAF is a novel tool that combines probabilistic techniques from the fields of population, energy, and economics with empirical data and probabilistic outputs from climate and impact models (Smith et al., 2022). The primary goal of the CCRAF is to evaluate the risks posed by global climate change and offer suggestions for effective policies that can manage these risks (Legget et al., 2003; Stolpman, 2012; Smith et al., 2022). Climate change adaptation models can be used to mitigate the consequences of climate change (Legget et al., 2003).

Smith et al. (2022) developed a framework for the evaluation of CCRM approaches. Although their study was based in the United Kingdom, the guiding principles developed can also be adopted internationally (Smith et al., 2022). The first key principle is analysing the context and key objectives of risk assessment; it also defines the key resources, audience as well as key stakeholders (Smith et al., 2022). The second element is identifying the steps to scope and analyse the potential climate change risks depending on the location (Smith et al., 2022). This is followed by a critical analysis and characterisation of the nature of the risk (Smith et al., 2022). The fourth guiding principle measures what is valued by the stakeholders involved, such as insurers, customers, or government bodies (Smith et al., 2022). The processing phase refers to the alignment of steps to prepare for the implementation of CCRAF (Stolpman, 2012; Smith et al., 2022). This is followed by the participation phase, which identifies the key stakeholders to execute CCRAF (Stolpman, 2012; Smith et al., 2022). Finally, risk communication refers to the process of exchanging information between risk assessors and risk managers to help users make informed decisions regarding risk management (Smith et al., 2022).

The CCRAF uses a variety of natural catastrophe models to promote climate change adaptation. For instance, the Oasis Loss Modelling Framework (Oasis LMF) platform was employed to develop new catastrophe risk models for flooding in the Philippines and cyclones in Bangladesh (Oasis, 2022). Punge et al. (2021) utilised a multivariate stochastic modelling approach based on the Willis European Hail Model, which is a European-based stochastic hail prediction model. Another approach is the ERA5 which is a global observation-based model that represents historical weather observations based on the European Center for Medium-Range Weather Forecasting (ECMWF) (Taszarek et al., 2021; Smith et al., 2022). Other alternative natural catastrophe modelling approaches include the Excess Heat Factor and the 90th percentile of the minimum daily temperature. A study conducted by Meque et al. (2022) used Principal Component Analysis (PCA), a statistical technique, to identify the dominant climatic factors for modelling the different types of heatwave behaviour caused by large-scale climate drivers. However, current natural catastrophe models do not incorporate real-time climate data that uses big data and machine learning models in the risk assessment of natural catastrophic events (Lyubchich et al., 2019; White et al., 2020; Fronzek et al., 2022; Trivedi, 2022). Climate change exacerbates weather hazards, and predictive analytics can aid in the assessment and quantification of disastrous events and prepare insurers to handle these risks (Lyubchich et al., 2019; Trivedi, 2022).

The results of these studies add to the knowledge of the variability and forecasting of climate change risks and have the possibility of being adopted by insurers to be incorporated in the underwriting processes (Punge et al., 2021; Meque et al., 2022; Oasis, 2022; Smith et al., 2022). However, the underlying research gap that surfaces across is that there is no concrete framework that can proactively quantify the impact of climate change and its contribution to the loss incurred by insurers; possible climate change adaptation responses mitigate costs from insured losses. There is also a gap between the role of regulatory bodies, political structures, and the academic community in collaborating to respond to climate change risks.

It is important for South African insurers to engage in the implementation of CCRM because this aids in contextualising climate change risks, including mitigation and adaptation, within the complex environment of the nation. The creation of the Presidential Climate Commission demonstrates that efforts to combat climate change are now important in the decisions and actions that are pertinent to the economy at the national level as part of the nation's Just Transition (Presidential Climate Commission, n.d.).

2.3 Conclusion of Literature Review

Cohen and Fischhendler (2022) suggest that natural catastrophe models are limited because they rely on past disaster information to estimate potential catastrophe characteristics and associated losses. To overcome this problem, it is necessary to use ML and AI statistical models, which can handle large amounts of real-time data. In the past, research on insurance risk management concentrated mainly on policy and regulatory frameworks for dealing with climate change risks. However, this study aims to enhance the methodology used to describe natural disasters more accurately. Specifically, the stochastic element of the model will model and sample distributions for relevant event properties separately rather than simply resampling past events to forecast future hazards. The gaps identified above highlight the relevance of researching the integration of predictive analytics into insurance risk-management processes and how this could be made possible by the CCRAF.

CHAPTER 3. RESEARCH FRAMEWORK

3.1 Introduction

Chapter 1.4 details the five questions this study intends to answer using the proposed research framework. These questions address how Santam can adopt and integrate a climate change risk assessment framework, predictive analytics, AI, and the use of big data to innovate insurance risk processes in the organisation, and how these could ultimately reduce potential losses due to natural catastrophe events through collaboration with relevant stakeholders such as regulators, government, customers, and academics. The literature review in Chapter 2 identifies the CCRM framework to be used as the basis of the study, as well as the main conceptual framework relevant to climate change adaptation. This chapter details how the concepts of the CCRM framework are used to inform the theory underpinning this study. This section also explores the types of variables used in the study and how they are related to the target variable. These are the main factors that influence climate change adaptation and insurers' capability to respond to climate change impacts. The chapter concludes by providing a summary of the literature review and the theoretical framework.

3.2 Theoretical Underpinnings

Insurance losses can be attributed to poor product design, improper underwriting processes, incorrect price setting, maladministration of claims, or insufficiently structured reinsurance, which cause an increase in losses for insurance companies (Trivedi, 2022). In addition to these insurance risks, climate change risks have also emerged, resulting in further losses for insurers. The projected consequences of climate change pose a significant risk to both human populations and ecosystems, with severe and widespread losses and damage anticipated worldwide (IPCC, 2022). According to the 2022 IPCC Working Group II report, the frequent occurrence of cascading extreme climate events results in higher levels of damage and losses (IPCC, 2022).

Due to the much higher number of unexpected claims brought on by these natural catastrophes, insurance companies have suffered greater financial losses. Recent studies have not developed a comprehensive framework to evaluate such complicated climate change risks (Simpson et al., 2021; Smith et al., 2022; Cohen and Fischhendler, 2022; Trivedi, 2022).

Empirical evidence highlights the intricacy of the interplay between various factors that contribute to the risk of climate change and how these risks can accumulate or have a cascading effect (Simpson et al., 2021). It is imperative that insurers enhance climate change risk assessment methodologies to facilitate better-informed decision-making processes to mitigate the adverse effects of climate change. Due to increasing losses, insurers are compelled to address the impact of the changing climate on their underwriting, pricing, and investment decisions, as well as their financial performance, without any further delay or avoidance.

The escalation of losses associated with climate-related risks, whether direct or indirect, raises concerns regarding the adequacy of insurers' efforts to anticipate and control their exposure to underwriting and investment portfolios as well as their financial stability (Trivedi, 2022). This study aims to incorporate predictive analytics into the CCRM framework as it connects the physical and socioeconomic determinants of climate change risk and attempts to cross sectoral and geographical barriers. This emphasis on interconnections among diverse risks across various industries and geographical areas is crucial because insurers must manage them regardless of the level of quantitative analysis available to guide decision making. The severity of each risk and the overall risk landscape may be overestimated if each risk is evaluated separately (Cohen and Fischhendler, 2022).

3.2.1 Climate Change Risk Assessment Framework

Climate change risk assessment frameworks have been developed to analyse and quantify the risks associated with climate change impacts. Simpson et al. (2021) presents a comprehensive framework for assessing complex climate change risks. This study emphasises the integration of physical climate hazards, exposure, vulnerability, and adaptive capacity across different sectors. A study conducted by van Vuuren et al. (2011) highlighted the importance of considering systemic interactions and uncertainties in risk analysis by proposing a framework that integrates climate change adaptation and mitigation strategies within a multiscale risk assessment framework. The study also considered the interactions between land-use change, greenhouse gas emissions, and climate change impacts in risk assessments (van Vuuren et al., 2011). Various studies have been conducted in the United Kingdom and United States for vulnerability assessment frameworks for climate change impacts by implementing climate projections, vulnerability analyses, and potential impacts on various sectors to assess climate-related risks. The framework provides insights into sector-specific risks and helps in the prioritisation of adaptation strategies (Füssel and Klein, 2006; Lowe et al., 2009).

Risk theory is used to assess threats, vulnerabilities, and potential effects and is the theoretical foundation of climate change risk assessment (Ranger and Surminski, 2014). It incorporates both physical and socioeconomic components and includes predictive analytics to determine the likelihood of climate-related events and to analyse the cascading impacts, uncertainties, and unintended consequences of climate change. Multiple interconnections and feedback loops characterise complex climate change systems (Simpson et al., 2021).

The concept of climate change adaptation encompasses techniques used to lessen susceptibility and improve an organisation's ability to withstand and recover from climate-related consequences (Simpson et al., 2021; IPCC, 2022). The ability of an organisation to absorb disturbances, adapt, and rearrange in response to shifting situations is emphasised by the concept of resilience (Simpson et al., 2021; IPCC, 2022). This requires a scientific understanding of climate systems, including the physical mechanisms causing climate change, past climate data, and future climate projections, which is the foundation of climate change risk assessment. Climate simulations and models are essential for estimating and forecasting the effects of climate change (Smith et al., 2022). Frameworks for integrated assessments consider a variety of climate change risks, including those related to the environment, the economy, society, and government. They seek to document the intricate relationships and trade-offs between many sectors and stakeholders, enabling a thorough assessment of the effects of and solutions to climate change (Simpson et al., 2021).

The assessment of the risks posed by climate change considers the uncertainty surrounding future climatic estimates, socioeconomic trends, and policy choices. Therefore, decision makers can make appropriate plans by using scenario analysis to evaluate a variety of probable adaptation strategies and their associated risks. These theoretical foundations serve as the basis for the creation and use of techniques, models, and instruments for the evaluation of climate change risk. They also promote the identification of adaptation options, support decision-making processes, and aid in constructing resilience to climate change effects.

A comprehensive CCRM framework is important for the successful implementation of a risk management plan (Simpson et al., 2021; Taszarek et al., 2021; Smith et al., 2022; Trivedi, 2022). In the short-term insurance sector, accurately assessing and determining the likelihood and severity of potential losses is challenging. For instance, estimating the probability of a building catching fire is more challenging than calculating the value of a building that has been destroyed in a fire. One approach is to determine using previously recorded information about similar instances. Therefore, gathering preliminary data is the most likely way to evaluate the risk. Consequently, insurers must gather essential information from various relevant data sources. The following have been identified as the main components of the climate change risk assessment framework, according to studies conducted by (Füssel and Klein, 2006; Lowe et al., 2009; Simpson et al., 2021; Smith et al., 2022; Cohen and Fischhendler, 2022).

3.2.2 Weather-related events

This component involves identifying and characterising climate-related events relevant to the region or system being assessed (Füssel and Klein, 2006). These include heat waves, storms, flooding, sea-level rise, droughts, and other changes in weather patterns. From a short-term insurance perspective, these events have the potential to damage or destroy property, vehicles, and other physical assets. It is crucial to recognise and comprehend these events to evaluate the potential risks and vulnerabilities related to climate change. Systematic identification and characterization of climate-related events are key steps in the risk assessment process for climate change (Simpson et al., 2021). In order to identify the hazardous threats particular to the area under evaluation, relevant data, scientific research, and climatic projections must be gathered and analysed to comprehend anticipated future changes in hazard incidence and intensity, it may also include evaluating historical data, climate models, and professional knowledge.

3.2.3 Exposure Assessment

The exposure assessment component focuses on understanding the extent to which the assets of interest are exposed to the identified climate hazards, and how this contributes to the financial losses incurred by insurers (Simpson et al., 2021). It involves quantifying the spatial, temporal, and financial dimensions of exposure and assessing the vulnerability of exposed elements (Simpson et al., 2021). Financial exposure analysis is the process of evaluating an organisation’s potential financial risks and vulnerabilities. It involves assessing the potential impact of various factors and events on the financial health and stability of an organisation. This analysis considers various factors, including climate change risks, market volatility, economic conditions, regulatory changes, and operational risks, among others.

Spatial exposure involves mapping and locating regions exposed to climate-related risks (Trivedi, 2022). Based on historical data, climate models and projections - this process involves identifying areas that are vulnerable to natural catastrophes. Temporal exposure is necessary to understand the time, frequency, and duration of climate-related risks in order to evaluate prospective changes in hazard occurrence and intensity over time, as well as in both current and future climatic scenarios (Trivedi, 2022).

It is important to implement sector-specific exposure to determine the vulnerability of specific industries to the risks associated with climate change (IPCC, 2022). Analysing the exposure to important ecosystems, human settlements, agriculture, water resources, and other vital sectors is one way to do this (Cutter et al., 2008). Understanding the distribution and characteristics of populations that are at risk, as well as information about their socioeconomic situation, access to resources, and ability to deal with and adapt to climate-related risks, are all part of this (IPCC, 2022).

Various data sources and methodologies, such as geographic information systems, remote sensing, climate models, and socioeconomic data are used in exposure assessments. To quantify and illustrate exposure levels, exposure assessment models combine data on hazard distribution, physical infrastructure, land use, population density, and other relevant characteristics. The results of the exposure assessment support the identification of vulnerable locations or assets and provide information on which to base risk management and adaptation plans (Cutter et al., 2008).

3.2.4 Vulnerability Assessment

Vulnerability assessments evaluate the sensitivity and adaptive capacity of exposed assets to the identified climate hazards (Hinkel, 2011; Simpson et al., 2021). It considers the characteristics, strengths, and weaknesses of a system, including its physical, ecological, social, and economic dimensions. An assessment of physical vulnerability examines how vulnerable infrastructure, natural systems, and physical assets are related to climate-related risks (Simpson et al., 2021). It considers factors such as structural integrity, risk exposure, and probability of harm or disturbance.

Understanding the susceptibility of ecosystems and biodiversity to the effects of climate change is the main goal of an ecological vulnerability assessment (IPCC, 2022). Social vulnerability assessments examine the socioeconomic elements that influence how sensitive and adaptable human populations are related to the effects of climate change. The ability of institutions, organisations, and governance systems to respond to the effects of climate change is the subject of institutional vulnerability assessment (IPCC, 2022).

When assessing vulnerabilities, both qualitative and quantitative techniques are frequently used, and information from a variety of sources, including surveys, interviews, socioeconomic indicators, and specialised knowledge, is included (Hinkel, 2011; Simpson et al., 2021). It seeks to pinpoint the primary causes of vulnerability, comprehend how they are connected, and gauge the overall degree of risk for a particular system or group of assets. The results of vulnerability assessment provide information on particular regions or components that are most sensitive to the effects of climate change (Hinkel, 2011; Simpson et al., 2021). They support the development of plans to increase resilience and decrease vulnerability as well as prioritise adaptation activities.

3.2.5 Impact Assessment

This component examines the potential impacts of climate hazards on exposed assets. It involves assessing both direct and indirect impacts such as physical damage, economic losses, disruptions to ecosystems, and social consequences (Simpson et al., 2021; IPCC, 2022). The impacts of climate change include physical, ecological, and socioeconomic impacts. Physical impact assessments examine how climate-related risks directly affect physical resources, infrastructure, and ecosystems. These impact models estimate the degree of physical harm, loss, or degradation caused by floods, storms, sea-level rise, or extreme temperatures (Simpson et al., 2021; Trivedi, 2022). A socioeconomic impact analysis examines how climate change affects people, communities, and various economic sectors. It considers elements such as variations in agricultural output, water accessibility, human health, livelihoods, infrastructure, and financial losses (Simpson et al., 2021; Trivedi, 2022; IPCC, 2022).

Impact assessments consider the links and cascading consequences of climate change across several sectors. It examines the likelihood of unintended consequences, such as the ripple effects of changes in one sector on another or the overall economy (Simpson et al., 2021). Integrating and interpreting data from many sources, such as scientific research, models, observations, and expert knowledge, is a key component of an impact assessment (Simpson et al., 2021). Quantitative techniques, such as economic valuation, cost-benefit analysis, and impact modelling, are frequently used to estimate the scope and importance of impacts (Simpson et al., 2021). The outcome of the impact assessments aids in comprehending the effects on various industries, identifying vulnerable regions, prioritizing adaptation strategies, and guiding decision-making processes.

3.2.6 Risk analysis using Predictive Analytics

Risk analysis includes information from risk identification, exposure, vulnerability, and impact evaluations to qualitatively evaluate possible current and future risks (IPCC, 2022). This can consist of calculating the probability of specific dangers occurring within a set timeframe, while considering historical data and climate models. Risk matrices or other tools of a similar nature are widely used to categorize and rate hazards (Trivedi, 2022). A risk matrix incorporates the likelihood and magnitude of risks to calculate the risk associated with distinct situations (Trivedi, 2022). This makes it easier to identify high-risk areas or areas that require immediate intervention.

This study proposes that predictive analytics should be included climate change risk assessment. Identifying uncertainties in climate change data, models, forecasts, and assumptions used in the evaluation are key components of predictive analytics. In addition, the range of potential outcomes and their accompanying confidence levels can be measured and reported using predictive analytics. Risk analysis can be performed in several ways, including quantitative studies using statistical models, probabilistic methodologies, and qualitative evaluations (Ranger and Surminski, 2014; Smith et al., 2022). It should be noted that the approaches selected depend on the data and resources at hand as well as the precise objectives of the risk assessment (Cohen and Fischhendler, 2022). The outcomes of the risk analysis provided insights into the nature and distribution of hazards associated with climate change effects. Risk analysis incorporates data from the assessment of hazards, exposure, vulnerability, and impact to evaluate the degree of risk associated with climate change quantitatively or qualitatively (Ranger and Surminski, 2014; Smith et al., 2022).

3.2.7 Climate Change Adaptation Measures

All the above-mentioned factors are interconnected and iterative, allowing for an ongoing process of assessment, refinement, and adaptation as new information becomes available or circumstances change. The framework helps understand the risks posed by climate change, thus informing decision-making processes and facilitating the development of effective adaptation and resilience strategies (which are the target variables of the study). The outcome of the risk assessments and analyses provides decision-makers with actionable information to support informed decisions and policymaking for effective climate change adaptation. The decision-making process focuses on identifying and evaluating various adaptation strategies to reduce vulnerability and enhance resilience to climate change. This involves assessing the feasibility, effectiveness, costs, and benefits of different adaptation measures.

The proposed conceptual framework aims to explore how predictive analytics can be applied to assess the impact of climate change on the short-term insurance industry, particularly focusing on Santam. Figure 1 below illustrates the proposed conceptual framework, which will be used as the basis for this study. It involves the identification of climate change-related events and how these influence the trends in property damages, weather-related insurance claims, and the financial losses incurred by insurers. The predictive analytics are based on the CCRAF, where policy regulations and the adaptive capacity of the organisation are considered to be moderating variables. The outcome of the framework is the adaptation benefits of implementing climate change-related risk reduction measures.

This conceptual framework incorporates literature from various studies including Füssel and Klein (2006), Lowe et al. (2009), van Vuuren et al. (2011), Lyubchich et al. (2019), White et al. (2020), Simpson et al. (2021), Punge et al. (2021), Cohen and Fischhendler (2022), Fronzek et al. (2022), Meque et al. (2022) and Smith et al. (2022).

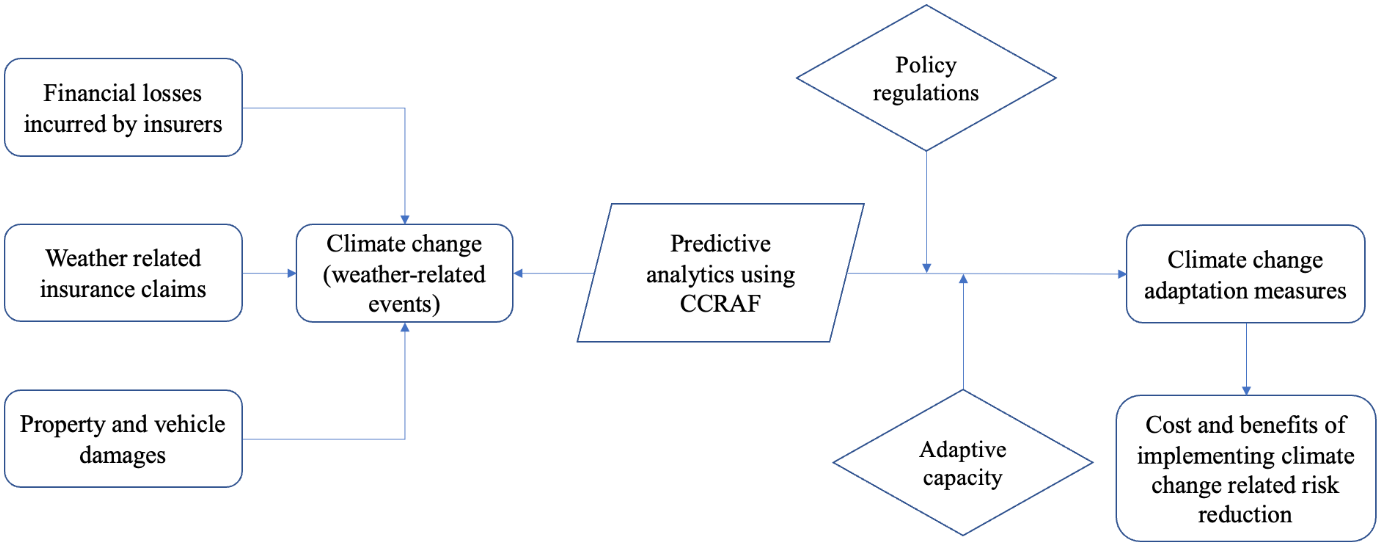


Figure 3.2-1: Conceptual framework

CHAPTER 4. RESEARCH METHODOLOGY

This study intends to explore the implementation of the multivariate regression analysis underpinned by the Climate Change Risk Assessment Framework in the insurance industry by answering the research questions specified in Chapter 1.5. The remainder of this chapter is structured as follows. Chapter 4.1 outlines the research approach that will be undertaken in this study. Chapter 4.2 identifies the research paradigm in line with the research objectives as well as the context of the study. The research design is discussed in Chapter 4.3, data collection in Chapter 4.4 as well as the data analysis (Chapter 4.5) which describes the reliability and validity measures used to determine the credibility of the study; this section also includes the ethical considerations that will be upheld during the study.

4.1 Research Approach

There are three main research approaches: quantitative, qualitative, and mixed methods. This study will use the quantitative research approach. This type of approach involves collecting and analysing numerical data to investigate the relationships between variables and identify trends (Creswell and Creswell, 2018). Data can be collected using various methods, such as surveys, experiments, or analysis of existing data. Earlier studies in climate change research employed quantitative methods to analyse historical numerical data and examine relationships between variables, for example, in a study conducted by Botzen et al. (2019) statistical analysis techniques were used to determine the relationship between temperature and hailstorm damage. Additionally, studies conducted by Cohen and Fischhendler (2022), Fronzek et al. (2022), Meque et al. (2022) and Smith et al. (2022) used statistical analysis, modelling and numerical simulations to assess climate change impacts, vulnerability, and adaptation. However, these studies were conducted in countries such as the United States of America, the United Kingdom, Israel, and the Netherlands, outside the context of South Africa and the insurance industry. This study will examine existing datasets that consist of longitudinal data related to weather-related insurance claims over time and climate change events that have been recorded in South Africa. This will also include various data sources that can be analysed to extract pertinent numerical data. The quantitative approach was chosen because the data that will be gathered will assist in hypothesis testing and explain the nature of the relationships between the variables used in the CCRAF to assess the impact of climate change-related events on insurance risk management in South Africa.

4.2 Research Paradigm

The positivist paradigm supports quantitative research methods, emphasizing objectivity, quantifiability, and the use of rigorous scientific methods to study and explain social phenomena (Khaldi, 2017). The positivist paradigm is rooted in the belief that knowledge can be obtained through the systematic observation, measurement, and analysis of observable phenomena (Rehman and Alharthi, 2016).

The positivist paradigm was chosen based on the nature of the research questions, as this study explores the impact of climate change on insurance risk management in South Africa. This study involves hypothesis testing and the investigation of relationships between various variables using quantitative data. The positivist paradigm was chosen because it seeks to generate findings that can be generalised and applied across different contexts. It also emphasizes replicability to verify the reliability and validity of the measures applied in the study and to establish cause-and-effect relationships (Rehman and Alharthi, 2016; Khaldi, 2017). The positivist paradigm assumes an objective reality that can be understood and measured through empirical observations (Khaldi, 2017).

4.3 Research Design

According to Myers et al. (2012), research design refers to a framework that guides data collection and analysis. This framework encompasses research objectives, data collection methods, variables and measures, data analysis techniques as well as the timeframe and scope of the study (Bryman, 2012; Myers et al., 2012). The case study design will be used for this research. This study follows the extensive analysis of the South African insurance industry with a particular focus on Santam. This study will consider the period between 2021 and 2022. This period was chosen because it is suitable for a time series analysis – a longitudinal study of climate change related events which have been recorded across a decade. This will assist in determining how predictive analytics can be applied in insurance risk management, in the context of the South African insurance sector, considering the impact of climate change.

4.4 Data Collection

Data collection methods, such as primary and secondary data techniques, are essential components of the research design (Sekaran and Bougie, 2016). Primary data collection methods involve gathering information from original sources (Sekaran and Bougie, 2016). This study will focus on secondary data collection. This process involves identifying published and unpublished work from secondary data sources based on the Climate Change Risk Assessment Framework in the South African non-life insurance industry. Secondary data sources consist of data points gathered by others for purposes other than the current study, including reports, publications as well as data and information available from websites.

This will be a longitudinal study using secondary data such as the localised climate data from the South African Weather Services, historical South African non-life insurance claims data, disaster risk assessments and climate change vulnerability reports from IPCC, World Bank (Climate Change Knowledge Portal) as well as the South African National Disaster Management Centre reports. The nature and significance of secondary data should be thoroughly reviewed before it is used, particularly for variables such as data timeliness, correctness, and relevance. Secondary data sources must be scrutinised to ensure that the collected data is current and relevant to the research objectives at hand. Cross-referencing and triangulation of multiple data sources is necessary to increase the accuracy of the data and reduce potential bias to ensure accurate and meaningful results during the stage of data analysis and interpretation of the results.

The remainder of this section documents the procedures and techniques employed in the data collection, population, and sampling design, as well as the research instruments used in the study. The population and sample size (Chapter 4.4.1). The sampling technique is discussed in Chapter 4.4.2 followed by the research instruments Chapter 4.4.3.

4.4.1 Population and Sample

Cohen et al. (2018) defines the target population as the larger group to which the researcher wants to generalise the findings of the study. It refers to the entire group of individuals, objects, or observations that meet certain criteria and are of interest to researchers. A research sample refers to a subset of individuals, objects, or observations selected from a larger population to participate in a study (Cohen et al., 2018). A sample is a representative subset of the population, and the data collected from the sample are used to make inferences and generalisations regarding the population as a whole. This study is limited to the insurance industry in South Africa, with a focus on Santam, a non-life insurer. This study explores how non-life insurance companies in South Africa are impacted by climate change and how they could reduce potential insurance losses through climate change adaptation frameworks.

4.4.2 Sampling Design

Cohen et al. (2018) defines sampling as the selection of a subset of a population for research purposes. Bryman (2012) distinguished between two types of sampling methods: probability sampling and non-probability sampling. For quantitative research, simple random sampling, stratified sampling, cluster sampling, systematic sampling, purposive sampling, convenience sampling, and snowball sampling are all used (Bryman, 2012). This study only looks at South Africa with the objective of understanding the impact of climate change-related risks in the insurance industry and how the CCRAF can be adopted by insurers to achieve climate change adaptation. The time series data that will be gathered span from 2011 to 2022. This data will be aggregated and compared on a yearly basis.

4.4.3 Procedure for Data Collection & Research Instruments

This study makes use of secondary data. The data collection process will be divided into two parts: insurance data and climate change risk events data. The following secondary data sources will be used to collect data points related to insurance:

- South African Insurance Association to obtain short-term insurance industry reports, statistics, and publications on various aspects of insurance including market trends, claims data, and regulatory information. This will also include economic and financial data, reports, and publications that offer insights into the insurance industry's performance, macroeconomic factors and regulatory environment.

- Santam’s annual reports, financial statements, market share, claims and product offerings.
- Insurance industry-specific publications and reports that focus on the South African insurance market from consulting firms such as Deloitte and PwC.

Additionally, the following secondary data sources will be used to collect datasets related to climate variables, climate models and impact assessments: Intergovernmental Panel on Climate Change, and United Nations Environment Programme as well as online databases from the South African Weather Services and National Disaster Management Centre.

The data collected from the above-mentioned secondary data sources will be accessed via their respective websites and the data will be transferred and stored in a password-protected personal computer. The data will be exported into a Microsoft Excel document where it will be cleaned and structured in preparation for import into Python version 3.6.4 where the data analysis process will be executed.

4.5 Data Analysis

This section discusses the platform and statistical techniques that will be employed in the analyses of the secondary data that has been collected, collated, and cleaned by the researcher. Data analysis typically follows the data collection process, whereby statistical analysis techniques are used to investigate underlying relationships to extract meaningful insights from the data and draw conclusions (Myers et al., 2010). All analyses in this study will be conducted using the SPSS statistics platform.

4.5.1 Descriptive Statistics

Data from various sources is be cleaned, aggregated, and profiled using descriptive statistics. These include standard measures of central tendency, such as the mean, median, and standard deviation (Field, 2013). The time series aspect of the analysis involves examining the frequency, severity, and seasonality of claims in response to climate-related events such as hailstorms, floods, or heatwaves. This can provide information on how the frequency or intensity of climate-related claims have changed over time. The analysis of South African geospatial data can highlight regions that are more susceptible to climate-related risks and guide insurance companies in pricing and risk management strategies. Trend analysis is conducted to ascertain whether long-term trends in insurance claims data can reveal patterns related to climate change. This analysis may involve identifying changes in the proportion of claims attributed to climate-related events compared with other causes, such as accidents or non-climate-related natural disasters. It can help insurance companies assess evolving risks and adapt their underwriting and pricing strategies accordingly.

4.5.2 Reliability and Validity

According to Myers at al. (2010), it is essential for a researcher to design a study by carefully selecting relevant and representative data sources, accounting for potential biases and confounding factors in order to improve the validity and reliability of the results. Cronbach's alpha is a widely used measure of reliability that assesses the extent to which the items in a scale or questionnaire consistently measure the same underlying construct (Amirrudin et al., 2020). A higher Cronbach's alpha value indicates greater internal consistency. In this study the aim is to have a Cronbach's alpha value that is greater than 0.7. The validity of the research instrument will be analysed by testing for correlations (Heale and Twycross, 2015).

4.5.3 Multivariate Regression Analysis Approach

Multivariate regression analysis is used to test the hypotheses, establish relationships between a single independent variable and multiple independent variables and generalise the results. This requires consideration of the dependencies and relationships among the variables. A regression model is be created in Python version 3.6.4 to analyse the relationship between multiple variables. Time series regression models are well-suited for analysing the impact of climate change related events on non-life insurance due to their ability to handle temporal dependencies, capture trends and patterns, account for seasonality, support forecasting, and capture dynamic relationships (Field, 2013; Sekaran and Bougie, 2016). This type of analysis can also provide a framework for examining how climate change-related factors influence non-life insurance outcomes over time and can inform decision-making in the insurance industry.

The estimated models of the study include three multivariate linear regression models with a focus on three independent variables. The first model will examine the weather-related insurance claims incurred by insurers. The second model will look at the overall net underwriting margin of Santam and the last model will assess the property net underwriting result of the insurer.

Time series regression analysis involves collecting data on the same variable at regular intervals, such as daily, monthly, and yearly (Field, 2013; Sekaran and Bougie, 2016). The focus of this design is to observe and analyse changes in a single variable or a set of variables over time (Sekaran and Bougie, 2016). The same variables are measured repeatedly over the designated time period; for instance, this study will observe non-life insurance claims, climate change-related events, and changes in other socioeconomic factors. It is important to examine trends, patterns, and fluctuations in variables of interest (Sekaran and Bougie, 2016). This is essential in the observation of weather-related event variables including their impact on insurance risk management. Time series analysis allows the researcher to assess the impact of a certain scenario over time. In this study the data collection process will include tracking weather-related claims as well as climate change related events over several years. It will also include the observation of temperature variations over the seasons.

Time series design allows for the identification and analysis of trends and patterns that can be picked up in data over time. It can reveal long-term changes, cycles, or seasonality in variables - providing valuable insights into underlying processes (Glass et al., 2008). By analysing historical data patterns, time series design enables researchers to develop models and make predictions regarding future trends or values (Glass et al., 2008). This can be useful for variables such as economics, finance, and meteorology. Time series analysis helps in the detection of anomalies, unusual observations or outliers that deviate from the expected pattern (Glass et al., 2008). This can lead to the detection of important events, irregularities, or exceptional conditions, which may require further investigation. Time series design also examines the interventions, policies, or external events on a variable of interest (Glass et al., 2008). By comparing the data before and after specific events, researchers can evaluate the effectiveness or consequences of actions or changes. It is often challenging to establish causal relationships based solely on time series data (Glass et al., 2008). The quality and accuracy of time series data are crucial for reliable analysis. Errors, missing values, or inconsistencies in data collection or recording can affect the validity of findings (Glass et al., 2008). Careful data management and cleaning are essential for ensuring data integrity. Analysing multivariate time series data with multiple variables can be complex and requires advanced statistical techniques (Glass et al., 2008). This approach often focuses on specific variables or a specific context, therefore, findings may have limited generalisability to other populations, settings, or time periods, as they are influenced by the specific conditions and characteristics of the observed time series (Glass et al., 2008). Other limitations include historical data availability, data gaps, or data of varying quality across different time points (Glass et al., 2008). Researchers must carefully consider these limitations and their potential impact on the validity and reliability of the analysis.

4.6 Ethical Considerations

It is imperative for researchers to adhere to ethical guidelines as well as regulations when conducting studies. Ethical considerations include ensuring confidentiality and anonymity to protect participants, promoting research integrity by conducting research in an ethical manner, and obtaining consent for the data that will be used in the study (Shamoo and Resnik, 2015). This study will use publicly available data sources that consist of insurance-related data as well as climate change-related data points and does not involve contact with any research subjects.

4.6.1 Permission to Conduct the Study

The researcher will apply for permission to conduct the study from the University of the Witwatersrand Research Ethics Committee. After approval is granted, the researcher will start the process for gathering data in compliance with the relevant ethics regulations and guidelines stipulated during the Master's in Business Administration Ethics training conducted by Professor Anthony Stacey.

4.6.2 Data Management

Effective data management is essential for maintaining the integrity, quality, and accessibility of collected research data and information. It supports data integrity, reproducibility, transparency, and confidentiality, while ensuring efficient data analysis and long-term data preservation. By implementing sound data management practices, researchers can improve the reliability and significance of their quantitative studies. The researcher will also ensure that the data is gathered ethically and stored securely in a local drive of a password-protected personal computer.

CHAPTER 5. RESEARCH RESULTS

This chapter presents the data analysis that was conducted using Python to assess the relationship between weather-related catastrophes and insurance claims (due to infrastructure and property damages) as well as the financial losses incurred by insurers. Descriptive statistics will be used to summarise the data used in the study. Thereafter, time series analysis will be used to provide trends and insights that are extracted from the data. The analyses conducted in this section focuses on addressing the research questions stated in Chapter 1.5.

The sourced data is in relation to the impact of weather-related catastrophes on insurance losses, refer to Figure 5.1 below which illustrates the year-on-year trend analysis of the total amount of claims paid out by Santam due to weather-related catastrophes in South Africa. The data shows that insured losses due to weather-related insurance claims have increased in the recent decades, with 2022 showing the highest total catastrophe claims due to the extreme weather events: flooding or hailstorms.

According to Figure 5.1, Santam experienced large losses in both the 2022 and 2023 periods. Heavy rainfalls leading to flooding in the Eastern Cape, Gauteng, KZN and Mpumalanga regions. This includes the Western Cape floods and fire claims; KZN floods and fire claims resulting in a decreased underwriting margin from 8% in 2021 to 5.2 in 2022 and subsequently 3.8% as of June 2023 (Santam Interim Report, 2023). This downward trend is of high concern for the Santam Group as the company targets a net underwriting result that is between 5 – 10% (Santam Interim Report, 2023). These catastrophe losses also resulted in a significant increase in the cost of reinsurance and a substantial decrease in net insurance funds due to the KZN claim pay-outs and contingent business interruption settlements.

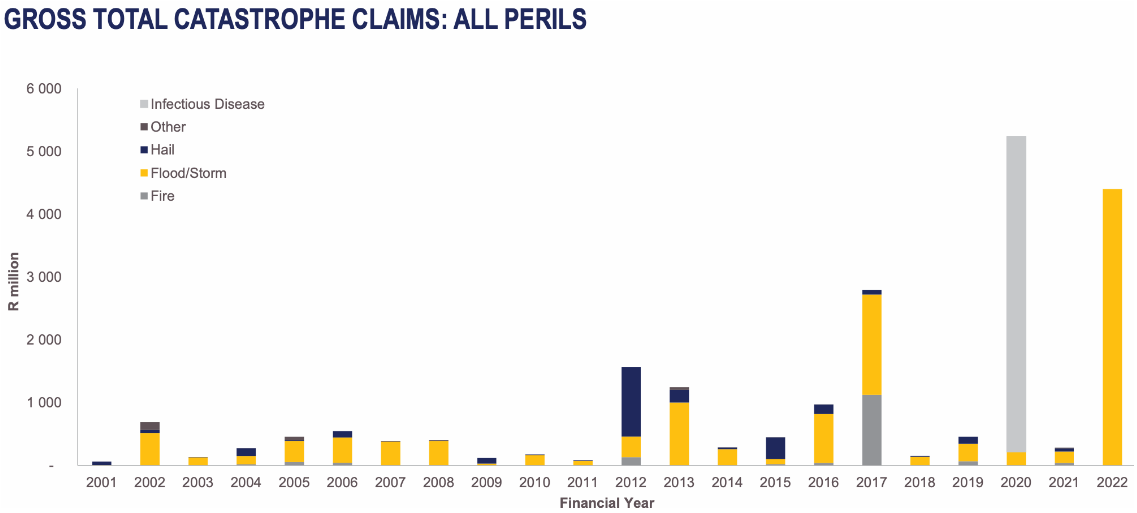


Figure 4.6-1: Santam Group catastrophe claims from 2001 to 2022. Sourced from the Santam Analyst Report (2022).

5.1 Descriptive Analytics

Davis-Reddy et al. (2019) state that weather-related events have become more frequent, severe, and widespread on a worldwide scale over the previous four decades and these events cause significant damage to property and infrastructure as well as an increase in fatalities, resulting in over US$5 billion in economic damages and weather-related disasters accounted for almost 90% of registered disasters from 2006 to 2019. Natural catastrophes are becoming more impactful and complex, as evidenced by the rise in linked insured losses, as observed in Figure 5.1. According to the World Economic Forum 2022 report, extreme weather-related events are one of the top five global hazards in terms of likelihood and severity of impact (World Economic Forum, 2022). Figure 5.2 below shows the year-on-year total number of natural catastrophe events which have caused significant damages and led to fatalities over the past four decades. This increasing trend is also observed in the South African context, as illustrated by Figure 5.3.

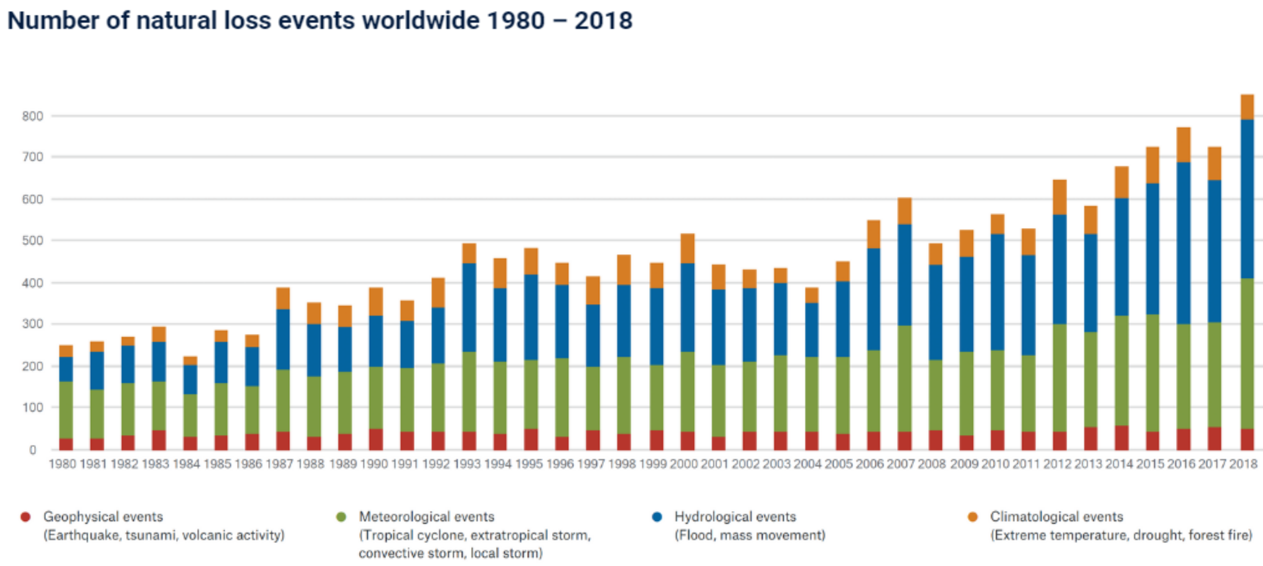


Figure 5.1-1: Number of natural catastrophes. Adapted from Munich RE NatCatService and SAEON (n.d.)

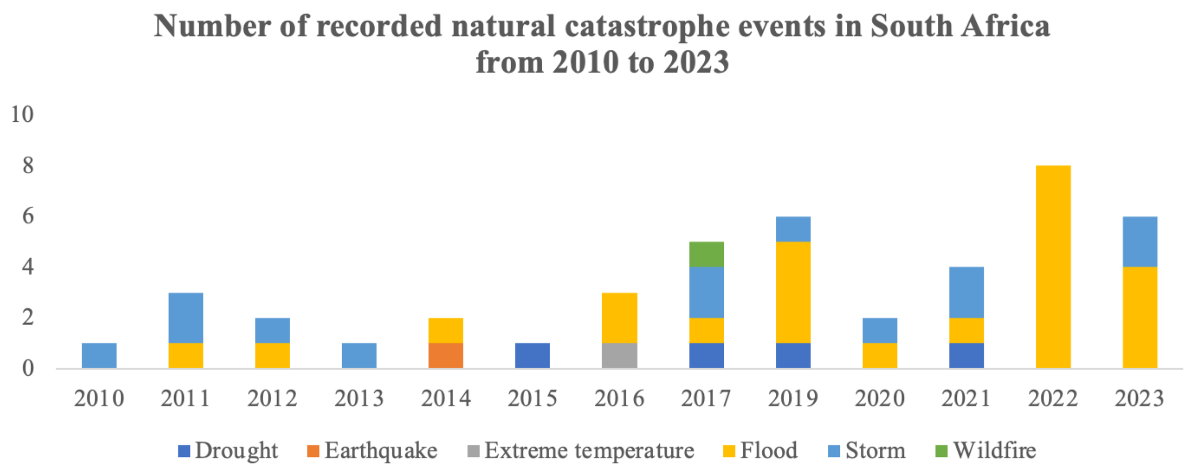


Figure 5.1-2: Number of natural catastrophe events from 2001 to 2022. Sourced from EM-DAT (2022).

The natural catastrophe events dataset is collected from the NatCatService and Emergency Events Database (EM-DAT), and the analysis is for the sample period of 2010 to 2023. Starting from 2010 is necessary as the general insurance market shifted to accommodate new and revised regulations and operations due to the 2008 financial crisis. These regulatory changes impacted the insurance and financial market conduct globally. The impact of these regulatory changes was not included in this study as there was no access to time series datasets. These legislative changes included the FAIS regulations and restructuring of short-term insurance products whereby insurers were paying close attention to the time lag between the rise in claims cost and the premium rate increases (SAIA, 2013). The industry also had to deal with increasing catastrophe risk exposures and climate change-related policies enforced by organisations such as the IPCC.

The insurance industry claims dataset was collected from the SAIA annual reviews, KPMG reports as well as the SARB online database. The data pertaining to Santam's profitability and financial standing was collected from the annual reports and the Santam insurance barometer survey. It must be noted that Santam first introduced this survey in 2019; thus, the data collected from this source is limited. The survey aims to identify insurance-related trends and highlights some of the significant challenges and changes in the insurance industry, including commercial lines, private entities and intermediaries.

This analysis involves describing the existing characteristics and trends in the data. The datasets used in this analysis were systematically collected without manipulating any variables, thus defining the characteristics of the raw data. This analysis is a precursor to the time series study, which involves identifying and measuring correlations between variables without any fundamental manipulations. This process is followed by exploring the relationships between different variables as per the research questions as well as the causes that underlie those relationships.

5.1.1 Financial data

This section aims to describe the financial data to understand the detailed attributes of the sample data. Descriptive statistics provide a macro and micro view of the data. These details also assist in identifying errors and anomalies in the collected datasets. This analysis is then used to inform the subsequent time series analysis in Chapter 5.2 below.

The key financial indicators include the industry claims incurred which is the percentage of claims incurred with respect to the amount of premiums earned. This variable is based on the year-on-year average claims ratio reported by non-life insurers in South Africa. It represents the profitability of the non-life insurance industry. The lower the claims ratio, the higher the profitability. The second and third financial indicators pertain to Santam's profitability. The net undewriting result and property net underwriting result are the difference between the premiums earned and the claims paid out including expenses and net reinsurance; the former refers to the overall profitability of the company whilst the latter refers to the profitability of the property insurance business unit.

Table 5.1-1 below, shows aggregated statistics of the dependent financial variables annually for Santam Group as well as the South African insurance industry, averaged over a period of 12 years from 2010 to 2022. Table 5.1-2 shows the percentage of missing values in the collected dataset.

Reviewing Table 5.1-1 below, it can be observed that Santam's financial data (explicitly referring to the profitability of the company) is negatively skewed, as indicated by the 50th percentile/median, which is consistently higher than the mean. This negatively skewed distribution implies that over the past 14 years, the dataset has had some relatively lower financial values – thus pushing the mean lower than the median. This observation can be supported by the short-term insurance industry, which recorded an unprecedented increase in claims due to weather-related catastrophic events, as seen in Figure 5.1. The opposite is observed when analysing the average claims incurred by insurers in South Africa. The data exhibits a positively skewed distribution, implying that the number of claims has increased significantly over the years, thus pulling the mean higher than the median.

Table 5.1-1: Descriptive analysis of the financial variables

	Industry Claims Incurred (%)	Property Net Underwriting Result (R million)	Net Underwriting Margin (%)	Net Insurance Result (%)
count	8.00	12.00	14.00	14.00
mean	61.29	-138.58	6.44	8.64
std	11.02	761.96	2.42	2.64
min	54.60	-2410.00	2.50	4.60
25%	56.65	-203.00	4.30	6.52
50%	57.60	27.00	7.05	9.15
75%	59.50	239.75	8.45	10.97
max	88.10	519.00	9.60	12.30

Santam's property net underwriting result shows a significantly higher standard deviation compared to the rest of the variables, indicating that the data has very high variability and is more spread out from the mean. Over the past decade, property insurance has experienced significant losses due to natural catastrophes across South Africa. The non-life insurance industry has continued to experience challenges around maintaining local, provincial and national infrastructure as this area naturally involves multiple stakeholders, including the municipalities. Fluctuating weather patterns continue to impact provinces such as KZN, Western Cape, Gauteng and the Eastern Cape. These regions have experienced some catastrophic events in the past ten years. For example, the excessive floods in KZN and Eastern Cape damaged numerous properties and infrastructure, increasing the property claims ratio. The subtropical storm also resulted in approximately 300 mm of precipitation in 24 hours in the KZN coastal area. This natural catastrophic event alone affected over 40,000 people and left a trail of destruction.

Table 5.1-2: Dataset quality assessment (completeness) of the financial variables

Variable	Count of values	Count of missing values	Percentage of missing values
Industry Claims Incurred (%)	8	6	42.86
Property Net Underwriting Result (R million)	12	2	14.29
Net Underwriting Margin (%)	14	0	0.00
Net Insurance Result (%)	14	0	0.00

5.1.2 Weather-related data

The following section illustrates the descriptive and trend analysis of the climatological variables over the period of 2010 to 2022. Tables 5.1.2-1 to 5.1.2-3 below show the descriptive statistics regarding the average minimum temperatures, average maximum temperatures as well as average precipitation from 2010 to 2022.

Table 5.1-3: Average minimum temperatures (°C) from 2010-2022

Year	count	mean	std	min	25%	50%	75%	max
2010	12.0	10.98	4.06	4.3	8.23	12.15	14.32	15.5
2011	12.0	10.42	4.26	2.5	7.85	11.35	14.10	14.9
2012	12.0	10.45	3.84	4.3	7.90	10.85	13.40	15.5
2013	12.0	10.70	3.72	5.3	7.85	10.80	13.80	15.5
2014	12.0	10.72	3.84	4.5	8.55	10.70	14.27	15.6
2015	12.0	11.38	3.70	4.4	9.95	12.00	13.88	16.2
2016	12.0	11.33	4.07	4.5	7.72	12.15	14.85	16.1
2017	12.0	10.90	3.27	6.0	7.98	11.00	13.82	15.2
2018	12.0	11.06	3.50	4.7	8.38	11.55	13.95	15.5
2019	12.0	11.58	3.68	5.1	9.48	12.30	14.90	15.4
2020	12.0	10.65	4.44	3.7	6.95	11.85	14.42	15.5
2021	12.0	10.60	3.81	3.3	7.60	11.25	13.35	15.5
2022	12.0	10.92	3.74	3.9	7.87	12.50	14.12	14.4

Table 5.1-4: Average maximum temperatures (°C) from 2010-2022

Year	count	mean	std	min	25%	50%	75%	max
2010	12.0	22.71	3.58	16.6	20.50	24.70	25.25	26.6
2011	12.0	21.95	3.87	15.1	19.08	24.05	24.95	25.7
2012	12.0	22.52	3.08	16.8	21.15	22.65	24.90	26.1
2013	12.0	22.86	3.40	17.8	19.60	24.05	25.55	27.4
2014	12.0	22.60	3.24	17.0	20.65	22.85	25.35	27.0
2015	12.0	24.26	3.97	16.8	22.88	24.65	27.33	29.4
2016	12.0	23.47	3.76	17.2	20.65	24.90	26.20	27.6
2017	12.0	22.81	2.86	18.4	19.73	24.15	25.18	25.7
2018	12.0	23.28	3.72	16.6	20.92	24.40	25.72	28.2
2019	12.0	23.87	3.16	18.8	21.40	24.55	26.65	27.9
2020	12.0	22.45	3.39	16.4	19.85	23.70	25.35	25.9
2021	12.0	22.49	3.24	16.2	20.05	23.90	24.60	25.8
2022	12.0	22.48	3.55	16.7	19.62	23.50	25.15	27.5

Table 5.1-5: Average rainfall (mm) from 2010-2022

Year	count	mean	std	min	25%	50%	75%	max
2010	8.0	122.82	81.44	29.4	83.12	104.95	150.78	268.9
2011	11.0	76.83	69.65	2.3	14.20	68.90	108.60	209.1
2012	10.0	66.68	49.64	0.2	24.42	70.50	94.80	143.0
2013	10.0	70.97	60.41	1.6	19.95	62.10	114.52	175.6
2014	11.0	53.61	63.50	0.2	4.00	16.20	108.30	176.4
2015	11.0	43.31	45.35	1.2	13.90	29.60	63.05	158.9
2016	11.0	73.08	68.60	3.0	13.10	50.40	118.75	210.0
2017	11.0	58.65	45.80	0.3	15.60	62.70	96.80	117.8
2018	10.0	51.98	38.19	1.0	22.90	50.90	81.70	116.2
2019	8.0	91.85	63.89	1.6	45.30	107.00	142.75	169.0
2020	9.0	76.60	48.91	4.0	56.20	76.60	116.40	146.8
2021	10.0	68.72	66.06	0.4	32.05	45.30	90.20	227.0
2022	10.0	115.17	77.38	5.3	49.30	115.70	162.40	230.0

Figures 5.1.2-1 to 5.1.2-3 below illustrate data collected over the period of 2010 to 2022 from the SAWS and the Climate Change Knowledge Portal; the average annual temperatures range from 2.5 to 23°C during the autumn/winter season and a yearly average of 14 to 29°C during

spring/summer. During the same period, the average annual precipitation ranges from 3.9 mm to 180.7 mm, with most rainfall experienced from October to April. 2010, 2023 and 2022 experience the top three highest rainfalls, respectively. South Africa is vulnerable to weather fluctuations and climate change since it relies heavily on agriculture and various other natural resources. Water is a scarce resource due to high temperatures, causing an increase in the evaporation rate of water reservoirs in large parts of the country. This impact was seen when the Western Cape experienced 'day zero'. South Africa's average annual temperature is 17.5°C, with an average annual precipitation of 74.6 mm. The highest precipitation occurs from November to March, while the lowest occurs from May to October.

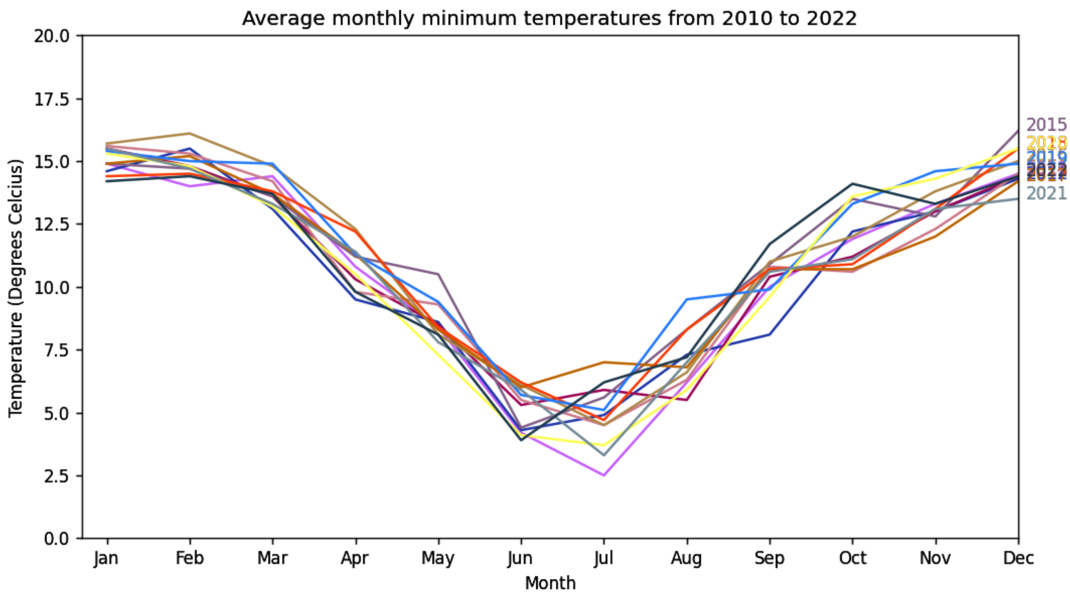


Figure 5.1-3: Average monthly minimum temperature year-on-year trends from 2010-2022

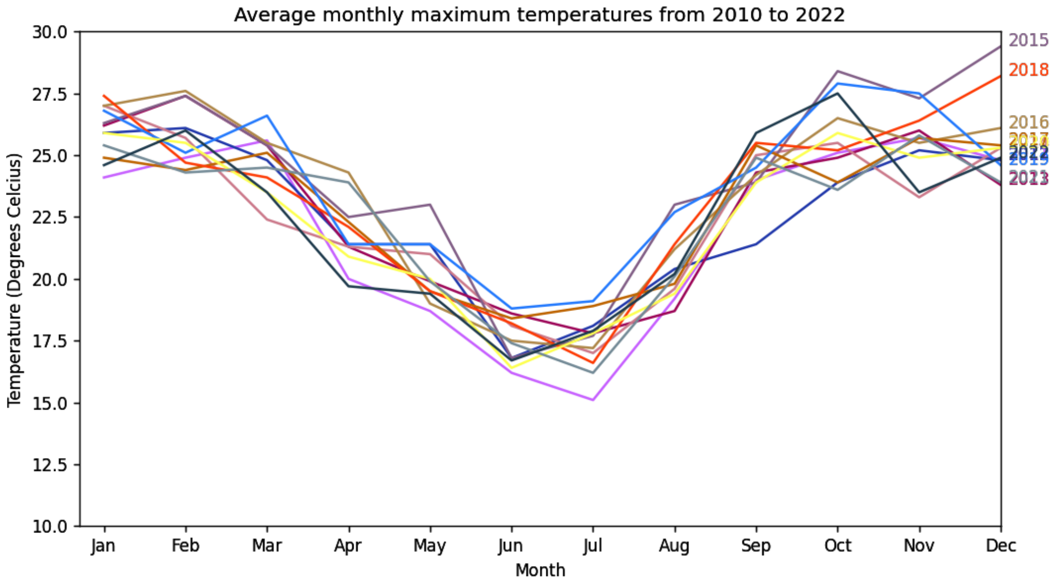


Figure 5.1-4: Average monthly maximum temperature year-on-year trends from 2010-2022

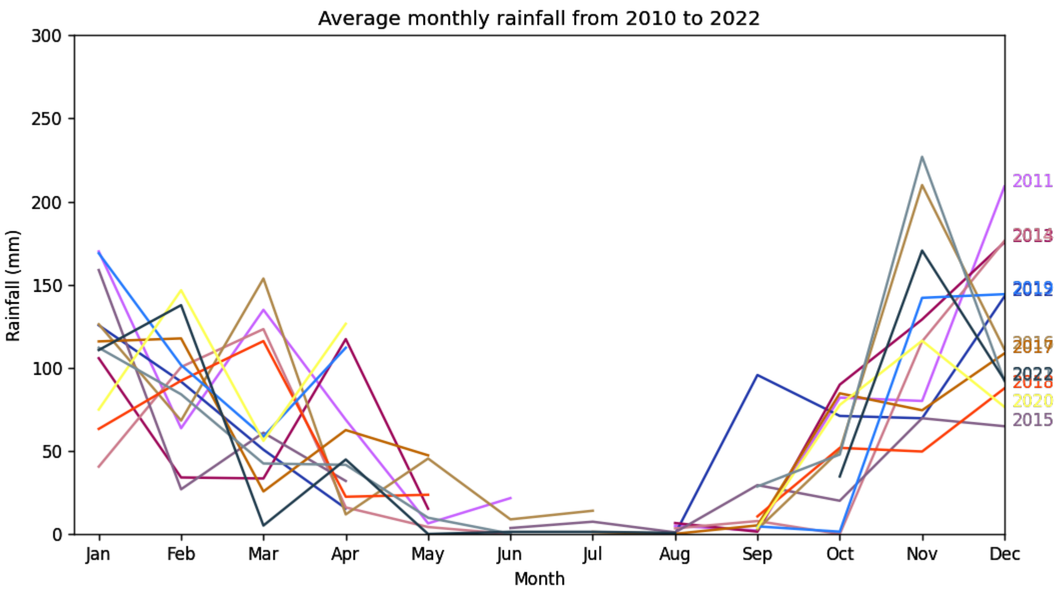


Figure 5.1-5: Average monthly rainfall year-on-year trends from 2010-2022

5.2 Hypothesis testing

This section presents the multivariate time series analysis of the weather-related variables and Santam's financial indicators to assess the potential exposure to natural disaster risks. Various studies have projected the potential impact of natural catastrophe events on future flood and storm damages; however, relatively few studies are related to the insurance industry (Botzen et al., 2019). This time series analysis includes the trends and correlations between the financial variables and the frequency of natural catastrophe events, temperature and rainfall indicators.

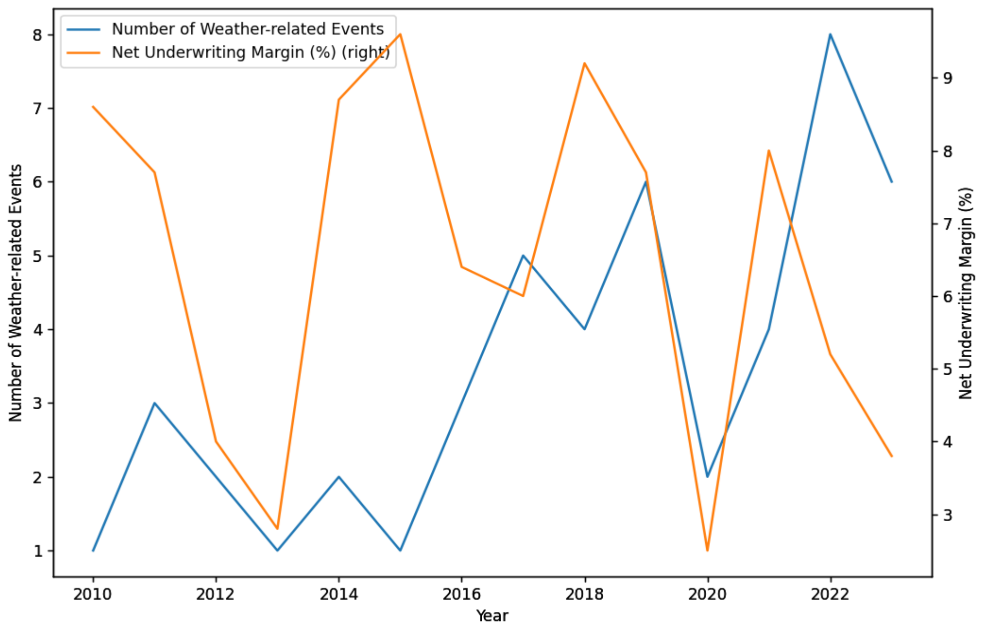


Figure 5.2-1: Net underwriting margin in relation to the number of weather-related events from 2010 to 2023

Figure 5.2-1 shows an increasing trend in the number of weather-related events. Santam's net underwriting margin fluctuates year-on-year. The year 2020 shows a significant trough in the company's net underwriting margin, at 2.5%, due to Covid-19, which resulted in increased commercial line claims as well as personal insurance claims (Santam Insurance Barometer, 2021). One of the main impacts of Covid-19 was contingent business interruption (CBI), which resulted in the company being taken to court by various companies, mainly in the hospitality industry (Santam Insurance Barometer, 2021). The settlement of the unprecedented CBI claims negatively impacted the company's net underwriting margin year on year in 2019/2020.

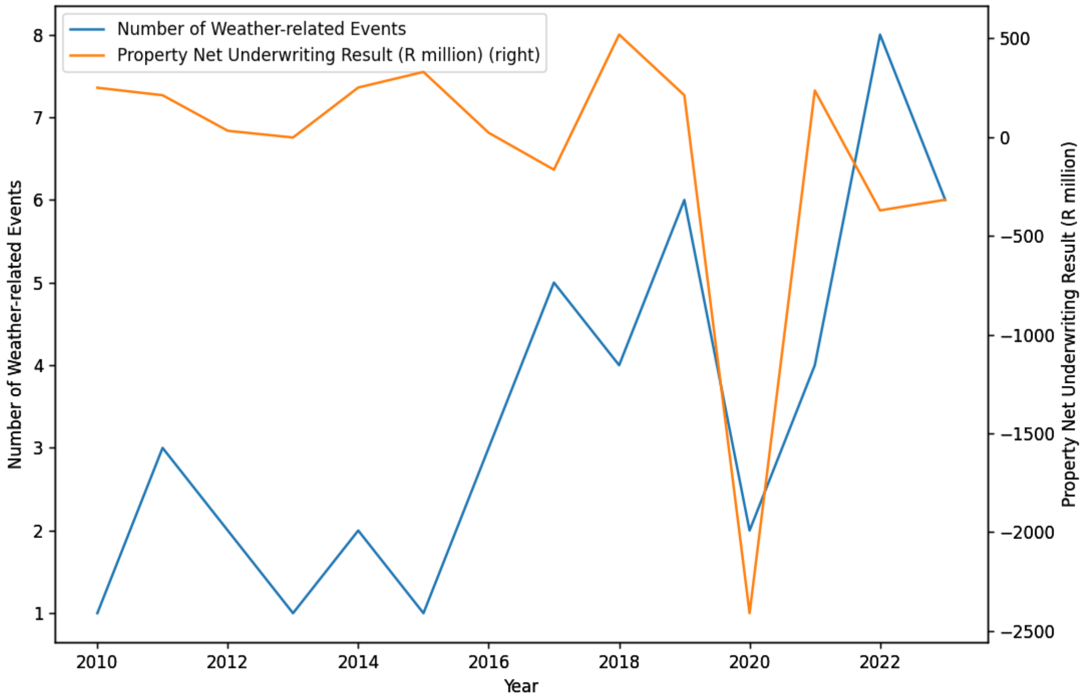


Figure 5.2-2: Property net underwriting result in relation to the number of weather-related events from 2010 to 2023

Figure 5.2-2 shows that over the years there has been an upward trend in weather-related events. The lowest property net underwriting margin is observed in 2020. According to the 2020 Santam financial report, property claims increased by 7%; the company experienced increased building and household claims due to fire damages and crime (Santam Insurance Barometer report, 2020). Household content claims also increased due to more people working from home.

Property and infrastructure are a significant area in the non-life insurance industry. Santam's objective is to minimise losses through partnerships with various municipalities and governments to ensure the upkeep of national and local infrastructure as well as upskill communities for preparedness in case of natural catastrophes. Regulatory frameworks have been developed to transform property and infrastructure insurance risks due to increased weather-related events and the pay out of claims after the fact. These are put in place to regulate insurance premiums and to ensure that reserves are enough to cover expected losses; this is to mitigate financial losses incurred by insurers.

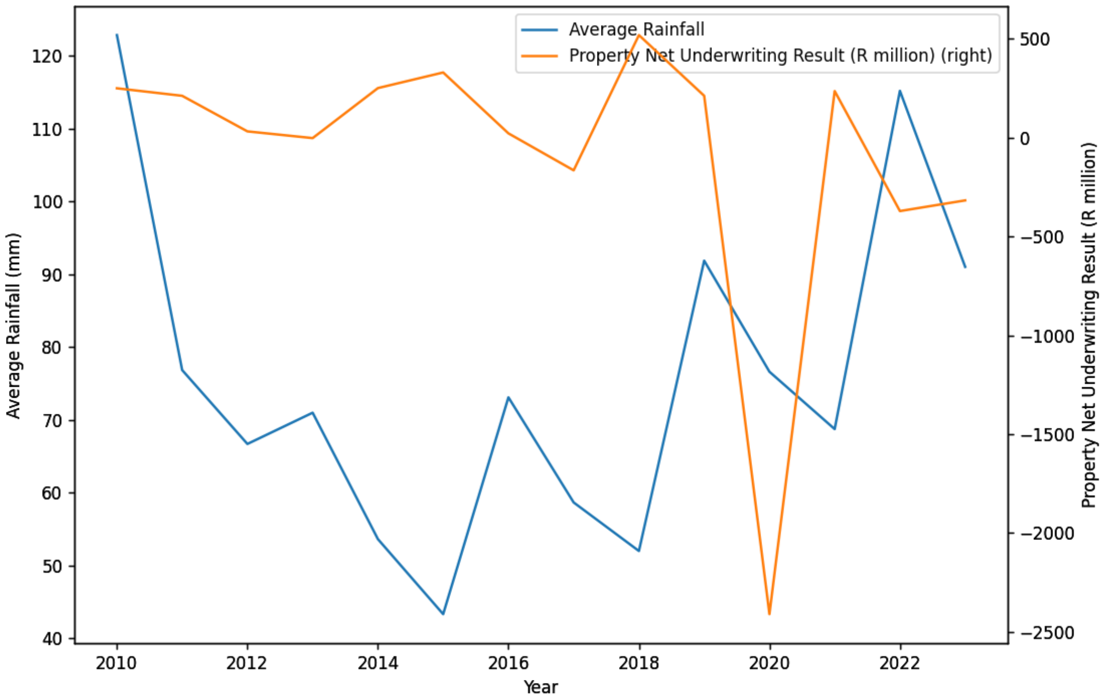


Figure 5.2-3: Property net underwriting result in relation to the year-on-year average rainfall from 2010 to 2023

Additionally, in 2021/22, there was a spike in natural catastrophe claims for property and infrastructure damages due to extreme weather conditions from 2021 to 2023. Santam experienced a surge in flood claims in 2022 relative to the preceding year, partially attributable to the repercussions of the 2022 KZN flooding. Due to the vast geographical areas impacted by above-average precipitation and flooding incidents, there was a concurrent surge in flood claims for property and building contents during the initial six months of 2023. Slightly more vehicle accidents were also caused by the intense rainfall, leading to increased motor claims. During the first six months of 2023, the Western Cape and various riverbanks in the Gauteng province experienced severe floods.

Overall, the insurance industry has been heavily affected by weather-related catastrophes. This is shown in Figure 5.2-4 below.

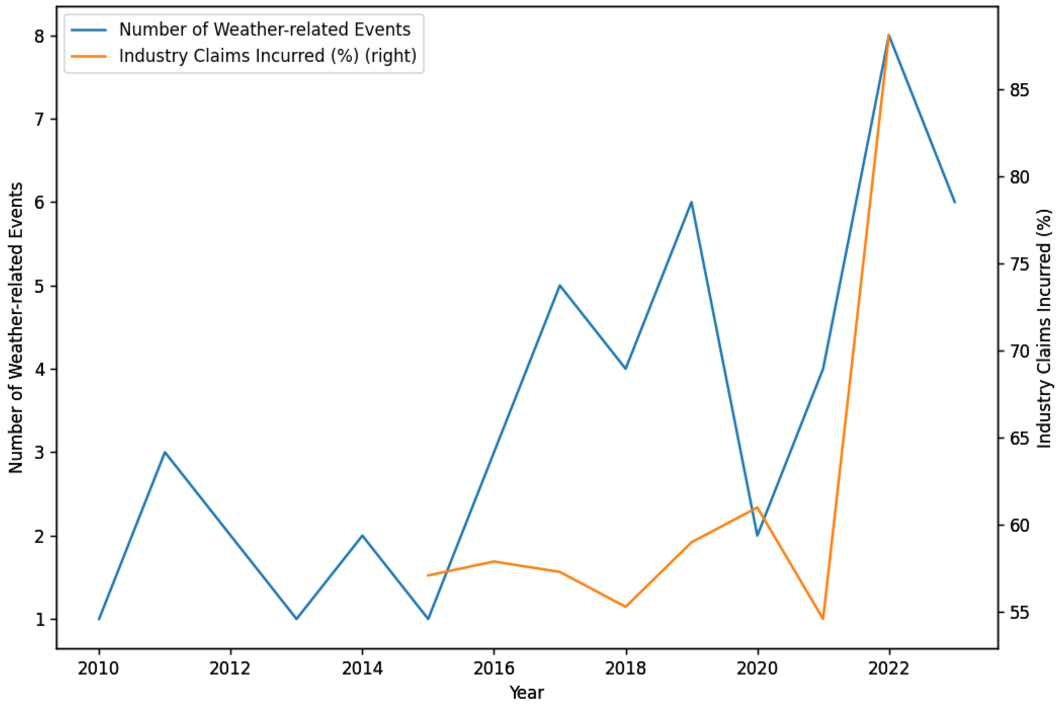


Figure 5.2-4: Insurance industry claims ratio in relation to the year-on-year average rainfall from 2010 to 2023

According to data collated from the 2023 KPMG insurance survey report, Figure 5.2-5 looks at the impact of precipitation on the percentage of claims incurred by South African insurance companies. It can be observed that there in an increasing trend between the average rainfall experienced and the insurance industry claims ratio.

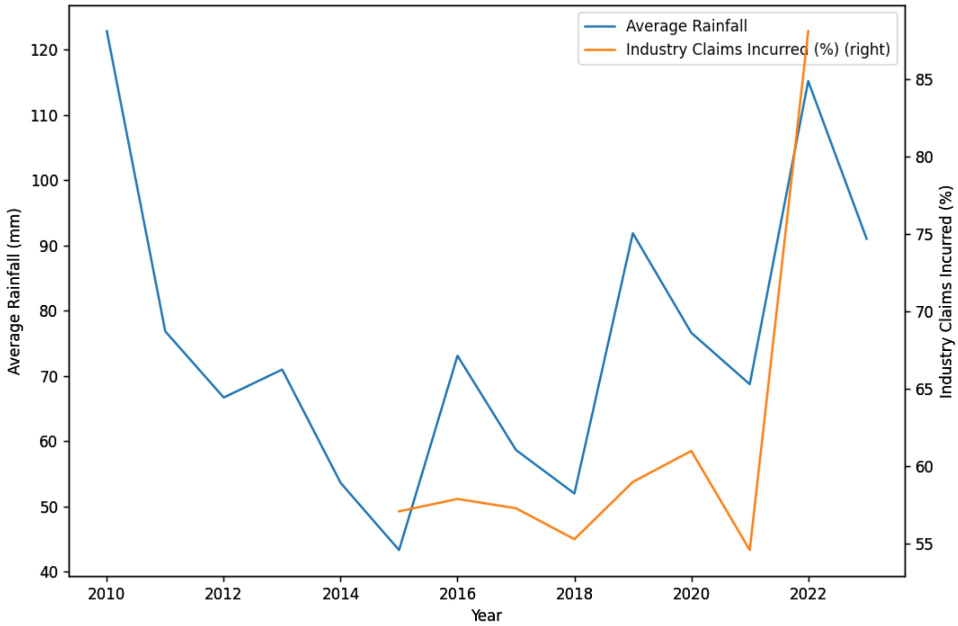


Figure 5.2-5: Insurance industry claims ratio in relation to the year-on-year average precipitation from 2010 to 2023

5.3 Model development

This section examines the relationship between weather-related events and weather-related insurance claims for the insurance industry as well as Santam Group; addressing the research questions in Chapter 1.5. It also assesses the how weather-related variables relate to the profitability of the property segment of Santam insurance. A correlation matrix is used to evaluate and quantify the relationship between each of the variables in the sample dataset. The following Pearson correlation coefficient formular is used to calculate the coefficients.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{(n\sum x^2 - (\sum x)^2)(n\sum y^2 - (\sum y)^2)}}$$

Where:

n is the number of (x, y) data points

$\sum x$ represents the sum of the x values

$\sum y$ represents the sum of the y values

$\sum xy$ represents the sum of the product of the x and y values

$\sum x^2$ is the sum of the squares of individual x values

$\sum y^2$ is the sum of the squares of individual y values

Table 5.3-1 shows the Pearson correlation coefficients between the dependent and independent variables. The dependent variables in this study are the finance-related variables: net underwriting margin, property net underwriting result and the industry claims incurred whilst all the weather-related variables (rainfall, weather-related events, maximum and minimum temperatures) are the independent variables.

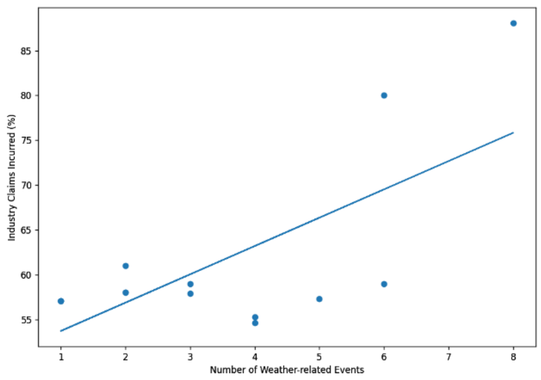
Table 5.3-1: Correlation Matrix

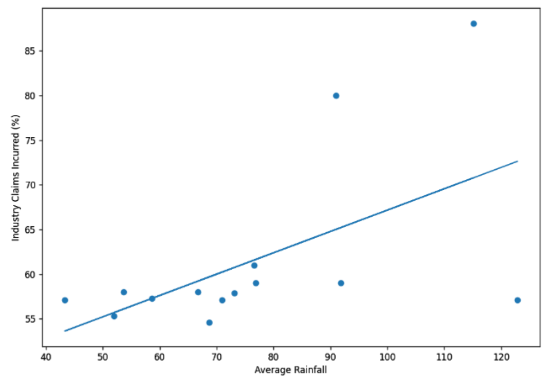
	Weather-related Events	Rainfall	Maximum Temperature	Minimum Temperature	Net Underwriting Margin (%)	Net Insurance Result (%)	Property Net Underwriting Result	Industry Claims Incurred (%)
Weather-related Events	1	0.37	-0.15	-0.014	-0.09	-0.17	-0.013	0.67
Rainfall	0.37	1	-0.33	-0.07	-0.21	-0.23	-0.16	0.8
Maximum Temperature	-0.15	-0.33	1	0.9	0.45	0.41	0.31	-0.38
Minimum Temperature	-0.014	-0.07	0.9	1	0.5	0.43	0.25	-0.13
Net Underwriting Margin (%)	-0.09	-0.21	0.45	0.5	1	0.97	0.68	-0.41
Net Insurance Result (%)	-0.17	-0.23	0.41	0.43	0.97	1	0.66	-0.46
Property Net Underwriting Result	-0.013	-0.16	0.31	0.25	0.68	0.66	1	-0.21
Industry Claims Incurred (%)	0.67	0.8	-0.38	-0.13	-0.41	-0.46	-0.21	1

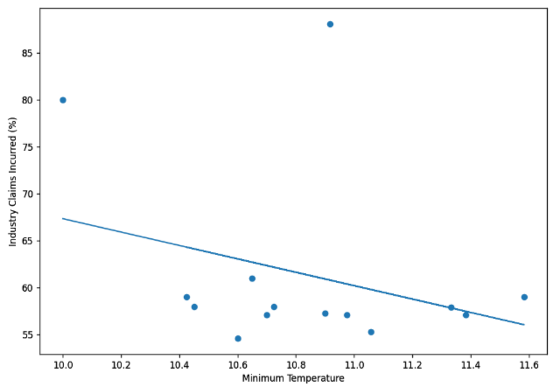
From the correlation matrix above, it is observed that industry claims incurred, and the weather-related events variables exhibit a moderately positive correlation. There is a moderately strong positive correlation between the industry claims incurred and rainfall; and is significant with a p-value < 0.05. There is a weak negative correlation between the industry claims incurred and the minimum and maximum temperature indicators. The property net underwriting result which shows a positive correlation between the temperature indicators and very weak correlation with the weather-related events and rainfall indicators. Similarly, the net underwriting margin has a moderately positive correlation between the maximum and minimum temperature indicators and exhibits a significantly weak negative correlation with the weather-related events and rainfall indicators.

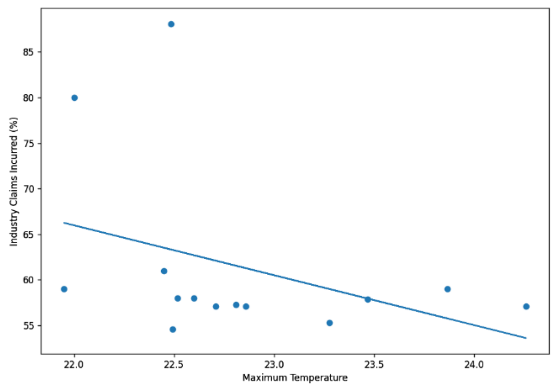
In addition to the correlation matrix above, the following figures illustrate graphical aspect of the strength and nature of the relationship between the dependent and independent variables. From the figures below, there is a distinct positive correlation, although weak, between the industry claims incurred and the weather-related events and rainfall indicators; whilst there is a negative correlation between the industry claims and the maximum and minimum temperature indicators. This relationship implies that the higher the frequency of weather-related catastrophes, the higher the number of weather-related claims.

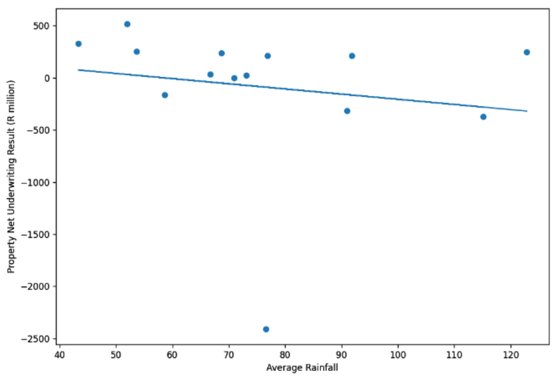
Additionally, there is a significant positive relationship between the property net underwriting result and the maximum and minimum temperature indicators whereby the data points clustered around the line of best fit. The higher the surface air temperatures, the higher the chances of heavy precipitation therefore increasing the probability of flooding and hailstorms, which in turn increases insurance claims due to flood and storm damage to property and infrastructure. Overall, this reduces the net underwriting result of the business.

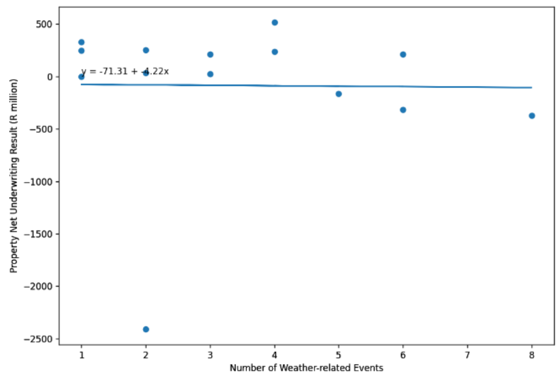

Industry Claims Incurred (%)
Number of Weather-related Events

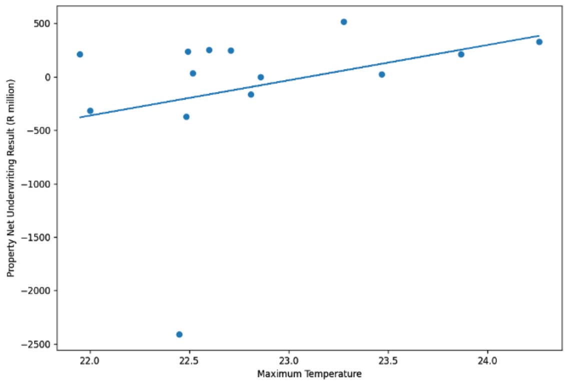

Industry Claims Incurred (%)
Average Rainfall

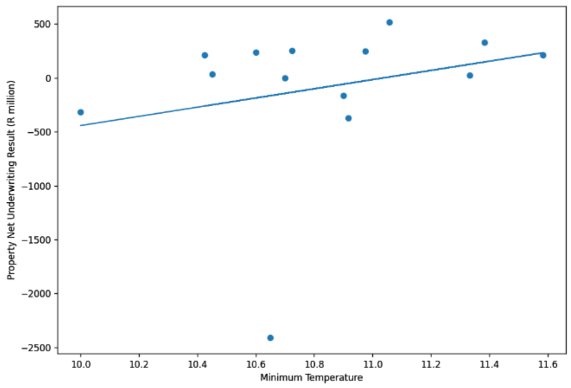

Industry Claims Incurred (%)
Minimum Temperature

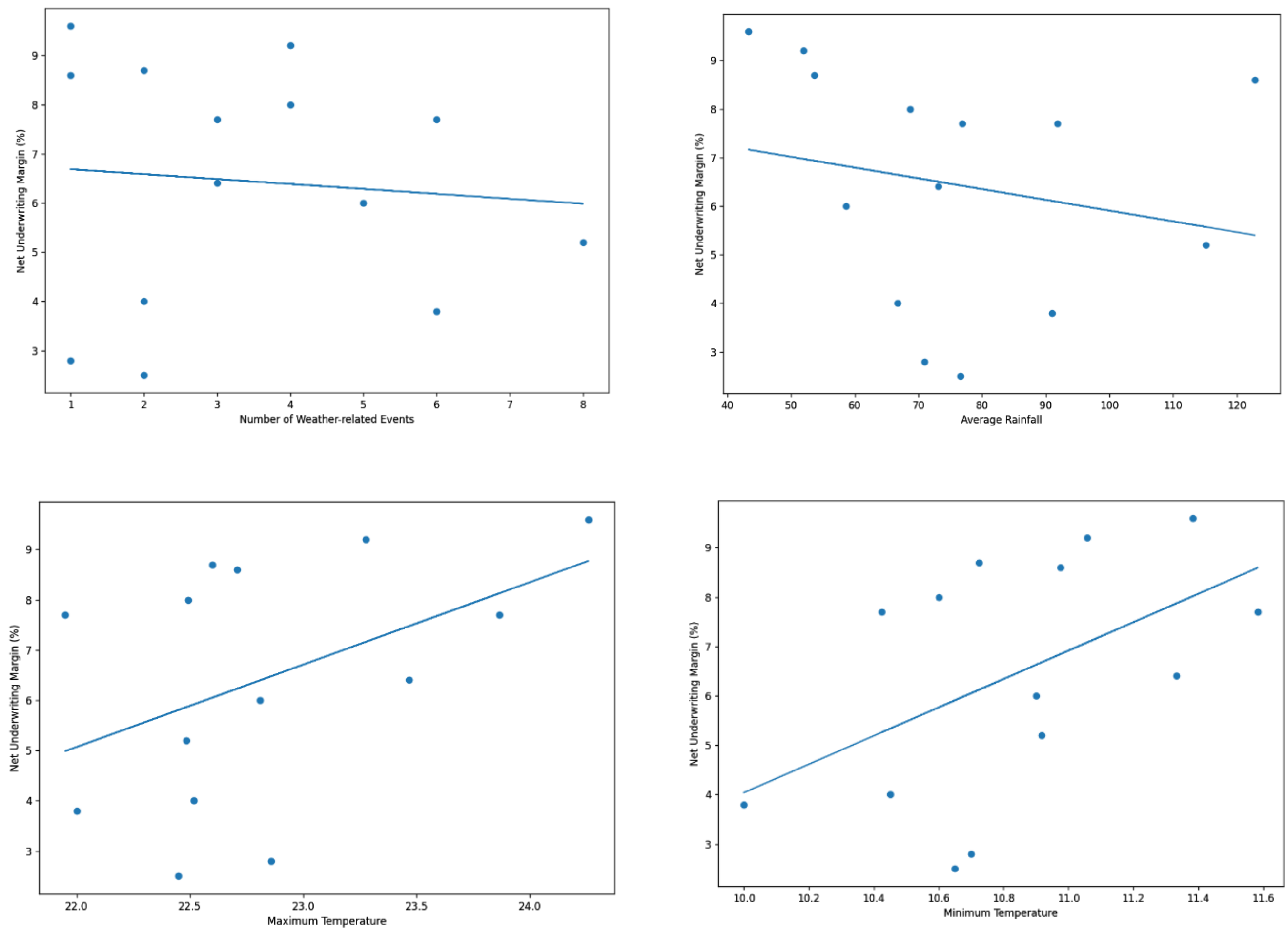

Industry Claims Incurred (%)
Maximum Temperature


Property Net Underwriting Result (R million)
Average Rainfall


y = -71.31 + -4.22x
Property Net Underwriting Result (R million)
Number of Weather-related Events


Property Net Underwriting Result (R million)
Maximum Temperature


Property Net Underwriting Result (R million)
Minimum Temperature



5.3.1 Climate Change Risk Assessment Framework

This section presents the multivariate regression models developed for the independent and dependent variables in this study. The model outputs regression coefficients which are then used to define the regression function with the best estimated weighting of the independent variables. The ordinary least squares technique is used to achieve these estimated weights. The sample dataset has four independent variables (x_1 to x_4), each contributing to one of the three dependent variables (y_1 to y_3). To initiate the predictive aspect of the CCRAF, the following multivariate regression models are developed and fit to training and test data sets.

The climate change risk assessment framework is based on a multivariate regression model, this is according to studies conducted by (Lowe et al., 2009; van Vuuren et al., 2011; Simpson et al., 2021; Smith et al., 2022; Cohen and Fischhendler, 2022). The relationships between the dependent (y) and independent (x) variables are further explored using multivariate time series analysis, assuming a linear relationship between x and y. The following equation represents the linear regression modelling component of the CCRAF:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \mathcal{E}$$

Where:

$\mathcal{E}$ represents random error

$\beta_0, \beta_1, \beta_2, \beta_3$ and β_4 are the regression coefficients

The independent variables are represented by the following:

x_1 is the number of weather-related events

x_2 is the average rainfall (mm)

x_3 is the average minimum temperatures (°C)

x_4 is the average maximum temperatures (°C)

The dependent variables (y) are represented by the following:

Industry claims incurred (%)

Santam's net underwriting margin (%)

Santam's property net underwriting result (R' million)

Model 1:

Model 1 looks at industry claims incurred as a dependent variable. The model results suggest that the independent variables included in the model have a strong relationship with the dependent variable. The R^2 value of 0.993 indicates that approximately 99.3% of the variance in the industry claims incurred is explained by the independent variables included in the model. This suggests that the model provides a significant fit to the data, indicating a strong relationship between the independent and dependent variables. The adjusted R^2 value of 0.990 takes into account the number of predictors in the model and provides a slightly more conservative estimate of the proportion of variance explained. It suggests that approximately 99% of the variance in the dependent variable is explained by the independent variables, considering the complexity of the model. The F-statistic tests the overall significance of the regression model. In this case, the high F-statistic value of 356.6 indicates that the overall model is statistically significant. The associated p-value (Prob (F-statistic) < 0.00001) is extremely low, suggesting strong evidence against the null hypothesis that all regression coefficients are zero. In summary, these regression results suggest that the model is highly effective in predicting the industry claims incurred. The high R-squared values, along with the significant F-statistic, indicate that the independent variables collectively have a substantial impact on the dependent variable.

Table 5.3.1-1: Model 1 results (y_1 = industry claims incurred)

	coefficient	**std error**	**t**	**p-value**
Number of weather-related events	2.7763	0.843	3.293	0.008
Average Rainfall	0.2285	0.081	2.825	0.018
Maximum Temperature	11.6867	4.277	2.732	0.021
Minimum Temperature	-21.4446	9.178	-2.337	0.042

The individual coefficients of the independent variables are examined in order to understand their specific contributions to the industry claims incurred. These coefficients represent the estimated impact of each independent variable on the dependent variable as shown in Table 5.3.1-1. The t-value of the number of weather-related events variable indicates that the coefficient is statistically significant at the 0.05 level. The low p-value (p = 0.008) indicates strong evidence against the null hypothesis. Similarly with the average rainfall variable, the t-value of 2.825 suggests that the coefficient is statistically significant at the 0.05 level. The p-value of 0.018 is below the significance threshold of 0.05, indicating that the coefficient is statistically significant. Regarding the maximum temperature variable, the t-value of 2.732 suggests that the coefficient is statistically significant at the 0.05 level. The p-value (p = 0.021) is below the significance threshold of 0.05, indicating that the coefficient is statistically significant. For the minimum temperature variable, the t-value of -2.337 suggests that the coefficient is statistically significant, and the p-value is less than 0.05 indicating that the coefficient is statistically significant.

Model 2:

Model 2 looks at net underwriting margin as a dependent variable. The R^2 value of 0.918 indicates that approximately 91.8% of the variance in the net underwriting margin percentage is explained by the independent variables included in the model. This suggests a strong relationship between the independent variables and the net underwriting margin. The adjusted R^2 value of 0.885 adjusts the R^2 value based on the number of predictors in the model, providing a more accurate estimate of the proportion of variance explained. It indicates that around 88.5% of the variance in the dependent variable is explained by the independent variables, considering the complexity of the model. The high F-statistic value of 27.91 suggests that the overall model is statistically significant, and the associated p-value (Prob (F-statistic) < 0.00001) is extremely low, indicating strong evidence against the null hypothesis that all regression coefficients are zero. Overall, the model demonstrates a strong explanatory power in predicting the net underwriting margin. The high R^2 values and significant F-statistic indicate that the independent variables included in the model collectively have a substantial impact on the net underwriting margin.

Table 5.3.1-2: Model summary for y_2 = net underwriting margin

	coefficient	std error	t	p-value
Number of weather-related events	-0.0586	0.320	-0.183	0.858
Average Rainfall	-0.0350	0.031	-1.141	0.280
Maximum Temperature	-2.2536	1.621	-1.390	0.039
Minimum Temperature	5.6082	3.479	1.612	0.041

However, upon further analysis, the coefficients of the independent variables and their specific contributions to the net underwriting margin are shown in Table 5.3.1-2 above. It can be observed that only two of the coefficients, specifically the minimum and maximum temperature, are statistically significant with p-values less than 0.05. Whilst the number of weather-related events and the average rainfall variables do not have a significant impact on Santam’s net underwriting margin result based on the current data.

Model 3:

Model 3 has the property net underwriting result as a dependent variable. This model has an R^2 value of 0.926 which suggests that approximately 92.6% of the variance in the property net underwriting result is explained by the independent variables included in the model. This is a version of the R^2 statistic that adjusts for the number of predictors in the model. The adjusted R^2 value of 0.896 indicates that about 89.6% of the variance in the dependent variable is explained by the independent variables, considering the complexity of the model. The low probability associated with this F-statistic (Prob (F-statistic) < 0.00001) indicates that the overall model is statistically significant.

Table 5.3.1-3: Model summary for y_3 = property net underwriting result

	coefficient	std error	t	p-value
Number of weather-related events	13.0468	109.177	0.120	0.907
Average Rainfall	-7.1969	10.474	-0.687	0.508
Maximum Temperature	-192.3104	553.934	-0.347	0.736
Minimum Temperature	443.9502	1188.665	0.373	0.717

The p-values of the individual independent variables are above 0.005. This implies that none of the independent variables individually have a statistically significant impact on the property net underwriting result. However, the p-value of the model is extremely low, indicating that the overall regression model is statistically significant, meaning that at least one independent variable in the model is contributing significantly to explaining the variance in the dependent variable, even though individually, the coefficients of the independent variables may not be statistically significant.

CHAPTER 6. DISCUSSION OF RESEARCH FINDINGS

This study shows that from a macro scale perspective, the insurance industry is vulnerable to the weather-related factors such as temperature, precipitation, and natural catastrophe events. These variables were found to be key indicators in the financial losses incurred by non-life insurance companies. This outcome is similar to the previous studies which assessed the impact of climate change on weather-related damages in various countries such as the Netherlands, Germany and the United Kingdom (Hubert 2004; Thieken et al., 2006 and Botzen & Van Den Bergh, 2013). The model performance was assessed against these benchmark models to ensure robustness and generalisability, however, due to the lack of expansive data, the models failed to generalise for more specific contexts such as the Santam's property and infrastructure business unit.

The models developed in Section 5.3 could be useful for the insurance industry to understand the factors influencing weather-related claims; assist insurance companies such as Santam to assess the financial performance of their property underwriting business as well as the profitability of the company as a whole. By understanding the impact of weather-related events and temperature on underwriting results, insurers can adjust pricing, coverage limits, or underwriting guidelines to manage weather-related claims risks effectively. This information can help insurers anticipate claim trends, set appropriate reserves, and adjust reinsurance strategies to mitigate financial risks associated with claims. Additionally, the models provide insights into the relationship between weather-related variables and insurance outcomes, allowing insurers to incorporate weather data into their risk management strategies. Santam can better quantify and manage weather-related risks, such as those associated with natural catastrophic events, which can have a significant impact on underwriting results and claims incurred. They can also use the findings from these models to develop more accurate pricing models, optimise reinsurance strategies, and enhance overall risk management practices, ultimately improving financial stability and competitiveness in the insurance market. Predictive analytics offer valuable insights into the impact of weather-related variables on insurance outcomes, enabling insurers to make informed decisions in risk management and strategic planning.

6.1 Policy implications and recommendations

There are several policies and regulations that must be considered by insurers when implementing forecasting and predictive analytics for weather-related insurance claims. The results of these predictive models have significant policy implications. Stringent data privacy and security regulations are essential to protect sensitive information used in these models. Risk assessment frameworks should be updated to incorporate predictive analytics, enabling more accurate forecasting of weather-related insurance risks. To ensure fairness, policies must regulate the use of predictive analytics in determining insurance premium, preventing discrimination and ensuring affordability, especially for high-risk populations. Transparency in the development and use of predictive models is crucial and requires disclosures from insurers. Regulatory frameworks must be adapted to include standards for predictive modelling and consumer protection laws should be strengthened to safeguard against potential abuses. Additionally, predictive analytics can inform public policies on climate change resilience and adaptation strategies, requiring collaboration between insurers, policymakers and researchers. Addressing potential environmental inequities is also critical, with policies ensuring equitable access to insurance for communities disproportionately affected by catastrophic weather-related events. Finally, cross-sector collaboration should be encouraged to optimise the use of predictive models, ensuring policies are informed by the latest research and technological advancements.

CHAPTER 7. LIMITATIONS, RECOMMENDATIONS AND CONCLUSIONS

This study sought to investigate how the insurance industry and companies such as Santam might use predictive analytics in insurance risk management to account for losses connected to climate change. The insurance industry's approach to managing climate change risk has received relatively little research. This research will examine the integration of various data sources and assess the possible risks associated with climate change that insurers face. This involves determining how weather-related insurance claims are affected by climate change-related occurrences and how this relates to damage to infrastructure and property. It will also look at how insurers may use quantitative risk models and predictive analytics to assess prospective hazards and calculate the financial losses they will incur. Using the suggested CCRAF, this study will also look into important internal and external components that go into developing predictive analytics models for climate change risk assessment. This will make the connection between occurrences brought on by climate change and insurance losses easier to explain.

7.1 Limitations

The developed models, specifically the property net underwriting result model, lack of statistically significant impact for the independent variables. This could be due to several reasons such as insufficient data. The dataset used for the multivariate regression analysis does not have enough observations or variability in the independent variables to detect significant effects on the dependent variable. And because the sample size is small, there is not enough variability in the independent variables, thus making it challenging to identify statistically significant relationships. The multicollinearity of the independent variables can also make it difficult to determine the unique contribution of each independent variable to the dependent variable, leading to coefficients that are not statistically significant.

Furthermore, it should be noted that there are several unobserved factors or variables that influence the dependent variable, such as socio-economic factors and policy regulations, but are not accounted for in the model. These factors could mask the effects of the independent variables included in the analysis. Addressing these issues often requires the collection of additional data to improve the robustness of the analysis.

7.2 Areas for further research

Improvements can be done on each model. This involves refining various aspects, including data quality, model specification, and interpretation. By implementing these improvements, the developed models can offer more accurate predictions and actionable insights for insurance risk management, thereby enhancing decision-making processes and optimising business outcomes. Employing techniques such as polynomial regression to capture nonlinear patterns in the data effectively. Identify and address outliers in the data that may disproportionately influence model estimates. Outliers can be managed through techniques such as data transformation. Incorporate temporal trends by including time-related variables to capture seasonal variations or long-term trends in weather-related claims. Enhance data quality, accuracy, and completeness by validating the quality of input data. Address missing values, outliers, and inconsistencies to improve the reliability of model estimates. Explore additional variables beyond weather-related factors, for example, demographic factors, economic indicators, regulatory/policy changes, or technological advancements that could be relevant predictors. Incorporating additional relevant variables can provide a more comprehensive understanding of the factors influencing financial losses due to weather-related catastrophes.

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Table 7.2-1: Consistency table

Author (Year)	Organisational Problem	Research Problem	Conceptual Frame Used	Research Gap
Tonmoy, F. et al. (2019)	Lack of internal formal structures to implement climate change risk assessment	Climate change risk analysis	Climate change adaptation	Lack of integration of the risk assessment process for climate change adaptation across the entire organisation
Shao, W. et al. (2019)	Flood risk analysis using customer behaviour	Lack of data driven decisions foe climate risk mitigation	Bayesian Network modelling	Data inaccuracies
ClimateWise (2021)	Lack of innovative insurance products and services	Insured losses attributed to climate change	Internet of Things (IoT)	Outdated pre-existing climate change models
Phibbs, S. (2022)	Modelling the impact of catastrophes	Impact of natural catastrophes in insurance risk management processes	Data analytics and modelling	Lack of accurate, current and real-time data