Preferences for index-based pasture insurance: a choice experiment in Limpopo Province, South Africa

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DECLARATION OF ORIGINALITY

I**, Bernard Manganyi**, declare that the dissertation I submitted for the Master of Science (MSc) in Agricultural Economics at the University of Pretoria is my work and has not previously been submitted by me for a degree at this or any other tertiary institution.

Signature:

Date: January 2022

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ABSTRACT

The impact of climate change intensifies drought risk, severely threatening subsistence farmers in developing countries. To deal with the effect of drought, subsistence farmers rely heavily on traditional mitigation and coping mechanisms; however, they are proved inefficient in dealing with the complete impact of drought. In this view, policymakers are increasingly interested in promoting Index-based Pasture Insurance (IBPI). This study's main objective is to assess the preferences of subsistence livestock farmers for IBPI. A discrete choice experiment approach and other survey methods (incentivised lottery games and self-reported risk preferences based on a Likert scale) were used to elicit preferences for insurance contracts, farmers' risk tolerance, and loss aversion. Data collection covered 110 subsistence livestock farmers identified using a simple random sampling method. Results show that sampled subsistence livestock farmers have a positive attitude towards IBPI contracts that hedge against drought-related pasture degradation. The conditional Logit (CL) model shows that farmers derive positive marginal utility from contracts that reimburse with feed and vouchers relative to cash and prefer transparent contracts. They also derive negative marginal utility from basis risk and premium as expected. At the same time, Latent Class (LC) model shows that farmers exhibit heterogeneous preferences for IBPI. Furthermore, farmers are loss-averse and medium risk-averse; however, loss aversion and risk-aversion did not significantly influence farmers' preference for IBPI. Therefore, the main recommendation for insurance providers is to consider the customisation of identified IBPI attributes when designing IBPI schemes to increase the likelihood of adoption by subsistence farmers.

Keywords: Climate change, Discrete Choice Experiment, Drought, Index-Based Pasture Insurance, Loss Aversion, Risk Aversion, Subsistence Farmers, Conditional Logit, Latent Class

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LIST OF ACRONYMS

CPT	Cumulative Prospect Theory
CVM	Contingent Valuation Methods
CL	Conditional Logit
DCE	Discrete Choice Experiment
FGD	Focus Group Discussion
FPI	Forage Production Index
EUT	Expected Utility Theory
IIA	Independence of Irrelevant Alternatives
IID	Independent Irrelevant Distribution
IBI	Index-based Insurance
IBLI	Index-based Livestock Insurance
IBPI	Index-based Pasture Insurance
IFWG	Intergovernmental Fintech Working Group
IRLI	International Livestock Research Institute
HB	Hierarchical Bayes
MXL	Mixed Logit
NOAACPC	Atmospheric Administrative Climate Prediction Centre
LC	Latent Class
NDVI	Normalized Difference Vegetative Index
RUT	Random Utility Theory
RPL	Random-Parameter Logit
SAIA	South African Insurance Association
PT	Prospect Theory
WTP	Willingness to Pay

CHAPTER 1 INTRODUCTION

1.1 Background

Climate change increases the odds of natural disasters in many parts of the world. Because of the effects of climate change, the severity, frequency, and duration of natural disasters such as floods and drought have worsened (Udmale et al., 2014). Among all the natural disasters, drought is the most prominent regarding the number of households it directly affects (Hewitt, 2014). Unlike abrupt natural disasters such as hurricanes and thunderstorms, drought duration is long, and it is often difficult to pinpoint its exact start and end times. Thus, it is challenging to define drought because of the complex variances in climatological and socioeconomic aspects linked to the scarcity of rainfall in several regions in the world. However, drought slowly prevails in specific geographical areas due to a continued rainfall deficiency over a certain period due to low or no rainfall, water levels in rivers and dames drop, and groundwater aquifers (Liu et al., 2019).

The consequences and effects of drought extend to society and other aspects of the economy (Orimoloye et al., 2019; Tfwala et al., 2018). Drought affects the agriculture sector disproportionately relative to other economic sectors worldwide. For instance, the agricultural industry absorbed about 83% of the financial losses from drought (Conforti et al., 2018). When drought extends beyond water shortage, crops wither, forage or fodder becomes scarce, and livestock is the most affected. In some cases, the quality and quantity of fodder and forage crops decrease significantly, thus altering livestock feeding patterns and nutritional status. As a result, livestock farmers face difficulties aligning their animals to the appropriate dietary requirements. Hence livestock succumbs to starvation and poor nutritional status. Because of the limited and unavailability of government intervention, farmers were then burdened with losing their livestock assets through the drought. Drought has ripple effects on food security and livelihoods, and the effects are usually high for subsistence farmers.

The effects of drought typically extend to the entire agricultural supply chain, thus causing substantial economic setbacks, especially in developing economies. An example of this was witnessed in developing countries between 2005 and 2015, where losses of about $96 billion were recorded in crops and livestock alone due to the devastating effects of drought (Conforti et al., 2018). Drought is the most costly impact of all-natural disasters in Africa and Latin America, where losses recorded for crops and livestock amounted to $13 billion and $10.7 billion, respectively (Conforti et al., 2018). Some sporadic occurrences of drought are because of El Nino conditions and, to a lesser extent, seasonal rainfall fluctuations (UNDRR, 2021). The proximity of the Kalahari Desert to South Africa has contributed to it being a semi-arid country, hence susceptible to repeated drought events. For instance, South Africa has recorded 12-years of drought occurrences in the past 20 years. The latest adverse drought events in South Africa lasted for three successive years of drier conditions between the years 2014 and 2016 (Baudoin et al., 2017). However, drought has continued to devastate some provinces, such as Eastern Cape, Limpopo, and North West, in 2019 and 2020 (AGRISA, 2019). Since a significant proportion of the affected areas have about 80% of agricultural land suitable for livestock farming, the livestock farming sector is dealt a severe blow.

The South African livestock sector is a dual system with a highly commercial and subsistence sub-sector. The subsistence sector contributes to the household economy, social status, and food security. However, the consequential impact of drought offsets the contributions of the subsistence livestock sector to the household economy because of insufficient coping capacity, leading to poverty. In order to address the problem of losing their livestock during drought periods, subsistence farmers adopt different coping mechanisms. These coping mechanisms involve the adoption of ex-ante and ex-post measures. Ex-ante measures include enterprise diversification, non-farm activities, saving and storing feed, establishing other assets base, and other social networks they can rely on when drought strikes. Ex-post measures include reducing the stock and drawing from savings and livestock selling, shifting to non-farming enterprises, and seeking help from social networks. However, the efficiency of these mechanisms relies on the total costs associated with them. When the cost of implementing a particular measure is high, they leave farmers with limited options, forcing them to rely on the government's post-disaster relief programs. Heavy reliance on government relief programs is not a practical option because they are reactive and inefficient in addressing the impact of drought. In addition, the government does not measure the losses incurred to compensate individual farmers according to their losses. At the same time, subsistence farmers perceive such measures as the best way to mitigate risk. In contrast, the government's help takes longer to arrive because of the inefficiencies of the administrative layers at both provincial and national levels of government, which result in high transaction and opportunity costs in providing drought relief to affected subsistence farmers.

The non-viability of the above mechanisms has led to more research on financial ways of addressing drought risks (Hassan, 2013). One of the recommended ways emphasized the need to design a more operative agricultural insurance that is more accessible to subsistence farmers. The South African agricultural insurance provides indemnity-based insurance schemes and covers crops and livestock, and it calculates the indemnity by assessing the proportion of damage in the field shortly after the damage occurs. This kind of insurance allows farmers to reduce susceptibility to volatile climatic conditions and allows the market to absorb a proportion of the cost while establishing themselves in the sector. However, livestock insurance is limited to mortality due to fire and lighting destruction, wild animal aggression, electrocution, floods, freezing or cold conditions, plant poising, disease plagues, thievery, and transit. No formal insurance product explicitly covers livestock against drought in South Africa, and the livestock sector remains susceptible to drought risk.

The absence of insurance against drought is attributed to two main reasons. As for other insurance mechanisms, information asymmetry allowing for adverse selection and moral hazard affects the supply and demand of insurance. Adverse selection is when potential insurance buyers have more information about their exposure to the risks covered than the insurance provider (Shettima, 2020). This behaviour leads to high participation by high-risk individuals and low involvement of low-risk individuals. These problems increase the transaction cost of providing insurance. Insurance providers reduce the burden by charging high premium rates (reducing the overall demand) or not insuring (reducing the offer). A moral hazard in insurance occurs when the insured person knows the insurer will pay for his mistakes, encouraging him to act in a riskier way. In addition, it is challenging to hedge drought risk because of the complexity of linking drought and damages it causes in the livestock sector.

Upon realizing this lack and in the quest to resolve it, the South African Insurance Association (SAIA) devised strategies for drought risk transfer for the livestock sector. They advocated for index insurance products that effectively transfer drought risk in the livestock sector (SAIA, 2020). They calculate insurance claims based on an index highly correlated to the actual losses at the farm level. It is a more affordable insurance product since it does not require a physical assessment of losses at the farm level and circumvents the problems associated with traditional agricultural insurance. To this effect, the Intergovernmental Fintech Working Group (IFWG) invited insurers to develop index insurance for the subsistence livestock sector that meets regulatory standards and the needs of subsistence farmers. The IFWG falls under the South Africa Reserve Bank Fintech unit, established in 2016 to understand the role of fintech and innovation in the South African financial sector and explore how regulators can assess the emerging risk and opportunities in the market. In response to the IFWG call, the South African Land and Agricultural Bank, a state-owned company known as the Land Bank, responded by developing an index pasture insurance product, which is still awaiting the approval of the insurance regulating authority. However, there is a limited research contribution on index insurance from the South African context. Most of the research contributions in the South African context focus on the weather-based crop insurance and left the index-based pasture insurance for livestock unexplored (Born et al., 2019; Wang et al., 2013).

Given this literature gap on index-based pasture insurance (IBPI), the need to assess preferences for this insurance product is a requisite. As recommended and discussed by Hassan (2013), offering affordable insurance to subsistence livestock farmers can reduce their vulnerability to drought risk. Since the South African subsistence livestock sector remains highly vulnerable to drought risk because of the lack of supplementary measures such as insurance policies that insure drought-related risks. The vulnerability is significantly high in provinces that make up large proportions of rural areas, which is the case with the study area of Limpopo Province. Therefore, this study will investigate farmers' preferences for IBPI using choice experiment methods. The study focuses on subsistence livestock farming communities in one of the drought-prone provinces in the Limpopo Province, South Africa.

1.2 Problem Statement

The design of index insurance products with a high likelihood of farmer adoption has been an issue globally. However, developing countries have been at the forefront of the development and design of index insurance. Some developing countries, such as Kenya, Ethiopia, and Mongolia, have tested index insurance products that protect farmers against drought risk (Amare et al., 2019; Chantarat et al., 2013). The fundamental problem with this design is that it acts as asset replacement insurance instead of asset protection. This design might not be feasible in specific countries because household-level livestock mortality data may not be readily available. In addition, household-level data increases the imperfect correlation between the index and livestock mortality (Ye et al., 2017).

In contrast, several developed countries, such as Canada, France, Spain, and the USA, have developed index insurance that protects livestock against drought-related pasture degradation using satellite technology (Vroege et al., 2019). Satellite imaginary applies to develop the index forage insurance. Because of this, SAIA proposed introducing a similar design insurance product that protects smallholder and subsistence livestock farmers against drought-related pasture degradation, which refers to as index-based pasture insurance (SAIA, 2019). Their proposal was commended by the World Bank and subsequently submitted to the government departments such as the National Treasury (NT) and the Departments of Agriculture, Land Reform, and Rural Development (DARLRD) for approval. These departments endorsed the proposal, where the preliminary market research showed that about 112,625 farmers are willing to take up index insurance (SAIA, 2019). The Land Bank Insurance Company (LBIC) is piloting index-based pasture insurance.

The unique advantage of IBPI is that it does not require historic drought-related livestock mortality data since it acts as an asset protection insurance that guards against drought-related pasture degradation. Pasture degrades due to drought when there is little or no rain within a year. Consequently, subsistence farmers must buy supplementary feed to sustain their herds. At the same time, farmers struggle to handle this additional feed cost because of less or no cash flow. This then instigates other secondary challenges such as insolvency, selling productive assets, unprecedented depreciation of livestock assets, and possibly going out of livestock production. These instances are severe in the drought-prone area like the selected study area, Makhado municipality, Limpopo Province, Northern part of South Africa.

Therefore, IBPI can mitigate drought-related pasture degradation risk by compensating farmers when the pasture degrades beyond a predetermined threshold. The predetermined threshold refers to a trigger level beyond which subsistence farmers receive compensation within the affected geographical area. However, IBPI does not act as a panacea since it exhibits shortcomings such as the basis risk. The basis risk refers to the aggregate of observable differences between individual and index predicted losses (Jensen et al., 2018). Basis risk is inevitable in index insurance and negatively affects the WTP for index insurance contracts.

Notwithstanding, a significant number of studies that assessed the WTP for index-based insurance omitted basis risk in their analysis (Abebe & Bogale, 2014; Budhathoki et al., 2019; Doherty et al., 2021; Fahad & Jing, 2018; Fonta et al., 2018; Oduniyi et al., 2020). Few studies inspect the impact of basis risk on this subject using intelligent approaches and aggregated data (Clement, Wouter Botzen, et al., 2018; Keeler & Saitone, 2020; Lampe & Würtenberger, 2020). As a result, they have very little to present in terms of trade-offs among important attributes of index insurance design and basis risk in the perspective of preferences under risk.

Other than basis risk, attitudinal factors such as risk preferences seem to affect the take-up of index insurance owing to uncertainty regarding the accuracy of the index that triggers the payment (Clarke, 2016; Hwang, 2021). To some extent, people deviate from the expected utility theory when making risky choices (Tversky & Kahneman, 1992). Therefore, individuals decide according to their perception of losses and gains, which leads to loss aversion. Loss aversion is the perception of the decision-making process regarding losses and gains (Schmidt & Traub, 2002). Other essential variables, such as insurance premium and other socioeconomic characteristics, can affect preferences for index insurance. Even though other studies have empirically tested the latter, the outcomes are not universal because of socioeconomic status differences across countries. This study sheds some light on the South African case using risk-related and other socio-economic variables.

1.3 Justification of Study

This study explores the preferences of livestock farmers for index-based pasture insurance (IBPI). Since IBPI is available in the South African insurance market, this study uses a discrete choice experiment (DCE) method to investigate farmers' preferences for IBPI. In this context, a discrete choice experiment describes, explains, and envisages preferences between two or more alternatives, such as buying IBPI contracts. The appealing advantage of a DCE experiment is that it can include a wide range of attributes that give a deeper understanding of farmers' preferences for IBPI. Concerning IBPI attributes, this is the first study to include basis risk and reimbursement methods attribute in a DCE design to the best of the authors' knowledge. Besides this, literature recognises the importance of loss aversion and risk aversion. As a result, this study also seeks to explore loss and risk aversion and tests their influence on the potential take-up of the IBPI scheme.

1.4 Research Questions

The study pursues to address the following questions:

1. Do farmers perceive traditional mitigation and coping strategies for drought as effective?
2. Are farmers willing to pay for index-based pasture insurance?
3. To what extent do loss aversion and risk-aversion affect farmers' preferences for IBPI?

1.5 Research Objectives

The primary aim of this study is to evaluate farmers' preferences for important attributes of IBPI within the jurisdiction of Mulima Village, Makhado Local Municipality, Limpopo Province, South Africa. In particular, the study will have the following sub-objectives:

1. Assess farmers' preferences for IBPI attributes.
2. Measure farmers' loss aversion and risk aversion, consequently inspecting how they affect farmers' preferences for index-based pasture insurance.
3. Characterizes farmers' management strategies for drought

1.6 Hypotheses

The study will test the following hypotheses:

1. Subsistence livestock farmers are unwilling to adopt IBPI as an additional mitigation mechanism for drought.
2. Loss aversion and risk aversion do not influence the adoption of the IBPI contract.

1.7 Research Scope

This study seeks to assess farmers' preference for index-based pasture insurance. The initial step was to identify relevant index insurance attributes and their levels through reviewing relevant literature and online focus group discussions with key informants, such as insurance companies, academia, farmers' organizations, and livestock farmers, that suit the description of the targeted sample. After that, a survey was designed, which included five sections: (1) introduction, (2) discrete choice experiment, (3) lottery game, (4) risk-taking attitudes, and (5) socioeconomic characteristics. The survey was piloted with 20 subsistence livestock farmers in the Vhembe District, Limpopo Province, South Africa. The results from the pilot informed the final survey design, which was implemented in the same district, but in different villages from the pilot study area. The final survey was implemented in June 2021 and lasted 35 days. It covered 110 subsistence farmers, a relatively small sample size due to the South African government lockdown regulations due to the global Covid19 pandemic. After successfully capturing and cleaning the data, R-statistical software was used to analyse data, specifically, the Apollo packages, a tool for choice model estimation and application.

1.8 Dissertation Outline

This dissertation consists of five chapters, including this first chapter. Chapter 2 covers a theoretical review of risk management strategies from the perspective of subsistence farmers and the development of agricultural insurance. It also presents an empirical literature review on demand for index insurance and how loss aversion affects preferences. Chapter 3 presents the procedures and methods used to carry out the study. The first section describes the study area, the second covers the experimental research design and data collection process, and the third describes econometric models used for data analysis. Chapter 4 presents the results and discussions. The results cover descriptive statistics, farmers' perceptions of drought, adoption of traditional drought management strategies, self-reported risk tolerance, and loss aversion. Chapter 5 concludes and gives policy recommendations drawn from the results analysed in chapter 4 and suggests potential considerations for future research informed by this study.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter presents the theoretical and empirical literature related to index-based pasture insurance. The theoretical literature covers risk management from the perspective of subsistence farmers and brings out the need for agricultural insurance, particularly index-based pasture insurance. Last, the empirical literature review focuses on preferences for index-based pasture drought insurance, considering how the loss aversion and risk aversion influence preferences for index-based pasture insurance.

2.2 Theoretical Literature Review

This section outlines risk in agriculture and how subsistence farmers address it. Further, it details index insurance schemes and their shortcomings. Last, present the importance of loss aversion in making economic decisions.

2.2.1 Risk in Agriculture

Agriculture is susceptible to varied risks rising from weather unpredictability, natural hazards, diseases, and market shocks (Singh et al., 2018). Risk is the likelihood of deviation between expected and actual outcomes; the divergence can be negative or positive (Arrow, 1981). However, decision-makers in agriculture give more attention to the possibility of adverse effects to avoid unprecedented loss (Anton, 2008). Anton (2008) and Kahan (2008) categorized sources of risk as marketing, financial, human, institutional, and production risks. Marketing risk refers to the uncertainties associated with the prices of inputs and outputs (Kahan, 2008). They relate financial risk to the responses of macroeconomic policy exchange and interest rates, which subsequently affect the cost of production, supply, and demand costs. Human risk refers to illness or death; for example, death or illness can affect the performance of the farm business. Institutional risk includes radical deviations in delivering services from organizations (e.g., financial institutions, farmers groups, inputs suppliers, and government) that support agricultural systems. The proportion of institutional risks is the uncertainty of government agricultural policies, such as subsidies and disaster aid. While production risk links to all events that make production outcomes uncertain, many agricultural outputs heavily rely on biotic processes that weather, and diseases can easily affect. Drought, floods, hail and diseases outbreak could damage crops and livestock. Amid all-natural disasters, drought positions first regarding the population directly affected (Hewitt, 2014). Drought is the most challenging and complex natural disaster (Mera, 2018). Unlike abrupt natural disasters such as thunderstorms and hurricanes, it is often difficult to pinpoint when the drought started or ended owing to the variances in climatological and socioeconomic aspects linked to water scarcity in several regions in the world.

Even though the definition of drought may differ by sector and region, typically, drought slowly prevails in specific geographical regions owing to continuous low rainfall for a certain period, reducing the water level in rivers, dams, and groundwater aquifers (Liu et al., 2019). The consequential effect of drought extends to society and other aspects of the economy (Orimoloye et al., 2019; Tfwala et al., 2018). According to Tfwala et al. (2018), drought takes different forms based on its effects. There are four types of drought classifications: (i) agricultural, (ii) meteorological, (iii) hydrological, and (iv) socioeconomic drought (Tfwala et al., 2018). Agricultural drought is attributed to soil moisture deficiency, whereas meteorological drought can result from rainfall deficiency and temperature rise above normal (Liu et al., 2016). Hydrological drought prevails owing to water cycle imbalances and causes of low rainfall in specific regions (Van Loon, 2015). Socioeconomic drought is because of the interaction of human and natural factors that can cause production losses, where water supply cannot meet demand (Cai et al., 2017).

2.2.2 Risk Management strategies

Risk management in agriculture is crucial; although reducing risks may not directly lead to increased income, the inability to manage risk can significantly affect farmers' income and food security (Aimin, 2010). Therefore, farmers require effective risk management strategies considering the connections and compromises between different risk management strategies and government policies (OECD, 2021). This ensures that risk management strategies do not entirely focus on increasing farm income at the expense of agriculture's resilience and sustainability. Risk management strategies can be classified into four primary categories: avoidance, reduction, sharing, and retention (Goh & Abdul-Rahman, 2013). Risk avoidance is refusing to accept or intervene to ensure the risk will not happen. Risk reduction is a strategy used to minimize risk likelihood and impact at an acceptable level. On the other hand, risk transfer involves shifting risk from one party to another third party without changing the total amount of risk.

Risk-retention requires acknowledging and accepting a specific risk while attempting to reduce it (Goh & Abdul-Rahman, 2013). Subsistence farmers mainly apply risk retention since they tend not to take the risk of climatic conditions to their farming income and livelihoods (Binswanger-Mkhize, 2012). However, their risk management varies according to the risk they seek to address. They addressed the infrequent and localized risk, resulting in minor losses through day-to-day farm management, early warning from the government, and an informal risk pooling mechanism. When farmers cannot address the infrequent and considerable risk using the strategies, they resort to traditional means to sell productive assets and reduce consumption. The government can intervene by providing disaster aid relief (FDRF, 2020). Also, farmers can transfer a proportion of risk to insurance companies and avoid overreliance on traditional mechanisms. Different risk management strategies that subsistence farmers primarily use are presented in Table 2.1 below.

Table 2.1 Risk management strategies

Risk	**Informal mechanisms**	**Formal mechanisms**	
	Household strategies	**Market**	**Government**
Non-specific	• Avoid exposure to risk • Planning for natural resource management	• Risk-reducing technologies (e.g., drought-resistant breeds)	• Agricultural research and extension services
Low	• Selecting low-risk commodities • Production diversification • Reserve inputs and produce	• Formal saving • Market price information • Forward pricing	• Early warnings • Weather information systems
Moderate	• Labour diversification • Risk pooling (peers, family members) • Forming producers' groups • Cooperatives • Traditional institutions and social arrangements	• Formal lending • Spreading sales • Direct Sales • Contract farming • Risk-reducing inputs	• Government-sponsored lending • Blended financing • Disaster-response social protection
Catastrophic	• Reduce consumption • Sell productive assets • Migration • Do nothing	• Insurance: Indemnity-based and IBI.	• Disaster aid reliefs • Social protection funds • Government subsidized insurance • Risk-sharing facilities

Source: (FDRF, 2020; Kahan, 2008)

Therefore, farmers combine the risk management strategies listed in Table 2.1 above, depending on the cost and benefits of each method. The most prevalent risk management strategy that farmers apply is risk-reducing inputs. They aim this strategy at improving the quality and quantity of produce. For example, fertilizers and pesticides can reduce the risk of low production output. In livestock farming, farmers can buy supplementary feed such as bales and fodder to minimize the risk of animal mortality because of starvation during the drought period– for those who can afford to buy it. In a study conducted in the drought-prone region of Free State, South Africa, Olaleye (2010) found that about 42.5% of subsistence farmers could buy supplementary feed for their animals during the drought. However, this strategy requires additional capital to implement.

For instance, during prolonged periods of drought, buying feed becomes very costly; as a result, many subsistence farmers cannot afford to bear the high feed cost (Jordaan, 2012). Farmers can spread livestock sales throughout the year while observing feeding, calving, and other farming operations. However, this strategy does not guarantee increased income but reduces the risk and ensures stable cash throughout the year. Specifically, this is applicable when farmers experience prolonged drought; they adopt early marketing, whereby they sell the weaker and older animals and keep those that might resist drought; or, in the worst case, they resort to selling all their animals to restock them once the grazing conditions have improved. However, this strategy could decrease revenue because subsistence farmers are commonly price takers and do not have much bargaining power. In a study conducted in the Western Cape Province of South Africa, most farmers confirmed they reduced their herd through early marketing to mitigate mortality (Fanadzo et al., 2021). This study confirmed earlier in a survey by Hudson (2002) that farmers in the same province sell their livestock after experiencing adverse drought conditions. This idea of selling their animals during drought relies on the environmental principles that advocate balancing the number of animals and the natural pasture (Ncube & Lagardien, 2015). For example, they addressed the degradation of grazing by maintaining the grazing capacity at an optimum level to prevent overgrazing through rotational grazing. Rotational grazing avoids overgrazing by migrating animals to other areas with better pasture when the current range is no longer in good condition. Farmers with more communal land for grazing avoid this strategy and desist from moving their animals.

Another method that farmers use is risk-reducing technologies such as resistant breeds. However, this is a long-term risk management strategy. Also, farmers can form traditional and social arrangements such as producers' groups and cooperatives as a strategy for risk pooling. This provides security through social networks, including friends, family, and community members who give farmers support by allowing their livestock to graze in their veld and other necessary support (Ncube, 2020). Moreover, farmers can affiliate with farming organizations where they benefit from receiving extension services and animal feed. In a study conducted in the KwaZulu-Natal province of South Africa, Lottering et al. (2020) found that these social systems play a critical role in reducing the impact of drought on farmers. However, Ubisi et al. (2017) reported that only 8.7% of subsistence farmers had these social networks. The latter was also justified in Bahta et al. (2016) study, and they found that farmers do not regard these social networks as effective means to reduce their vulnerability to drought. The problem with the traditional drought mitigation mechanisms is that their effectiveness relies on the total cost. When the cost to implement each strategy is too high, farmers consider other risk reduction mechanisms such as agricultural insurance–yet not practical in subsistence farming communities of South Africa. Also, traditional strategies cannot easily absorb drought-related losses (Binswanger-Mkhize, 2012).

2.2.3 Agricultural Insurance

The agricultural industry is susceptible to economic losses due to weather peril, e.g., drought, floods, hailstorms, diseases, drastic decline in market prices, and spikes in prices (Nnadi et al., 2013). Because of these, farmers mitigate these risks by applying traditional mitigation mechanisms, which are arguably ineffective–as discussed in the previous section because the cost of these mechanisms is typically beyond the budget constraints of farmers. Here, farmers can consider transferring the whole or part of their losses to the agricultural insurance market. Agricultural insurance is one financial tool used to manage agricultural risks by protecting farmers against losses due to weather catastrophes (Kang, 2007). As a result, the design of inclusive agricultural insurance has attracted enormous research interest from academia and policymakers. Depending on the method used to assess the damages or losses, insurance can be categorised into indemnity-based and index-based insurance (Carter et al., 2014). Indemnity-based insurance uses actual losses incurred by clients to calculate the claims, which require physical assessment at the farm level. Index-based insurance uses indexes such as regional average yield, rainfall verified at the closest weather station, and average vegetative index to calculate the claim (Mookerjee et al., 2014). The computed indices must correlate with the losses at the farm level and both the insurer, and the insured must not influence the index.

2.2.3.1 Indemnity-based Insurance Schemes

Indemnity-based insurance schemes cover crops and livestock, but only at a limited level. Indemnity-based crop insurance includes: (i) named peril crop, (ii) multiple peril crop, and (iii) revenue crop insurances (Partridge & Wagner, 2016). Named peril crop insurance protects crops against losses from a specific peril such as hail, floods, frost, and fire. However, hail is the most common peril usually covered under this insurance scheme. In a study by Mahul and Stutley (2010), about 69% of 65 surveyed countries offer peril insurance. Multiple crop insurance covers losses from all-natural disasters, including biological and climatic perils. The indemnity calculation is according to yield shortfalls below a predetermined threshold multiplied by a pre-specified price (Partridge & Wagner, 2016).

Revenue crop insurance extends multi-peril insurance based on physical damage assessment and crop prices. This insurance reimburses policyholders when revenue falls below expected due to lower yield and crop price (Roberts, 2005). Under indemnity-based insurance, they provide traditional livestock insurance on a limited scale, covering death from natural peril such as fire, lightning, cold conditions, plant poisoning, disease plagues, and thievery.

However, this excludes diseases such as epidemics (Mahul & Stutley, 2010). The premium determination relies on prescribed average mortality rates within a predetermined age, plus risk and administration cost.

The establishment of premium is based on the law of large numbers–a statistical and probability theory principle that uses a large sample to estimate an event, where the outcome may be closer to the average population (Smith & Kane, 1994). This law envisages the risk of losses or claims of policyholders so that the established premium can be close to expected losses (Tinungki, 2018). However, this concept of a law of large numbers becomes less effective in the event of severe covariate risks (Barnett et al., 2008). This is common in insurances that protect against disasters like fire, floods, drought, and diseases because they can easily affect many policyholders simultaneously (Mahul & Stutley, 2010). In this case, the disaster insurance system can easily collapse owing to information asymmetry (Günther & Harttgen, 2009).

Information asymmetry is associated with inadequate information prevalent in any economic transaction process (Barnett et al., 2008). This creates a strategic behaviour based on the reluctance in risk valuation. Here, the potential insurance policy buyers have more information concerning their exposure to risks than the insurance provider, for example, (i) concealed information resulting in adverse selection and (ii) concealed action leading to moral hazard (Shettima, 2020). Adverse selection is the one that complicates the underwriting of risks since the underwriters lack the relevant information, which then leads to policyholders' misjudgment (Barnett et al., 2008). Because of concealed information about the level of risk, clients at high-risk purchase insurance more than those at low risk. Consequently, the insurance program will likely accumulate losses surpassing the projections in launching the premium rates. In order to offset this impact, the insurer may charge high premium rates.

Conversely, moral hazards assume changing behaviour by clients after purchasing an insurance contract (Vroege et al., 2019). This behaviour disadvantages the insurance providers since it exposes them to a higher risk than expected relative to the initial premium they charged. In order to solve the problem of adverse selection and moral hazards, the insurer shares some risks with the policyholders (Barnett et al., 2008). This is done by introducing the deductibles–an amount that an insurance policyholder must pay for an insured loss.

Alessie et al. (2020) assessed the importance of deductibles in moral hazards and adverse sections in healthcare insurance. They found deductibles are effective in reducing moral hazards in healthcare insurance utilization. However, adverse selection and moral hazards still plague the agricultural insurance market amid deductibles, as the problems are highly prevalent in low-income areas due to low production unit areas (Goodwin, 2001). As a result, underwriting and monitoring services to circumvent information asymmetry is relatively high, consequently increasing the transaction costs of providing insurance. Transaction costs are the expenses of administering the economic systems of firms (Williamson, 1979). Each type of transaction is associated with the coordination cost of monitoring, controlling, and managing transactions. Decision-makers use such costs to decide to use a firm structure or source from the market; for instance, they can compare internal production costs with transaction costs (Young, 2013). The transaction costs of providing insurance are more expensive in remote areas than in urban areas because of the long distances that insurance agents and loss assessors must cover. Also, the transaction cost of marketing and motoring insurance is much higher in low economies of scale policies than in higher economies of scale policies. Therefore, transaction costs are another cause of the low penetration of indemnity-based insurance in rural areas. The shortcomings of indemnity-based insurance are addressed through index-based insurance.

2.2.3.2 Index-based Insurance (IBI)

In order to address the effects of transaction costs, governments and insurance policymakers promote IBI as an alternative to IBI. IBI is an innovative financial tool to mitigate weather-related risks in the smallholder and subsistence agricultural sector (McIntosh et al., 2013).

Contrary to indemnity-based, IBI does not rely on the outcome of the physical assessment of damage on the farm level. It is, however, based on indices such as a regional average yield, rainfall recorded at the closest weather station, and average vegetative indices highly correlated with farm yields (Vroege et al., 2019). Here, indemnification occurs when the loss passes a predetermined trigger level.

IBI is classified into three different schemes: (i) area yield insurance, (i) weather index insurance, and (iii) satellite insurance. Area yield insurance indemnifies when the yield deficit is relative to the predetermined yield in one year in the same area. This area is a group or district homogenous in production and yields (Mahul & Stutley, 2010). Weather index insurance indemnifies based on independent weather indices closely correlated with actual farm-level losses. In this kind of insurance, the reimbursement calculation depends on the deviation of weather parameters from the predetermined level (Clarke, 2016; Mahul & Stutley, 2010). IBI can use different weather indices, such as precipitation, temperature, wind, and solar radiation. These indices must be entirely independent of farmers' decisions at the farm level. An independent organisation must administer them to circumvent the influence of both the insured and insurer (Vroege et al., 2019). Last, satellite insurance uses time-series remote sense imaginary (De Leeuw et al., 2014). It uses NDVI to measure the canopies' reflection in the red and infrared regions as the underlying insurance index. The NDVI is more reliable in detecting the prevalence of drought in grasslands, and its predictions are typically good with limited errors (Yengoh et al., 2015).

Most index-based livestock insurance products are categorised under satellite insurance. Satellite imagery such as index forage insurance is already adopted in developed countries like Canada, France, Spain, and the USA (Vroege et al., 2019). Forage insurance is designed using two indices: (i) precipitation index is, also known as moisture deficiency insurance (MDI), and (ii) NDVI (Roznik et al. (2019)). The MDI protects farmers against rainfall deficiency during the rainy season and derives its index from the rainfall data collected from the nearest weather station. While satellite yields insurance functions using remote sensing, known as the forage production index (FPI). Therefore, FPI is a resultant of NDVI, while the calculation of NDVI values uses surface reflectance information gathered by satellite remote sensing platforms. The collection of these values is on a square kilometre grid resolution that covers the forage growing location.

Airbus offers forage insurance in France based on a biophysical parameter index that measures the proportion of ground covered by forage. They collected these index values at a 300 x 300 m resolution grid, averaged at the municipal level from which premium rates are established (Roumiguié et al., 2015; Vroege et al., 2019). In the USA, the United States Department of Agriculture (USDA offers pasture insurance) under the directorate of the Risk Management Agency (RMA) (Keeler & Saitone, 2020). They marketed pasture insurance under Pasture, Rangeland, and Forage (PRF), which uses interpolation in the gridded precipitation index. Here, the reimbursement is triggered when accumulated precipitation in the grid cell where the farmers are located is below the predetermined level (Roznik et al., 2019). The precipitation index uses National Oceanic Atmospheric Administrative Climate Prediction Centre (NOAA CPC) data, where each grid is about 17 x 17 miles.

The unique advantage of IBI schemes necessary for subsistence livestock farmers is that (i) provides symmetric information for both insurer and the insured, (ii) remote assessment of pasture degradation, and (iii) indemnification is fast since a physical assessment of individual losses is not a requisite, and (iv) IBI successfully reduces the transaction costs of providing insurance which makes insurance premium cheaper and circumvent problems of information asymmetry (Jensen et al., 2018). Also, it has the potential to absorb a proportion of income risk and encourage farmers to invest in high-risk production commodities and new technologies (Amare et al., 2019). Amid growing interest in IBI, Binswanger-Mkhize (2012) cautions about too much hype about quickly making IBI a product that can successfully transfer the risks to the insurance market at an affordable premium in developing countries. He cited the prerequisite to designing sustainable IBI products to use the underlying index that is highly correlated with the yield at the farm level. In addition, this index must be self-governing, transparent, and inclusive to farmers, and a long time series (e.g., at least ten years) index must be open and available in the future.

IBI is not a universal solution since it exhibits other insurance problems. The main issue with IBI is that it relies on the representative index that captures the co-variance risks uniformly, assuming farmers within the same jurisdiction face homogeneous exposure to climatic hazards. At the same time, heterogeneity exposure to climatic hazards introduces basis risk. Basis risk exists when an imperfect correlation exists between an index and individual losses (Clement, Botzen, et al., 2018; Clement, Wouter Botzen, et al., 2018; Jensen et al., 2016; Jensen et al., 2018; Tadesse et al., 2015). There are three types of basis risk: (i) design basis risk, (ii) spatial basis risk, and (iii) temporal basis risk (Dalhaus & Finger, 2016). Design basis risk exists when the index omits some crucial information relevant to predicting losses at the farm level. Spatial basis risk emerges when an unprecedented distance between the index points, such as the weather station and the protected asset's location. In comparison, temporal basis risk prevails when there is a bias in average temporal observation because it averages observations into months and relates a plant's susceptibility to its biological life cycle (Dalhaus & Finger, 2016).

There are, however, research developments that suggest newer approaches to reducing the basis risk. For example, Dalhaus and Finger (2016) showed that basis risk could be minimized by incorporating phenological observations in IBI design. Similarly, Dalhaus et al. (2018) compared different weather insurance schemes to manage drought risk in solitary phases of plant development. In their approach, the insurance period differs according to time and planetary occurrence times of development phase stem elongation, anthesis, and ear appearance. Their results showed a significant improvement in reducing spatial basis risk in weather insurance products. In their analysis, they observed that the utility gain is the one that reveals the potential benefits for both policyholders and insurance providers. In another study, Conradt et al. (2015) proposed a quintile regression approach to interpret the functional correlation between variables. They tested this using thirty-one-year-long time series data of farm wheat yield data. Their results revealed that the quintile regression approach found the yield-index dependency and led to high-risk minimization than the standard ordinary least squares (OLS). Pelka and Musshoff (2013) found that using mixed indices can reduce the basis risk; however, mixed-index insurance appeared not attractive to trading partners. Regardless of the effort to reduce basis risk, it remains one of the most pervasive and biggest hurdles to overcome in IBI.

2.2.4 Loss Aversion

Conventionally, it is assumed that individuals value their utility according to their expected utility. However, individuals violated EUT when presented with risky prospects (Tversky & Kahneman, 1979). Probability weighting-inconsistencies in the evaluation of probabilities and loss aversion. Loss aversion is a crucial concept that has increasingly received attention in behavioural economics analysis. However, the lack of a universal definition of loss aversion limits how it can be estimated. Scholars have tried to provide several definitions of loss aversion. However, it is the definitions provided by Tversky and Kahneman (1979), Köbberling and Wakker (2005), and Abdellaoui et al. (2008) that seem to be more acceptable since they classify most respondents according to their attitudes towards losses and gains. This suggests that subjects value losses more than gains, resulting in a steeper utility for losses than gains. Tversky and Kahneman (1979) proposed that the value function is defined as deviation from a reference point; this deviation can turn into gains and losses, where the value function is concave for gains and convex for losses. According to Abdellaoui et al. (2008) individuals evaluate outcomes in gains and losses regarding a reference point and are more sensitive to losses and gains.

Loss aversion can be determined using original prospect theory (Tversky & Kahneman, 1979) and cumulative prospect theory (CPT) (Schmidt & Zank, 2005). Using CPT, a decision-maker will be indifferent between accepting and rejecting the lottery if $W^{+}(0.5)U(G) = W^{-}(0.5)U(G)\lambda$, where L denotes losses and G denotes gains the lottery, λ denote loss aversion coefficient, and U(x) represents utility outcomes (Gächter et al., 2021). The probability weight for fifty per cent chance of gaining or losing is characterised by W^{+} and W^{-}. As a result, loss aversion can be simply calculated as a ratio of gains and losses (G/L). The value function in losses and gains is presented in Figure 2.1 below.

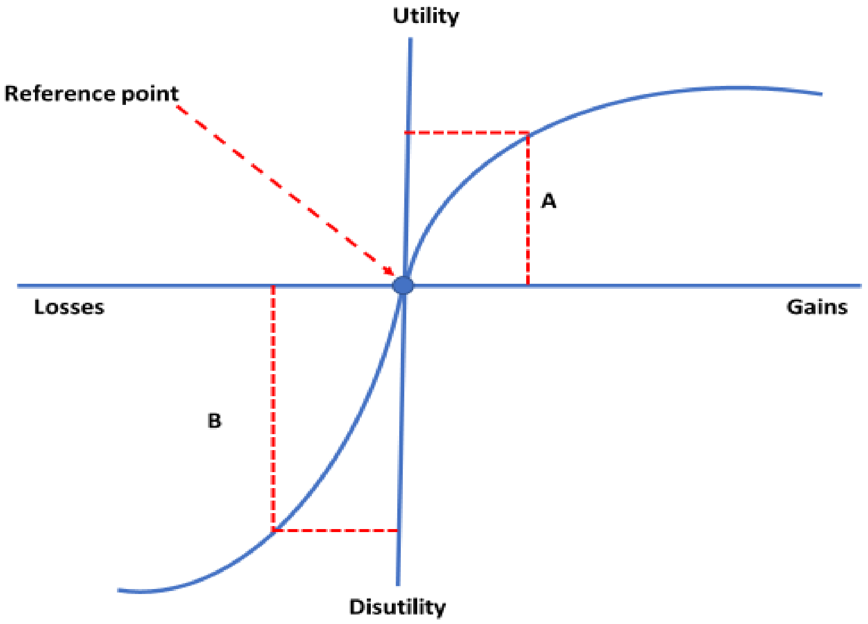


Figure 2.1 Utility in the domain of gains and losses

As shown in figure 2.1, changing the reference point can turn gains into losses and vice versa. The portion of the value function, which represents losses, is steeper than the portion that resents gains. This means that each unit of loss resulting from moving from the reference point to the left produces a greater disutility than each unit gained by moving from the reference point to the right. This is how prospect theory explains the concept of loss aversion by allowing the value function to vary between losses and gains, where losses hurt more than commensurate gains feel good. The curvature of the value function in the domain of gains and losses defines the extent of loss aversion. In contrast, individuals are risk-averse in the realm of gains (concave down) and risk-loving in the realm of losses (convex up).

2.3 Empirical Literature

This section reviewed empirical literature relevant to the demand for insurance. Specifically, reviewed studies assessed preferences for insurance contracts' unique attributes. Also, studies have examined the impact of loss aversion on WTP.

2.3.1 Preferences for Index-based Insurance

Despite shortcomings of basis risk, IBI is increasingly piloted in developing countries (Miranda & Farrin, 2012). This is justified by the increasing interest in assessing preferences for IBI. A plethora of studies used the CVM and survey-based methods to measure preferences for IBI products (Abebe & Bogale, 2014; Budhathoki et al., 2019; Fahad & Jing, 2018; Fonta et al., 2018; Oduniyi et al., 2020). On average, these studies found farmers are WTP for IBI, but insensitivity scope and potential biases limit the outcomes of these studies. Conversely, DCE provides natural internal scope since it presents multiple respondents' alternatives (Atkinson et al., 2018). Also, DCE is more informative than CVM and other survey methods because it gives respondents more chances to express their preferences for a valued service over a range of prices. Moreover, DCE is more accurate in eliciting marginal utility to pay for various service attributes. It also gives meaningful insight into attributes' trade-offs (Phong et al., 2021).

The unique advantage of DCE is that it can inform policy in designing customized IBI products that farmers can adopt. Doherty et al. (2021) explored the preference for insurance against extreme weather events using the DCE with 270 farmers. Their DCE design incorporated three attributes: (i) duration of insurance contract, (ii) method of damage assessment with two levels, i.e., traditional and weather-based index insurance, and (iii) annual cost for insurance. They used CL and RPL models to estimate their models. Their experiment showed that 69% of farmers showed a positive attitude towards insurance.

The CL model included interaction terms regarding the socioeconomic and farm characteristics, including feed storage, currently insured, concern regarding extreme events, and risk preferences. Their results show farmers with farm insurance policies prefer more extended contracts and are willing to pay €22.26 for an additional year of insurance. On the contrary, the leading coefficient of duration attributes is negative, suggesting that farmers have a negative attitude towards extended insurance and are willing to forgo €22 to avoid more extended insurance contracts. On the other hand, 31% of farmers showed a negative attitude towards insurance since they always chose the “non-insurance option.”

Regarding the assessment method, the coefficient of interaction between farmers concerned with extreme weather and weather-index insurance was positive and significant. These farmers were willing to pay about €74 for weather-index insurance relative to on-farm assessment. However, the main coefficient of weather insurance was not substantial, suggesting that the preference for weather-index insurance over indemnity-based insurance is driven by farmers concerned about extreme weather. The RPL model did not include interaction terms; the output showed that farmers would pay €74 to avoid insurance for another year. Concerning the assessment method, farmers are eager to pay €141 for weather-index insurance relative to on-farm assessment. Also, farmers have a premium of €222 to avoid staying without insurance.

Another study by (Akter et al., 2016b) assessed gender and product design effects on farmers' preferences. Their design presented hypothetical crop IBI as different bundling options with financial savings, e.g., total return, partial return, and no return. They included three attributes: (i) deposits, (ii) bad time payment, and (iii) guaranteed reasonable time payment. It also accounted for the influence of trigger levels; however, it presented as choice questions instead of attributes. They used the LC model to estimate their two models. Approximately 59% of the sample size forms the first segment in the first model, while 41% forms the second segment. Respondents in the first segment showed a negative attitude towards insurance, while the second showed a positive attitude.

The coefficient of deposit attributes was significant with low demand for IBI because of high deposits. Also, the coefficient of bad and guaranteed payment was substantial, representing high demand as a high good and bad payment. The segment membership coefficient suggests that female respondents were more insurance averse than males. The antagonistic insurance group was less likely to choose the full return option than partial, no return, and status quo. However, for the insurance favouring group, the full, partial, and no return coefficient is statistically significant. The trigger levels did not influence insurance choices in the first segment; surprisingly, lower trigger levels affected insurance choices in the second segment. Among other factors, risk-averse individuals were likelier to choose the full return option, and time preference was not a significant determinant. On average, insurance-averse farmers' WTP for standalone insurance is $2, significantly different from zero. At the same time, the insurance-loving group's willingness to pay is below $13.

Sibiko et al. (2018) explored smallholder farmers' preferences for weather index insurance in Kenya. Their survey included non-insured and ever-insured farmers. Their DCE design had five (5) attributes: (i) premium rate, (ii) trigger level, (iii) distance from the weather station, (iv) transparency, and (v) contracted party. They analysed the choice data using the RPL model, and the result showed that farmers have a positive attitude toward insurance since the Alternative Specific Constant (ASC) is significantly negative. All attributes conformed to prior theoretical expectations and were significant except for the 20% trigger level, suggesting that farmers prefer contracts that pay earlier. The coefficient concerning the transparency attribute was significantly positive, meaning that farmers prefer contracts that provide regular communication relating to weather data. The distance from the weather station was statistically negative, suggesting that farmers prefer contact with a shorter distance to the weather station. Also, farmers preferred group insurances more than individual insurances. Farmers were willing to pay approximately 7.6% of their expected harvest. The mean WTP for transparent contracts is about 8.35% of their usual crop. Famers are willing to pay 0.41% less for a contract that starts to pay at a -40% trigger level.

The studies above show that farmers show strong heterogeneity in preferences for IBI. However, the crucial basis risk attribute that significantly influenced the insurance uptake was omitted (Carter et al., 2017). Moreover, there is little evidence on how IBI design, socioeconomic characteristics, and attitudinal factors such as loss aversion and risk aversion influence uptake of IBI.

2.3.2 The Design and Uptake of IBI

The features or attributes of IBI can significantly influence the uptake rate. For instance, when IBI products are subsidized, arguably, the uptake can improve because farmers are very sensitive to price. Supporting this, Smith and Watts (2009) showed that subsidies for IBI were necessary for persuading farmers to accept insurance contracts. Conversely, McIntosh et al. (2013) revealed a significant discrepancy between ex-ante WTP pay and ex-post WTP amid subsidy. Their results showed that subsidy highly influenced the ex-ante WTP, while subsidy had little impact on the actual WTP. On top of this, there was no correlation between ex-ante and true WTP. They associate this outcome with challenges related to institutional and implementation efficiency. However, these conditions do not harmonise with households with heterogeneous financial muscles and risk profiles. Hill et al. (2019) revealed that framing price reduction as a subsidy does not influence farmers' WTP, although demand for IBI remains overly price sensitive. This outcome emphasized that subsidy alone is unlikely to significantly improve the demand for IBI.

Moreover, supply factors such as marketing strategies and distribution channels influence farmers' demand for IBI (Castellani & Vigano, 2017). This is because distribution channels and marketing systems impact inclusiveness and trust in insurance (Castellani & Vigano, 2017). Generally, farmers seek reference cases before purchasing the insurance. For example, more farmers can have trusted reference points if reputable individuals purchase insurance, developing positive attitudes towards insurance (Cole et al., 2013). In strengthening inclusiveness, providing credit can give more farmers financial muscles and increase their propensity to participate in IBI (Giné et al., 2008). Hypothetically, the uptake of IBI can improve when bundled with credit or low-interest loans because many farmers can have start-up capital (Miranda & Farrin, 2012). However, Giné and Yang (2009) conducted a randomized field experiment on bundling insurance and credit, with outcomes that provide disputing results. They found that bundling insurance with credit does not influence the insurance demand because farmers perceived they would pay high-interest rates on loans and face high default penalties.

Apart from the above-detailed design issues, basis risk is still a prominent problem in IBI. Basis risk emerges owing to the weak correlation between an index and losses is expected to protect against (Carter et al., 2017; Dalhaus & Finger, 2016). Nevertheless, eliciting the impact of basis risk on demand for IBI is still challenging. This is because farmers in many developing countries do not have experience with the index's performance. Because of this lack of experience, farmers lack information concerning the accuracy and errors of the index. In some cases, farmers have little or no data; the key concern is that they may adopt riskier hedging decisions regarding insurance coverage, leading to higher basis risk (Jensen et al., 2018). Moreover, the credibility of an index depends on regional factors that are not included in econometric models.

To resolve this, basis risk needs to be categorically divided into spatial basis risk, design risk, and temporal basis risk. A significant number of studies on IBI reveal that basis risk has a negative impact on IBI uptake (Clement, Wouter Botzen, et al., 2018). However, fewer studies used household-level data to assess the impact of basis risk on IBI. For example, a study by Gaurav and Chaudhary (2020) reveals that when farmers are presented with information concerning basis risk, farmers have a significant and negative attitude towards weather insurance. However, when the information on basis risk is coupled with subsidies, the negative impact on insurance demand can be reduced. Apart from design issues, other factors such as attitudinal or behavioural can influence IBI uptake (Carter et al., 2017).

2.3.3 Behavioural Factors and the Uptake of Index Insurance

Recent research developments in insurance reveal the transition to behavioural economics. Many studies used lab experiments and field data to explore how an individual's life decisions deviate from classical economic theory that assumes perfect rationality and informed homo economicus (Corcos et al., 2020). Behavioural or attitudinal factors influencing the demand for IBI are well explained in behavioural economics (Clarke, 2016), demonstrating cognitive and cultural norms on individual decision-making. They also provide insight into how those decisions differ from those specified in classic economic theory (Lin, 2010; Teitelbaum & Zeiler, 2018). Moreover, social psychologists Kahneman, Tversky, and Thalers have been vocal about transitioning behavioural economics to inspect the role of loss aversion, ambiguity, emotions, framing, and a reference point in an individual's decision-making (Thaler et al., 1997; Tversky & Kahneman, 1992)

Concerning cultural norms, other communities view IBI as a lottery, which conflicts with a taboo against betting on adverse outcomes. Carter et al. (2015) confirmed that farmers perceive IBI as a lottery that exhibits uncertainty regarding the insured risk and index accuracy in measuring loss at the farm level, particularly for those with low literacy levels. Typically, the comprehension of IBI products requires proper education regarding how products work. Also, trust appears a severe concern since they pay premiums on the onset of insurance indemnity, which leaves clients at risk of experiencing a breach of the insurance contract. Therefore, improved comprehension of index insurance and trust in insurance are essential factors of demand for IBI. Concerning the latter findings, households purchase IBI after witnessing that someone in their community has received insurance compensation (Cole et al., 2014).

Risk aversion is another attitudinal factor influencing the demand for insurance, which reflects the individuals' attitude toward accepting uncertainty regarding the state of their wealth. This affects farmers' WTP for insurance products (Patt et al., 2009). Jin et al. (2016) used multiple price list (MPL) experiments to elicit risk preference. They found that farmers are moderate risk-averse; however, risk aversion has a significant positive correlation with IBI uptake. In contrast, a study conducted in South Africa found that risk aversion is related to the low adoption of insured technologies (Visser et al., 2019). Increasing evidence reveals that people's perception is often biased and deviate from rational expectations. As a result, considering subjective biases when eliciting risk preferences is crucial to circumvent overestimations (Delavande, 2008). Fezzi et al. (2021) assessed risk preferences relative to insurance; they found that farmers are moderately risk averse. After comparing their estimates with existing literature, they found that accounting for subjective biases can stabilize risk parameters across the context.

In addition, many studies show that ambiguity causes decision-makers to deviate from expected utility models (Barham et al., 2014). Ambiguity-averse individuals prefer known risks over unknown risks and prefer choices that exhibit a known probability of outcomes than unknown (Snow, 2011). In IBI, farmers seem to be sceptical about purchasing IBI contracts since they are not particular about indemnity time. The IBI may repay when it is not needed and cannot do so when desperately needed. As a result, ambiguity-averse individuals will unlikely be willing to purchase IBI contracts. This outcome agrees with the Ellsberg Paradox, which supports that individuals prefer events that display known probabilities over unknown probabilistic. Thus, this may limit farmers' ability to assess if insurance can cover their production risk; hence, their demand for insurance becomes limited.

A study conducted by Bryan (2019) using data from Malawi and Kenya conjectured that ambiguity aversion influences insurance demand because farmers who are ambiguity averse are likely to be risk-averse. However, the effects of ambiguity aversion may decrease with an increase in the experience of the commodity. Providing incentives, such as subsidies and other short-term policies, can also reduce ambiguity aversion; however, testing this expectation is a prerequisite. Belissa et al. (2020) assessed the risk aversion and ambiguity aversion in the framework of the IBI uptake amongst smallholder farmers. Their results revealed that risk aversion has a positive impact on IBI uptake. Risk aversion increases the number of months that households stay in the IBI adoption. On the other hand, ambiguity aversion significantly decreases the adoption of IBI. As a result, farmers become more ambiguous about whether the contract accurately reflects their actual loss realization because of basis risk. This outcome supports that even if risk-averse farmers are willing to adopt IBI contracts to ensure their risk, the inherent ambiguities in insurance may negatively influence the actual uptake. The above description pronounces insurance demand preferences based on the expected utility; however, an individual's behaviour is inconsistent with the expected utility.

Another inconsistency in expected utility theory emerges when loss aversion, diminishing sensitivity, and probability weighting are not accounted for when analysing decision-making at risk (Abdellaoui et al., 2007). An important riddle in demand for IBI is that individuals underinsured low probability events with high losses outweigh the low risk. Because of this tendency, the take-up for disaster insurance is exceptionally low, even in the well-structured insurance market. People prefer to purchase insurance premiums that exceed expected losses substantially. For instance, more people are too willing to pay for an insurance contract for a cell phone due to overestimating the loss (Grubb, 2015). This behaviour in insurance demand violates the standard decision-making theory under risk, expected utility theory (EUT) (Hwang, 2016). Under the EUT, they motivate respondents to purchase insurance only if premiums are actuarially fair. Thus, fitting the demand for low deductibles in EUT results in an improbable high-risk aversion. Therefore, loss aversion is one of the essential characteristics of prospect theory (PT), which was brought forth by (Tversky & Kahneman, 1979, 1992).

2.3.4 Elicitation of Loss Aversion

Several studies have analysed the influence of loss aversion using different experimental designs (Gächter et al., 2021; Charles A Holt & Susan K Laury, 2002; Liu, 2013). The dominant experiment used to elicit loss aversion is incentivised lottery games. This is commended for effectively estimating loss aversion among subjects with low literacy levels because it is easy to implement (Charles A Holt & Susan K Laury, 2002; Liu, 2013). For example, Tanaka et al. (2010) used incentivised lottery experiment guided by prospect theory, which estimated three parameters: (i) loss aversion, (ii) risk aversion, and (iii) probability weighting. In their investigation, subjects play a game with three series of lottery questions with a probability of losing or winning a certain amount of money. After playing the game, a bingo cage with 35 numbered balls was used to determine which prospect to play for real money. The loss aversion parameter was then determined using switching points. The findings show that individuals in wealthier villages are less loss-averse and risk-averse to financial risk than in low-income villages. Because of the unique advantages of the method used by Tanaka et al.

(2010), Elaine M Liu (2013) followed the same method because it can accommodate both expected utility and prospect theory. This design allows the experiment's findings to determine whether the expected utility or PT fits the data. They find evidence of loss aversion; farmers who are loss averse are more passive to adopting new technology, while those that are less loss averse would accumulate more wealth from the proposed new technological innovations because they are more likely to adopt new technology earlier.

Abdellaoui et al. (2008) analysed loss aversion under prospect theory. Their procedure comprises three stages: (i) the first stage approximates utility based on gain prospects, (ii) respondents are asked to choose prospects in the gain domain only and compare specific outcomes, and (iii) prospects associated with gains. The second stage involved estimating the utility in terms of loss prospects. Here, respondents are asked to choose alternatives to the losses and compare specific outcomes with prospects associated with loss. The third stage entails mixed losses and gains; respondents were asked to choose prospects, including losses and gains. Their study differed from other studies because they used hypothetical lotteries instead of real ones. They found evidence of loss aversion at both aggregate and individual levels.

He et al. (2019) assessed the role of risk preference and loss aversion in farmers' energy-efficient appliance behaviour in China. They followed Charles A. Holt and Susan K. Laury (2002) experimental design and found a loss-aversion parameter of 2.68, indicating loss aversion. Their results show little evidence of loss and risk aversion effects on energy-efficient appliance use. In addition, they found that socioeconomic characteristics such as age, gender, education, family location, and perception of climate change significantly affect willingness to adopt and use energy-efficient appliances. Lampe and Würtenberger (2019) examined the influence of loss aversion on demand for IBI considering basis risk. In their study, they used readily available randomized controlled treatment data. They accounted basis of risks in their model, with the assumption that, given the losses, there is a probability that insurance does not cover the loss in the event of loss or pay-out with no losses. The authors used two reference points, 'with insurance' and ' without insurance,' for two different farmers, insurance-illiterate and insurance-literate. They started by analysing insurance with a reference point presented by wealth without coverage and further analysed insurance demand with a reference point presented by perfect insurance. The empirical results show that loss aversion was negatively related to the take-up rate among insurance illiterate farmers.

Another study by Hwang (2016) explored how loss aversion impacts the up-take behaviour of health insurance using PT. The study used American Life Panel data divided into two sample sizes, all U.S families (342) and low-to-moderate income U.S families (840). In their research, the reference point was 'living without insurance.' The estimation of loss aversion adopts the use of a lottery task, where respondents are asked to state whether they are willing to play a lottery game or not. The empirical results showed that loss aversion significantly influences the demand for insurance. Loss-averse individuals showed low WTP for insurance and are unwilling to pay for health insurance in a hypothetical contract. They also discovered no significant difference in demographics in the two groups, comparing high loss-averse and low loss-averse groups in terms of age, education, wealth, and gender.

Slingerland (2017) examined the impact of loss and ambiguity aversion on WTP for IBI. They elicited loss aversion using a lottery choice task, with six lottery choices presented in gains and losses. Respondents had a 50% chance of winning and a 50% of losing a certain amount of money. They fixed gain prospects throughout the game while they varied loss prospects. After eliciting loss aversion, respondents were presented with a WTP game and stated their maximum willingness to pay. The loss aversion parameter in the overall observation is λ=3; 59 respondents rejected all choice tasks, resulting in a loss aversion parameter: $\lambda \geq 3$. Thirty-six respondents accepted all games, resulting in a score of $\lambda \geq 0.857$. The empirical analysis lottery task showed that the loss aversion coefficient changes from negative for convectional insurance to positive for weather-based index insurance.

2.4 Concluding Summary

This chapter reviewed theoretical and empirical literature relevant to the research problem of this study. Theoretical literature review accomplishes that though farmers try to manage drought risk through traditional risk management strategies, most subsistence farmers are still vulnerable to drought risk. A way to supplement these mechanisms is through agricultural insurance; however, the penetration of traditional agrarian insurance is challenging in substance farming communities. The major hurdles to expanding indemnity insurance in subsistence farming systems are information asymmetry, which increases the cost of offering agriculture insurance. In order to circumvent these hurdles, literature proposes index insurance as an alternative financial tool that can eliminate the problems of traditional insurance. Notwithstanding, index insurance does not act as a panacea because it faces other insurance problems. The major problem in index insurance is basis risk, which negatively influences the uptake of index insurance.

The theoretical review section further presented the elicitation of preferences using the non-market valuation method. This section accomplishes DCE is more effective than the contingent valuation method because of its natural aptitude to assess preferences in-depth. Also, issues must be considered when conducting a choice experiment are presented. Last, the study presented and explained the concept of loss aversion; this confirms that people deviate from expected utility theory and evaluate utility from the perspective of losses and gains, while they are more sensitive to losses than gains. In terms of the empirical literature, the accomplishment is that many studies assessed the preferences for index insurance using CVM and general surveys. This section discovers that farmers have a positive attitude towards index insurance. However, it did not give a comprehensive insight into attribute preferences. Because of this, several studies assessed farmers' preferences for index insurance using DCE. Nevertheless, they omitted crucial attributes, such as basis risk and reimbursement methods. At the same time, basis risk influences the demand for index insurance (Carter et al., 2017; Dalhaus & Finger, 2016).

Concerning reimbursement methods, this study conducted qualitative research with key informants (e.g., insurance companies, farmers' organizations, and stock exchange) and farmers that fit the description of the targeted respondents; the outcome shows that farmers prefer different modes of reimbursement, such as cash, supplementary animal feed, and voucher. However, according to the author, this has not been covered in the literature. The empirical review also focused specifically on the index insurance design and uptake. Several studies, e.g., McIntosh et al. (2013), Smith and Watts (2009), and Hill et al. (2019), find mixed results regarding subsiding index insurance. Also, the budding of insurance with other financial services, such as micro-loans or credit, was reported to influence the uptake positively (Miranda & Farrin, 2012). Behavioural factors, ambiguity averse, cultural norms, subjective biases, risk attitude, and loss aversion influence insurance uptake.

CHAPTER 3 METHODS AND PROCEDURES

3.1 Introduction

This chapter describes the study area, methods, processes, and procedures followed to achieve the objectives of this study. The primary focus of this chapter is to detail the elicitation procedure for loss aversion and risk aversion with a brief explanation of how the survey was implemented. Also, it describes how DCE was conducted – from the identification of attributes to experimental design. Last, the chapter presents the method employed for data analysis using specific econometric models. Words such as subsistence farmers, respondents, and policyholders might be used interchangeably with no change of meaning.

3.2 Area of Study

The designated area of study is Mulima village, in the jurisdiction of Makhado Local Municipality in Limpopo Province, in the northern part of South Africa. The geographical map in Figure 3.1 shows the designated area of study. Makhado local municipality was selected as a representative study area because economic growth and sustenance rely on agriculture, with most of the population deriving livelihoods through subsistence farming. Also, this area is vulnerable to drought since it receives an average of 450 millimetres of rainfall in summer. This rainfall is considerably low on average, exacerbated by the high temperature, ranging from 18 ^{o}C to 28 ^{o}C–averaging 25.5 ^{o}C (Makungo et al., 2019). As a result, the prevalence of drought presents a significant problem for this area, which predominantly thrives on subsistence farms.

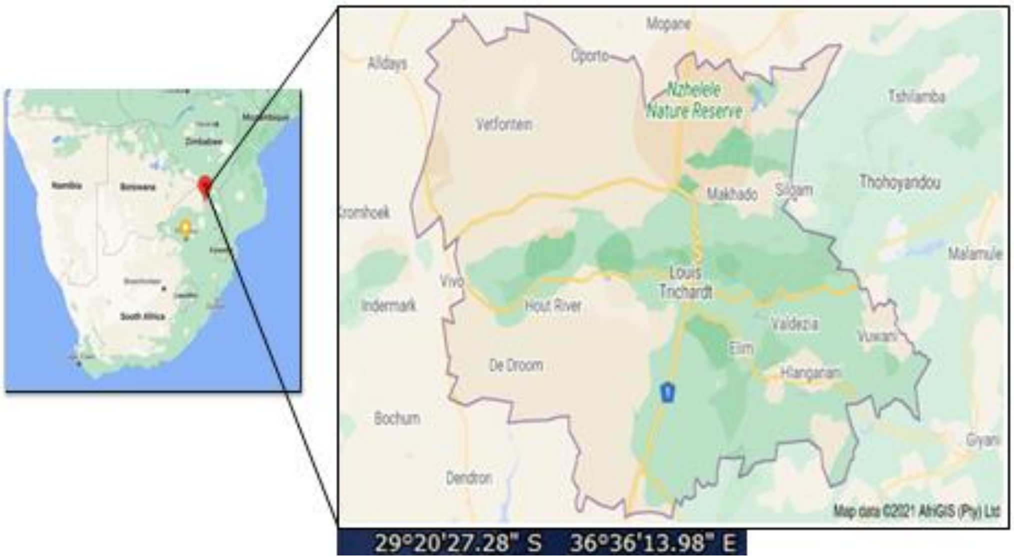


Figure 3.1: The Designated Area of Study, Makhado local municipality, Limpopo

3.3 Eliciting Preferences for Hypothetical Products

The availability of market information regarding price and cost is essential for assessing consumers' preferences for new products and services introduced in the market (Abdullah et al., 2011). However, market information for new products is not available in some instances. In this case, (i) stated preferences (SP) and (ii) revealed preferences (RP) have been developed to elicit the preferences of consumers (Mark & Swait, 2004). RP involves eliciting the value consumers attach to a good by observing the demand for the good in the market. SP method uses people's response statements regarding their preferences to estimate the change in utility associated with a proposed advance in the quality or quantity of a good or service. SPs are explained in a hypothetical context and assess the correlation between attributes using existing or generic alternatives. They can also measure multiple observations for each respondent. However, stated preferences do not precisely present changes in the market and individual limitations effectively (Alberini, 2019).

The reliability of this method heavily relies on respondent comprehension and commitment to answering the choice questions. The SP approach incorporates contingent valuation (CV) and choice experiments (CE). According to Portney (1994), CVM uses a structured survey to elicit respondents' preferences for hypothesized program or project. This method asks respondents to state their WTP or accept a good or service. However, CVM faces massive criticism regarding the legitimacy and consistency of its results and the impact of several biases (Venkatachalam, 2004). The primary concerns with the application of CVM have been the possibility of biases such as (i) starting point bias, (ii) information bias, (iii) strategic bias, (iv) hypothetical bias, (v) payment vehicle bias, and (vi) incongruity between WPA and WTP (Tietenberg & Lewis, 2018).

The starting point bias emerges in asking the subject to choose their WTP from a pre-defined range of possibilities. In contrast, information bias occurs when the subject feels forced to value a service that they have little or no knowledge of service in question—strategic bias results from a position whereby subjects intentionally give biased responses to influence their interest. In contrast, hypothetical bias is due to subjects being presented with unrealistic choices. Another problem arises from the difference between WTP and WTP compensation because respondents state a much higher willingness to accept (WTA) than a WTP. Economic theory suggests that WTP and WTA must be equal (Tietenberg & Lewis, 2018). As a result, DCE is commended for estimating preferences better than CVM.

3.4 Conducting Discrete Choice Experiments

DCE elicits preferences by asking respondents to choose between alternatives described by attributes and their levels (Sumani, 2018). DCE can deal with scenarios with multiple dimensions. This is because of its aptitude to identify the worth of individual attributes of good or service (Hanley et al., 2001). The CVM method can also elicit a preference for a particular good or service attribute. For instance, CVM can include a series of scenarios in a survey. However, this approach is expensive and cumbersome to implement. In addition, DCEs can measure marginal values of change in several service attributes. The DCE approach is typically helpful in analysing specific policies rather than focusing on the shortcoming or gains of the services (Hanley et al., 2001). Also, it circumvents the ambiguous estimation of respondents' WTP by counting instead on rankings, scores, or choices amongst a series of alternative packages indirectly inferred.

Nonetheless, the major shortcomings of DCE are the cognitive burden resulting from complicated alternatives that have many attributes and levels. Presenting respondents with many choices sets causes difficulties in making rational choices because of high learning and fatigue. Respondents then resort to using a rule of thumb to ease decision-making (Hanley et al., 2001). The alternation of decision-making rules motivates respondents to choose excellent alternatives. However, the choice may not necessarily be the best option. Another problem is that the DCEs are sensitive to experimental design–from identifying the attribute and their levels to the final presentation of choice sets.

The primary goal in analysing DCE data is to explore the strength of preferences for each attribute and their levels that describe the research problem. DCE is appropriate for testing research hypotheses in preferences study because it derives preferences from an estimate on a similar scale and is used to estimate the marginal rate of substitution, representing the WTP (Kjaer, 2005). DCE relies on the theoretical framework of random utility theory (RUT) (Cunningham et al., 2017). RUT emanates from the assumption that each individual is a coherent decision-maker and takes full advantage of utility relative to their choices (Cascetta, 2009). Mainly, RUT resonate with the subsequent presuppositions: (i) an ordinary individual presented with a series of alternatives perceives a utility and decides on the alternative that makes the most of this utility, and (ii) the utility allocated to alternatives counts on the number of measurable attributes and their levels, and (iii) utility allocated by an ordinary individual to an alternative is unobserved by an investigator wishing to measure preferences; as a result, a random variable must represent utility (Cascetta, 2009; Hess & Daly, 2013; Louviere et al., 2000; Pearce et al., 2006; Ryan et al., 2007). The validity and success of DCEs depend on prerequisite steps such as (i) identification of attributes and levels, (ii) construction of an experimental design, (iii) questionnaire development, (iv) piloting, (v) data collection, and (vi) econometric analysis (Hanley et al., 2001; Lancsar & Louviere, 2008; Mangham et al., 2008; Ryan et al., 2012).

3.4.1 Identifying attributes

Identifying attributes and levels is crucial in designing the choice sets because the attributes describe the good or intervention in question. In this phase, the investigator must know distinct features the research problem covers to describe the range of attributes (Tinelli, 2016). The most prominent way of identifying the attributes and their levels is through (i) the review of the available conceptual and policy outcomes, (ii) theoretical arguments, (iii) focus groups discussion (FGD) with experts and potential users of the good or service, as well as (iv) quantitative research methods of policy issues (Abiiro et al., 2014).

A detailed literature review on the subject can reveal a comprehensive list of theoretical attributes, which can, but not essentially, be included in the final DCE design (Abiiro et al., 2014). Including the attributes identified through literature is easy, but this can omit significant attributes (Kløjgaard et al., 2012). The prerequisite for the attributes to be included in the DCE is that the target group must consider them very important, elicit their preferences, and reflect on issues in the local context. A qualitative study within the local context is required (Mangham et al., 2009). The advantage of conducting qualitative research is that it improves the validity of DCE and reveals other essential attributes that are not covered in the literature but are relevant to the studied area (Abiiro et al., 2014). Also, it reduces the chances of omitting relevant attributes and their levels (Coast et al., 2012).

The attributes and levels must be exhaustible and measurable; simultaneously, the framing of attributes must not be ambiguous and statistically correlated. They must be controllable and described to allow trade-offs (Ryan et al., 2012). Inter-attribute correlation can misestimate the primary effects of a single attribute on the response variable (Mangham et al., 2009). The reliable attributes and their levels in DCE must be pertinent to the intervention in the question of the targeted population (Bech et al., 2011; Kjaer, 2005; Mangham et al., 2009; Vroege et al., 2019). These attributes can be qualitative or quantitative, contingent on the description of the service services (Ryan et al., 2012). Amongst other attributes, including cost attributes enables estimating the WTP amid the non-monetary and cost attributes (Akter et al., 2016a)

There are no limitations on the number of attributes used in a DCE, but some studies have included less than ten attributes to ensure that respondents reflect on all listed attributes (Lancsar et al., 2017; Ryan et al., 2012). For example, Mangham et al. (2008) stated that presenting too many attributes might motivate respondents to adopt the most straightforward choice rule in which they focus on one attribute or subclass of attributes. To validate all this, expert opinion, focus group discussions, and pilot studies within the jurisdiction of the study area are recommended.

3.4.2 Experiment design

After successfully identifying the attributes and their levels, the investigator can design a proposed choice set of different amalgamations of attributes and levels (Kløjgaard et al., 2012). However, carefully considering how many profiles can be presented in the survey is essential. Presenting respondents with a complete set of choice profiles is a full factorial design. Typically, the number of possible profiles is given by a^n, where the term a represents several different attribute levels, and the exponent n is a possible number of attributes. When the number of attributes has different levels, the number of possible assumed profiles is given by $k^a \, x \, l^b$, where the terms k and l represent different attribute levels. At the same time, the exponents a and b are the possible attributes (Tinelli, 2016). However, factorial design usually is not feasible since it yields too many choice profiles.

Essentially, a factorial design with five attributes and four levels would, for instance, yield *625* (5^5) possible alternatives (Mangham et al., 2008). Here, factorial designs are used to lessen the number of choice profiles to a controllable level at which elicitation of preferences is possible. Orthogonal design is widely applied to achieve the latter. Orthogonal is an essential property of experimental design that requires a strictly independent variation of levels across attributes, in which attribute levels appear at the same frequency in combination with all other attribute levels (Johnson et al., 2013). This is supported by level balance, which is the property that requires each level within attributes to appear with the same frequency, so that choice profiles can have the same probability of being chosen.

Following the above protocols, the researcher must decide how to design a choice set. If the binary choice is used where respondents are requested to make a first-rate between two alternatives, with responses as "yes'' or ''no," then choice sets designed from orthogonal are options (Ryan et al., 2012). If respondents are requested to choose between alternatives, these alternatives need to be combined in a choice set. Another important property that requires the investigator's attention is minimum overlap, which requires no repetition of attributes within the choice. This ensures attribute levels differ across the choice set to abstract maximum data from the subjects. The D-efficiency method is mainly applied to meet the conditions of level balance (Kuhfeld, 2003; Turner & Coote, 2017). Once the choice sets have been derived, it is crucial to decide whether to use a forced-choice or opt-out option (Ryan et al., 2012). The forced-choice alternative only gives respondents one choice, whereas an opt-out option allows respondents not to make any choice presented to them. The opt-out option's inclusion improves the design since it represents a baseline alternative that corresponds to the status quo and enhances the realism of the design since the status quo represents the choice that the respondent's current affords (Mangham et al., 2009). If the status quo is omitted in the design, it compels the subjects to make one choice, which may not accurately reflect their choice.

It is also essential to decide if they must present choices as labelled or unlabelled regarding the choice set. Unlabelled choices mean that the title of each choice does not give the respondent any information concerning the choice, whereas labelled choices allow the title of choice to provide information about the choice (De Bekker-Grob et al., 2010). Once the choice sets are designed, the survey must be of considerable length to ease respondents' understanding and bear no cognitive burden. Here, the researcher must be cognizant of how many choices sets respondents can answer before their concentration span expires (Ryan et al., 2012). In many studies, choice sets vary from 12 to 18 (Lancsar et al., 2017; Ryan et al., 2009). When fractional design cannot reduce choice profiles to a required number, the design can be divided into two blocks.

3.4.3 Survey Design

After designing the experiment, the researcher can design a structured DCE survey, where the first section of the survey introduces the survey to the respondents. The most crucial aspect here is explaining the reasons for conducting the study: (i) reasoning for selecting participants, (ii) who will administer the survey, and (iii) how the outcomes of the study are going to be used (Mangham et al., 2009; Ryan et al., 2012). The respondents must also be introduced to the DCE experiment by explaining the unique attributes and levels. After that, a section must present warm-up questions followed by an example of a choice set. Then, the debriefing questions regarding making choices must follow: (i) how difficult was the choice task? (ii) What attributes and levels influenced their choice? The investigator can get additional information regarding cost attributes by asking contingent valuation questions, for example, how much a respondent is WTP to attain a particular service. In order to have a clear-cut on factors that influence preferences, the survey can include additional information on socioeconomic characteristics (Ryan et al., 2012).

3.4.4 Pre-testing the Survey

Having covered the concept of survey design, the investigator can develop a DCE survey and pilot with a targeted group within the jurisdiction of the study area. Piloting entails focus group discussion (FGD) and interviews concerning structured questions. The main structured questions that need to be addressed during the piloting study include: (i) do respondents comprehend the description of attributes and their levels, (ii) can they handle the number of attributes and alternatives presented to them, and (iii) do subjects understand the choice task (Ryan et al., 2012).

3.4.5 Data collection and capturing

The researcher can collect data using different methods, such as (i) the self-administered method, (ii) completion in the classroom, and (iii) trained enumerators interviewing respondents individually (De Leeuw, 2008). These methods can administer both paper-based and computer-based questionnaires for data collection. The process of data coding may proceed after the required data has been collected, where the specification of response and explanatory variables may be the levels of the attributes used to describe a choice set. The most common way to organize DCE data is to create rows to capture the data corresponding to each profile. However, this depends on the model and statistical software or package the researcher intends to use. There are two popular ways of organising data in table formats: long and wide. Long formal takes one row per alternative, while wide-format takes one row per set.

After the data has been organized and categorized, the investigator can code them into a series of variables in the regression model. Effects of coding and dummy-variable coding are standard methods used to code categorical data in DCE experiments. Effects coding uses only zeros, ones, and minus to convey all necessary categorical information of attribute levels. In contrast, dummy-variable coding uses only one and zeros to give categorical information about attribute levels. One level is excluded in each coding method to avoid perfect collinearity (Louviere et al., 2000; Ryan et al., 2012). In dummy variable coding, we set a dummy to one when the qualitative level is present and zero when not. The choice of coding depends on the research questions; however, effect coding is the most applied method because it can reduce the correlation between main and interaction effects.

3.4.6 DCE Data analysis

Understanding the fundamentals of the statistical techniques that can analyse choice data is a prerequisite. There are several methods for analysing DCE data: (i) Conditional Logit (CL), (ii) Random-Parameter Logit (RPL), which is also called a Mixed Logit Model (MXL), (iii) Hierarchical Bayes (HB), and (iv) Latent-Class Method (LCM) (Francis et al., 2019; A. Brett Hauber et al., 2016). The conditional logistics (CL) model method is based on a random utility model for estimating mean preferences, which relates to the likelihood of choice between two or more alternatives (A Brett Hauber et al., 2016). The utility function in CL is described by the latent utility function expressed by the attribute levels in the choice, plus the random error component representing possible omitted utility. Then, the overall utility derived from consuming a particular good is the sum of deterministic and stochastic components (McFadden, 1974; McFadden & Train, 2000). CL is straightforward; however, it assumes an independent, irreverent alternative (IIA) property (Dahlberg & Eklöf, 2003). The IIA property implies that the fraction of the probabilities of choosing two choices does not rest on the attributes of any other options in the choice set (Hahn et al., 2020). As a result, CL suffers from restrictive substitution patterns and the inability to model preference heterogeneity.

Because of the shortcomings mentioned above, they propose the mixed logit model as one alternative (Paz et al., 2019). The mixed logistics model is highly flexible in any random utility model (Lee et al., 2016). It was discussed in Dekker (2016) that the advantages of the mixed logistics model entail modelling the heterogeneity in the pattern of alternatives across respondents, non-constant error variance across alternatives because of relaxation of independence and identically distributed errors terms, and accounts for relationships in alternative observation by the same individual. The mixed logit model's output comprises the parameters' mean and standard deviation. Here, the mean represents an average preference for attributes, while the standard deviation affords imperative information regarding the diversity of preferences (Paz et al., 2019). Alternatively, the latent class (LC) model can analyse preference heterogeneity. The underlying theory of LC stipulates that a discrete number of classes suffices to account for heterogeneity (Shen, 2009). As a result, latent classes capture the preference heterogeneity within the population. Each class presents different parameters in the corresponding utility; however, it does not vary within the class. The number of classes needs to be stated before estimating the LC model. The final selection of the number of classes depends on the validity of the results; the researcher must be able to make statistical inferences. The investigator can evaluate this using AIC, BIC, Pseudo $R^{2,}$ and the likelihood ratio test (Sfeir et al., 2021). LC model has been used to assess preference for insurance and adopting climate change adaptation technologies (Akter et al., 2016a; Birol et al., 2009).

The investigator can also consider using hierarchical Bayes (HB). HB procedure syndicates the prior distribution of the parameters with individual-specific choice data to estimate reliable posterior distribution for each individual (Mohammadi et al., 2020). However, in the HB method, preference estimates are updated iteratively, leading to difficulties in describing this method and apprehensions that it is less translucent than other methods. HB does not approximate the sample-wide mean preference magnitude but constructs them from estimated individuals' preferences. In this method, the analyst needs to extrapolate the full effects of using standard deviations instead of the global estimate of preferences (Lancsar et al., 2017). This makes it impossible to examine the implication of preferences for any given individual sample.

3.5 Sample Size

To this effect, there is no standard procedure for determining sample size in DCEs. Nonetheless, several sample determination techniques are commonly used in discrete experiment studies, detailed in studies by Ben-Akiva et al. (1985), Johnson and Orme (2010), and Louviere et al. (2000). We adopted the rule of thumb suggested by Johnson and Orme (2010) in this current study owing to its simplicity. The formula used to compute the sample size is as follows: $N \geq \frac{500c}{ta}$ where N =number of respondents, a = number of alternatives concerning a task, $t =$ number of tasks, and c = the highest number of levels given any other attribute. This formula ($N \geq \frac{500(3)}{(6)(3)} = 83$) computed a minimum sample size of 83 respondents.

3.6 Sampling

To ensure that respondents comprehend the context of the research survey, respondents had to meet the criteria-subsistence livestock (cattle, goat, sheep) farmer. In this criterion, subsistence farmers engage in farming activities to sustain their livelihoods and only trade if there is a surplus. We obtained a list of subsistence farmers that meet the above-described criteria from the local tribal office in the study area. The list contained 400 subsistence livestock farmers. Therefore, simple random sampling randomly selected 110 subsistence livestock farmers from the list. Due to the global COVID-19 pandemic restrictions, the study was limited in scope. These included restricted movement and proximity of people, such that the study could not get enough responses from subsistence farmers.

3.7 Data Collection

Data collection comprised two phases, i.e., survey piloting for pretesting and the final data survey implementation. Pretesting and final data collection were conducted in the jurisdiction of the Makhado local municipality between March and July 2021. The pilot survey had 20 respondents, while the total sample size was 110, using random sampling. Due to the global COVID-19 pandemic restrictions, the study was limited in scope. These included restricted movement and proximity of people, such that the study could not get enough responses from subsistence farmers. After the survey piloting phase, the final survey was implemented, which comprises five (5) sections: (i) background, (ii) choice experiment, (iii) self-reported risk tolerance, (iv) lottery game, and (v) socio-demographic questions. The background section introduced subsistence livestock farmers to index-based pasture insurance (IBPI) regarding its operation, triggering of the compensation, and advantages and disadvantages.

Subsequently, the farmers were shown how to choose options when presented with a choice set, which was a choice card. In each of these choice sets, farmers were presented with options to choose from, and they were asked which option they would prefer if we showed the scenario in real life in the upcoming season. Farmers were advised to respond as if they had to pay real money based on the premium list for the insurance contract. Furthermore, the respondents were asked to make choices based on only the scenarios presented. If they could not afford to pay for the contracts they were interested in, or if none of the proposed contracts was acceptable, they could select the "opt-out" option. Debriefing questions assessed how respondents made their choices, and their understanding followed this. Also, a question regarding the maximum WTP for the IBPI contract was asked. Questions regarding the difficulty of making a choice and strategies used when making a choice were presented. The risk aversion section used an eleven-point scale (i.e., 0–10), where 0 shows the absolute non-willingness to take the risk, whereas 10 shows complete willingness to take risks. Farmers were then requested to play an incentive lottery game that involved winning or losing a certain amount of money. Last, the socio-demographic section collected data on subsistence farmers' socio-economic characteristics, exposure to drought risk, drought management strategies, and access to weather information.

3.8. Characterization of Drought Management Strategies

The study used a semi-structured survey to characterise drought management strategies adopted by the farmer; in addition, a five-point Likert Scale (1-strongly agree, 2-agree, 3-neutral, 4-disagree, and 5-strongly disagree) was used to record farmers' perceptions regarding the ability to deal with the real impact of drought.

3.9. Elicitation of Risk Aversion

Risk aversion used self-reported questions regarding willingness to take risks in general and animal management contexts. The procedure required that the respondents openly state their desire to take a risk on an 11-point scale. Using this method, the presentation of the category of risk-taking is as follows: (1) 0-2 low risk-taking, (2) 3-7 medium risk-taking, and (3) 8-10 high risk-taking (Dohmen et al., 2011). In addition, farmers had to compare themselves with other farmers within the community in terms of risk-taking, scaled from 1 to 5. Dohmen et al. (2011) confirmed that general global risk questions could arguably measure risk aversion. Therefore, this study included risk aversion variables (two variables in the general and animal management domain) in the DCE model as interaction terms to test their influence on the preferences of substance livestock farmers for IBPI. An example of risk aversion questions is presented in Table 3.1. Furthermore, an OLS regression was used to get an insight into the factors that influence risk aversion. Here, two risk aversion calculated in general and animal management domain were used as dependent variables, while socioeconomic characteristics such as gender, age, education, and land size, to mention few, were used as independent variables.

Table 3.1 Risk aversion: the case of animal management

1. Think about decisions regarding the management of your animals. Regarding these decisions, are you a person who is fully willing to take risks, or do you try to avoid taking risks? Please tick a box on the scale below, where 0 means 'I avoid entirely taking any risk' and ten means 'I am fully prepared to take high risks,'

0	1	2	3	4	5	6	7	8	9	10

2. How would you compare yourself with other members of your community? Please tick a box on the scale below when thinking about decisions related to the management of your animals:

1	I usually take much fewer risks than other members of my community
2	I usually take fewer risks than other members of my community

3	I usually take the same amount of risks as other members of my community
4	I usually take more risks than other members of my community
5	I usually take much more risks than other members of my community

3.10 Elicitation of Loss aversion

The study designed a simple lottery game based the design on the work of (Gächter et al., 2021). However, this current study used balls instead of dice to ease the game and accommodate respondents with low literacy levels. This design effectively elicits loss aversion under the concept of cumulative prospect theory (CPT). Therefore, 110 respondents participated in the experiment. The lottery game entails six (6) choice lottery tasks that involve a 50% chance of winning and a 50% chance of losing a certain amount of money. Before the experimentation began, respondents were incentivized with 25 ZAR (1.56 USD)– the equivalent of the South African minimum hourly wage for participation and avoided net losses from playing a lottery game. In this lottery task experiment, losses varied from 8 ZAR (0.5 USD) to 23 ZAR (1.44 USD), while gains remained constant at 20 ZAR (1.25 USD). Then, respondents were required to decide whether they wanted to accept or reject some or all the six lotteries, which means they wanted to play or reject the game. If they reject all lotteries, they only gain incentivised value-25 (1.56 USD) ZAR to avoid net loss. The simplified version is presented in Appendix 8.2, the questionnaire. A list of lottery tasks presented to the respondents is shown in Table 3.4.

Table 3.2 Illustration of lottery game matrix

	Lottery	Accept	Reject
L1	If the coin turns up heads, the respondent loses 8 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.		
L2	If the coin turns up heads, the respondent 11 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.		

L3	If the coin turns up heads, the respondent loses 14 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.
L4	If the coin turns up heads, the respondent loses 17 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.
L5	If the coin turns up heads, the respondent loses 20 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.
L6	If the coin turns up heads, the respondent loses 23 ZAR; if the coin turns up tails, the respondent wins 20 ZAR.

Primary data collected by the author

After completing the six lottery questions/games listed in Table 3.4, the enumerator inserted numbered balls in a bag. These numbered balls represented the lotteries that the respondents had accepted. Then, randomly drew a numbered ball from the same bag, determining the row the respondent will play for real money. For example, if one draws ball number two, the respondent will play row two (2) for real money. In the best situation for respondents, when the lottery outcome was positive, the enumerator would pay them 25 ZAR (1.56 USD) as a participation compensation plus 20 ZAR (1.25 USD) that they earn by winning a game. However, since we gave the respondents an initial amount of money at the beginning of the lottery game, they never had to pay back the enumerator. The enumerator had to deduct the losses from the initial payment respondent received as an incentive in the worst-case situation. The study employed the cumulative prospect theory proposed by Tversky and Kahneman (1992) to estimate loss aversion. Cumulative prospect theory uses cumulative rather than separable decision weights as a corrective measure to the original prospect theory (Tversky & Kahneman, 1979) for violating stochastic dominance. It also addresses uncertainty outstandingly, i.e., in case of unknown probabilities and diminishing sensitivity (Booij et al., 2010). This theory stipulates that people evaluate lotteries in terms of gains and losses. It also defines that subjects are more sensitive to losses than commensurate gains. The indifference equation is defined as follows:

$$w^{+}(0.5)v(G) = w^{-}(0.5)\lambda^{risk}v(G) \quad (3.1)$$

Where L represents the losses, G represents the gains in each lottery, $v(x)$ is the utility of outcome given gains and losses, and λ denotes the loss aversion coefficient in the lottery. While $w^{+}(0.5)$ and $w^{-}(0.5)$ represent the 50% probability of losses and gains in the lottery game(Gächter et al., 2021). This study further assessed the effects of probability weighting and diminishing sensitivity on loss aversion given four assumptions:

- Probability weighting and diminishing sensitivity are unimportant, meaning that w= 1 and $\alpha = \beta = 1$. Therefore, the estimation of loss aversion is as follows: $\lambda = G/L$, where G remains constant, and L is determined by the last lottery task accepted.
- Probability weighting affects loss aversion; however, diminishing sensitivity does not ($\alpha = \beta = 1$); therefore, loss aversion is calculated as follows: $\lambda = w\left(\frac{G}{L}\right)$
- Probability weighting does not impact loss aversion but diminishing sensitivity $\lambda = \left(\frac{G^{\alpha}}{L^{\beta}}\right)$
- Probability weighting and diminishing sensitivity have an impact on loss aversion $\lambda = w\left(\frac{G^{\alpha}}{L^{\beta}}\right)$

Following the assumptions mentioned above, the study elicited four loss aversion parameters. The first loss aversion parameter (λ_1) is elicited from the loss of the last lottery task accepted before switching to reject, assuming no probability weights and diminishing sensitivity for gains and losses. In contrast, the second (λ_2) and third (λ_3) loss aversion parameters follow the same procedure but assume probability weighting and diminishing sensitivity, respectively. The fourth loss aversion parameter (λ_4) accounts for probability weighting and diminishing sensitivity. This study used diminishing sensitivity estimates (i.e., α=0.72 and β=0.73) from the survey by Abdellaoui et al. (2007) and probability weighting estimates (i.e., W^{+} (0.5)=0.394 and W^{-}(0.5)=0.456) from the study by Abdellaoui (2000). The determinants of loss aversion are explored using ordinary least squares (OLS) regression. Four loss aversion variables are dependent variables, and socioeconomic characteristics are explanatory variables in this case. Then, loss aversion parameters were included in the DCE model to test their influence on the preferences of subsistence livestock farmers for IBPI. However, only the fourth loss aversion parameter (λ_4) was retained in the DCE due to its statistical inferences validity.

3.11 Implementation of the Discrete Choice Experiment method

A DCE involves establishing and analysing choice data by formulating a hypothetical market. Choice analysis entails choice sets, where each set includes a group of mutually exclusive hypothetical alternatives amongst which respondents are required to choose the preferred one. Alternatives are described in terms of attributes, and each attribute can take several levels. However, there is an implicit trade-off amongst attributes in different options in the choice set when individuals make choices. The choice of attributes and levels requires a good understanding of the attributes influencing farmers' preferences. In particular, the most challenging issue is incorporating all attributes relevant to the decision-maker and will affect their decision. However, too many attributes may lead to a cognitive burden on respondents. Therefore, significant time was spent organizing qualitative open surveys with farmers and experts to obtain a reasonably sized set of attributes. The subsequent analyses will assume that respondents choose alternatives that yield the highest level of utility (Lancsar & Louviere, 2008; Louviere et al., 2000).

3.11.1 Elicitation of Attributes and their Levels

The design of DCE is a multi-step process involving: (i) identification of attributes and their levels, (ii) experimental design, (iii) development and survey piloting, (iv) data collection, and (v) analysis and interpretation. First, the conceptual attributes were identified through a literature review that applies to index insurance. The reviewed literature was limited to empirical studies and theoretical frameworks on index-based insurance published between 2010 and 2020. A list of conceptual attributes and their levels are presented in Table 3.3

Table 3.3 Conceptual Attributes and their levels

Attributes	Potential levels	References
Policyholders	Individuals, groups,	(Sibiko et al., 2017)
Strike levels	Range of strike levels from 15% to 30%	(Chantarat et al., 2013)
Transparency	Provide regular information regarding index performance	(Schwarcz, 2013; Sibiko et al., 2017)
Bundled insurance	Credit, savings	(Akter et al., 2016b; Farrin & Miranda, 2015)
Subsidized premium	Different subsidy rates from 20% to 50%	(Carter et al., 2017)
Insurance Provider	The central government, private insurance companies, micro-credit providers, and local cooperatives.	(Brouwer & Akter, 2010)
Basis Risk	Range of predicted percentage of index errors	(Clement, Botzen, et al., 2018; Vroege et al., 2019)

In order to further determine the legitimacy, relevance, and additional attributes, focus group discussions were conducted with livestock farmers. In this case, the selection criteria focused on the condition that farmers must actively farm livestock so that they contribute profoundly. In total, enumerators conducted the two focused group discussions comprising 20 farmers. These farmers actively farm livestock on public land in communal areas, with 60% male and 40% female. This composition differs slightly from the actual livestock farmers' populace in the Limpopo Province. According to Lehohla (2013), 49% of female and 51% of male livestock farmers in the Limpopo Province. The study consulted a list of experts who constitute the critical information from different institutions. These institutions entailed insurance companies (Land Bank South Africa, Swiss Re, and Santam), government officials, academia, red meat farmers organizations, and the Johannesburg Stock Exchange (JSE) between August and September 2020. The participants were requested to give their insights concerning the possible attributes of index-based pasture insurance. They were also asked to rank the attributes according to their importance, relevance, and practicability in managing drought risk. As a result of this comprehensive engagement, four attributes were most important, tabulated in Table 3.4.

Table 3.4 Attributes and Levels

Attributes	Levels
Transparency	Receive Weekly Updates, No Weekly Updates
Premium to pay	100 ZAR, 250 ZAR, 400 ZAR
Reimbursement method	Feed, Cash, Voucher
Basis risk	1 out of 10 times, 2 out of 10 times, 3 out of 10 times

Primary data collected by the author

There are three non-monetary attributes, i.e., transparency, reimbursement method, and the basis risk. The cost attribute, referred to as the premium, is included to estimate the marginal rate of substitution, which can be interpreted as WTP for the different contract attributes. In this experiment, the insurance contract has a value of 5000 ZAR (315.05 USD), which is interpreted as covering one livestock unit for a single rainy season. This aims to protect subsistence farmers from running a risk of experiencing a deficient pasture because of drought. Three possible insurance premiums, i.e., 100 ZAR (6.30 USD), 250 ZAR (15.75 USD), and 400 ZAR (25.20 USD), were proposed to be paid by farmers for their IBPI contracts. The data collected from the Land Bank of South Africa guided the determination of premiums.

The outcomes from focus group discussions and consultations revealed that farmers prefer different modes of receiving claim pay-out. To this effect, three methods of reimbursement were essential to subsistence farmers. As a result, the reimbursement method was included as one attribute in the DCE design. The reimbursement attribute takes either of these forms: (i) voucher, (ii) cash, and (iii) feed. If the prospective policyholder chooses the voucher option as the preferred mode of insurance compensation, they will receive their payout in a voucher, equivalent to the insurance payout. This voucher does not expire, is limited to purchasing supplementary feed and veterinary services, and is redeemable at any feed retail store in South Africa. If the policyholder chooses the cash option as a mode of insurance compensation, they will receive a pay-out to their bank accounts. Lastly, if they choose feed as the reimbursement mode, they will receive their payout as supplementary feed equivalent to the insurance payout suitable for their herd. The insurance contract specifies the type of preferable animal feed. In the event of feed delivery, the insurance company is the one that will cover the transportation costs.

The consideration of the basis risk attribute is motivated by the large body of literature that advocates that it has a significant influence on the WTP for IBPI, albeit being omitted in some studies (Clement, Wouter Botzen, et al., 2018; Gaurav & Chaudhary, 2020; Jensen et al., 2016; Jensen et al., 2018). In this context, basis risk is the possibility of receiving insurance compensation lower than actual losses incurred. To put this in the perspective of the study area, the herd grazes in only one part of the local municipality; therefore, pasture might not degrade evenly throughout the municipality. There might be a slight possibility of receiving less or higher compensation due to the difference between the average pasture degradation of grazing territory and the municipality. Since this study only focuses on the possibility of receiving less payment, the basis risk ranges between 8 to 16 out of 100 times. In this case, the basis risk has three levels, i.e., the possibility of being reimbursed more petite than the actual damage in 8, 12, or 16 out of 100 times.

Following literature and consultations, transparency was perceived as an essential attribute influencing farmers' preferences for IBPI. Transparency means that the insurance contract provides information about an index's performance. Therefore, the potential policyholders can receive information through satellite reports regarding pasture degradation in their respective areas from an independent weather service body, such as the South African Weather Services (SAWS). This information will help if pasture degradation in a specified area has reached the predetermined trigger level corresponding to the insurance contract. This would also help farmers make informed decisions regarding their cash flows and production plans in the upcoming seasons. Here, transparency is associated with two options, so potential policyholders can choose from two options: (i) a transparency contract and (ii) a non-transparent contract. In case (i), potential policyholders can receive weekly updates. Receiving weekly updates means that policyholders will receive updates regarding the pasture degradation levels that determine the insurance pay-out through Short Message Service (SMS). On the other hand, option (ii) means that policyholders receive no weekly updates. Thus, if a particular potential policyholder opts against receiving weekly updates, there will be no communication regarding the pasture degradation levels in their grazing territory. We show how the IBPI works in terms of the trigger levels and possible insurance compensation in Table 3.5.

Table 3.5 Trigger Levels and Possible Pay-out for an Insured Value of 5000 ZAR

Compensation of a contract depends on a 20% Trigger Level											
Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	≥60%
Compensation (ZAR)	0%	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000
Compensation of contract depends on a 30% Trigger Level											
Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	≥60%
Compensation (ZAR)	0	0	0	2500	2917	3333	3750	4167	4583	5000	5000

Primary data collected by the author

The trigger level is the minimum level of pasture degradation that defines the risk profile. Policyholders receive insurance compensation whenever pasture degradation passes the predetermined trigger that aligns with the purchased insurance contract. Table 3.3 shows how IBPI compensates at 20% and 30% trigger levels. It is important to note a perceptible relationship between the pay-off and the trigger levels. Evidence of this relationship is straightforward because each trigger level pays differently from the others. Given this correlation, choice sets are associated with trigger levels. Since choice sets are divided into two blocks, each block is coupled with two trigger levels: (i) 20% and (ii) 30%. This combination yields four (4) scenarios: (i) 20% trigger level and block one, (ii) 30% trigger level and block one, (iii) 20% trigger level and block two, and (iv) 30% trigger level and block two. The explanation of the payment and trigger levels is classified into four cases to avoid the cognitive burden.

Case one: When the pasture degradation is 0%, it means that the pasture degradation is below all trigger levels. Therefore, potential policyholders of IBPI associated with 20% or 30% trigger levels will not receive compensation.

Case two: When the pasture degradation has reached a 20% trigger level, the potential policyholders of IBPI contracts associated with a 20% trigger level will be reimbursed 1,667.00 ZAR (105.04 USD). However, policyholders of a contract associated with the 30% trigger level do not qualify for reimbursement since pasture degradation has not reached its respective trigger level.

Case three: When the pasture degradation has reached the 30% trigger level, policyholders that purchased insurance contracts associated with the 30% trigger level will receive an indemnity of 2,500.00 ZAR (157.52 USD).

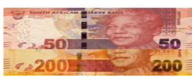
Case four: When the pasture degradation reaches the 60% mark, it has degraded beyond the limit level. Here, policyholders may receive compensation of 5,000.00 ZAR (315.05 USD), equating to their insurance value. No additional payment beyond 5,000.00 ZAR (315.05 USD) can be made to the clients.

3.11.2 Construction of the choice sets

3.11.2.1 Pre-testing phase

Based on the identified attributes and levels, this study used a design with two blocks and nine choice sets using Ngene software (Metrics, 2014). This design required many choice sets due to the absence of prior information about the parameters. Also, two different trigger levels were used. Each block was associated with the 20% and 30% trigger levels, yielding four treatments, and each respondent was presented with only one of the four treatments. An example of a choice card is shown in Table 3.2, which shows that each choice card was presented with trigger levels and expected compensation showing how insurance compensation is triggered, whose primary purpose was to remind respondents how the payments are triggered at these different trigger levels (20% and 30%).

Table 3.1 Example of the choice card for a trigger level set at 30%

	Contract A	**Contract B**	**Option C**
Reimbursements will be paid as:	Feed 	Cash 	Stay without Insurance
Transparency	No Weekly Updates 	Receive Weekly Updates 	
Basis Risk	8 out of 100 times	12 out of 100 times	
Premium to pay	250 ZAR 	100 ZAR 	

The reminder of trigger levels and their expected compensation											
Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	>60%
Compensation (ZAR)	0	0	0	2500	2917	3333	3750	4167	4583	5000	5000

As shown in Table 3.2, these choice cards entailed three non-monetary attributes, i.e., transparency, reimbursement method, basis risk, and one cost attribute. The non-monetary attributes were coded as dummy variables, while the monetary attributes were incorporated as continuous variables. Each choice card had options, i.e., A, B, and C, where options A and B represented insurance contract options, while option C represented the "opt-out." As stated earlier, the "opt-out" option is the choice of staying without insurance, meaning that respondents prefer none of the two contracts.

Before choice experiment scenarios were presented to respondents, the concepts of IBPDI, from its fundamentals to trigger levels and how pay-outs are made, were introduced. The respondents fully grasped the proposed insurance's details and operational intricacies. This might have been because of the absence of a language barrier since the presentation was done in their local language, which is also the enumerators' first language. As a result of the first language playing a significant role, there was no practical difficulty in understanding and responding to the questionnaire. Regarding the choice experiment, the attributes and trigger levels were explained. Here, the study observed that the understanding of the procedure was unclear; the description of attributes, attribute levels, and the insurance compensation was repeated until an adequate understanding was confirmed. After good comprehension of how choices are made, the enumerator presented the actual choice sets. The study observed that the respondents had no comprehension challenges in this exercise. However, because of their low literacy levels, the ability to make choices relied on how the best enumerator explained the explanation. As a result, out of the 20 respondents, 16 confirmed they did not have difficulty completing the alternatives, except that the nine (9) choice sets were too much for them.

3.11.2.2 Final design

The second design was constructed using the pre-test result to obtain preliminary information, which allowed us to create a D-efficient design using the Ngene software (Metrics, 2014) again. The D-optimal criterion is broadly used as a measure of efficiency because of its insensitivity to the scale of parameters. The use of prior information helped in creating choice sets with fewer scenarios. Therefore, a design with 12 choice sets was generated, each comprising three alternative-two index-based pasture programs and one showing" opt-out," i.e., a non-insurance option. These scenarios were divided into two blocks of six scenarios. The choice sets and their allocation into the two blocks are presented in appendix C. Again; the survey was divided into four treatments: (1) block 1 /trigger 20%; (2) block 1/trigger 30%; (3) block 2/trigger 20%; and (4) block2/ trigger 30%.

3.12 Modelling Individual Preferences

The choice data analysis was based on Random Utility Theory (RUT) developed by McFadden (1974). This enabled the estimation of unobserved utility derived by farmers from IBPI using two components. The first term is the deterministic component expressed by indirect utility V, donated as a function of attributes. The second term is stochastic, an error term that captures unobserved factors that influence utility. Therefore, the overall utility derived from purchasing IBPI is the sum of the deterministic and error component:

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \beta X_{ni} + \varepsilon_{ni} \,, \tag{3.2}$$

Where U_{nk} is the overall utility that an individual n derives from a chosen alternative i, $V_{ni,}$ is the deterministic and observable component of utility that depends on the alternative's attributes and levels. X_i denotes a vector of attributes, and β is the coefficient vector.

Whereas ε_{ni} is a stochastic component that accounts for unobservable impacts on choice (e.g., missing attributes). The assumption is that an individual n would prefer an alternative i from a specific choice set, $C \in (1, \ldots, S)$ in utility U, conditioned that it is greater than or equal to the utilities of any other choice in the choice set. Therefore,

$$P_{ni} = \Pr\left[V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \; ; \; \forall_j \in s_{n,i \neq j}\right] \tag{3.3}$$

Assuming that error terms are independent and identically distributed (i.i.d.) and Type 1 error distribution holds, (3.1) yields a conditional logit model, presented:

$$P_{ni} = \frac{\exp\left(u\beta X n_i\right)}{\sum_k \exp\left(u\beta X_{ni}\right)} \; . \tag{3.4}$$

In (3.3), the term u is the scale parameter assumed to be 1, and β is a vector of the parameter. However, the above-described application assumes homogeneity of preferences among different respondents. Here, mixed logit can account for heterogeneity in preferences. However, it does not explain the underlying factors of heterogeneity and requires a large sample size. Because of this limitation, this study used the latent class (LC) model to elicit farmers' preferences for IBPI (Birol et al., 2009). This approach illustrates a population on a finite and identifiable number of classes or groups of individuals that are determined endogenously by data. The allocation of an individual into a particular class is probabilistic and relies on the socio-economic and psychometric factors of the respondents. Assuming components in a population and that individual *j* belongs to a class $(c = 1, \ldots, C)$. The utility parameters in (3.1) are expressed in segment-specific form, and (3.3) becomes:

$$P_{ni|s} = \frac{\exp\left(u_c \beta_c X_i\right)}{\sum_n \exp\left(u_c \beta_c X_j\right)}, \tag{3.5}$$

where u_c and β_c are scale parameter and segment-specific utility, respectively. The class membership probability function categorizes respondents into one class is given.

$$M^{*}=\lambda_c Z_c + \varepsilon_c, c = 1, \ldots\ldots, C, \tag{3.6}$$

Where Z the observed characteristics such as their socioeconomic and psychometric characteristics. Therefore, the error terms are assumed to be independently and identically distributed across individuals, following Type 1 error distribution and scale factor α. Following the latter assumptions, the likelihood of respondent i being categorised into a class c is expressed:

$$P_{nc} = \frac{\exp\left(\alpha\lambda_c Z_n\right)}{\sum_{c=1}^{C}\exp\left(\alpha\lambda_c Z_n\right)} \tag{3.7}$$

Where Z the observed characteristics such as their socio-economic and psychometric characteristics. Therefore, the error terms are assumed to be i.i.d. across individuals, following Type 1 error distribution and scale factor α. Following the latter assumptions, the probability of respondent i belonging to class c is expressed as follows:

$$P_{ni=}\left[\frac{\exp\left(u_c\beta_c X_i\right)}{\sum_k \exp\left(u_c\beta_c X_j\right)}\right]\left[\frac{\exp\left(\alpha\lambda_c Z_n\right)}{\sum_{c=1}^{C}\exp\left(\alpha\lambda_c Z_n\right)}\right] \tag{3.8}$$

This model allows discrete choice data and respondents' characteristics to explain choice behaviour. The latent class takes the product of conditional distribution and the likelihood of being in a class, where classes are finite analogue to random parameter distribution. Here, the distribution is well specified, and the joint probability can be estimated. Based on the estimates of latent class, it is possible to evaluate marginal willingness to pay and trade-offs between attributes.

3.12.1 Index-based Pasture Insurance Utility Functions

Following the theoretical framework described above, the indirect utility that farmers derive from adopting IBPDI is specified by the conditional logit model as follows:

$$V = \beta_1\, ASC + \beta_2 Transparency + \beta_3\, Voucher\; + \beta_4\, Feed + \beta_5\, BasisRisk + \beta_6\,(BasiRisk * Educ) + \beta_7\; Premium + \beta_8\;(Premium * Educ)\;, \tag{3.9}$$

Where ASC represents an alternative specific constant, presented non-insurance option in a choice set. In (3.8), ASC equals one for the IBPI contract option and zero for the non-insurance option or the status quo. We modelled transparency as a dummy variable, i.e., one and zero. One equal receiving weekly update regarding index performance and zero otherwise. In the reimbursement method, voucher and feed were also modelled as dummy variables and were compared with cash as the base level. The basis risk and premium as continuous variables, while betas β_{1-8} indicates mean coefficients of marginal utility that the farmers derive from each attribute. The coefficient signs give the direction of preference, i.e., positive or negative, meaning that farmers can derive positive or negative marginal utility from a particular attribute. However, the coefficient must differ significantly from zero to ensure that farmers derive marginal disutility or marginal utility from a specific attribute. In addition, ASC interacted with socio-economic characteristics to inspect the diversity of farmers' preferences for IBPI. Therefore, (3.9) can be extended as follows:

$$V = \beta_1\,(ASC * LossAversion) + \beta_2\,(ASC * RiskAversion) + \beta_3\,(ASC * ArableLand) + \beta_4\,(ASC * DroughtFrequency) + \beta_5(ASC * WeatherForecast) + \beta_6\,(ASC * TriggerLevel2) + \beta_7 Transparency + \beta_8\, Voucher\; + \beta_9\, Feed + \beta_{10}\, BasisRisk + \beta_{11}\,(BasiRisk * Educ) + \beta_{12}\; Premium + \beta_{13}\;(Premium * Educ). \tag{3.10}$$

The utilities of IBPI in the latent class model are estimated as follows:

$$V = \beta_{ab} ASC + \beta_2 Transparency + \beta_3 Voucher + \beta_4 Feed + \beta_5 BasisRisk + \beta_6 Premium + \beta_Z (ASC * Z) \quad (3.11)$$

Similarly, ASC equals zero for the non-insurance option and one for the IBPI contract; the beta coefficient of ASC varies across classes. In our study, beta coefficients for ASC for classes one and two are fixed, whereas β_Z shows the coefficient of socio-economic characteristics that determine the probability of farmers belonging to a particular class, and *Z* is a vector of socio-economic factors.

3.12.2 Marginal Rate of Substitution (MRS)

The standard consumers' theory suggests that the marginal rate of substitution (MRS) can be computed by taking a partial derivative of (3.1) concerning two attributes, subsequently calculating their ratio (Lancsar & Louviere, 2008). Typically, the MRS is interpreted as the WTP, which can be computed by taking the ratio of non-monetary and monetary attribute coefficients specified in (3.1), as follows:

$$WTP = -\frac{\beta\_nonmonetary\ attribute}{\beta\_monetary\ attribute}. \quad (3.12)$$

This ratio is known as implicit price; however, specifying the standard errors for implicit price ratios is more complex. Three common approaches are broadly applied to estimate WTP: (i) delta method and (ii) Krinsky and (iii) Robb parametric bootstrapping method (KR) (Krinsky & Robb, 1986). The delta method provides a well-behaved finite estimate of asymptotic variance. In contrast, the KR approach involves simulating multiple draws from the distribution of the structural parameter of the WTP ratio (Carson & Czajkowski, 2019). The ratio of the simulated coefficient provides empirical distribution, which is used for calculating its mean, median, and standard deviation.

Nonetheless, Carson and Czajkowski (2019) emphasized that these two methods do not produce valid estimates. For instance, they criticized the delta method for producing a misleading finite and often reasonable standard error estimate while the valid quantity is undefined. However, the KR approach always shows the degenerate nature of the WTP ratio with a large enough sample size. However, these problems have not discouraged the application of these methods to estimate WTP. The underlying reason is that the techniques are convenient for using and producing credible confidence intervals.

CHAPTER 4 RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the research results, beginning with descriptive statistics of subsistence livestock farmers in Mulima Village, Makhado Municipality, Limpopo Province, South Africa. After that, farmers' mitigation and coping strategies are discussed and followed by risk aversion and loss aversion results. Then, farmers' preferences for IBPI are discussed.

4.2 Descriptive Statistics

The Summary statistics of subsistence farmers are presented in Table 4.1. The sample of 110 farmers who participated in the study comprised 61% male and 39% female. Education plays a vital role in the comprehension and adoption of insurance products; in this study, 39% of the respondents do not have formal education, while the remaining proportion has formal education. The respondents are categorised as subsistence farmers since they have an average of 18 livestock. Even though the herd size is small, data shows that they have been farming for ten years. This shows that livestock farming is crucial for their livelihood. However, drought complicates their farming. Respondents experienced at least two years of drought in the past five years. They recorded an average of six livestock mortality, a 40% mortality relative to the mean herd size. Another critical constraint that farmers face is limited access to private farming land and overage; farmers have 2.77 hectares of arable land. They rely more on an open-access grazing system, where they can only manage to sustain a specific herd size due to high competition for natural grazing. Also, some traditional drought management mechanisms are difficult to implement in such a system. For instance, rotational grazing is challenging to adopt in an open access grazing land because there are no demarcations. Because of the lack of proper demarcations of the communal grazing lands, the animal disease can easily be transferred from one herd to another, and livestock theft becomes a severe problem. These glitches affect their income from livestock farming, at most 75,259.41 (5,017.29) per annum. Almost half (46%) of the respondents receive government social grants that supplement their livestock sales income. Also, financial assistance is limited because the data shows that only 33% of respondents have access to formal credit.

Table 4.1 Summary Statistics

Statistic	Description	Mean	Standard deviation
Age	Number of years	56.28	14.78
No education	Dummy	0.39	0.46
Primary education	Dummy	0.24	0.43
Secondary education	Dummy	0.40	0.49
Tertiary education	Dummy	0.07	0.26
Herd size	Number of livestock	18.35	14.25
Arable land	Hectares	2.77	2.57
Household size	Number of households	5.44	1.95
Male	Dummy	0.61	0.49
Female	Dummy	0.39	0.49
Drought occurrences in the past five years	Number of years	2.39	1.15
Drought-related livestock mortality	Number of livestock mortality	5.66	7.67
Access to formal credit	Dummy	0.33	0.47
Social grant beneficiaries	Number of efficacies	0.46	0.50
Number of years in farming	Number of years	11.89	7.91
Income	ZAR (US dollars)	75,259.41 (5,017.29)	60,087.07 (4005.80)
Number of respondents	110		

The author collected primary data

4.3. Drought Mitigation and Coping Mechanisms

Subsistence livestock farmers in the study area are highly dependent on rainfall to have enough natural grazing to sustain their livestock herd from one growing season to the next. Rain-fed subsistence livestock farming typically relies on summer rainfall, starting in late October and ending in March. When the rain comes later than expected, farmers wait for it or take the necessary coping measures to circumvent livestock mortality and loss of cash inflow. A coping strategy is a measure that farmers employ to master, live with, reduce, or minimize the effect of drought once it occurs (Pandey & Bhandari, 2009). If farmers cannot implement these measures, they may risk losing the market value of their livestock assets because of drought-related complications (e.g., diseases, starvation). Since losing income and livestock herd directly affects the farmers' livelihoods, they sometimes devise livestock management strategies to prepare for the expected effects of drought before it occurs; this is referred to as mitigation measures (Rosenzweig & Tubiello, 2007). However, these strategies differ from community to community, depending on the community settings, the culture, the natural resources, and the social and economic capital. The primary mitigation and coping mechanisms reported by the subsistence livestock farmers in the study area are tabulated in Table 4.2.

Table 4.2 Mitigation and Coping Mechanisms for Drought used by farmers

Mitigation Mechanisms	N (%)	Coping Mechanisms	N (%)
Use rotational grazing	89 (88.10%)	Ask for external support	64 (63.40%)
Store feed	74 (73.30%)	Government relief	52 (51.50%)
Resistant breeds	54 (53.50%)	Reduce stocking rate	46 (45.50%)
Mixed farming	48 (47.50%)	Sell livestock	40 (39.60%)
Sell stock more often	44 (43.60%)	Migrate	35 (34.70%)
Save money	35 (34.70%)	Draw from saving	26 (25.70%)
Rainwater harvest	34 (33.70%)	Take credit	4 (4.00%)
Plant pasture	7 (6.90%)	Increase daily labour	1 (1.00%)
Buy insurance	0 (00.00%)	Insurance compensation	0 (0.00%)

The author collected primary data

4.3.1 Drought Mitigation mechanisms

As shown in Table 4.2, the most common mitigation strategy is rotational grazing. A total of 89 (88.1%) farmers used rotational grazing as a strategy to prepare for prolonged dry periods. This strategy extends the grazing season and reduces farmers' dependency on stored feed and supplements. However, rotational grazing is expensive to execute because it requires more fencing and accessible water points, which is even worse in communal farming settings due to open access to grazing and water. The second common mitigation strategy is storing feed, where 74 (73.3%) of farmers practice this strategy.

Typically, they store residuals of corn, vegetables, and soybeans. However, this mechanism requires the farmers to have nutritional knowledge regarding each residue to avoid any dietary complications associated with each crop residual (Gertenbach & Dugmore, 2004). About 47% of farmers said they apply mixed farming as a mitigation strategy. Mixed farming comprises multiple farming activities (e.g., crop, livestock, off-farm business) running simultaneously, leading to complex management, monitoring, and maintenance strategies than farmers focusing on one agricultural commodity (Schiere et al., 2006). Its advantage is that it stabilizes subsistence farmers' income, keeps the farmland in continuous production, and subsequently enhances profits. It is also a way to buffer against climatic conditions. However, it is impossible to upscale and realise large economies of scale because mixed farming requires farmers to have comprehensive knowledge of various agricultural commodities, which can be very challenging for many subsistence farmers due to the lack of extension services for multiple enterprises. Approximately 43% of the sampled farmers often sell livestock to avoid mass livestock mortality. About 34.7% of farmers save money to prepare for drought events. Furthermore, 33.7% of farmers harvest rainwater to prepare for water deficits during prolonged drought. With all the challenges and associated risks listed above, none of the randomly sampled farmers uses insurance as a mitigation strategy, and the reason for not purchasing insurance are listed in Table 4.3.

Table 4.3 Reason for not purchasing insurance

Reason for not purchasing insurance	**N (%)**
It is expensive	69 (63.00%)
I lack trust in insurance,	2 (1.80%)
It takes a long to pay	3 (2.70%)
I do not need it.	15 (14.00%)
I do not have the information	21 (19.00%)

The author collected primary data

Farmers cited that their main reasons for not purchasing insurance are associated with not having a market for livestock insurance that hedges against drought risk. Among other reasons, 69% of farmers perceive insurance as an expensive option for drought mitigation due to low financial options and source of income. They have negative attitudes towards livestock insurance because of a lack of awareness or information. At the same time, a small proportion of farmers indicate that they lack insurance trust. About 15% of farmers stated that they do not need insurance, while 19% said they lacked information about livestock insurance.

4.3.2 Coping Strategies

Most farmers (63.4%) seek external support during drought as an adaptation strategy. The external support means farmers can receive support from producers' groups, cooperative groups, and non-governmental organizations regarding extension services, cash transfers, and feed supplements. Also, they can receive support from social networks, including friends, family, and the community (Ncube, 2020). In a study conducted in the KwaZulu-Natal province of South Africa, Lottering et al. (2020) found that external support plays a critical role in reducing the impact of drought on farmers. However, Ubisi et al. (2017) reported that only 8.7% of subsistence farmers had these social networks. The latter was also justified in a study by Bahta et al. (2016), who found that farmers do not consider these social networks effectively reducing their vulnerability to drought. About 55.5% of the farmers confirmed that they rely on government drought relief programs to cope with the impact of drought. However, farmers' reliance on government drought relief programs is problematic. First, government drought relief measures are reactive and inefficient in addressing the full impact of drought. The government does not measure accumulated losses to compensate individual farmers accordingly appropriately. Second, government drought relief programs encourage subsistence farmers to perceive them as a standard measure to cope with the impact of drought, which is not the case. The reason for this is that the government's assistance takes a long time to arrive due to inefficiencies of the administrative layers at both provincial and national levels. These failures result in high transaction and opportunity costs in providing drought relief to the affected subsistence farmers.

Farmers also mentioned that this strategy comes with additional costs since the government does not deliver feed directly to their respective locations. Instead, the government stores feed in a particular area, and each farmer must have means of transport to collect the feed. As a result, it limits farmers from accessing these services and carries the burden of drought at their own expense. Approximately 39.6% of the respondents perceive stocking rate reduction as an essential coping strategy. The stock reduction strategy is an early marketing strategy that farmers adopt as an option to sell their livestock to save them from dying during drought and raise capital to restock when the conditions are favourable. However, its shortcoming is that many subsistence farmers might not restock when the conditions become favourable because of the constraints, including lack of income at that point in time. Another underlying reason for some subsistence farmers selling livestock is that it is one requirement to qualify for government relief schemes (Fanadzo, Ncube, French, & Belete, 2021). In instances where drought has caused severe pasture degradation, farmers also consider migrating animals to regions with sufficient natural pasture. Regarding access to financial services, only 4% of farmers take formal credit, while 25.7% withdraw from their savings to cope with drought.

4.4 Farmers’ Ability to Manage Drought

Respondents were asked to give their perceptions regarding their ability to deal with the impact of drought. Table 4.4 shows farmers' general perceptions of drought management

Table 4.4 Farmer's perception regarding drought management

Questions	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
I have recorded livestock mortality in the past 5 years due to drought	45,5%	18,8%	18,81%	16,83%	0,00%
I do not have the full capacity to deal with drought	54,46%	8,91%	3,96%	31,68%	0,99%
The impact of drought complicates my farming business	60,00%	20,00%	15,00%	5,00%	0,00%

I have received drought relief from the government in the past years	0,00%	11,88%	4,95%	76,24%	6,93%
I can deal with the impact of drought on my own	0,00%	23,76%	6,93%	29,70%	39,60%
I am willing to pay for index insurance as soon as it is available	5,94%	51,49%	2,97%	37,62%	1,98%
Drought is frequent in my area	64,36%	2,97%	1,98%	30,69%	0,00%

The author collected primary data

As presented in Table 4.4, about 64% of the subsistence farmers strongly confirmed losing their livestock due to drought in the past five years. Regarding the total capacity to deal with drought, 55% of farmers strongly agreed that they do not have the total capacity to deal with the impact of drought, which complicates their farming business. Most farmers also stressed that they did not receive drought relief funds from the government in the past five years. At the same time, many farmers, i.e., approximately 69%, stated (agree and strongly agree) that they could not deal with drought independently. About 67% of the farmers experienced frequent drought events within the area. The conclusion drawn from the above results was that subsistence livestock farmers have existing traditional mitigation and coping mechanisms. However, these mechanisms are associated with shortcomings that prohibit them from dealing with the impact of drought.

4.5 Risk Aversion

The study found a significant heterogeneity of risk-taking among subsistence livestock farmers. The risk-taking distribution appears normal and concentrated around medium risk in both domains. The peak at zero is higher in general than in animal management, suggesting that farmers show a low-risk attitude in animal management compared with the general domain. The risk-taking distribution is presented in Table 4.5.

Table 4.5 Distribution of risk-aversion

Risk-taking Scale (0-10)	R1: General		R2: Animal management	
	N	%	N	%
0	14	(13.86%)	9	(8.91%)
1	2	(1.98 %)	0	(0. 00%)
2	4	(3.96%)	2	(1.98%)
Total Risk averse (0,1,2)	20	(19.9%)	11	(10.89%)
3	7	(6.93%)	7	(6.93%)
4	14	(13.86%)	12	(11.88%)
5	15	(14.85%)	5	(9.90%)
6	11	(10.89%)	9	(8.91%)
7	15	(14.85%)	13	(12.87%)
Total Risk neutral (3-7)	61	(61.39%)	46	(54.54%)
8	9	(8.91%)	16	(15.84%)
9	5	(4.95%)	15	(14.85%)
10	5	(4.95%)	8	(7.92%)
Total Risk takers (8-10)	19	(18.81%)	39	(38.61%)

Scale: 0 shows complete unwillingness to take the risk, 10 indicates complete willingness to take the risk

The author collected primary data

Farmers also had to compare themselves with other community members in terms of risk-taking in general and animal management domains, which is presented in Table 4.6. The distribution is right skewed in both domains, with a peak between zero and three. This distribution shows that farmers consider themselves more risk-averse than the other members of the community in both domains.

Table 4.6 Distribution of risk-aversion in comparison with other community members.

Risk-taking	R1: General		R2: Animal management	
	N	%	N	%
1	20.00	(19.80%)	18.00	(17.82%)
2	34.00	(33.66%)	23.00	(22.77%)
3	25.00	(24.70%)	27.00	(26.73%)
4	17.00	(16.83%)	27.00	(26.73%)
5	5.00	(4.95 %)	6.00	(5.94%)
Total	101	(100%)	101	(100%)

Scale: 1- I usually take much fewer risks than other members of my community, 5- I usually take much more risks than other members of my community

The author collected primary data

The OLS regression is used to gain insight into factors influencing risk aversion. Risk aversion variables (R1 and R2) presented in Table 4.7 were used as the dependent variables, and socioeconomic characteristics (e.g., age, education, income, gender) were used as explanatory variables. The variance inflation factor (VIF) was used to detect multicollinearity; all VIF values are less than 2, indicating the absence of multicollinearity. The coefficient is negative and significant in age, with a magnitude of 0.05 and 0.6 in general (R1) and animal management (R2) domains, respectively. Therefore, an increase of ten years of age decreases the risk-taking by 0.5 in R1. For example, switching from 8 to 7.5 in risk-taking requires ten years of age. Gender only plays a significant role in animal management; female farmers are more risk-averse than male farmers. Also, farmers with high farming experience are more risk averse.

Table 4.7 Estimation results for the determinants of risk-aversion

	Dependent variable:	
Explanatory variables	**R1**	**R2**
Age	-0.05**	-0.06**
	(0.02)	(0.02)
Female	-0.70	-1.03*
	(0.601)	(0.55)
Education	0.15	0.24
	(0.34)	(0.31)
Income	-0.00	-0.00
	(0.00)	(0.00)
Drought frequency	-0.07	0.31
	(0.27)	(0.24)
Weather forecast	0.30	0.58
	(0.58)	(0.53)
Livestock sales	0.11	0.06
	(0.13)	(0.13)

Herd size	0.01	0.04
	(0.029)	(0.026)
Farming experience	-0.08*	-0.07**
	(0.04)	(0.04)
Arable land	0.14	0.07
	(0.11)	(0.10)
Single	-0.16	0.30
	(0.80)	(0.74)
Constant	7.94***	8.10***
	(2.06)	(1.89)
Observations	101	101
R2	0.19	0.32
Adjusted R2	0.09	0.23
Residual Std. Error (df = 89)	2.73	2.50
F Statistic (df = 11; 89)	1.89*	3.78***
Note: *p<0.1; **p<0.05; ***p<0.01		

The author collected primary data

4.6. Loss Aversion

Table 4.8 presents summary statistics of loss aversion parameters with the four hypotheses about the coefficients ω, α, and β. The first loss aversion parameter (λ_1) is elicited from the loss of the last lottery task accepted before switching to reject, assuming no probability weights and diminishing sensitivity for gains and losses. The second (λ_2) and third (λ_3) loss aversion parameters follow the same procedure but assume probability weighting and diminishing sensitivity, respectively. In contrast, the fourth loss aversion parameter (λ4) accounts for probability weighting and diminishing sensitivity. The study used incentivised lottery experiment to elicit loss aversion assuming that maximum acceptable loss is at the midpoint of switching from accepting to rejecting a lottery task. In this experiment, most respondents switched from accepting to rejecting before the midpoint of the lottery task that gives negative expected values. Furthermore, farmers did not switch back to accepting other lotteries after rejecting a particular lottery task.

Table 4.8 Implied loss aversion

Lottery Task	Acceptable loss	ω=1 α=1 β=1	ω=0.864 α=1 β=1	ω=1 α=0.72 β=0.73	ω=0.864 α=0.72 β=0.73	Frequency
		λ_1	λ_2	λ_3	λ_4	
1.Reject All	<8 ZAR	>2.5	>2.16	>1,89	>1,64	18 (16%)
2.Accept_L1, reject L2 to L6	8 ZAR	2.50	2,16	1,89	1,64	15 (14%)
3.Accept_L2, reject L3 to L6	11 ZAR	1.81	1,57	1,50	1,30	25 (23%)
4.Accept_L3, reject L3 to L6	14 ZAR	1.43	1,24	1,26	1,09	30 (27%)
5.Accept_L4, reject L4 to L6	17 ZAR	1.18	1,02	1,09	0,94	18 (16%)
6.Accept_L5, reject L6	20 ZAR	1.00	0,86	0,97	0,84	4 (4.0%)
7.Accept ALL	23 ZAR	≤0.86	≤0,75	≤0,88	≤0,76	0 (0.0%)
	Median	1.81	1.57	1.500	1.30	
	Mean	1.762	1.53	1.45	1.26	

The author collected primary data

About 96% of the farmers accepted lottery tasks with positive expected values, suggesting loss aversion. Only 4% accepted a lottery task with negative expected values, suggesting they are not loss averse. All loss aversion parameters have a median value greater than one, suggesting that farmers exhibit loss aversion in all four assumptions. Figure 4.1 shows the distribution of loss aversion parameters.

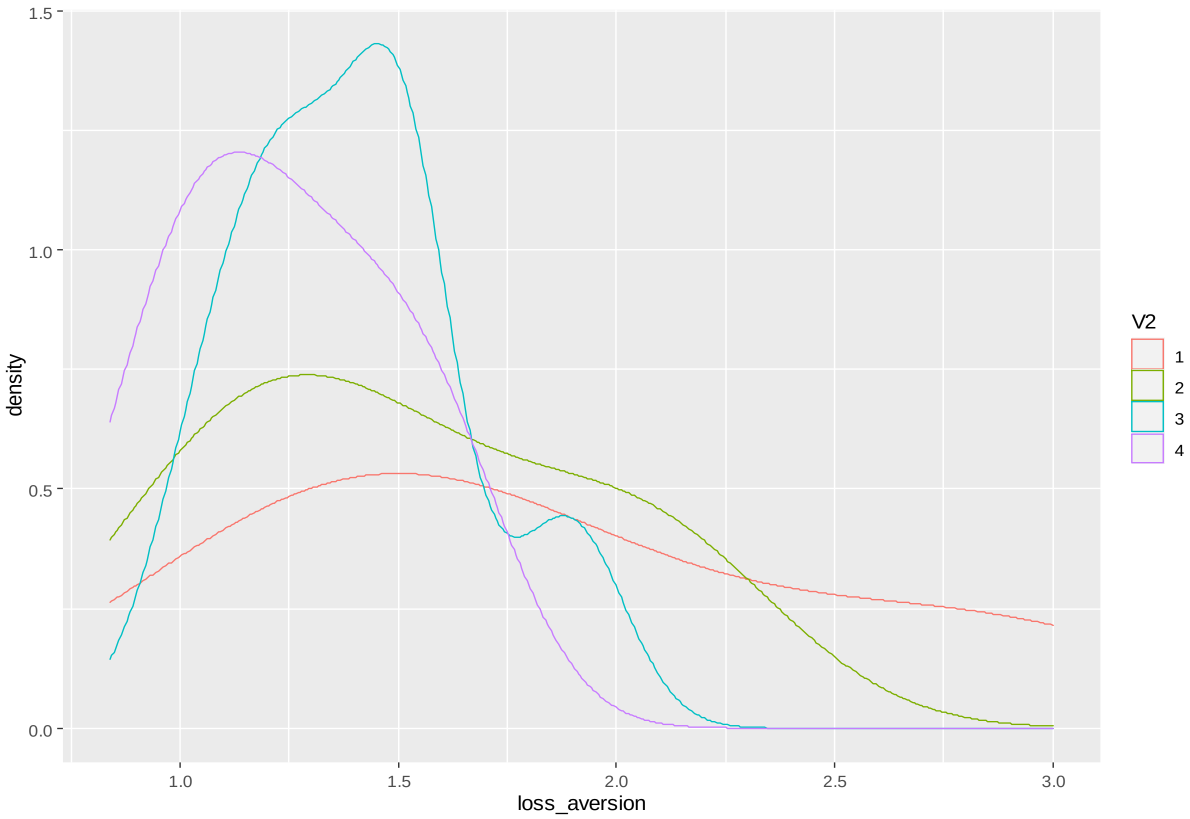


Figure 4.1 Density distribution of loss aversion parameters

As illustrated in figure 4.1, the distribution of four loss aversion parameters (λ_{1-4}) is skewed to the right and is concentrated on the range λ>1, which is equivalent to loss aversion as opposed to loss tolerance, λ<1. However, the fourth loss aversion parameter has a narrow bell curve concentrated around the mean (1.259). Therefore, it has a slight standard deviation, suggesting more reliability in making valid statistical inferences. The range of loss aversion reported in this study falls within the range reported in other studies that assumed probability weighting and diminishing sensitivity (Booij et al., 2010). This study further explored the determinants of loss aversion using OLS. The results are shown in Table 4.9.

Table 4.9 Estimation results for the determinants of risk-aversion

	Dependent variable:			
	λ_1	λ_2	λ_3	λ_4
Age (in years)	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.0)	(0.00)	(0.00)
Female	-0.02	-0.01	-0.01	-0.01
	(0.10)	(0.090)	(0.055)	(0.063)
Education	0.05	0.04	0.03	0.03
	(0.12)	(0.10)	(0.06)	(0.07)
Income	-0.00*	-0.00*	-0.00*	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
Drought frequency	0.05	0.05	0.03	0.03
	(0.04)	(0.04)	(0.02)	(0.03)
Weather forecast	0.04	0.03	0.02	0.03
	(0.10)	(0.09)	(0.05)	(0.06)
Livestock sales	-0.03	-0.03	-0.02	-0.02
	(0.02)	(0.02)	(0.01)	(0.01)
Herd size	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.00)	(0.00)	(0.00)
Single	0.01	0.01	0.01	-0.00
	(0.14)	(0.12)	(0.07)	(0.09)
Constant	1.13***	0.98***	0.93***	1.06***
	(0.29)	(0.25)	(0.15)	(0.18)
Observations	101	101	101	101
R2	0.24	0.24	0.25	0.25
Adjusted R2	0.17	0.17	0.17	0.18
Residual Std. Error (df = 91)	0.48	0.41	0.25	0.29
F Statistic (df = 9; 91)	3.23***	3.24***	3.29***	3.39***
Note:	*p<0.1; **p<0.05; ***p<0.01			

Primary data collected by the author

The results show that the coefficient of the female dummy variable is not significantly different from zero, suggesting that males and females are equally risk-seeking in the domain of losses. This is in line with the study by Brunette and Jacob (2019), who found that gender did not influence loss aversion. In contrast, a large body of the literature suggests that females are more loss-averse than males (Harrison & Rutström, 2008; l'Haridon & Vieider, 2019; Schmidt & Traub, 2002). However, Brooks and Zank (2005) found that females are less loss averse than men. The second demographic variable is age; older farmers are significantly more loss-averse than younger farmers. These results conforms to

Hjorth and Fosgerau (2011), which report that loss aversion increases with age. However, other studies find different results, where older people are less loss-averse than young adults (Blake et al., 2021). The third demographic variable is education; the coefficient is positive, deviating from the theoretical expectation that it reduces loss aversion. However, it is not statically different from zero in all four models, suggesting that it did not influence loss aversion. Also, having access to weather forecast information did not significantly influence farmers' loss aversion.

Similarly, Do Hwang (2021) found that access to weather forecasts did not influence loss aversion. Nevertheless, the expectation is that farmers with access to the weather forecast, such as El Niño and La Niña events, are less averse than those with access to such information. As expected, income has a negative and significant coefficient in all models; income reduces loss aversion. Other variables, such as drought frequency, livestock sales, herd size, and marital status, did not significantly influence loss-aversion in all four models.

4.7 Choice experiment data preparation

The study inspected DCE data before estimation. As a result, nine (9) farmers exhibited a protesting attitude toward IBPI because they always chose the non-insurance option. Following debriefing questions, respondents' underlying reason for protesting against IBPI was that they perceived traditional mitigation and coping strategies as effective and cheaper and were not interested in insurance products given their attributes. This study hypothesized that they did not consider any of the attributes, which would cause bias in the results. Binswanger-Mkhize (2012) supports the latter by suggesting that farmers do not passively accept the farming system's risk to their livelihoods and profits. As a result, these farmers mitigate ex-ante and ex-post risk by adopting traditional strategies. After excluding farmers with protesting behaviour reduced, the sample size from 110 to 101, giving 606 observations in DCE models. Each respondent was presented with six (6) choice cards with three alternatives, giving rise to 1818 alternatives.

About 93% of the options represent IBPI, while only 7% represent the "no insurance" option. Among the levels of the attributes, there was no observable correlation that could cause severe estimation problems. Two conditional logit models were estimated; in the first one, education interacted with basis risk and premium. In this case, the latter interactions were based on the hypothesis that level of education significantly influences how respondents comprehend how index insurance operates from premium to the implication of basis risk. For example, a study by Gaurav and Chaudhary (2020) showed that farmers who completed undergraduate studies had lower WTP for IBPI. This is because educated farmers are likelier to understand the intricacies of basis risk on IBPI. In the second model, interactions from the first model are retained, and ASC interacted with socioeconomic characteristics such as loss aversion, drought frequency, trigger level, access to weather information, and risk aversion

However, this study detected a significant correlation between loss aversion and risk aversion. As a result, a simultaneous assessment of loss aversion and risk aversion was avoided to circumvent possible multicollinearity problems; hence, not presented in the model. Therefore, the interaction between ASC and risk aversion without including the loss aversion parameter in the model was positive and insignificant in both animal management and general domains. This suggests that risk aversion did not influence the uptake of IBPI. Some studies report different results regarding the influence of risk aversion on adopting insurance or modern farming technology. For example, Sibiko et al. (2018) found that ASC interaction with self-reported risk attitude in a choice experiment gave a positive and significant coefficient, however deviating from theoretical expectations that risk-averse farmers have a high propensity to take up insurance. Do Hwang (2021) reported that the self-reported risk tolerance variable had no explanatory power to explain insurance uptake. Brick and Visser (2015) found that risk-averse farmers are likely to opt for traditional agricultural practices and are less likely to use modern farming inputs. To this effect, the conditional logit model does not give an insight regarding preference heterogeneity; therefore, the CL estimates are extended by using the latent class model to account for preference heterogeneity.

4.7. 1 The Conditional Logit Model

The estimates from conditional logit models are presented in Table 4.10. The model statistics such as AIC, BIC, log-likelihood, and pseudo-R^2 show that the first and second models are a good fit. These model statistics suggest that the attributes and their levels provide meaningful information and improve the capacity to estimate farmers' preferences for IBPI. However, both models present expected and unexpected results. In the first model, most attributes are significant and conform to theoretical expectations. The ASC coefficient is negative and significant, suggesting that respondents have a positive attitude towards IBPI that protects their livestock against starvation caused by drought-related pasture degradation.

The significant and positive coefficient for transparency shows a preference for receiving weekly updates about index measurements, indicating that information transparency and frequent communication regarding index performance can strengthen farmers' confidence in IBPI. The reimbursement attribute was assigned three levels, i.e., cash, feed, and voucher, where cash was treated as the reference base level. The voucher had a positive coefficient that conforms to theoretical expectations. However, it was not significantly different from zero, suggesting that farmers do not perceive vouchers as an essential attribute. At the same time, the mean coefficient of feed is positive and significant at a 1% level, suggesting that farmers derived positive marginal utility from the IBPI contracts that reimburse in terms of feed compared with cash. This outcome was expected because the DCE debriefing survey suggests that most farmers confirmed that they paid more attention to feed as a mode of payment when making their choices. However, a small proportion of respondents mentioned cash as their preferred reimbursement mode. The motivation for low preference for cash as a mode of reimbursement is the eagerness to circumvent the possible deviation of spending the insurance pay-out on the intended purposes. Moreover, farmers want to leverage on convenience in terms of purchasing feed since the transaction cost of procuring feed on their own is high because they are situated in a remote area with limited access to roads and means of transportation

Table 4.10 Conditional model estimates

	Model 1		Model 2	
Variables	**Coefficient**	**s.e.**	**Coefficient**	**s.e.**
ASC	-1.26***	0.32	0.24	0.91
Transparency	0.33***	0.09	0.33***	0.09
Reimburse method				
Voucher	0.18	0.13	0.18	0.12
Feed	0.77***	0.13	0.77***	0.13
Basis risk	-0.46*	0.28	-0.52*	0.29
Basis Risk x Education	0.25*	0.10	0.27**	0.10
Premium	-0.21*	0.09	-0.22*	0.09
Premium x Education	0.01**	0.04	0.10**	0.04
ASC x Size of arable land (hectares)	-	-	-0.26 **	0.09
ASC x Drought Frequency	-	-	-0.29 *	0.14
ASC x Loss aversion (λ_4)	-	-	-0.13	0.32
ASC x Trigger level 2	-	-	-0.25	0.34
ASC X Weather forecast	-	-	0.13	0.32
Model statistics				
AIC	1049.21		670.09	
BIC	1084.47		615.92	
Rho-square	0.22		0.24	
Final log-likelihood	-516.61		-509.19	
Number of individuals	101		101	

Signif. Codes: *, **, and * indicate significance at 1%, 5%, and 10% level, where s.e stands for standard error.**

The author collected primary data

As expected, basis risk gives farmers disutility because it puts them at risk of receiving low insurance reimbursement relative to losses incurred; the coefficient is negative and significant at a 10% level. Conversely, farmers with an additional level of education deviated from the theoretical expectation because basis risk does not decrease their likelihood of purchasing insurance. Their preference weight for basis risk is -0.21936 (-0.46450+0.24514), suggesting that farmers with one additional educational level have lower negative marginal utility for basis risk than farmers with lower education levels. At the same time, it is expected that farmers' level of education improves their ability to perceive, interpret, and respond to a new event in the context of risk. Therefore, farmers with a high level of education will have a robust negative sensitivity to basis risk. Jensen et al. (2018) tested the impact of IBLI knowledge on the demand response to basis risk by interacting basis risks with an indicator variable that represents participation in a randomised educational game. They find that increased IBLI knowledge through participation in randomised education games significantly increased negative sensitivity to basis risk. There was a minimal relationship between basis risk and demand among those who did not participate in educational games.

The leading coefficient of farmers' preference regarding premium is negative and significant, which conforms to the theoretical expectation that farmers derive disutility from premium. The interaction coefficient is positive and significant; this suggests that farmers with one more education level have a preference coefficient of -0.19 (-0.21 + 0.013). Therefore, they have lower negative marginal utility for money than less educated farmers. Since the absolute value of the marginal utility decrease with education, the WTP for the premium attributes increases with education.

Regarding the second model, the introduction of interaction parameters with the ASC did not change the magnitude and significance of the parameters of model 1. The first interaction is between ASC and the loss aversion parameter (λ_4), which simultaneously assumes probability weighting and diminishing sensitivity. Using the latter parameter instead of the other three-loss aversion parameters, the density curve is clustered around the mean, which signifies a low standard deviation, which can yield reliable statistical inferences. The negative coefficient sign suggests that loss-averse farmers are more willing to take up IBPI contracts. However, the coefficient is not statistically different from zero, suggesting that loss aversion does not influence the uptake of IBPI. The results do not improve when ASC interacts with other loss aversion parameters. Conversely, Do Hwang (2021) found that loss aversion substantially reduces the likelihood of taking health insurance. In contrast, a study conducted in South Africa in the context of small-scale farmers showed that the higher the loss aversion, the greater the likelihood of taking up technology bundled with insurance (Visser et al., 2020).

The interaction between ASC and drought frequency is negative and significant at the 10% level. This suggests that farmers vulnerable to drought are more likely to adopt IBPI to improve their status quo. Similar results were reported in Castellani et al. (2014), showing that farmers who experienced lower frequency drought are less likely to purchase index insurance. This shows that farmers are aware of their risk exposure and are willing to take necessary steps to mitigate it. It will be expensive for insurance providers to service insurance contracts since farmers with high-risk profiles will likely take up insurance. When ASC interacted with the trigger level, the coefficient was positive and insignificant, suggesting that trigger levels did not influence preferences for IBPI. This result contradicts what was reported by Sibiko et al. (2018), who observed significant heterogeneity concerning trigger levels. Some farmers prefer IBPI contracts with lower trigger levels because they start reimbursing them early before much damage is done. In comparison, (Akter et al., 2016b) found that insurance-averse farmers prefer index-based insurance associated with lower trigger levels since they cover the high risk of rainfall deficiency. Simultaneously, in a segment with farmers favouring insurance, it was observed that trigger levels did not significantly influence the insurance choice.

Regarding weather forecasts, the theoretical expectation is that farmers tend to adjust the demand for insurance according to their anticipated weather conditions in the upcoming season. In this case, the results show that having access to weather forecast information such as El Niño, La Niña, and other weather conditions does not significantly influence the WTP for IBPI. In comparison, Jensen et al. (2018) found that farmers with access to information revealing bad rangeland conditions had a high likelihood of purchasing insurance. The interaction between ASC and the size of arable land is negative and significant, which indicates that farmers with large size of land are likely to take up insurance contracts.

4.7.2 The Latent Class (LC) Model

The study used the latent class model to capture farmers' preference heterogeneity for IBPI. First, three models that contained two to four classes were estimated in search of an optional number of classes to keep. The model fit statistics of the three models are presented in Table 4.11

Table 4.11 The latent class model selection criteria

	Class 2	Class 3	Class 4
AIC	1029.92	1024.60	1023.61
BIC	1109.25	1156.80	1208.70
LL	-496.96	-482.30	-469.81
Number of parameters	18	30	42
Sample Size	101	101	101

The author collected primary data

The model fit statistics entails AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), and LL (Log-Likelihood) across two to four classes of models (Boxall & Adamowicz, 2002). The BIC is minimum in the two-class model, suggesting that adding more classes does not improve model fit. As several classes are added, AIC decreases. However, the marginal change of AIC beyond two classes is significantly small, suggesting that adding more classes beyond two classes does not generate a statistical improvement in the model. Therefore, jointly considering the above criteria, the two-class model was retained. Another reason to prefer the two-class model over other models is that the utility coefficients in the two-class model are more interpretable than in other models. Since the latent class model is an extension of the conditional logit model, the AIC and BIC of the two models were directly compared. This comparison reveals that the LC model is an improvement over the CL model. The results for the two-class latent class model are in Table 4.12. Latent class estimates show heterogeneous preferences for IBP attributes. Here, farmers had a 53% probability of belonging to the first class and a 47% probability of belonging to the second class. In terms of the class membership probability model, the socioeconomic characteristics of farmers did not significantly influence the probability of belonging to a particular class, except for livestock sales. This suggests that farmers who sold one additional livestock unit in the previous year are likelier to belong in the second class than those who sold more miniature livestock. Jensen et al. (2018) found no clear and robust relationship between index insurance and socioeconomic characteristics (e.g., age, assets, wealth, education, gender, household head, herd size). The ASC across the two classes was fixed with a negative and significant coefficient at a 1% level, suggesting that farmers in both classes have a positive attitude towards IBPI. The essential attributes in the first and second classes conform to theoretical expectations and are significant, yet some deviate.

Table 4.12 Latent class model estimates

		Class 1		Class 2	
Variables	**Description**	**Estimate**	**s.e.**	**Estimate**	**s.e.**
ASC	Non-insurance option=1, 0 otherwise	-1.98***	0.43	-1.98***	0.43
Transparency	Receive weekly index update=1, 0 other wise	0.86***	0.25	-0.35*	0.18
Reimburse method					
Voucher	Voucher as mode of reimbursement=1, 0 cash	-0.13	0.145	0.27**	0.18
Feed	Feed as mode of reimbursement=1, 0 cash	0.64***	0.22	1.10***	0.28
Basis risk	Risk of receiving lower reimbursement	0.59**	0.27	-0.57*	0.30
Premium	Premium to be paid	0.16**	0.08	-0.30***	0.09
Class membership probability model					
Livestock sales	Animals sold the previous year	-0.26*	0.13	-	-
Size of arable land	Size of arable land (in hectares)	0.17	0.18	-	-
Weather forecast	Receive weather forecast=1, 0 otherwise	0.91	0.55	-	-
Young farmers	Respondents that are at most 50 years old	1.08	0.69	-	-
Drought Frequency	Frequency in past five years	-0.17	0.24	-	-
Loss Aversion	Loss-aversion (accounting PW and DS)	0.72	0.85	-	-
Model statistics					
Segment probability	Probability of individual belonging to segment	0.53		0.47	
AIC	Akaike Information Criterion	1029.89		-	
BIC	Bayesian Information Criterion	1109.21		-	
Rho-square	McFadden Pseudo R square	0.2536		-	

LL (0, whole model)	log-likelihood	-665.76	-
LL (final, whole model)	Final log-likelihood	-496.94	-
Number of respondents in the model		101	
Signif. Codes: *, **, and * indicate significance at 1%, 5%, and 10% level, where s.e standards for standard error.**			

The author collected primary data

The transparency attribute conforms to theoretical expectations regarding the first class since the coefficient is positive and significant at 1%. This outcome suggests that farmers categorized in the first-class prefer IBPI contracts that provide weather information through a weekly short messaging service (SMS) detailing the index's performance. In the reimbursement case method, the mean coefficient of the voucher is negative and insignificant, suggesting that farmers in this class do not perceive vouchers as an essential mode of reimbursement compared to the option of cash. At the same time, the mean coefficient of feed is positive and significant at a 1% level, suggesting that farmers perceive feed as an essential mode of reimbursement compared to cash. The mean coefficient of basis risk is positive and significant at the 5% level, which deviates from the theoretical expectation that farmers derive disutility from basis risk. Also, the premium is positive and significant at a 5% level, deviating from the theoretical expectation that farmers derive negative marginal utility from the premium attribute. These deviations are concerning since the first class is larger than the second. In the case of basis risk, this deviation can be attributed to misunderstanding the basis risk concept and its implications. This necessitates further research in finding an appropriate way to express basis risk, particularly in the local language. Farmers derive positive utility from premium attributes, which deviate from the expectation that they derive negative marginal utility.

The transparency attribute is negative and significant at the 10% level in the second class, and this deviates from theoretical expectation since it is expected that farmers will prefer index insurance contracts that are more transparent. Concerning the reimbursement method, the mean coefficient of voucher and feed are positive and significant at 10% and 1% levels, respectively. This result shows that farmers in the second class derive a positive marginal utility from the IBPI contract that reimburses the insurance claim in vouchers and feeds instead of cash. Regarding the basis risk, as expected, the mean coefficient is negative and significant at a 10% level, suggesting that the farmers categorised in the second class prefer IBPI contracts with a lower basis risk. Concerning the premium attribute, the mean coefficient is negative and significant at a 1% level, showing that the farmers prefer IBPI contracts with a lower premium as they derive disutility from the premium as expected.

4.7.3 Willingness to Pay (WTP)

The study used the delta method to elicit WTP for IBPI attributes in this section. The WTP values and the 95% confidence intervals estimated from CL are shown in Table 4.13.

Table 4.13 WTP estimates from CL model without interaction.

	Value (ZAR)	Confidence Interval
Transparency	155.50	[-16.63, 327.66]
Voucher	86.62	[-61.94, 235.17]
Feed	362.60	[0.92,724.31]
Basis Risk	-220.10	[-498.05 57.76]

The author collected primary data

The WTP values show the strength of farmers' preference for IBPI attributes expressed in South African Rands (ZAR). The values of the WTP suggest, ceteris paribus: (i) on average, the marginal improvement of the transparency attribute increases the WTP by 155.50 ZAR (9.77 USD), and (iii) offering IBPI contracts that reimburse farmers in terms of feed rather than cash increases the WTP by 362.60 ZAR (22.78 USD). Also, offering IBPI contracts that reimburse farmers in vouchers increases the WTP by 86.62 ZAR (5.44 USD). Farmers derive negative marginal utility from basis risk; as a result, their WTP decreases by 220.20 ZAR (13.83 USD) for IBPI contracts that exhibit basis risk. In this case, they require a premium to be reduced by 220.20 ZAR (13.83 USD) to take up the insurance contract that displays basis risk. The WTP values and confidence interval estimated from the LC model are presented in Table 4.14. However, the essential attribute (premium) in the first class deviates from theoretical expectations; as a result, farmers' WTP in the first class is not computed.

Table 4.14 The WTP estimates from latent class model-Class 2

	Value (ZAR)	Confidence Interval
Transparency	-116.40	[-230.14 -2.70]
Voucher	91.56	[-17.91 ,201.03]
Feed	364.60	[105.88, 623.37]
Basis Risk	-188.90	[-392.28, 14.57]

The author collected primary data

The WTP estimates show that farmers' WTP for IBPI in the second class increases by 91.56 ZAR (5.75 USD) if the contract compensates for vouchers relative to cash. Moreover, the WTP increases by 364.6 ZAR (22.91 USD) when the IBPI contract reimburses in terms of feed instead of cash. Farmers derive negative marginal utility from basis risk; as a result, their WTP decreases by 188.90 ZAR (11.87 USD) for IBPI contracts that exhibit basis risk. In this case, they require a premium to be reduced by 188.90 ZAR (11.87 USD) to take up the insurance contract with basis risk.

CHAPTER 5 DISCUSSIONS

5.1 Introduction

The chapter discusses the results based on the three study-specific objectives: (1) characterize farmers' mitigation and coping strategies for drought; (2) assess farmers' preferences for IBPI attributes and (3) measure farmers' loss aversion and risk aversion, consequently inspecting how they affect farmers' preferences for index-based pasture insurance.

5.2 Characterization of drought management strategies

Regarding drought management, the observation is that all subsistence livestock farmers in the study area never had any formal agricultural insurance experience and relied on traditional mitigation and adaptation strategies. The most adopted mitigation strategies are rotational grazing, storing maize and other crop residues as feed, resistant animal breeds, mixed farming, and reducing stock through sales. On the other hand, the most adopted coping mechanisms include government post-disaster relief aid, reducing stock rate, and migration. Amid traditional mitigating and coping mechanisms, farmers are still vulnerable to drought risk. In our study, most farmers strongly agreed to have lost their animals due to the previous drought events. Moreover, most farmers strongly confirm that they cannot deal with the full impact of drought by only adopting traditional strategies. The potential benefits of traditional strategies are flawed by the high competition for common natural resources such as grazing land and water.

5.3 Farmers' preferences for IBPI attributes

Hassan (2013) assessed drought management strategies and potential economic policy instruments in South Africa. He recommended an urgent need to design more effective drought risk insurance schemes to provide better access to emerging smallholder farmers. The South African Insurance Association also backs this. However, limited research focuses on how to help farmers mitigate drought-related risk through insurance in South Africa. This current study contributes to this void by assessing the preferences of subsistence livestock farmers for IBPI based on four attributes: (i) transparency, (ii) reimbursement method, (iii) basis risk, and (iv) premium.

5.3.1 Transparency

Transparency attributes advocate for providing real-time data about the status of pasture degradation. An independent entity such as South African Weather Services (SAWS) can be responsible for providing this real-time weather information to the farmers. De Meza et al. (2010) investigated the effects of transparency in insurance markets; they found that transparency makes consumers feel less pressured by insurance providers and more confident in purchasing decisions. The findings of this study conform to the latter because, in the CL model, farmers derived positive and significant marginal utility from receiving real-time data regarding the index's performance that translates to pasture degradation levels. This suggests that providing farmers with regular communication concerning pasture measurements can significantly improve the demand for pasture insurance. On average, the marginal improvement of transparency attributes increases farmers' mean WTP by 155.50 ZAR (9.77 USD). Sibiko et al. (2018) found similar results, where farmers derive significant and positive marginal utility from index-insurance contracts. Transparent contracts provide regular information regarding the performance of the index. However, the study found heterogeneity of preferences regarding transparency in the latent class model. In the first class, farmers derived positive and significant marginal utility. In contrast, in the second class, the coefficient is negative and significant, suggesting that 47% of the farmers in the sample size perceive transparency differently from other farmers.

5.3.2 Reimbursement Method

Regarding the reimbursement attribute, this attribute captures preferences of the mode of receiving indemnity. It includes three attribute levels: (i) cash, (ii) voucher, and (iii) feed, suggesting that farmers can choose either of them as a form of insurance compensation. Compensation in the form of cash is paid directly to the farmers' bank accounts, while vouchers can be sent electronically or via post. On the other hand, insurance compensation in the form of feed can be delivered to the respective location of the farmer, with the transportation and administration costs covered by the insurer. This approach has been successful in social protection programs such as disaster and food aid offered by governments and non-governmental organizations (Gadenne et al., 2021). Following this approach, beneficiaries are saved from incurring the cost of procuring the goods in the market and protected from escalating prices. Also, it can limit spending on unintended goods or services. Hence, the theoretical assumption is that compensating farmers solely in cash might not be optimal for subsistence livestock farmers. This is because subsistence farmers are already confronted with barriers to market access, limiting them from buying necessary supplementary feed, fodder, and veterinary services for their livestock at affordable prices. At the same time, those who can access the market might incur high transport and search costs for purchasing feed. All these might distort the policyholder's benefits from the insurance. The issue of high transport costs was observed in the study area because most farmers stressed that they consistently failed to collect the feed provided by the government since it was far from their physical address. As a result, it is crucial to test this intervention since the primary focus of IBPI is to save animals from starvation caused by drought-related pasture degradation.

Regarding famers’ attitude towards reimbursement, the results show a positive attitude toward the reimbursement method attribute presented for IBPI. It was remarkable that farmers derive positive and significant marginal utility from IBPI contracts that reimburse in terms of feed compared to cash. This attribute had the highest preference weight amongst all other attribute levels. On average, farmers are WTP about 362.60 ZAR (22.78 USD) for an IBPI contract that pays out an insurance claim in terms of feed. At the same time, the estimates show that the coefficient for the voucher is positive and insignificant, suggesting that farmers do not prefer vouchers as a mode of payment compared to cash. However, preference heterogeneity regarding the reimbursement method was observed. The latent class model shows that farmers in the second class perceive vouchers as an essential attribute since they derive positive and significant marginal utility from contracts that reimburse vouchers compared to cash. Also, they are WTP 91.56 ZAR (5.75 USD) for IBPI, which compensates in terms of vouchers.

5.3.3 Basis Risk

The third attribute is basis risk, inherent to IBPI products and occurs when pay-outs rely on an index poorly correlated with actual losses experienced by the insurance policyholder. Basis risk can lead to higher or lower pay-outs; however, this study focuses on the scenario where basis risk may cause lower insurance pay-outs. Also, there are different basis risks, such as design basis risk, spatial basis risk, and temporal basis risk, which are well detailed in the study by Dalhaus and Finger (2016). However, this study focuses on the design basis risk, which exists when the index omits some crucial information relevant to predicting losses at the farm level. This study presents a design-basis risk of getting a lower pay-out than expected. The study observed that the basis risk attribute coefficient is negative and significant at 10%. Noting that the sample size is relatively small, this outcome is crucial. However, education decreases the negative marginal utility of basis risk, which deviates from the expectation that farmers with a level of education will better understand shortcomings associated with basis risk and derive disutility from it.

Further analysis in the latent class model shows that farmers respond differently to basis risk. The basis risk attribute coefficient is positive and significant in the first class, suggesting that some farmers do not derive disutility from basis risk. In contrast, the basis risk is negative and significant in the second class, meaning that farmers in the second class derive negative marginal utility from the basis risk attribute. At the same time, they require a premium for IBPI attributes to be reduced by 188.90 ZAR (11.87 USD ZAR for them to adopt

IBPI. Above all, farmers show a positive attitude to IBPI because they significantly derive negative marginal utility from the status quo or an option of staying without IBPI. The maximum premium used for the choice experiment design is 400 ZAR. In monetary terms, the choice experiment reveals that farmers are willing to forgo about 597.00 ZAR (37.49 USD) to avoid the non-insurance option.

In comparison, some farmers declared a maximum WTP for IBPI of 600 ZAR in the debriefing survey. This suggests that the study could have explored a more comprehensive range of premiums, which can be done in further research. The above analysis shows that farmers are eager to adopt IBPI but have specific preferences for IBPI attributes.

5.3.4 Premium

The results show that farmers have derived disutility from premium as expected. Conversely, the disability decreases with education; farmers with one more level of education have their WTP for premium attribute increase with education. The latent class model shows that 53% of respondents derive positive marginal utility from the premium attribute. At the same time, 47% of the respondents derive negative marginal utility from premium attributes. These disparities regarding premium attributes can be attributed to why some farmers were WTP more than what was presented in the choice experiment. The maximum premium was 400.00 ZAR in the choice experiment design. While, in the debriefing survey, some farmers directly stated a maximum WTP of 600.00. ZAR. In this view, using a wide range of premium levels would give expected results. Another related aspect is the possibility that premium attributes were not considered when choosing. Here, further research is necessary to explore attribute non-attendance.

5.4 Loss aversion and risk aversion

Recent research focuses on the determinants of farmers' preferences for insurance while considering psychological attitudes guided by PT (Lampe & Würtenberger, 2020). PT suggests that people undergo distinct processes when making decisions. In this process, individuals are expected to edit complicated decisions into simple decisions, usually specified in terms of losses and gains under risk prospects, referred to as loss-aversion (Tversky & Kahneman, 1992). For instance, farmers need to simplify insurance purchasing decisions in losing a premium payable to the insurer and a chance of gaining the amount of compensation in the event of a loss. This study used incentivised lottery experiment to measure loss aversion assuming diminishing sensitivity and probability. The findings showed that farmers were loss averse because about 96% of farmers accepted lottery games with a positive expected value. On the other hand, only 4% of farmers accepted lottery tasks that give negative expected outcomes.

All four-loss aversion parameters are more significant than one, suggesting that farmers exhibit loss aversion in all specified assumptions; however, the magnitude of loss aversion parameters is smaller than the 2.25 estimated by Tversky and Kahneman (1992). In comparison, Harrison and Rutström (2009) and (Gächter et al., 2021) _ENREF_75 follow assumptions like this study, where they found that the loss aversion coefficient is very close to our results. Regarding the factors influencing loss aversion, only education and income significantly influence loss aversion. Furthermore, the influence of loss aversion on the preferences of subsistence livestock farmers for IBPI was assessed. The theoretical expectation is that loss-averse farmers are willing to improve their status quo. Therefore, they will be willing to take up IBPI that can protect their livestock against starvation caused by drought-related pasture degradation.

Nonetheless, our results show that loss aversion did not influence farmers' preferences for IBPI. Other studies found that loss aversion significantly influences farmers' decisions in adopting insurance. Visser et al. (2019) found that loss-averse small-scale farmers in Western Cape, South Africa, are willing to adopt technology bundled with insurance that has an essential role in hedging risk. However, they covered a larger sample size than our study, so this study cannot make a specific conclusion.

The results reveal that many farmers take medium risks in all domains, suggesting they are medium risk averse. In overview, farmers show more high-risk tolerance in animal management than general. Using OLS regression, the study found a significant impact of age, farming experience, and gender on the willingness to take risks in the general and animal management domains. As expected, female farmers are more risk-averse than male farmers, and risk aversion increases with age. Also, farmers with high farming experience are more risk-averse. Dohmen et al. (2011) used a similar approach to ours; they observed similar results regarding age and gender in the general domain. The results also show that risk aversion did not influence farmers' preferences for IBPI.

In contrast, in a choice experiment, Sibiko et al. (2018) found that risk-averse farmers do not have a positive attitude towards index-based insurance. Do Hwang (2021) reported that risk aversion does not have explanatory power to explain insurance uptake. Akter et al. (2016b) tested the influence of risk aversion in a choice experiment; they found that risk-averse farmers are more likely to be insurance averse.

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

Livestock farming is an essential source of livelihood for substance farming households and reduces their economic vulnerability. The advantage of farming with livestock is that they are mobile assets for many subsistence farmers who do not own their farmland. Also, they can graze on the communal land and be kept in the compound. In natural disasters, such as drought, the main strategies that subsistence livestock farmers have been adopting in response to drought-related risk are traditional mitigation and coping mechanisms and post-disaster aid relief (Mare et al., 2018). This study found similar results. However, some coping mechanisms require additional capital to be effective. In most cases, drought risk overstretches the capacity of traditional mitigation mechanisms, causing vulnerable subsistence livestock farmers to slip into poverty and remain trapped. Because of this, scholars and policymakers commend agricultural insurance, particularly index-based insurance, as a supplementary risk management mechanism owing to its unique advantages (Miranda & Farrin, 2012).

The South African Insurance Association (SAIA) highlighted the need to design IBPI that is likely to be adopted by subsistence livestock farmers in South Africa (SAIA, 2019). As a result, this study gives policymakers and insurance providers insight into the preference of subsistence livestock farmers for IBPI. Since IBPI is not currently offered in South Africa, the study used the discrete choice experiment approach with a random sample of 110 subsistence farmers within Mulima Village, Makhado District Municipality, Limpopo Province, South Africa. Given the challenges associated with traditional ways of managing drought, subsistence livestock farmers are willing to improve their status quo by adopting IBPI, which protects their livestock against drought-related pasture degradation. The results reveal that subsistence livestock farmers prefer more transparent IBPI contracts. Providing farmers with regular information regarding the index's performance improves their likelihood of adopting IBPI. This information will help farmers improve their farming practices in the upcoming seasons and implement corrective measures ahead of bad weather. This communication needs to be sent timely and regularly to be effective. A similar approach was adopted in India, where PepsiCo offers capacity building and information exchange through index insurance products. Here, policyholders are given technical advice on production practices, weather information, and advisories through text messaging (Hazell et al., 2010). Therefore, insurance providers can expand this attribute by offering different information to assist farmers in accomplishing their farming goals while maintaining sufficiency and profitability.

Subsistence livestock farmers also prefer IBPI, which reimburses insurance claims in feed and vouchers compared to cash. Therefore, the agricultural insurance providers must consider designing IBPI products that can pay insurance claims using different methods, such as cash, voucher, and feed, to attract large economies of scale relevant to their preferences. This can solve other procurement challenges concerning supplementary feed and other crucial farming services. Another critical issue is basis risk since the large body of literature reports that it reduces the likelihood of taking up IBPI. This study also shows that average subsistence livestock farmers have significant negative sensitivity to basis risk. Also, it was observed that education reduces the negative impact of basis risk on demand for IBPI because farmers with a high level of education significantly opted for IBPI contracts with high basis risk. Therefore, insurance providers need to provide more specific educational programs on how index insurance works to improve the uptake. However, the latent class analysis observed significant heterogeneity regarding basis risk. About 53% of subsistence livestock farmers did not derive disutility from basis risk, while 47% of farmers significantly derived disutility from basis risk. Given this evidence, insurance providers must consider ways to address the adverse effects of basis risk on WTP for IBPI. This is because basis risk also complicates the regulatory framework for insurers. For instance, South Africa's regulatory framework for IBPI is still approved; therefore, designing index insurance that exhibits a minimal basis risk is essential.

To address the negative effect of basis risk on the preferences for IBPI, insurance providers can collaborate with the government to subsidise a portion of the IBPI premium. Several studies reported that the negative effect of basis risk on WTP decreases when the premium is subsidized (Gaurav & Chaudhary, 2020; Jensen et al., 2018). Also, Mahul and Stutley

(2010) conducted a survey combining 65 developing and developed countries and found that approximately two-thirds of the countries provide substantial subsidies for agricultural insurance. The subsidy can also help in terms of premium since this study found that farmers derive negative marginal utility from premium attributes, which means they prefer IBPI contracts with a lower premium. Another way of minimising the effect of basis risk is to cover low-frequency high covariate risk such as drought that affects many farmers simultaneously in a region. As a result, the losses of individual farmers are more likely to correlate to the index (Hazell et al., 2010). The findings of this study support this because farmers that frequently experience drought are willing to uptake index-based pasture insurance contracts.

Moreover, there is a growing interest in using satellite measurements such as vegetative index, soil moisture, and cloud cover to design index insurance products with limited basis risk. However, the shortcoming of using the latter indexes is that farmers might exhibit protesting behaviour against the underwriting index-based contract based on ''unobservable'' indexes. This brings in the importance of the transparency attribute when designing index insurance, which is already discussed earlier.

Regarding the influence of socioeconomic characteristics on farmers' preferences for IBPI, the study found that loss aversion and risk aversion do not influence the adoption of IBPI. Conversely, several studies found that risk aversion and loss aversion significantly influence uptake for index insurance (Hwang, 2021; Lampe & Würtenberger, 2020; Visser et al., 2019, 2020). Since the sample size of this study is relatively small compared to other studies, this study cannot strongly confirm the latter contrast. Also, it was observed that farmers with sizeable arable land are more longing to adopt IBPI. This suggests that policymakers in government need to provide subsistence farmers with access to land to promote general entrepreneurship among subsistence livestock farmers and desire to seek resilience to climate change through adopting the latest technologies, not limited to IBPI. Above all, the findings of this study suggest that IBPI that does not account for the heterogeneity of preferences regarding crucial attributes might not realise significant demand. As a result, insurance providers must consider the diversification of features of IBPI after observing all regulatory requirements.

The limitations of this study are the small sample size, choice experiment hypothetical biases, and assumptions regarding diminishing sensitivity and probability weighting. As a result, this study suggests that further research be conducted using different methods such as contingent ranking, contingent rating, and paired comparison with large sample size. The approach to analysing how loss aversion affects farmers' preferences can be improved using choice experiment data pivoted around the reference alternative or the status quo. The utility function can be articulated in losses and gains around the status quo without altering the linearity in the parameter assumptions underlying the random utility model (Mao et al., 2019; Masiero & Hensher, 2010; Scott & Witt, 2020).

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8. APPENDIX

8.1 QUESTIONAIRE

1. Informed Consent for Participation

Dear Respondent:

You are invited to participate in an interview of an academic study conducted by Bernard Manganyi, MSc Agricultural Economics student in the Department of Agricultural Economics, Extension, and Rural Development, University of Pretoria. The study aims to assess your perceptions about the Index-based Livestock Insurance scheme/policy. Kindly note that your participation in the survey is voluntary, and you are welcome to stop me anytime.

Kindly note the following:

This interview is conducted solely for academic research, and we will exclusively use the information for educational purposes. Your responses will be confidential and according to the University of Pretoria Ethics Committee requirements. Your participation is entirely voluntary; you do not have to participate if you do not want to. If you agree to participate, you have the right only to answer questions you choose to respond to. The potential risks are minimal, and we will maintain any confidential information you might share with us. The discussion will take 60 minutes of your time. For any queries or comments concerning this study, please contact my academic advisors: Dr Selma Karuaihe and Prof. Damien Jourdain, Email: Selma.karuaihe@up.ac.za or damien.jourdain@cirad.fr, Tel: +27 (0)12 420 4659.

NB: Do you voluntarily agree to participate in this survey? Yes / No

If yes, we will continue with the interview.

If no, we do not continue with the interview.

I would like to record the discussion with your consent. If you do not permit me to record the conversation, I will take some notes to remember the essential comments you will make during the survey.

2. Background

This study defines drought as a period when vegetation growth is deficient due to rain. Since your livestock production depends mainly on natural pasture availability, feeding them during drought is crucial. Farmers use several methods to address drought risks, such as self-insurance, stock rate reduction, resistant breeding farming, and loans. The study aims to assess the demand for index-pasture drought insurance as one of the economic tools recommended to address drought risk. Other methods include remote sensing technology, which allows monitoring of the condition of an area's natural pastures, providing information through a Normalised Difference Vegetative Index (NDVI). The NDVI data is available in real-time every ten (10) days with the most extended time series since 1981. These data are computed reliably at high spatial resolution

($8km^2$). The NDVI data compare the current state of vegetation against the long-term average conditions to detect anomalies and drought. This indicates that remote sensing technology is more advanced and better than the conventional ways of risk mitigation against drought.

A drought might result in a pasture deficit scenario, which can devastate livestock production. These can cause acute starvation, weight loss, poor carcass quality, and secondary effects such as diseases and mortality. These can have an immense impact on the farm business's cash flows. A strategy to cope with drought events will circumvent animals' unprecedented slaughtering due to starvation, ensure that animals are kept alive throughout their production cycle, and allow farmers to hold onto livestock value. One recommendation is to practice supplementary feeding during drought to offset the pasture deficit. However, many farmers cannot afford to procure enough additional feed during the drought period. Therefore, the IBPI provides a solution to this predicament. The index-based pasture drought insurance would provide the means to procure supplementary feed during drought events. The amount of feed (or its monetary equivalent) will depend on pasture degradation. The indemnity will start only when the pasture degradation is above the trigger level. Different trigger levels are possible, but we will concentrate on an insurance scheme with a trigger level of 30% for this interview. This insurance only covers one rainy season (i.e., November to March)

3. Your current adaptation practices

I would like to get your view on how you prepare your farm to cope with drought events.

Please respond to the following questions:

2.1. What coping measures do you employ amid droughts?

2.2. What measures do you implement to equip yourself to handle the effects of future drought events?

2.3. How effective are your coping and preparation measures in handling the effects of drought?

2.3.1. Measures you use when faced with drought:

2.4. Are there some things you would be willing to improve your coping capacity with drought events? (0) No (1) Yes

2.4.1. If yes, which measures would you like to improve?

2.4.2. In your view, how would the improvement help you?

2.4.3 If you are unwilling to improve, is it because the current measures work better? Please elaborate/explain.

4. Explanation of Index-based Drought Insurance

Insurable unit: You protect your animals against starvation due to pasture degradation because your animals rely on natural pasture. One large stock unit (LSU) 's insurable value is equivalent to the value of supplementary feed required to feed an animal throughout the insured period. In this survey, we use a scenario of an insurable value of 5,000.00 ZAR per larger livestock.

Premium: To purchase this insurance, you must pay a once-off premium. However, this premium can vary depending on the type of insurance contract you want to buy. The premium is payable before the start of the insurance period.

Insurable period and sale date: The insurance covers five (5) months, from November to March each year, when the expectation is that rain and pasture will be abundant. Sales of insurance contracts will open in July and close in September every year.

In return, you will receive compensation triggered when the pasture degradation is beyond the predetermined trigger level. Trigger level is the minimum level of pasture degradation that defines your risk profile. Once pasture degradation passes the predetermined trigger that aligns with your insurance contract, you start receiving insurance compensation accordingly.

You will have the choice between three modes of receiving your insurance pay-out: (1) Cash, (2) Animal feed, and (3) Voucher

Transparency: Transparency means providing pasture degradation information (i.e., satellite reports) by an independent institution (e.g., South African Weather Services) that shows if your insurance compensation is triggered. Therefore, providing you with pasture degradation levels reports regularly strengthens the transparency of the insurance contract.

Basis Risk: Basis risk manifests when pasture degradation in your grazing area does not correspond to the actual pasture degradation detected by the Normalised Difference Vegetation Index (Satellite measure). The Normalised Difference Vegetation Index (NDVI) is calculated and averaged at the district level. Typically, your herd grazes in only one part of the district, and the degradation of the pasture is not even throughout the community; therefore, there is a slight possibility that: your grazing area is more degraded than the calculated average. In such a case, you are exposed to the risk of receiving compensation corresponding to a lower degradation level; for example, the level of pasture degradation in your area is at 60%, while the average degradation level in the district is 50%. Then you will be compensated based on the 50% pasture degradation level rather than 60%. Compensation may correspond to a higher degradation level if your area is less degraded than the average. For instance, if the degradation level is at 40%, the average pasture degradation in the district is at 60%. You will be compensated based on the 60% pasture degradation level rather than 40%. We call this the basis risk. It ranges between 8 to 16 out of 100. In this survey, however, we will focus on the possibility of receiving less compensation.

5. Trigger Level and Compensation

We are going to present you with different index-based pasture drought insurance contracts. All these contracts depend on the scenarios presented as follows:

Index-based pasture drought insurance compensates you with a maximum value of 5,000.00 ZAR

Insurance contracts are based on a 20% trigger level; after the pasture degradation has surpassed 20%, you receive compensation. Index insurance contract compensates the maximum value of your insurance value when the pasture degradation is beyond a 60% degradation level

The possible compensation of an index-based pasture drought insurance contract based on a 20% trigger level is presented in the Tables below:

State of Pasture	Degradation Levels (%)	Compensation (ZAR)
	Normal	00.00
	20%	1,667.00
	Beyond 60%	5,000.00

Compensation of a contract that is based on a 20% Trigger Level

Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	Beyond 60%
Compensation (ZAR)	0	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000

Case No 1: The pasture degradation is 0%. In this case, the degradation is below the trigger level, and you will not receive any compensation.

Case No 2: The pasture degradation is 20%. In this case, the degradation is beyond the trigger level. You are entitled to receive a compensation of 1 667 ZAR. You will continue to receive payment at different degradation levels, given that pasture continues to degrade beyond the 20% trigger level.

Case No 3: The pasture degradation is beyond 60%. In this case, the degradation is beyond the limit level. You will receive a compensation of 5,000 ZAR, which is equivalent to your insurance value. After receiving a maximum payment of 5,000 ZAR, there is not any additional payment you are entitled to receive.

Did you understand how index-based pasture drought insurance works? (0) No / (1) Yes

If No, we go through the explanation again

If yes, we proceed to the choice experiment questions.

6. Explanation of Attributes

Transparency means that the insurance contract does not exhibit confidential information since you can receive data (e.g., satellite reports) regarding pasture degradation in your area from an independent weather service provider (e.g., the South African Weather Services). This information will help you know if pasture degradation in your region has reached the predetermined trigger level that corresponds to your insurance contract. This information will be simplified for your better understanding. Transparency is associated with two options. This means that you can choose from two possible options: receive weekly updates (transparent contract) and (2) do not receive a weekly update (non-transparent contract).

Reimbursements will be paid in the form of A refund that can be delivered to you in three different modes of payment. You can receive your insurance compensation through various methods of payment such as (1) voucher, (2) Cash, and (3) Feed, depending on your preference.

Insurance premium to pay: The insurance premium is the amount you need to pay for the insurance contract. In this case, the insurance contract has a value of 5000 ZAR. Therefore, there are three possible insurance premiums that you can pay for insurance depending on the characteristics of each insurance contract: 100 ZAR, 250 ZAR, and 400 ZAR.

Basis risk: The basis risk is the possibility of receiving lower insurance compensation than actual losses you have incurred. IBI relies on satellites measure (NDVI) that detect pasture degradation in the district's average pasture degradation. However, your herd grazes in only one part of the district. Therefore, pasture might not degrade evenly throughout the community; as a result, there might be a slight possibility that you receive less compensation due to the difference between the average pasture degradation in your grazing territory and district. We call this the basis risk; it ranges between 8 to 16 out of 100 times. In this case, there are three possibilities: 8 out of 100 times, 12 out of 100 times, and 16 out of 100 times.

The table below illustrates the IBI contracts' attributes and their levels.

1. PREMIUM TO PAY		
100 ZAR	**250 ZAR**	**400 ZAR**
100.00 ZAR insurance premium means you will have to pay 100.00 ZAR for the IBI contract covering you for five months (Nov-March).	250.00 ZAR insurance premium means you will have to pay 250.00 ZAR for the IBI contract covering you for five months (Nov-March).	400.00 ZAR insurance premium means you will have to pay 400.00 ZAR for the IBI contract covering you for five months (Nov-March).
2. BASIS RISK		
8 out of 100 times	**12 out of 100 times**	**16 out of 100 times**
8 out of 100 basis times risk means that there is an eight out of 100 chance that you will receive less compensation than what you can expect to receive	12 out of 100 times basis risk means that there is a 12 out of 100 chance that you will receive less compensation than what you can expect to receive	16 out of 100 times basis risk means that there is a 16 out 100 chance that you will receive less compensation than what you can expect to receive
3. REIMBURSEMENTS WILL BE PAID IN THE FORM OF:		
Feed	**Cash**	**Voucher**
If you select feed as a mode of insurance payment, you will receive your pay-out in the form of drought supplementary feed equivalent to the insurance pay-out, which is suitable for your herd. The specification of the type of preferable animal feed will be on the contract. In the event of feed delivery, the insurance company will cover all transport costs.	If you choose cash as a mode of insurance compensation, you will receive a pay-out to your bank account	Suppose you choose a voucher as a mode of insurance compensation; you will receive your pay-out in the form of a voucher, equivalent to the insurance pay-out. This voucher expires after 12 months, and you can redeem it at any feed retail store in South Africa. However, this voucher is only limited to buying supplementary feed products.

4. TRANSPARENCY		
Receive Weekly Updates	**No Weekly Updates**	
If you choose this option, you will receive weekly updates regarding the pasture degradation levels determining the insurance pay-out. You will receive this information through Short Message Service (SMS) or Email on your phone.	If you choose this option, you will not receive any information regarding the pasture degradation levels.	

The table below illustrates attributes and their levels in pictograms.

Attributes	Level 1	Level 2	Level 3
Transparency	Receive Weekly Updates 	No Weekly Updates 	
Reimbursements will be paid in the form of:	Feed 	Cash 	
Premium to pay	100 ZAR 	250 ZAR 	400 ZAR 
Basis Risk	8 out of 100 times	12 out of 100 times	16 out of 100 times

7. Choice Experiment: Example

We will present you with six (6) cards in the choice experiment scenarios. Each card will represent a choice you will have to make between insurance contracts. The cards will look like this:

	Option A	Option B
Transparency	Receive Weekly Updates 	No Updates 
Reimbursements will be paid in the form of:	VOUCHER	Cash 
Premium to pay	1OO ZAR 	250 ZAR 
Basis Risk	8 out of 100 times	12 out of 100 times

Compensation of a contract that is based on a 20% Trigger Level

Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	Beyond 60%
Compensation (ZAR)	0	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000

Which option would you choose?

1. Contract A
2. Contract B
3. None of the two insurance contracts

The card above presents two index-based drought pasture insurance contracts that rely on a 20% trigger level. However, their presentation is about the mode of reimbursing your insurance pay-out, transparency, basis risk, and premium that you need to pay. The card has options A, B, and C. Options A and B represent insurance contracts. In contrast, option C represents the option of staying without insurance, which means you prefer none of the two contracts.

You need to choose which option you would choose if they were presented to you in real life for next year's season (Nov-March). Please respond as if you must pay real money for the insurance contract based on the prices shown. If you know you cannot afford to pay for the contract at either of the prices shown, please select the 'None of the two insurance contracts' option. Please make a choice based on the choice card scenario presented to you.

Did you understand the task? Yes / No. If No, I will explain the card again; we proceed to real-choice experiment scenarios.

8. Real Choice Experiment Scenarios

Please consider an index-based pasture drought insurance contract with a 20% trigger level and different characteristics in the figure below, and answer question one (1).

	Contract A	Contract B
Reimbursements will be paid in the form of:	Feed 	Cash 
Transparency	No Weekly Updates 	Receive Weekly Updates 
Basis Risk	16 out of 100 times	8 out of 100 times
Premium to pay	250 ZAR 	250 ZAR 

Compensation of a contract that is based on a 20% Trigger Level

Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	>60%
Compensation (ZAR)	0	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000

1. Which option would you choose?

1. Contract A
2. Contract B
3. None of the two insurance contracts

2. Please consider an index-based pasture drought insurance contract with a 20% trigger level and different characteristics in the figure below, and answer question two (2).

	Contract A	Contract B
Reimbursements will be paid in the form of	Feed 	Cash 
Transparency	Receive Weekly Updates 	No Weekly Updates 
Basis Risk	8 out of 100 times	16 out of 100 times
Premium to pay	400 ZAR 	100 ZAR 

Compensation of a contract that is based on a 20% Trigger Level

Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	>60%
Compensation (ZAR)	0	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000

2. Which option would you choose?

1. Contract A
2. Contract B
3. None of the two insurance contracts

3. Please consider an index-based pasture drought insurance contract with a 20% trigger level and different characteristics in the figure below, and answer question three (3).

	Contract A	Contract B
Reimbursements will be paid in the form of:	Cash 	VOUCHER
Transparency	No Weekly Updates 	Receive Weekly Updates 
Basis Risk	12 out of 100 times	12 out of 100 times
Premium to pay	100 ZAR 	400 ZAR 

Compensation of a contract that is based on a 20% Trigger Level											
Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	>60%
Compensation (ZAR)	0	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000

3. Which option would you choose?

1. Contract A
2. Contract B
3. None of the two insurance contracts

4. Please consider an index-based pasture drought insurance contract with a 20% trigger level and different characteristics in the figure below, and answer question four (4).

	Contract A	Contract B
Reimbursements will be paid in the form of:		Cash 
Transparency	Receive Weekly Updates 	No Weekly Updates 
Basis Risk	16 out of 100 times	8 out of 100 times
Premium to pay	100 ZAR 	400 ZAR 

Compensation of a contract that is based on a 20% Trigger Level

Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	>60%
Compensation (ZAR)	0	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000

4. Which option would you choose?

1. Contract A
2. Contract B
3. None of the two insurance contracts

5. Please consider an index-based pasture drought insurance contract with a 20% trigger level and different characteristics in the figure below, and answer question five (5).

	Contract A	Contract B
Reimbursements will be paid in the form of:	VOUCHER	Cash 
Transparency	No Weekly Updates 	Receive Weekly Updates 
Basis Risk	8 out of 100 times	16 out of 100 times
Premium to pay	250 ZAR 	250 ZAR 

Compensation of a contract that is based on a 20% Trigger Level

Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	>60%
Compensation (ZAR)	0	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000

5. Which option would you choose?

1. Contract A
2. Contract B
3. None of the two insurance contracts

6. Please consider an index-based pasture drought insurance contract with a 20% trigger level and different characteristics in the figure below, and answer question six (6).

	Contract A	Contract B
Reimbursements will be paid in the form of:	Cash 	Feed 
Transparency	Receive Weekly Updates 	No Weekly Updates 
Basis Risk	12 out of 100 times	12 out of 100 times
Premium to pay	400 ZAR 	100 ZAR 

Compensation of a contract that is based on a 20% Trigger Level

Pasture Degradation	0%	20%	25%	30%	35%	40%	45%	50%	55%	60%	>60%
Compensation (ZAR)	0	1667	2083	2500	2917	3333	3750	4167	4583	5000	5000

6. Which option would you choose?

1. Contract A
2. Contract B
3. None of the two insurance contracts

8. Choice Experiment Debriefing Questions

9.1 Which one of the following statements best describes how you made your choices within each scenario? Please select one answer:

9.1.1 I looked at all choices carefully and chose the one that was the most beneficial form

9.1.2 I chose randomly without regard to the choices

9.1.3 I always chose the "None of the two insurance contracts" option

9.1.4 Other:

9.2 If you always chose the option" None of the two insurance contracts," could you state why you never opted for an insurance contract?

____
____

9.3 If you did not choose 9.2 (random choices), how did you consider the different attributes when making your choices?

9.3.1 I looked at and compared all the attributes before making choices

9.3.2 I ignored some attributes when making choices: yes/no

9.3.2.1 If yes, which attributes did you ignore (several choices possible)

Yes/No	Attributes
	Mode of reimbursement
	Transparency
	Basis risk
	Premium to pay

9.3.3 I looked at some attributes more precisely, and if some levels were not satisfactory, I would not choose the option.

9.3.3.1 If yes, what attributes and levels?

Attributes	Level	Minimum / Maximum
Mode of reimbursement		
Transparency		
Basis risk		
Premium to pay		

9.3.4 If none of the above; please describe:

____

9.4 What would be your maximum willingness to pay (WTP) for an IBI contract ____________________________________ ZAR

9.5 What would be the characteristics of the insurance that would influence your WTP for an IBI contract: ____

9.6 In general, how clear were the instructions to undertake the choice questions?

9.6.1 Very clear

9.6.2 Clear

9.6.3 Neither clear nor unclear

9.6.4 Unclear

9.7 In general, how difficult was it for you to choose? Please select one answer.

9.7.1 Very difficult

9.7.2 Difficult

9.7.3 Neither easy nor difficult

9.7.4 Easy

9.7.5 Very Easy

9. Risk Attitude

Kindly answer the following questions regarding your general risk-taking:

10.1. Are you generally a person who is fully willing to take risks, or do you try to avoid taking risks in general? Please tick a box on the scale below, where zero (0) means 'I avoid taking any risk' and ten (10) means 'I am fully prepared to take many risks.

0	1	2	3	4	5	6	7	8	9	10

10.2. How would you compare yourself with other community members in terms of risk-taking in general? Please tick a box on the scale below:

1 I usually take much fewer risks than other members of my community

2 I usually take fewer risks than other members of my community

3 I usually take the same amount of risks as other members of my community

4 I usually take more risks than other members of my community

5 I usually take much more risks than other members of my community

10.3 Now, think about decisions regarding the management of your animals. Regarding these decisions, are you a person who is fully willing to take risks, or do you try to avoid taking risks? Please tick a box on the scale below, where 0 means 'I avoid taking any risk' and ten means 'I am fully prepared to take many risks,'

0	1	2	3	4	5	6	7	8	9	10

10.4 How would you compare yourself with other members of your community? Please tick a box on the scale below when thinking about decisions related to the management of your animals:

1 I usually take much fewer risks than other members of my community

2 I usually take fewer risks than other members of my community

3 I usually take the same amount of risks as other members of my community

4 I usually take more risks than other members of my community

5 I usually take much more risks than other members of my community

10. Lottery Game

You are now kindly invited to play the next lottery game:

Before starting the game, you will receive **25 ZAR** for your participation. We will propose a game that entails six (6) choice lottery tasks. In this lottery task, you need to decide whether you want to accept every six lotteries, which means that you want to play the game **OR** reject, which means that you do not want to play the game, and there will be no compensation. In case you agree to play the game: we will flip the coin. If the coin turns up heads, you won, and you lose if it turns up tails. Please analyse these lotteries very carefully since your choice will influence the final payoff you receive.

After completing six (6) lottery questions, we will insert numbered balls representing the lotteries you have accepted in a bag. Then we will draw one numbered ball from the same bag, determining which row of choice we will play for real money. For example, if we draw a ball numbered two, we will play a row two (2) for real money. You must be conscious that a lottery task contains the probability of winning and losing a certain amount of money. However, since you were given an initial amount of money at the beginning of the lottery game, you will never have to pay us some money. We will deduct from the initial payment you received in the worst-case situation. In the best case (for you), when the lottery outcome is positive (for you), we will give you a total amount of **R25 (your initial gift) plus R20 (earning from the lottery) = R45**

Table 23: Lottery Game

Lottery	**Reject**	**Accept**
If the coin turns up heads, you lose R8; If the coin turns up tails, you win R20		
If the coin turns up heads, you lose R11; If the coin turns up tails, you win R20		
If the coin turns up heads, you lose R14; If the coin turns up tails, you win R20		
If the coin turns up heads, you lose R17; If the coin turns up tails, you win R20		
If the coin turns up heads, you lose R20; If the coin turns up tails, you win R20		
If the coin turns up heads, you lose R23; If the coin turns up tails, you win R20		

To better explain the game, let us look at two (2) examples:

Example 1:

Let us take a scenario where you accepted the lotteries L1 and L2; you rejected L3, L4, L5, and L6. After you choose, we insert balls numbered 1 and 2 into a bag and drew one. Our hypothetical draw gives a "2", which means we will play the lottery L2 with real money.

To do so, we flip a coin:

If the coins turn tail, you won R20 from this lottery, and we will give you a total amount of R25 (your initial gift) + R20 (you are earning from the lottery) = R45

If the coins turn heads, you lost R11 from this lottery, and we will give you a total amount of R25 (your initial gift) minus R11 (your loss from the lottery) = R14

Example 2:

Let us take another scenario where you accepted the lotteries L1, L2, L3, and L4 and rejected the lotteries L5 and L6. After choosing, we insert four balls numbered 1 to 4 into a bag and draw one ball. Our hypothetical draw gives a "4", which means we will play the lottery L4 with real money.

To do so, we flip a coin:

If the coins turn tails, you won R20 from this lottery, and we will give you a total amount

of R25+R20 = R45.

If the coins turn heads, you lost R17 from this lottery, and we will give you a total amount

of R25-R17 = R8.

11. Socioeconomic Characteristics

Questions	**Codes**	**Response**
1. Gender of the respondent	(0) Female; (1) Male	
2. Marital Status	(1) Married; (2) Single; (3) Never Married; (4) Separated; (5) Widow/Widower	
3. Are you the head of your household?	(0) No; (1) Yes	

4. If No, how are you related to the head of the household?	(1) Parent; (2) Grandparent; (3) Child; (4) Sibling; (5) Wife; (6) Other, please specify	
5. Education	(1) No formal education; (2) Primary Education; (3) Secondary Education; (4) Tertiary Education	
6. Age (in years)		
7. How many people are currently living in the household?		
8. What type of land do you use for farming?	(1) Communal; (2) Private; (3) Rental; (4) Other, please specify	
9. In the type of land you use for farming, what is the size of arable land (hectares)?		
10. What is your primary farming enterprise?	(1) Livestock; (2) Grain; (3) Fruits; (4) Crops; (5) Other, please specify	
11. Do you have additional farm labour?		
12. Type of labour you have?	(1) Family labour; (2) Casual Labour; (3) Other, please specify	
13. Are you a full-time farmer?	(0) No; (1) Yes	

14. If you are not a full-time farmer, which other job do you do or have?		
15. What time of the year do you actively farm as a part-time farmer?		
16. How many years have you been farming?		
17. What is the primary source of your income?	Social Grant; Livestock Sales; Formal Employment; Non-farming Business; Other, please specify	
18. What is the amount generated from the primary source of income in the past year?		
19. Do you have any agricultural insurance?	(0) No; (1) Yes	
20. Do you have home insurance?	(0) No; (1) Yes	
21. Do you have a funeral cover?	(0) No; (1) Yes	
22. Do you have car insurance?	(0) No; (1) Yes	
23. Do you have health insurance?	(0) No; (1) Yes	
24. Are you affiliated with any burial society?	(0) No; (1) Yes	
25. If you have never bought any kind Of insurance, what was your reason?	(1) It is expensive. (2) No transparency; (3) It takes a long to pay; (4) I do not need it; (5) I do not have information; (6) Other, please specify;	

26. Are you affiliated with any saving scheme/Stokvel?	(0) No; (1) Yes	
27. If yes, how much do you contribute per month?		
28. Did you receive any drought relief From the Government or Non-Governmental organisations?	(0) No; (1) Yes	
29. If yes, what kind of assistance did you receive it?	(1) Supplementary feed; (2) Money; (3) Voucher; (4) If other, please specify	
30. Do you need credit for Your farming operations?	(0) No; (1) Yes	
31. What kind of credit can you access?	(1) Formal credit; (2) Informal credit; (3) Other (Specify)	
32. Did you borrow money from an informal Credit provider in the past three years?	(0) No; (1) Yes	
33. If yes, how much did you borrow?		
34. Did you borrow money from a formal credit provider in the past three years?	(0) No; (1) Yes	
35. If yes, how much did you borrow?		
36. What was the main reason for borrowing?	(1) Household needs. (2) Farming costs. (3) School fees. (4) If other, please specify	
37. Is drought a problem in your area?	(0) No; (1) Yes	
38. How many years would you say you suffered from drought in the past five years?		

39. In those years, how many animals did you lose due to drought?		
40. How many animals did you sell during the drought period?		
41. Did you manage to recover from the loss caused by the drought?	(0) No; (1) Yes	
42. If yes, how many years did you take to recover?		
43. Now, are you prepared for future drought events?	(0) No; (1) Yes	
44. How many animals do you currently own?		
45. How many livestock units did you sell in the past year?		
46. Do you have access to communal grazing?	(0) No; (1) Yes	
47. Are you affiliated with any farmer's organizations?		

12. Risk Exposure

To what extent do you perceive the following factors as sources of risk in your farming operation? Please complete the Table below.

Risk type	**Is it a Risk?** (0) No; (1) Yes	**Overall severity** (1) Very High (2) High (3) Moderate (4) Low **(5)** Very slow
1. Animal diseases		
2. Drought		
3. Floods		
4. Veld fires		
5. Predators		

6. Tribal regulations		
7. Livestock theft		
8. Thunders storms		
9. Market Prices		
10. If other: Specify		

13. Mitigation and Coping Mechanisms for Drought

In the past five (5) years that you have experienced drought, what kind of mitigation and coping strategies have you applied?

Tick the relevant options provided in the boxes below:

Mitigation Mechanisms	**Responses**	**Coping Mechanisms**	**Responses**
1. Breed resistant breeds		1. Take credit	
2. Use rotations		2. Sell livestock	
3. Sell stock more often		3. Reduce stocking rate	
4. Plant pasture		4. Draw from saving	
5. Buy insurance		5. Increase daily labour	
6. Rainwater harvest		6. Depend on government relief	
7. Save money		7. Migrate	
8. Mixed farming		8. Insurance compensation	
9. Store feed		9. Ask for external support.	
10. None of the above		10. None of the above	
11. If other, please specify		11. If other, please specify	

14. Perception of Drought Risk

Please consider the statement regarding management of drought and exposure to drought in the Table below. Please scale the extent to which you agree or disagree with the comments using a scale of 1 to 5 (Strongly Agree to Disagree Strongly)

Statements	1. Strongly Agree	2. Agree	3. Neutral	4. Disagree	5. Strongly Disagree
1. I have recorded livestock mortality in the past years due to drought					
2. I do not have the full capacity to deal with drought					
3. The impact of drought complicates my farming business					
4. I have received drought relief from the government in the past years					
5. I can deal with the impact of drought on my own					
6. I am willing to pay for index insurance as soon as it is available					
7. Drought is frequent and severe in my area					

15. Access to Weather Information

Questions	**Response**
1. Do you have access to weather information?	(0) No; (1) Yes
2. If yes, how often do you receive weather information?	(1) Daily. (2) Weekly. (3) Monthly
3. How do you access weather information?	(1) Radio; (2) Television; (3) Community members; (4) District weather station; (5) Online; (6) If other, please specify
4. What kind of information do you receive?	(1) Temperatures; (2) Rainfall; Winds; (3) Hail; (4) Veld fires; (5) Thunderstorms; (6) All of the above. (7) Other, please specify
5. Do you receive a seasonal rain forecast?	(1) Yes; (0) No
6. Do you get informed if you will experience low rainfall (Elino) in the year?	(1) Yes; (0) No
7. Do you get informed if you will experience high rainfall (Lanina) in the year?	(1) Yes; (0) No

End of the questionnaire. Thank you for your participation!

8.2 CHOICE SCENARIOS

BLOCK 1

Block 1 - Scenario 1

	alt1	alt2
Payment method	Feed	Cash
NDVI reading	No NDVI	NDVI Weekly
Basis risk (probability of not being reimbursed even if drought higher than threshold)	16%	8%
Premium for 4000 ZAR insured	250 ZAR	250 ZAR
Choice question:		

Block 1 - Scenario 2

	alt1	alt2
Payment method	Feed	Cash
NDVI reading	NDVI Weekly	No NDVI
Basis risk (probability of not being reimbursed even if drought higher than threshold)	8%	16%
Premium for 4000 ZAR insured	400 ZAR	100 ZAR
Choice question:		

Block 1 - Scenario 3

	alt1	alt2
Payment method	Cash	Voucher
NDVI reading	No NDVI	NDVI Weekly
Basis risk (probability of not being reimbursed even if drought higher than threshold)	12%	12%
Premium for 4000 ZAR insured	100 ZAR	400 ZAR
Choice question:		

Block 1 - Scenario 4

	alt1	alt2
Payment method	Voucher	Cash
NDVI reading	NDVI Weekly	No NDVI
Basis risk (probability of not being reimbursed even if drought higher than threshold)	16%	8%
Premium for 4000 ZAR insured	100 ZAR	400 ZAR
Choice question:		

Block 1 - Scenario 5

	alt1	alt2
Payment method	Voucher	Feed
NDVI reading	No NDVI	NDVI Weekly
Basis risk (probability of not being reimbursed even if drought higher than threshold)	8%	16%
Premium for 4000 ZAR insured	250 ZAR	250 ZAR
Choice question:		

Block 1 - Scenario 6

	alt1	alt2
Payment method	Cash	Feed
NDVI reading	NDVI Weekly	No NDVI
Basis risk (probability of not being reimbursed even if drought higher than threshold)	12%	12%
Premium for 4000 ZAR insured	400 ZAR	100 ZAR
Choice question:		

BLOCK 2

Block 2 - Scenario 1

	alt1	alt2
Payment method	Voucher	Feed
NDVI reading	NDVI Weekly	No NDVI
Basis risk (probability of not being reimbursed even if drought higher than threshold)	16%	12%
Premium for 4000 ZAR insured	400 ZAR	400 ZAR
Choice question:		

Block 2 - Scenario 2

	alt1	alt2
Payment method	Feed	Voucher
NDVI reading	NDVI Weekly	No NDVI
Basis risk (probability of not being reimbursed even if drought higher than threshold)	12%	8%
Premium for 4000 ZAR insured	100 ZAR	400 ZAR
Choice question:		

Block 2 - Scenario 3

	alt1	alt2
Payment method	Cash	Feed
NDVI reading	No NDVI	NDVI Weekly
Basis risk (probability of not being reimbursed even if drought higher than threshold)	16%	8%
Premium for 4000 ZAR insured	100 ZAR	250 ZAR
Choice question:		

Block 2 - Scenario 4

	alt1	alt2
Payment method	Voucher	Cash
NDVI reading	No NDVI	NDVI Weekly
Basis risk (probability of not being reimbursed even if drought higher than threshold)	8%	16%
Premium for 4000 ZAR insured	250 ZAR	250 ZAR
Choice question:		

Block 2 - Scenario 5

	alt1	alt2
Payment method	Feed	Voucher
NDVI reading	No NDVI	NDVI Weekly
Basis risk (probability of not being reimbursed even if drought higher than threshold)	12%	12%
Premium for 4000 ZAR insured	400 ZAR	100 ZAR
Choice question:		

Block 2 - Scenario 6

	alt1	alt2
Payment method	Cash	Voucher
NDVI reading	NDVI Weekly	No NDVI
Basis risk (probability of not being reimbursed even if drought higher than threshold)	8%	16%
Premium for 4000 ZAR insured	250 ZAR	100 ZAR
Choice question:		