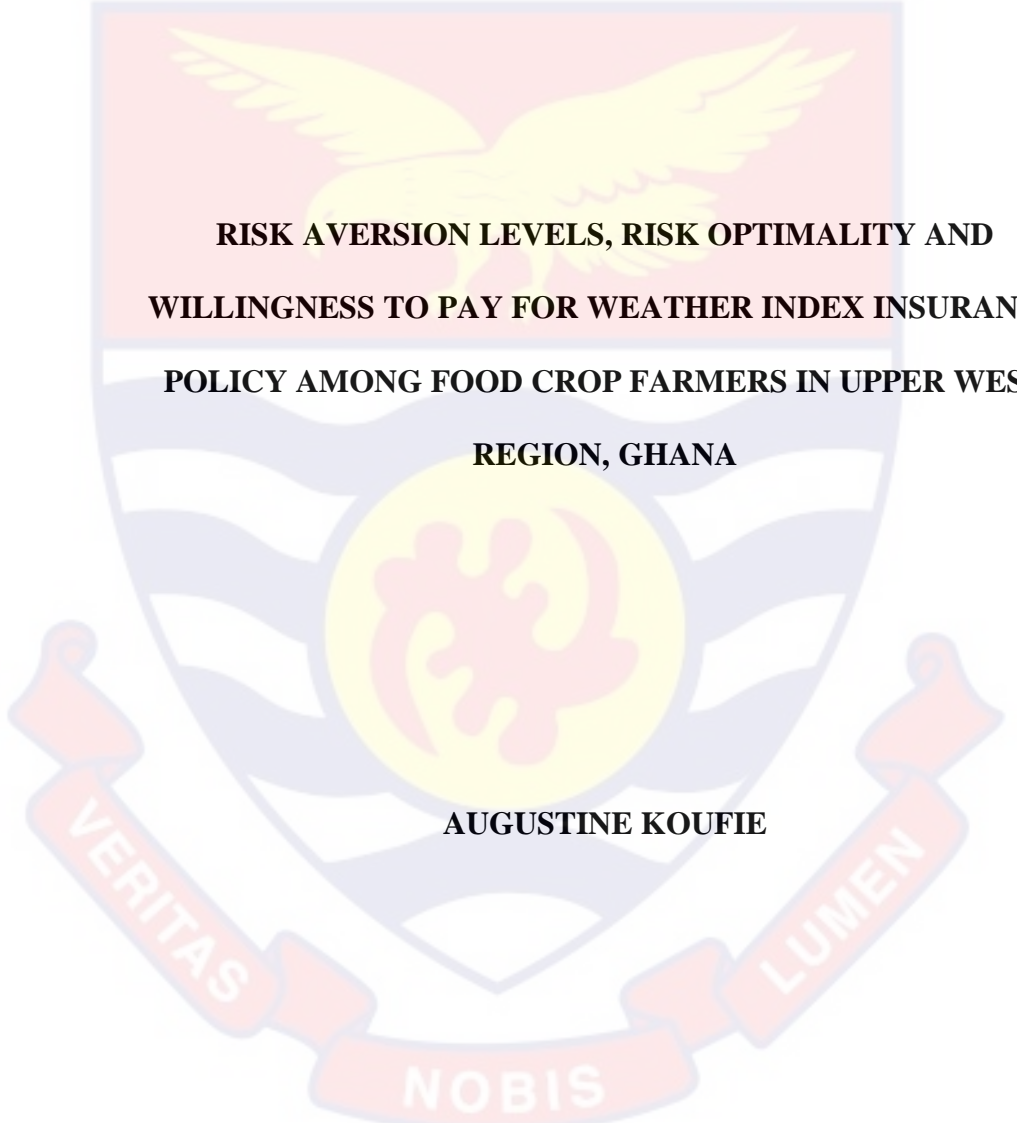


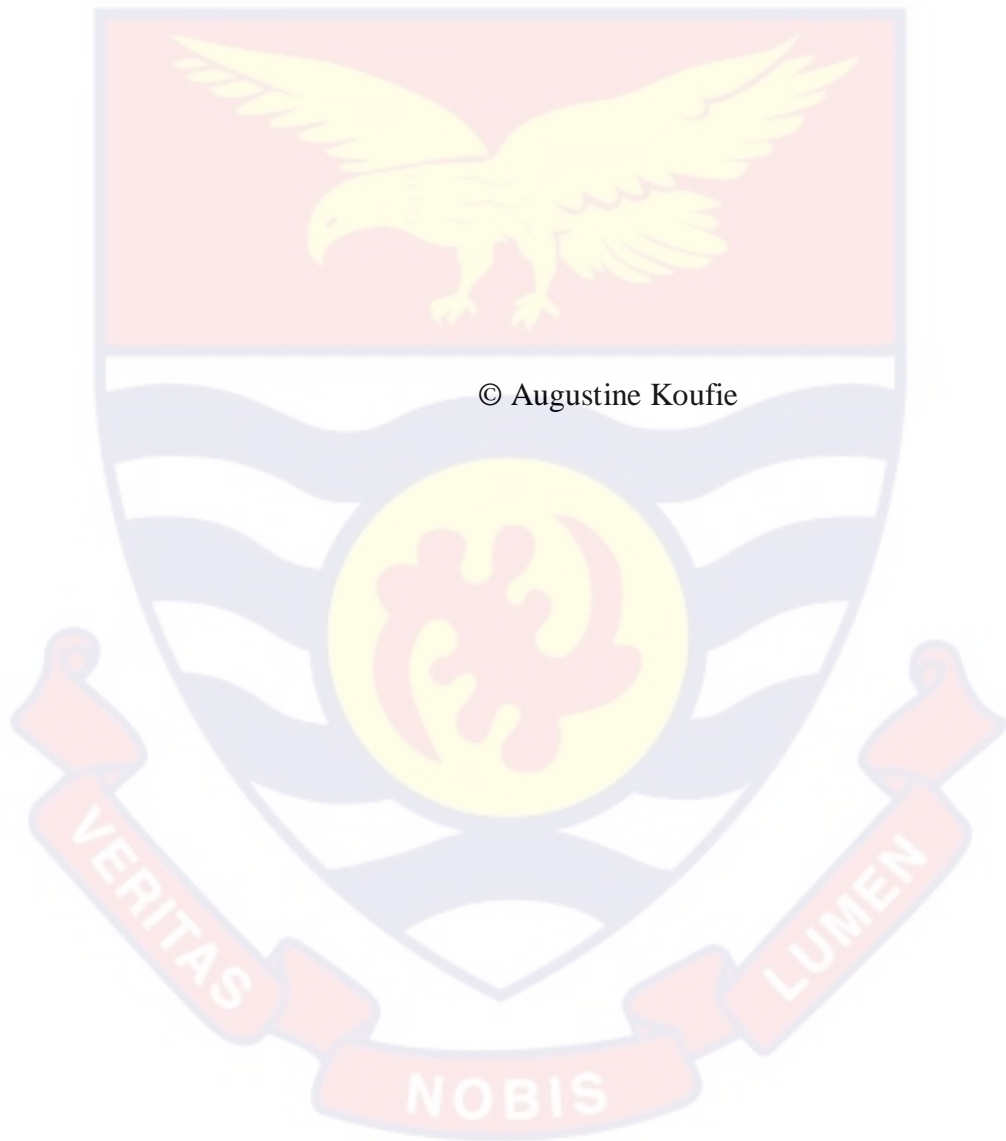
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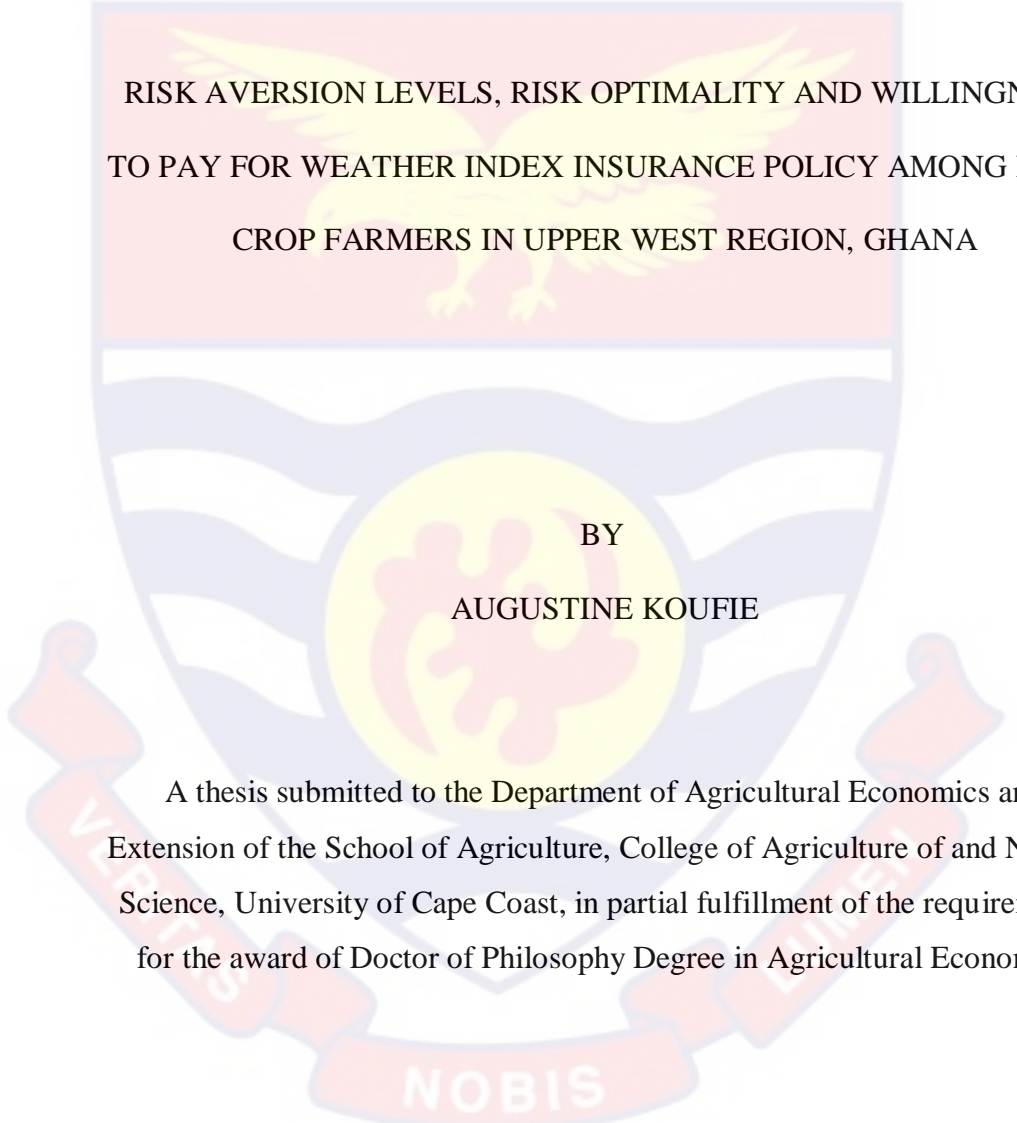
**RISK AVERSION LEVELS, RISK OPTIMALITY AND  
WILLINGNESS TO PAY FOR WEATHER INDEX INSURANCE  
POLICY AMONG FOOD CROP FARMERS IN UPPER WEST  
REGION, GHANA**

**AUGUSTINE KOUFIE**

**2024**



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The background of the page features a large, faint watermark of the University of Cape Coast crest. The crest is a shield-shaped emblem. At the top is a yellow eagle with its wings spread. Below the eagle is a white banner with blue wavy lines. In the center is a yellow circle containing a red silhouette of a person. At the bottom is a red banner with the word 'NOBIS' in white capital letters. The text of the thesis title is overlaid on the upper portion of this watermark.

RISK AVERSION LEVELS, RISK OPTIMALITY AND WILLINGNESS  
TO PAY FOR WEATHER INDEX INSURANCE POLICY AMONG FOOD  
CROP FARMERS IN UPPER WEST REGION, GHANA

BY  
AUGUSTINE KOUFIE

A thesis submitted to the Department of Agricultural Economics and Extension of the School of Agriculture, College of Agriculture of and Natural Science, University of Cape Coast, in partial fulfillment of the requirements for the award of Doctor of Philosophy Degree in Agricultural Economics

AUGUST 2024

## DECLARATION

### Candidate's Declaration

I hereby declare that this thesis is the result of my original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature:..... Date.....

Name: Augustine Koufie

### Supervisors' Declaration

We hereby declare that the preparation and presentation of this thesis was supervised in accordance with the guidelines on the supervision of the thesis laid down by the University of Cape Coast.

Principal Supervisor's Signature ..... Date .....

Name: .....

Co-Supervisor's Signature ..... Date .....

Name: .....

## ABSTRACT

Climate variability and production risks continue to threaten the livelihoods of food crop farmers in northern Ghana, particularly in the Upper West Region. In response, this study investigates farmers' preferences and their willingness to pay for weather index insurance (WII), analyzes their level of risk aversion, determines risk-optimal farm plans, and examines the factors influencing both subscription and subscription intensity to WII policies. Secondary data on rainfall, maximum and minimum temperature (1976–2023) were obtained from the Ghana Meteorological Agency (GMet), while primary data were collected from randomly sampled food crop farmers in the Upper West Region. A range of analytical methods were employed, including the Target-MOTAD model, Multiple Price List method, Modified Mann-Kendall and Sen's slope tests, Kendall's coefficient of concordance, the Mixed Logit model, and the Negative Binomial Hurdle Model (NBHM). The study addresses a methodological gap by applying NBHM and Zero-Inflated Negative Binomial models as advancements over the Poisson regression model, and the Mixed Logit model as an enhancement over the Multinomial Logit. Model fit and performance were assessed using AIC, BIC, Log-likelihood, rootograms, and the Vuong test. The findings reveal an increasing trend in rainfall, maximum, and minimum temperatures in the region, though the increase in rainfall is statistically insignificant. Farmers were found to be highly risk averse and significantly preferred WII policy attributes such as prompt claim payouts, rainfall data from GMet, low premiums, subsidies on agricultural inputs, and deferred payments. Interlinking credit with insurance was the least preferred option. Farmers expressed willingness to pay GH¢5.38 for rainfall data, GH¢6.67 for subsidies, and GH¢13.91 for deferred premium payments. Risk-optimal farm plans, involving 1.5 hectares of soybean and 0.33–0.42 hectares of sorghum, generated higher incomes (GHS 9403.42 and GHS 9835.10) compared to farmers' current plans (GHS 7412.97). Approximately two-thirds (64%) of food crop farmers had subscribed to WII, yet only 39% of cultivated land was covered. The NBHM demonstrated superior empirical performance in modeling count data with excess zeros and dispersion issues, while the Mixed Logit model more effectively captured both observed and unobserved heterogeneity in preference data. Key factors significantly influencing subscription and intensity include age, sex, farm size, experience, education, prompt insurance payment, extension services, credit access, and risk-efficient income. In conclusion, farmers in the Upper West Region face high climate risk and exhibit strong risk aversion, which influences their preference for specific WII features and farm planning strategies. Adoption of risk-efficient production plans can enhance income and affordability of insurance premiums, thereby increasing WII participation. It is recommended that the Ministry of Food and Agriculture (MOFA) and the Ghana Agricultural Insurance Pool (GAIP) promote risk-efficient farm planning through extension services, integrate insurance into national agricultural policy, tailor WII products to farmers' needs, and intensify farmer education to build trust and understanding around WII schemes.

## KEY WORDS

Food Crops

Subscription

Subscription Intensity

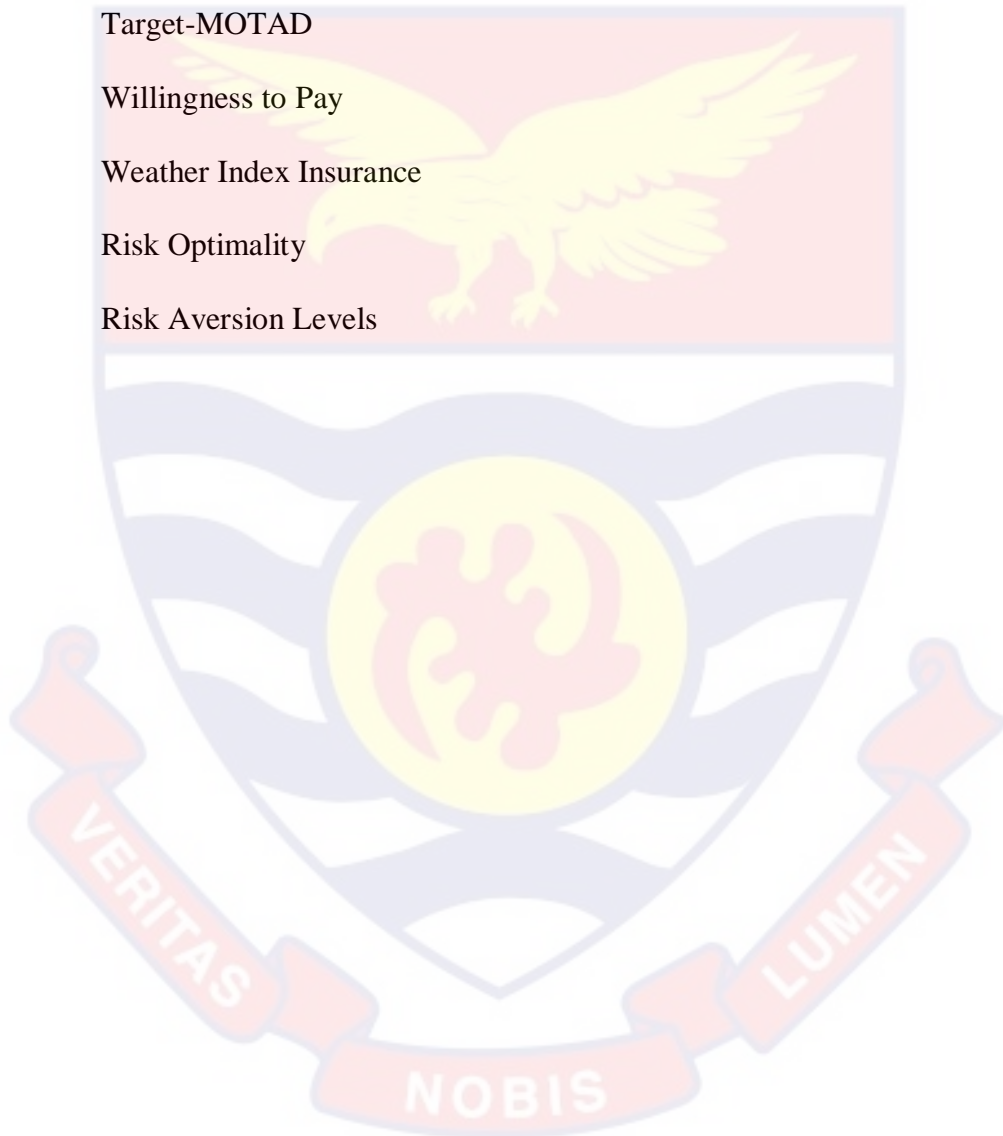
Target-MOTAD

Willingness to Pay

Weather Index Insurance

Risk Optimality

Risk Aversion Levels



## DEDICATION

To the Late Juliana Cobbina (Auntie Julie)



## ACKNOWLEDGEMENTS

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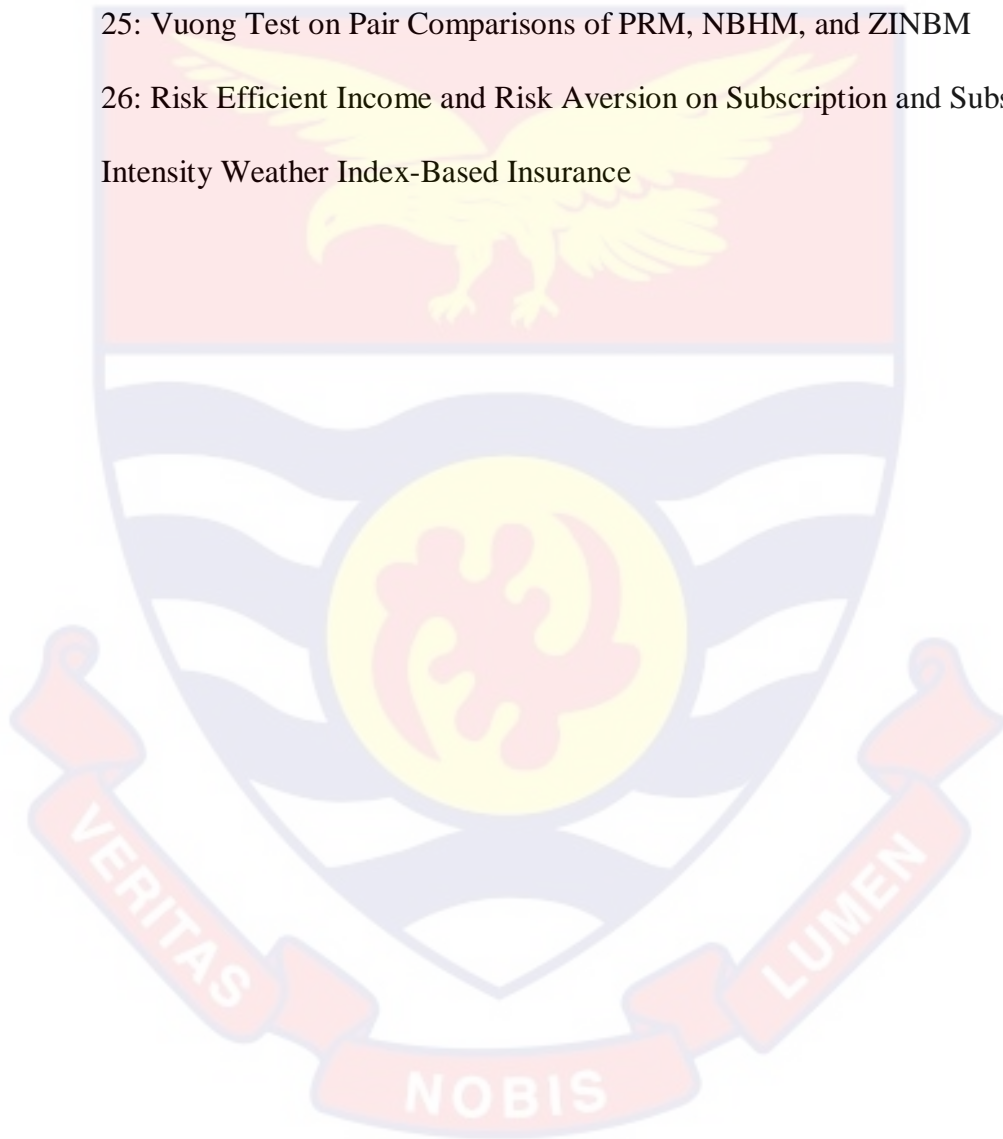
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## LIST OF ACRONYMS



LP	Linear Programming
WII	Weather Index Insurance
T-MOTAD	Target Minimization of Total Absolute Deviation
MOTAD	Minimisation of Total Absolute Deviation
TAD	Total Absolute Deviation
QP	Quadratic Programming
GAIP	Ghana Agricultural Insurance Pool
DCE	Discrete Choice Experiment
MPCI	Multi-Peril Crop Insurance
SSD	Second-Order Stochastic Dominance
UWR	Upper West Region
RUT	Random Utility Theory
EMV	Expected Monetary Value
CE	Certainty Equivalent
GDP	Gross Domestic Product
FAO	Food and Agriculture Organisation
MoFA	Ministry of Food and Agriculture
WTP	Willingness to Pay
GSS	Ghana Statistical Service
SPSS	Statistical Package for the Social Sciences
Df	Degree of Freedom
FAPDA	Food and Agricultural Policy Decision Analysis
ELCE	Equal Likely Certainty Equivalent

MPL	Multiple Price List
CLP	Conventional Linear Programming
TLU	Tropical Livestock Unit
LCM	Latent Class Model
MNL	Multinomial Logit
MIXL	Mixed Logit
IIA	Independent Irrelevant Alternative
PS	Preference Space
WS	Willingness to Pay Space
GM	Gross Margin
TR	Total Revenue
PRM	Poisson Regression Model
AIC	Akaike Information Criteria
BIC	Bayesian Information Criteria
LL	Log-likelihood
ZINBM	Zero-Inflated Negative Binomial Model
NBHM	Negative Binomial Hurdle Model
Std	Standard Deviation
GMet	Ghana Meteorological Agency
ASC	Alternative Specific Constant
RAVL	Risk Aversion Levels
FOSTAT	Food Science and Technology Association of Thailand

## CHAPTER ONE

### INTRODUCTION

#### **Background to the Study**

Agriculture plays a critical role in both developed and developing countries, providing sustenance and fueling industrial development (FAO & FAPDA, 2015). In Sub-Saharan Africa (SSA), it is seen as a key driver for economic growth, poverty reduction, and ensuring food security for its population (Kwadzo, Kuwornu, & Amadu, 2018). This sector is characterized by smallholder farmers, typically cultivating limited landholdings and relying heavily on rain for their crops (Yesuf & Randy, 2018).

Despite their significant economic contributions, the livelihoods of farmers in Sub-Saharan Africa (SSA) remain highly vulnerable (Mersha, 2018). Adverse factors such as unpredictable weather patterns, volatile market prices, and recurrent crop failures continue to undermine agricultural stability and contribute to persistent food insecurity (Yesuf & Randy, 2018; Mersha, 2018). This vulnerability is largely linked to the region's dependence on rain-fed agriculture. According to Shumba (2022), any shift in weather conditions can have devastating consequences for agricultural yields (Shumba, 2022).

Global warming is further exacerbating the impacts of erratic weather patterns and climate extremes (Cole, Regan, & Sheldon, 2021). Despite these challenges, farmers have developed various coping mechanisms over time, both formal and informal, to manage weather variability and climate risks (Hill, 2017). Informal strategies often involve on-farm practices like crop rotation, but their effectiveness can be limited in the face of increasingly unpredictable weather conditions (Hill, 2017).

These informal mechanisms, whether implemented before (ex-ante) or after (ex-post) a weather event (e.g., selling assets, borrowing, shifting to lower-risk crops), may not be sufficient to adequately manage climate risks (Kurukulasuriya & Mendelsohn, 2021). Ankrah, Agyei-Holmes, and Boakye (2021) asserted that some coping strategies employed by smallholder farmers in developing countries can inadvertently trap them in poverty cycles due to limited effectiveness or negative long-term consequences.

Agricultural insurance emerges as a potential solution for smallholder farmers to manage climate risks more effectively (Yesuf & Randy, 2018). This approach offers a robust method to improve farm production, income, and overall well-being. Among various coping mechanisms, weather index-based insurance is particularly promising for climate risk management in developing countries (Horton & Keith, 2019). Studies by Shirsath, Mali, and Islam (2021) highlight the potential benefits of weather index insurance, including increased income, greater economic security, and improved peace of mind for farmers facing a less uncertain future.

Weather index-based crop insurance (WII) has emerged as a potentially transformative market mechanism for low-income countries (Barnett & Mahul, 2017). Unlike traditional agricultural insurance, which can be unsustainable in these contexts (Feng, 2021), WII offers a viable alternative by transferring weather-related risks from farmers to insurance providers. This is crucial for resource-poor households, as improved risk management can enhance their immediate well-being and pave the way for long-term income growth (Cole et al., 2021).

Several factors contribute to the increasing popularity of WII, as emphasized by Abebe and Bogale (2014). Jensen, Akperov, and Mokhov (2017) point to the transparency and ease of verification for policyholders as key strengths of WII. This transparency minimizes the potential for manipulation, as payouts are based on objective and readily available weather data used to assess risk accurately. Ellis (2016) also asserted that WII boasts relatively low delivery costs and minimal delays in payouts. Most importantly, WII payouts are demonstrably linked to fluctuations in household income and consumption risks faced by farmers. This strong connection ensures that WII directly addresses the challenges that farmers encounter.

In Ghana, weather index-based insurance (WII) is becoming an increasingly important tool for farmers to manage risk (Antwi, 2016). The government introduced WII with the specific aim of assisting farmers to cope with the challenges posed by climate variability and natural disasters (Ankrah et al., 2021). The primary objective of WII programmes in Ghana is to protect farmers from the uncertainties and financial losses that can result from unfavourable agricultural seasons. The objective of weather index-based insurance (WII) is to provide payouts based on weather data rather than individual farm yield assessments. This approach is designed to enhance farmers' risk tolerance and lessen the impact of weather-related crop damage. The aim is to achieve this by smoothing income fluctuations and stabilising production levels for participating farmers (Ellis, 2016; GAIP, 2021).

Ellis (2016) details how Ghana's Agricultural Insurance Pool (GAIP) leverages weather and harvest data to predict potential crop yield losses for key crops like maize, millet, sorghum, soybeans, and groundnuts. This WII

program goes beyond simple risk transfer, as Addey, Jiang, and Osanyintuyi, (2021) highlight its growing role in building climate resilience among farmers, particularly in the semi-arid savannah zone of Northern Ghana. The program equips farmers with tools and knowledge to navigate the challenges of a changing climate. Despite, these advantages, WII programme penetration remains low (Fiala, 2017). The low uptake of the WII program is primarily due to a lack of awareness of its benefits among farmers and the financial constraints faced by many smallholder farmers (GAIP, 2021).

Udo, Kesit, and Igwe (2015) propose that implementing optimum farm planning could be a support policy to the WII, as this will serve as a strategy to address the income limitations of farmers, potentially improving their overall financial status and making WII participation more feasible. Farm planning involves crucial decisions for resource allocation. Farmers typically grapple with two primary criteria: maximizing cash returns on their existing resources or maximizing overall utility (Udo et al., 2015). The latter approach seeks a balance between increasing expected income and minimizing income variability, reflecting the inherent risks associated with agriculture.

Unpredictable weather patterns, pests, and diseases are just a few of the risks inherent to agricultural production (Sarul & Sahin, 2015). Therefore, farm planning goes beyond simply identifying the most profitable crops. Given the inherent risk in agriculture, selecting "risk-optimal" crops is equally important (Koufie, 2020). This complexity of balancing risk and return has been effectively addressed through the use of linear programming models (Hazell & Norton, 1986). These models offer a flexible framework for informed decision-making. As Larkai (2019) highlights, there are two main types of linear

programming models: conventional and stochastic. The conventional model focuses on maximizing a single objective function under defined constraints. The risk programming model extends this approach by incorporating a risk component, allowing for more nuanced decision-making in the face of agricultural uncertainties.

### **Statement of the Problem**

In Ghana, the Upper West Region is a major hub for food and livestock production, contributing about 34.6% to the nation's food basket and recording a farm household population of 73.5% (Abdul-Razak & Kruse, 2017; MOFA, 2017). Despite this, it remains one of the most climate-vulnerable regions, frequently facing droughts, floods, and erratic rainfall, all of which threaten agricultural productivity and farmers' livelihoods (Amponsah, Mensah & Ampaw, 2018; Harrison, 2014). These climatic events disrupt planting and harvesting schedules, making effective risk management strategies essential. Traditionally, smallholder farmers in the region have managed production and climate risks informally, often incurring significant losses (Dembele, 2018). In response, the Government of Ghana and stakeholders introduced weather index-based insurance in the region to provide market-based risk protection (Adiku, Debrah-Afanyede, Greatrex, & MacCarthy, 2017; GAIP, 2023). However, adoption has remained very low, thus, just 27% of farmers nationally and 23% in the Upper West Region have subscribed over the past decade (GAIP, 2023).

Factors accounting for this low uptake include limited awareness, distrust due to delayed or insufficient payouts, low income levels, lack of preferred policy attributes, and misalignment with farmers' specific needs

(Fiala, 2017; Adiku et al., 2017; Addey, Jatoe & Kwadzo, 2021). In particular, the absence of tailored insurance products for specific crops and local weather conditions further discourages adoption. A critical knowledge gap exists regarding farmers' risk attitudes, preferences, and the characteristics they value in weather index insurance policies. Without this understanding, it is difficult to design products that meet their needs and encourage wider adoption. Understanding these factors is vital for enhancing policy effectiveness and increasing uptake. According to Udo et al. (2015), improving farmers' income under risk requires a risk-optimum farm plan, an approach that can complement weather index insurance and support access to credit, advisory services, and risk mitigation strategies (Koufie, 2020).

Empirical research on weather index insurance and risk-optimum farm planning is limited, particularly in the Upper West Region where the policy was piloted. Existing studies have largely focused on the farmers' willingness to pay and factors influencing willingness to pay overlooking farmers' preferences and subscription intensity (ie. studies such as, Haruna, 2015; Udo et al., 2015; Ellis, 2016; Boateng-Gyambiby, 2019; Ankrah et al., 2021; Shumba, 2022). This is a significant gap, as understanding subscription intensity provides insights into the level of commitment and financial sustainability of the insurance scheme.

While income constraints are often cited as barriers to adoption, studies have often overlooked how farmers could make more profitable and resilient production choices under climate variability. Integrating a risk-optimal farm plan could address this by supporting informed decisions on crop diversification, input use, and resource allocation thereby reducing

vulnerability and improving income stability. Additionally, most farm planning studies (Udo et al., 2015; Dembele, 2018; Larkai, 2019; Koufie, 2020; Twumasi, 2022) use conventional linear programming models, which assume certainty and ignore the inherent risks in agriculture. The Target-MOTAD model, which minimizes income deviation from a target level, addresses this limitation by incorporating risk (income deviations) considerations, offering a more realistic planning tool under climate uncertainty. Given these geographic, knowledge, and methodological gaps, this study explores farmers' risk aversion levels, risk-optimality and willingness to pay for weather index-based insurance in the Upper West Region of Ghana.

### **Purpose of the Study**

The main objective of the study was to examine farmers' risk aversion levels, risk efficient plan and willingness to pay for weather index insurance policy in the Upper West Region of Ghana.

### **Research Objectives**

1. to examine farmer's attitude towards risk amidst climate variability and change.
2. to determine the risk optimum farm plan that the farmers should operate in order to get the maximum return in the face of production and climatic risk.
3. to estimate farmers' preferences and willingness to pay for weather index insurance.
4. to analyse the effect of risk optimum income and risk attitude of farmers on their subscription and subscription intensity of the weather index based insurance policy.

### **Research Questions**

1. What is the farmer's attitude towards risk amidst climate variability and change?
2. What is the risk optimum farm plan that the farmers should operate to get the maximum return in the face of production and climatic risk?
3. What are the farmer's preferences and willingness to pay for weather index insurance?
4. How will risk optimum income and risk attitude of farmer's influence their subscription and subscription intensity of the weather index-based insurance policy?

### **Significant of the Study**

The study contributes to the knowledge on weather index insurance and risk-optimum farm plan by examining the risk aversion levels of food crop farmers, their preferred weather index insurance attributes, and willingness to pay for the preferred weather insurance product. It goes further to determine a risk-efficient farm plan that provides the farmer with a higher income. The study then investigates the effect of the risk-efficient income and risk aversion levels on their subscription and subscription intensity of the weather index insurance. This study is necessary because it considers the risk-optimum farm plan as a support plan to the weather index-based insurance policy.

To the farmer, the findings of the study are of important, as it shows the risk-efficient plan that they should adopt in order to earn a higher income that will enable them to be able to afford the premium. Furthermore, the findings of the study provide a flow scheme to guide climate-sensitive farm decision for farmers, insurance companies, governmental and non-governmental

organisations, policy makers and other key stakeholders in the insurance sector in an attempt to pursue resilient agriculture.

For policymakers, the study provides policy insights that show that to make weather index based insurance attractive for farmers to subscribe, policymakers should consider prompt payout of compensation and also focus on the crops provided by the T-MOTAD model as this could serve as a source of cash income and also a primary source of food security. Finally, the findings of the study serve as reference material and a guide for future researchers who wish to conduct the same or related research on weather index based insurance and risk-optimum farm plan.

#### **Delimitation of the Study**

The study focused on risk aversion levels, risk optimality, and willingness to pay for a weather index-based insurance policy among food crop farmers in the Upper West Region of Ghana. The study was conducted in only two districts out of the eleven (11) districts, namely the Wa West district and the Wa Municipality. Additionally, the study also focused on selected crops such as sorghum, soybean, maize, millet, rice, and groundnut, as these crops are the main ones covered by the WII insurance policy. A structured questionnaire, administered through a multi-stage sampling technique, was used in this study to collect choice experiment data from food crop farmers in the Upper West Region of Ghana. Descriptive statistics, Modified Mann-Kendall trend test and Sen's slope test, multiple price lists, multinomial logit model, mixed logit model, Target-MOTAD, as well as count regression models such as Poisson regression model, hurdle negative binomial model, and zero-inflated negative binomial model were the statistical analytical tools used for

the study. The variables for the study included premium, subsidy, fertilizer, labor, capital, land, risk aversion levels, risk-optimum income, and socio-economic characteristics such as age, sex, education, land size, awareness, weather information, etc.

### **Limitation of the Study**

The study, although, comprehensive, had certain limitations. Therefore, identifying these limitations would not be sufficient without acknowledging the reasons for them, the impossibility of fully overcoming them, and the efforts made to minimize their impact. For example, relying on farmers' recall of past practices and yields may introduce potential biases and inaccuracies. This limitation arose from the general lack of written records or farm documentation in the study area. While more objective data would have strengthened the study, access to such records was not possible. To minimize recall bias, the researcher used triangulation techniques such as cross-checking information with local agricultural officials, neighboring farmers, and community leaders whenever possible. In addition, language barriers between the researcher, enumerators, and some respondents hindered effective communication and data collection. Therefore, local interpreters were used to bridge this gap.

### **Definition of Terms**

**Linear Programming Model:** The most popular, frequently used MP model is the conventional LP model. This model is used in terms of maximizing a linear objective subject to linear constraints. The model is popular and a lot of software is available to run the model of any magnitude. The LP model assumes that the objective function of a farmer is linear, but this is not the case. Several studies, such as those by Udo et al. (2017) and Hakam (2021), among

others, pointed out that the objective function of a farmer is a utility function. Thus, the utility function is quadratic because the function is subject to diminishing marginal utility. Therefore, because of the limitations of the LP, the quadratic programming model (QP) and its linear forms were developed to draw reliable plans.

**T-MOTAD:** The model involves maximizing the expected utility of income subject to resource constraints and risk constraints. The Target MOTAD has a linear objective and constraint function, so the linear programming algorithm can be used to solve problems (Tauer, 1983; Kaiser & Messer, 2011). Therefore, the Target MOTAD is superior to other risk programming models. Thus, the solutions of the Target MOTAD model on the efficient frontier are second-degree stochastic dominance (SSD), and plans that are not feasible are not included in the solution.

**Risk Attitude of Farmers:** The degree of risk acceptance exhibited by farmers varies considerably. Some farmers are more willing to accept risk than others. The term "risk attitude" is defined as a state of mind with regard to those uncertainties that could have a positive or negative effect on objectives. It may be more simply defined as a chosen response to the perception of significant uncertainty. The financial ability of the farmer to accept a small gain or loss is often related to their attitude to risk. The risk attitude of farmers is classified into three categories: risk averse, risk neutral, and risk loving/taking.

**Willingness to Pay:** Willingness to Pay (WTP) is defined as the maximum amount or value a customer is willing to pay for a product or service. In the context of this study, the product under consideration is the weather index-based insurance policy. Consequently, the willingness of a farmer to pay

for such an insurance policy may vary considerably from one individual to another. This variance is often attributed to differences in the customer's income, risk attitude, and socio-economic characteristics, such as age, income, gender, education, etc.

**Weather Index-Based Insurance:** Willingness to Pay (WTP) is defined as the maximum amount or value a customer is willing to pay for a product or service. In the context of this study, the product under consideration is the weather index-based insurance policy. Consequently, the willingness of a farmer to pay for such an insurance policy may vary considerably from one individual to another. This variance is often attributed to differences in the customer's income, risk attitude, and socio-economic characteristics, such as age, income, gender, education, etc.

**Premium:** A premium is an amount of money paid periodically by the insured to the insurer to cover the risk in question. In an insurance contract, the risk is transferred from the insured to the insurer. In exchange for assuming this risk, the insurer levies a premium. The premium is determined by a number of factors, including age, type of employment, and medical conditions. The frequency of premium payments may vary, with options including monthly, quarterly, semi-annually, annually, or as a single premium.

### **Organisation of the Study**

The study was structured into eight chapters. The first chapter of the study was devoted to an overview of the background, the statement of the problem, the research questions and objectives, the significance of the study, and the limitations and delimitations. Chapter two presents a review of the relevant literature, illuminating, random utility theory, utility maximisation

theory, Lancaster theory, food crop farming systems, crop enterprise pattern and risk, weather index insurance policies, and empirical literature related to objectives of the study. It also presents a conceptual framework for the study.

Chapter three presents the methodology, which includes an account of the research procedures and techniques employed. This chapter outlines the research philosophy, study area, research design, population, socio-economic characteristics of the study population, sampling technique, data collection, data analysis, and data processing. Chapter four discussed the risk attitude of the farmer amidst climate variability as well as the risk-efficient farm plans that farmers should operate in order to achieve higher income.

Chapter five analysed and discussed the preferences of the farmers and the value they place on weather index insurance, as well as the farmers' willingness to pay for the preferred weather index insurance product. Chapter six analysed and discussed the influence of risk-efficient income and the risk attitudes of the farmers on their subscription and subscription intensity to weather index-based insurance. Chapter seven presents a summary of the study's findings, conclusions, and recommendations, as well as suggestions for future research.

## CHAPTER TWO

### LITERATURE REVIEW

#### **Introduction**

This chapter provides an overview of the food crop farming systems, techniques used, theories and empirical studies that provide a background and basis for the current study. The chapter commences with a review of theories; the random utility theory, utility maximisation theory and Lancaster theory. This is followed by review of techniques used and overview of food crop farming systems, crop mix enterprise and risk, balancing risk and returns in crop combination and an empirical literature review on the risk attitude of farmers amidst climate variability, their preference and willingness to pay for weather index insurance, the risk optimum farm plan, and the influence of risk-efficient income and risk attitude on subscription and subscription intensity of weather index insurance. The chapter concludes with a conceptual framework that illustrates the interrelationships between the study's variables and a chapter summary.

#### **Theoretical Framework for the Study**

##### **Introduction**

This study adopts a utility-based framework to model and analyze farmers' decision-making under risk and uncertainty. Grounded in the utility maximization theory, the research assumes that farmers aim to choose production strategies and risk management tools that maximize their expected utility rather than merely their expected income. The Random Utility Theory underpins the estimation of discrete choices, such as farmers' willingness to pay for weather index insurance, while Lancaster's Theory provides the

foundation for decomposing the utility of insurance products into their constituent attributes. These interrelated theories are applied systematically across all research objectives to ensure a consistent and behaviorally sound analytical approach. In economic literature, the theory behind farmers' choices regarding agricultural insurance is based on principles from microeconomics, specifically Lancaster's theory of consumer preferences (Lancaster, 1966). This theory, along with random utility theory and utility maximisation theory, forms the foundation for choice models used in economics (Jaffry et al., 2014). Therefore, the theories of random utility, utility maximisation and Lancaster's theory of consumer preferences form the basis of this study. These theories are reviewed below to demonstrate how the study fits into the wider theoretical framework.

### **Random Utility Theory**

Building on the foundation of microeconomic theory, Random Utility Theory (RUT) offers a framework for the analysis of farmers' decisions regarding agricultural insurance (Loureiro & Umberger, 2007). This theory postulates that rational farmers, operating within budgetary constraints, select the insurance option that maximises their expected utility. The application of RUT enables researchers to infer the relative preferences of farmers by examining their choices between different insurance products defined by their specific attributes. Accordingly, a farmer's utility derived from an insurance product can be conceptualised as comprising two components: a deterministic component reflecting objectively measurable benefits, and a random component capturing unobserved factors influencing the decision (e.g., risk aversion). This is mathematically expressed as follows:

$$U_{ni} = V_{ni} + \mu_{ni} = \beta X_{ni} + e_{ni} \quad (1)$$

Where utility obtained by individual ( $i$ ) from good ( $I$ ) is given by,  $U_{ni}$ , where  $V_{ni}$  is the deterministic and observable part of this utility, which is related to the attributes of the insurance product. The term  $e_{ni}$  represents the error term, or the random component of the utility, which is unobservable to the researcher.

The deterministic component,  $V_{ni}$ , of function (1) is further characterised as the vector,  $(X_{ni})$ , of the exogenous attributes' times the vector of the coefficients  $\beta$  for the attributes, and is assumed to be linear in parameters. This leads to the perceiving of utility as a random variable and to perform a probabilistic choice analysis where the individual makes a choice between insurance product, and depending on the resulting utility levels (Bateman *et al.*, 2002). A farmer will select an agricultural insurance product if the condition  $U(i) > U(j)$  is met. The conditional probability that a farmer ( $n$ ) prefers agricultural insurance product with attributes over a different choice set is:

$$P_n(i) = P_i[(V_{ni} + \ell_{ni}) > (V_{nj} + \ell_{ni})] = P_i[(V_{ni} - \ell_{ni}) > (V_{nj} + \ell_{ni})], i, j \in \beta \quad (1.1)$$

### Assumptions of Random Utility Theory

Random Utility Theory (RUT) is based on the hypothesis that individuals are rational decision-makers, seeking to maximize utility relative to their choices.

The RUT makes the following assumptions:

- i. The generic decision-maker ( $i$ ) considers  $m_i$  mutually exclusive alternatives when making a choice, which together comprise the individual's choice set. The choice set may include different decision-makers.

- ii. The decision-maker ( $i$ ) assigns a perceived utility, or "attractiveness,"  $U_j^i$  to each alternative ( $j$ ) from the individual choice set and selects the alternative that maximizes this utility.
- iii. The utility assigned to each choice alternative is dependent on a number of measurable characteristics, or attributes, of the alternative itself and of the decision-maker. This can be expressed as  $U_j^i = U^i(X_j^i)$ , where  $X_j^i$  is the vector of the attributes relative to alternative  $j$  and to decision-maker  $i$ .
- iv. The utility assigned by decision-maker  $i$  to alternative  $j$  is not known with certainty by an external observer (analyst) due to a number of factors that will be described later. Consequently, this must be represented by a random variable.

In relation to the aforementioned assumptions, it is not always possible to predict with certainty the alternative that the generic decision-maker will select, given that external factors may influence their decision. It is also possible to express the probability of selecting alternative  $j$ . Given the individual's choice set  $I^i$ , the probability that the perceived utility of alternative  $j$  is expressed as:

$$p_i[j/I^i] = Pr[U_j^i > U_k^i \quad \forall k \in I^i, k \neq j] \quad (1.2)$$

The perceived utility  $U_j^i$  can be expressed as the sum of the systematic utility  $V_j^i$ , which represents the mean or expected value of the utilities perceived by all decision-makers having the same choice context as decision-maker  $i$  (same alternatives and attributes), and a random residual,  $\varepsilon_j^i$ , which is the unknown deviation of the utility perceived by the user  $i$  from this value. This is expressed as:

$$U_j^i = V_j^i + \varepsilon_j^i \quad \forall j \in I^i \quad (2.0)$$

### Utility Maximization Theory

The concept of utility maximisation is a central tenet of consumer demand theory (Jiang, 2014). This theory postulates that consumers engage in a deliberate process to achieve the highest level of satisfaction (utility) derived from consuming goods and services. This fundamental assumption underpins the study of consumer behaviour, with significant implications for the understanding of demand patterns (McFadden, 1974). It is assumed that consumers make choices, particularly regarding purchases, with the goal of maximizing their satisfaction (Oliver, 2014).

The utility theory and consumer demand analysis both rely on the notion that utility reaches its peak at the point of diminishing marginal utility (Leightner, 2005). In a formal sense, the utility maximisation principle stipulates that consumers should allocate their budget in such a way that the last dollar spent on each product yields an equal amount of additional marginal utility (Khamis, & Kamarudin, 2023). In essence, this principle suggests that consumers strive to distribute their limited resources in a way that optimizes their satisfaction from consumption.

### The Assumptions Underlying the Maximisation Theory

Utility Maximisation theory rests on several key assumptions that simplify consumer behavior for economic modeling (McFadden, 1974).

- i. **Rational Decision-Making:** Consumers are assumed to act rationally, seeking to maximize their utility (satisfaction) derived from their purchases. This principle suggests that consumers carefully consider the benefits they expect from different options before making choices.

- ii. **Budget Constraints:** Consumers face limitations due to their finite resources. This translates to a budget constraint, restricting the total amount they can spend on goods and services.
- iii. **Well-Defined Preferences:** Consumers possess distinct preferences for different goods and services. This allows them to rank options based on the level of satisfaction they expect to receive (Lancaster, 1966). These preferences are assumed to be complete and transitive, meaning consumers can compare any two options and have a consistent preference order.
- iv. **Price Consideration:** Every good or service has a price, forcing consumers to make trade-offs when allocating their limited budget (Mankiw, 2020). Consumers are assumed to be aware of these prices and factor them into their decision-making process.

These core assumptions provide a foundational framework for analysing consumer choices and predicting demand patterns within economic models. However, it is important to recognise that these assumptions may not perfectly reflect real-world consumer behavior, which can be influenced by various psychological and emotional factors (Thaler & Sunstein, 2008).

### **Lancaster's Theory**

Lancaster's theory offers a distinctive perspective on consumer behaviour by introducing a multidimensional framework (Cheng & Li, 2020). This framework serves as a bridge, connecting economic theory with the multi-attribute models widely used in behavioural science research (Lancaster, 1966). The core difference lies in the source of utility: Lancaster postulates that utility is derived from the inherent features (attributes) of goods, rather than the goods

themselves (Moresino, 2019). This stands in contrast to traditional demand theory, which assumes goods directly generate utility.

Lancaster's theory posits that consumption is an activity where goods serve as inputs, used individually or in combination, to yield a collection of desired characteristics as outputs (Lancaster, 1966; Moresino, 2019).

Consequently, utility and preference orderings are based on these collections of characteristics. Goods only indirectly influence these preferences through the attributes they possess (Moresino, 2019).

#### **Assumptions under Lancaster theory are summarized below**

This section presents the core assumptions underlying Lancaster's theory of consumer behavior. In contrast to traditional models that place emphasis on the utility of goods, Lancaster proposes a distinct perspective.

#### **Assumptions:**

- i. **Utility from Attributes:** Consumers derive satisfaction (utility) from the inherent characteristics or attributes of farm products, not the products themselves. For instance, the taste, freshness, and versatility of a tomato, rather than the tomato itself, contribute to its utility for a home cook.
- ii. **Multifaceted Produce, Shared Attributes:** Lancaster acknowledges that farm products possess a bundle of attributes. A plump, juicy tomato might offer not only flavor but also disease resistance (important for home gardeners). Furthermore, many attributes are shared across different products. Freshness might be a sought-after attribute in both tomatoes and leafy greens.

- iii. **Emergent Utility through Combinations:** This theory suggests that combining farm products can create entirely new attributes and generate utility distinct from the individual components. For example, pairing a flavorful tomato with fresh herbs might create a taste synergy for a salad, exceeding the benefits of either ingredient alone.

These core assumptions form the foundation of Lancaster's theory. By shifting the focus from the products themselves to the underlying attributes that drive preferences, Lancaster offers a richer framework for understanding consumer behavior at farmers' markets and the creation of value for both farmers and consumers.

#### **How these Aforementioned Reviewed Theories Relate to this Study**

The study was based on the theories that had been reviewed. The Random Utility Theory (RUT) has a relationship with the choice experiment model. The study employed a Discrete Choice Experiment (DCE) approach, which is based on the Random Utility Theory (RUT), Utility Maximisation Theory, and Lancaster's theory. This helped to explain why, “all other things being equal”, farmers in the Upper West Region of Ghana would select a particular farm plan or hypothetical weather index insurance policy from a range of optimum plans and index insurance policy options respectively, given that it offers the greatest utility or satisfaction. A discussion on how the theories relate to the study is given as follows:

- i. **Random Utility Theory (RUT):** RUT acknowledges the inherent randomness in individual choices. Even when presented with seemingly identical options, unobserved factors can influence farmers' preferences for specific weather index insurance policies or a particular farm plan.

This theory accounts for these variations in decision-making behavior (McFadden, 1974).

- ii. **Utility Maximization Theory:** This theory posits that farmers, as rational economic agents, strive to maximize their satisfaction (utility) when selecting an insurance policy. Applied to weather index insurance, risk optimum farm plan, and risk attitude, farmers will carefully evaluate the benefits offered by various policies or farm plan and choose the one that provides the greatest level of security and financial protection in the face of production or weather-related risks.
- iii. **Lancaster's Theory:** This theory goes beyond the insurance policy itself and focuses on the specific features or attributes that it offers. Farmers derive utility from attributes such as premium cost, basis risk, claim payout speed, potential linkages between credit and insurance, and the availability of discounts or subsidies. Farmers will consider these attributes and select the policy that offers the optimal combination for their specific needs and risk tolerance.

By integrating these theoretical perspectives, the study aims to determine the risk optimum farm plan, risk aversion levels, preferences and willingness of farmers to pay for a weather index insurance policy as well as their subscription and subscription intensity of the WII policy. The core assumption is that farmers will choose a farm plan or WII policy that offers the combination of attributes that maximizes their expected utility. This approach sheds light on the features most valued by Ghanaian farmers and ultimately aids in the development of weather index insurance products that are better tailored to their risk management behaviour and preferences.

## **Risk Estimation Techniques for Farm Plan and Risk Attitude of Farmers**

To gain an understanding of the economic behaviour of farmers, it is essential to assess the risk status of individual farmers. It is therefore crucial to understand how farmers respond to risk and their attitude towards risk when designing intervention programmes for or modelling a risk farm plan for them.

Consequently, in order to comprehend their behaviour, it is necessary to measure their risk attitude. The risk behaviour of farmers can be estimated or elicited. There are two basic approaches to measuring the risk attitude or behaviour of farmers: observed economic behaviour and the experimental method. This have been elaborated below.

### **Observed Economic Behaviour**

This approach employs both risk programming models and econometric models to estimate or calibrate the risk decision-making of farmers and their attitude risk.

### **Mathematical and Econometric Approach**

Mathematical and econometric approach are used to estimate risk or risk behaviour. The principle governing these approaches is the comparison of the attitude or behaviour observed by farmers or agricultural producers in relation to their output and input choices to predict behaviours of farmers by incorporating risk into the model (Cheng & Li, 2020). Currently, risk programming model at the farm-level decision analysis is often used rather than econometric models (Hakam, 2021). A number of risk programming models have been used in agriculture and food production analysis, including quadratic risk programming, minimisation of total absolute deviations (MOTAD), Target MOTAD, discrete sequential and chance-constrained programming.

Some decision theorists believe that objectively based risk measures are irrelevant in decision analyses because decision makers subjectively interpret risk (Anderson et al., 1977; Hakam, 2021). These thinkers argue that risk must be assessed subjectively by asking the decision maker for probability (Hakam, 2021). They further noted that risk should be judged subjectively for both positive and normative behavioural outcomes (Cheng & Li, 2020). However, Binswanger (1980) emphasizes the challenges and high costs associated with accurately measuring subjective risk preferences. He argues that for normative (prescriptive) applications, analysts should rely on historical risk data rather than subjective measures. However, in these normative applications, Binswanger (1980) emphasizes the importance of using the most accurate time series data available to create objective risk assessments. The resulting risk measures can then be presented to decision-makers, who can adjust them to incorporate their own personal risk tolerances. Quadratic risk programming, MOTAD and Target MOTAD have been further discussed below.

### **Quadratic Risk Programming**

Quadratic risk programming (QRP) is a mathematical modeling technique used in agricultural economics to analyze farm-level decision making under risk (Hazell & Norton, 1986; Hakam, 2021). It builds upon the Expected Income-Variance (E-V) criterion, which assumes farmers prioritize both the average profitability (expected income) and the associated risk (variance) of their chosen farm plan.

QRP incorporates the concept of risk aversion, where farmers are assumed to prefer plans with lower variance for a given expected income level (Markowitz, 1959). This translates to iso-utility curves that are convex to the

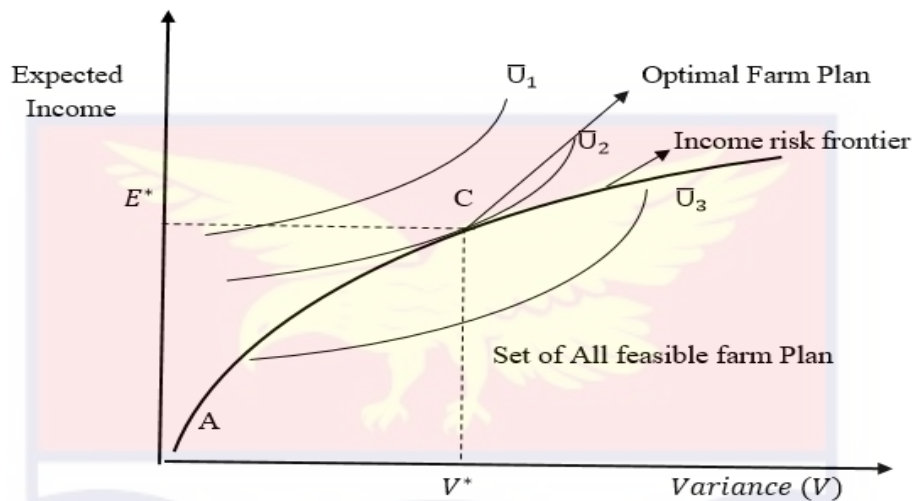
origin, implying a diminishing marginal benefit of increasing income as risk rises (Markowitz, 1959). Furthermore, Freund (1956) suggests that farmers will only accept higher variance if it is accompanied by a more than proportional increase in expected income. Mathematically, this translates to a specific form of the farmer's utility function, typically assumed to be quadratic and concave.

From a rational decision-making perspective, farmers seek a balance between minimizing risk (variance) for a given expected income level and maximizing expected income for a given level of risk tolerance (Hazell & Norton, 1986; Hakam, 2021). QRP helps identify this optimal farm plan by incorporating risk directly into the objective function. QRP models risk explicitly by considering revenue variability within the objective function. It assumes perfect knowledge (certainty) regarding resource endowments and technical parameters (Hazell & Norton, 1986; Kaiser & Messer, 2011).

The model then optimizes the farm plan by minimizing the variance (risk) subject to resource constraints, while simultaneously maximizing the total gross margin (revenue minus variable costs). This is achieved by iteratively increasing the total gross margin and variance until the maximum achievable gross margin is reached under the resource limitations. The solution involves minimizing both covariance and variance (risk) within the set constraints.

From Figure 1, the plan that farmer A would prefer would be different from that of farmer B. However, farmers are risk-averse and would normally choose farm plans with minimum variance (Hakam, 2021). Figure 1.0 shows that farm plans below the income risk curve are feasible but not optimal, and as mentioned above, the optimal plan is the plan generated at the point where

the iso-utility curve is tangent to the income risk curve, which can be seen at point (C). The QRP model solutions do not satisfy the second order stochastic dominance (SSD) test (Kaiser & Messer, 2011).



*Figure 1:* Graphical Determination of the Optimal Farm Plan in the E-V  
**Source:** Adapted from Hakam (2021)

### **Minimisation of Total Absolute Deviation (MOTAD)**

MOTAD is a mathematical technique proposed by Peter Hazell in 1971 as a linearised version of quadratic risk programming models (Kaiser & Messer, 2011). The intuition behind MOTAD was that instead of measuring risk using the nonlinear variance-covariance approach, researchers should use the linear approximation of expected income variability (Feng, 2021). Due to certain shortcomings of the quadratic risk programming model, such as algorithmic problems and lack of computer programming software, it is difficult to run large MP models. Peter Hazell in 1971, then a Ph.D. student in agricultural economics at Cornell University, developed the MOTAD to overcome the shortcomings of the quadratic risk programming model (Kaiser & Messer, 2011).

In measuring risk, MOTAD models use the total absolute deviation (TAD) from expected net returns to represent risk. Hazell (1971) suggested that it is possible to minimise the negative part of the TAD when the expected returns of crop enterprises are the sample means. MOTAD solutions can be derived by first determining the maximum expected income using the conventional LP model. The MOTAD model is then incorporated and the maximum expected income is parameterised as the maximum at different income and risk levels (Hakam, 2021). A major drawback of this model is that the E-V pair generated from its solution does not meet the requirement of second-degree stochastic dominance (Kaiser & Messer, 2011).

#### **Target Minimization of Total Absolute Deviation (Target-MOTAD)**

Target-MOTAD was developed by Tauer (1983) to improve on the shortcomings of MOTAD and the quadratic risk programming model (Hakam, 2021). The solution of Target-MOTAD is efficient because it satisfies the criteria of second-degree stochastic dominance (Kaiser & Messer, 2011). The Target-MOTAD differs from the MOTAD in that it adds a new constraint that sets a target level for the farmer's total revenue. Therefore, any returns below this target are called deviations. The model involves maximising the expected utility of income subject to resource and risk constraints. Target MOTAD has a linear objective and constraint function, so the linear programming algorithm can be used to solve the problems (Tauer, 1983).

#### **Experimental Approach (Risk Aversion Estimation)**

This approach to measuring risk relies on subjective assessments of farmers' risk tolerance. In contrast, the experimental approach utilizes various techniques within applied economics literature to elicit data on growers' risk

aversion and overall risk attitudes. These measures can be derived from several frameworks, including the expected utility framework, responses to Likert-scale questions, safety-first risk preference measures, or prospect theory (Pennings & Garcia, 2013). Sartwelle (2011) observed that this approach can be categorised according to the type of question used, namely Likert scale-based questions, multi-item questions or hypothetical decision responses such as a lottery choice method. These are presented and discussed in more detail below.

### **Direct Method/Multi-Item Questions**

This method employs a straightforward questionnaire to elicit risk behaviour. Questionnaires have been used to obtain individuals' self-reported risk preferences in a variety of circumstances. Respondents are presented with a broad question or a series of questions, after which they are asked to rate themselves on a specified scale. This method posits that each person has a single, constant risk preference that guides their behaviour in all areas of life. This approach cannot be associated with an economic theory or even a utility function. However, they are normally used in conjunction with a lottery-based approach.

### **Lottery Choice Method**

This approach of estimating farmers' risk aversion level comprises multiple price lists (MPL) and equal likely certainty equivalent (ELCE). These methods are the most notable as proposed by Eckel and Grossman (2008) and Holt and Laury (2002). The multiple price list approach is regarded as the gold standard for assessing risk preference in individuals. Nielsen et al. (2013) emphasised the importance of MPL, noting that they enable the estimation of

relevant utility function parameters, are incentive-compatible, and can be designed to control for framing effects. Conversely, the ELCE (equally likely certainty equivalent) method is a commonly employed approach for eliciting the utility function of Von Neumann-Morgenstern.

### **Food Crop Farming Systems in Northern Ghana**

In Ghana, the agricultural landscape can be broadly categorized into four distinct zones, each shaped by unique climatic and weather patterns (Nin-Pratt & McBride, 2014). The southern regions are characterised by high rainfall and fertile soils (with the exception of the Coastal Savanna). These conditions are ideal for a variety of perennial food and cash crops. Plantain, cassava, cocoa, coffee, yam, and cocoyam flourish in these zones (Bellon et al., 2020; Kotu et al., 2017). In contrast, the Northern Savanna experiences significantly lower rainfall (around 1000 mm) and has poorer soils that are often degraded. This zone is dominated by farming systems that center around cereals and legumes, although yam and cassava are also important crops in some areas (Bellon et al., 2020; Kotu et al., 2017). Encompassing roughly 40% of Ghana's total land area and spanning five regions (MoFA, 2017), the Northern Savanna exhibits variations in cropping patterns across these regions.

While the overall farming systems share similarities, specific crop preferences differ among the regions within the Northern Savanna (Ellis, 2016; Kotu et al., 2017). Maize receives the greatest emphasis in the Northern, Savannah, North East, and Upper West regions, with farmers allocating more resources to its cultivation. Millet holds greater significance in the Upper East region, where it is considered a more favorable grain compared to maize. Sorghum is another crucial crop, ranking second in the Upper East and Upper

West regions but fourth in the Northern region (where rice takes its place). Rice cultivation is also important in the Upper East and Northern regions but less prevalent in the Upper West.

Groundnut is the leading legume crop in the Northern and Upper West regions, while cowpea takes precedence in the Upper East. However, market forces can influence these preferences. For instance, the rising price of soybeans has incentivized some farmers to reduce groundnut and maize cultivation in favor of soybeans. Beyond these primary crops, farmers cultivate a variety of other options with economic value, including yam, cassava, sweet potato, tomato, pepper, onion, and mango (Ellis, 2016).

### **Concepts of Risk Optimality and Resource Allocation Pattern**

The concept of risk optimality in agricultural decision-making refers to the balancing point at which a farmer maximizes expected utility by selecting a combination of production strategies that align with their risk preferences and income objectives (Mutua et al., 2020). Rather than focusing solely on profit maximization, risk-optimal decisions consider the trade-off between risk and return, especially in uncertain environments like agriculture (Hill et al., 2013). A farmer with high risk aversion may prefer a production plan with lower but more stable returns, whereas a less risk-averse farmer may choose a strategy that has the potential for higher income but with greater variability (Matsuda et al., 2019).

The idea of a "risk-optimal farm plan" captures this nuance, suggesting that farmers naturally gravitate toward combinations of crops, technologies, and insurance mechanisms that offer the best balance between income and risk exposure given their unique utility functions (Lyer et al., 2019). This concept

is especially relevant in the context of weather index insurance, as it offers a formal mechanism to reduce downside risk, thereby shifting the farmer's optimal decision frontier (Chantarat et al., 2018). Linked closely to this is the concept of resource allocation pattern, which refers to how farmers distribute limited resources such as land, labour, capital, and time across various agricultural and non-agricultural activities to achieve their production and livelihood goals (Ali et al., 2021).

Resource allocation decisions are influenced by numerous factors including risk perception, expected returns, market accessibility, and institutional support (Chantarat et al., 2018). In contexts where climate variability or market instability is high, resource allocation patterns tend to be more conservative, often favouring subsistence crops or diversified portfolios to hedge against income shocks (Shrum & Travis, 2022). However, access to insurance products like WII can alter this allocation pattern by reducing perceived risk, thereby encouraging farmers to invest more heavily in high-return or input-intensive crops (Haile et al., 2020). In this sense, insurance not only functions as a safety net but also as a facilitator of more efficient and productive resource use. Therefore, these concepts form a critical foundation for understanding farmer behaviour in the context of agricultural risk management (Donkor et al., 2021).

Risk optimality helps explain why farmers may not always adopt high-return strategies if they come with increased risk, while resource allocation patterns reflect the practical translation of those preferences into everyday farming decisions. The interaction of these two elements provides insight into

why some farmers adopt weather index insurance readily while others remain hesitant, despite apparent benefits.

### **Crop Mix Enterprise and Risk**

Farmers across Sub-Saharan Africa navigate a complex web of risks that threaten their yields and incomes (Hakam, 2021). In response, many have turned to a time-tested strategy: crop enterprise mix or diversification (Asante et al., 2017). This practice, defined as cultivating multiple crops with available resources, offers a two-fold benefit. It not only mitigates production risks but also promotes dietary diversity within households (Asante et al., 2017). Asravor (2019) highlights the specific challenges faced by farmers in Ghana's Northern Region: yield variation risk and market risk. To buffer themselves from these uncertainties and stabilize production and income, farmers adopt a multi-cropping approach.

Crop enterprise mix essentially functions as an insurance policy, reducing overall risk in agricultural production (Ellis, 2016). However, like any risk-reduction strategy, it comes at a cost – potential forgone returns. The inherent uncertainty associated with agriculture poses a constant challenge for farmers (Maurer, 2014). From unpredictable price fluctuations to variations in yield and financial risks, the agricultural sector faces a multitude of threats. Crop production, the primary focus, is particularly vulnerable to external factors. Weather variations can significantly impact yields, with droughts and floods potentially leading to complete crop failure.

Similar to other risk-mitigation strategies, crop mix enterprise necessitates a trade-off. By spreading resources across multiple crops, farmers may sacrifice some potential revenue they could have earned by specialising in

a single, high-yielding crop (Ellis, 2016). The key to effective risk reduction through crop mix enterprise or crop diversification lies in the correlation between chosen crops. Markowitz (1959) emphasizes that crops with returns that are not perfectly correlated (meaning a price increase in one crop does not automatically lead to price increases in others) contribute to a more risk-averse portfolio. As farmers expand their crop portfolio, their overall exposure to risk is reduced due to the combined effect of price and yield fluctuations diminishing at a decreasing rate (Michael & Margot, 2000).

Hakam (2021) also suggests that the inherent risk profile of individual crops within the portfolio can influence the overall risk reduction. Drawing from portfolio theory, it is can understand that incorporating both high-risk and low-risk crops into the existing cropping system demonstrably reduces risk. The extent of this risk reduction depends on several factors: the number and risk profiles of the crops included, the proportion of each crop within the portfolio, and the degree of correlation between the chosen crops. By strategically selecting crops with low correlation in returns, farmers can achieve a portfolio risk that is even lower than the individual risk associated with any single crop (Markowitz, 1959; Michael & Margot, 2000; Hakam, 2021).

### **Balancing Risk and Income Returns in Crop Mix Enterprise Selection**

Farmers naturally strive to maximize their well-being by choosing productive activities that align with their resources and available opportunities (Ogurtsov et al., 2008). However, given the inherent risks in agriculture, strategies to mitigate these uncertainties can be highly beneficial. This means farmers prioritize not only achieving high average returns but also minimizing

the variability (standard deviation) of their future net income. Risk-averse farmers can significantly reduce risk by incorporating multiple land-use options into their operations, particularly those with returns that fluctuate independently (low correlation). In simpler terms, when profits from one crop decline, another may experience unexpected gains, thereby buffering the impact of economic fluctuations (Knoke et al., 2020).

Crop mix or diversification involves cultivating various crops on separate, manageably sized plots of land, facilitating the potential for agricultural intensification through mechanization. A well-established method for identifying the optimal crop mix is the mean-variance approach. This approach outlines strategies for allocating resources among different crops to maximize economic returns for a given level of risk tolerance. By carefully selecting the proportion of resources dedicated to each crop, farmers can achieve a desired balance between risk and return.

### **Weather Index-Based Insurance**

Weather index insurance has its roots in weather derivative markets, where corporations managed weather-related risks (Smith & Glauber, 2012). The pioneering work of Halcrow (1948) and Dandekar (1977) established the foundation for applying these principles to the agricultural sector, particularly in developing countries. Weather index insurance provides a solution to the challenge of asymmetric information in agricultural insurance markets. By basing payouts on objective weather data, it avoids issues like adverse selection and moral hazard, which can plague traditional systems that rely on individual farm assessments (Tadesse et al., 2015). Furthermore, weather index insurance

reduces the costs associated with verifying individual farm losses (Sande, 2017).

Weather index insurance focuses on a specific weather parameter, such as rainfall, which is measured over a defined period at a designated weather station (Sande, 2017). This data is used in conjunction with historical information to establish thresholds and payout limits. The insurance can be designed to protect against extreme weather events, such as excessive or insufficient rainfall (Khandker et al., 2010). Payouts are triggered when the realised value of the chosen weather variable falls outside the predetermined thresholds. The indemnity amount is then calculated based on a pre-agreed sum insured per unit deviation from the index (Wang et al., 2022). This approach provides a transparent, objective, and efficient system for managing agricultural risks.

### **Overview of Weather Index-Based Insurance in Ghana**

In Ghana, the agricultural sector is exposed to climatic risks such as weather shocks that create unfavorable conditions for farmers, making it challenging for them to achieve optimal yield and profit (Sande, 2017). In order to address the climatic challenges facing the agricultural sector in Ghana, a project was initiated in 2009 by German International Cooperation (GTC) and Innovative Insurance for Adaptation to Climate Change (Feed the Future, 2012; Ellis, 2016). The objective of the project was to develop an insurance product that would be of benefit to farmers and be economically viable (GAIP, 2013).

The weather index insurance product is currently being operated by GAIP in the three northern regions of Ghana: Upper West, Upper East and Northern. As noted by Karlan et al. (2013), the initial coverage of the weather

index insurance was limited to maize. However, this has since been expanded to include rice, soya bean, sorghum and millet. The insurance scheme is based on automated weather stations that record climatic data on rainfall, temperature, wind and relative humidity. Consequently, data on rainfall amount are utilised to ascertain the occurrence on the farm and to determine claim payments. Therefore, if the recorded rainfall falls below a specified level, it is indicative of an expected crop loss on the field, resulting in payouts.

### **Factors accounting for Low Participation in Weather Index Insurance**

Weather Index Insurance (WII) has emerged as a promising tool for managing agricultural risks associated with climate variability (Mude et al., 2015). However, its uptake remains disappointingly low among smallholder farmers across many developing countries (Greatrex et al., 2015). Several interrelated factors contribute to this low participation. One of the most frequently cited barriers is the limited awareness and understanding of WII among farmers. In many rural contexts, the concept of insurance particularly index-based insurance is not well understood (Carter et al., 2017). For example, in Ghana, over 64% of uninsured farmers reported that their reason for not subscribing to WII was simply a lack of knowledge about how the scheme works (Donkor et al., 2021). This challenge is echoed in Kenya, where inadequate information dissemination and weak extension services have led to mistrust and confusion regarding the benefits and mechanics of WII products (Chantararat et al., 2018). Similarly, studies in Malawi have highlighted that farmers often perceive insurance premiums as investments expecting returns, leading to dissatisfaction when no payouts occur (IntechOpen, 2019).

Another critical issue is the problem of basis risk, which occurs when the insurance payout does not align with the actual losses experienced by the farmer. This mismatch often arises from the use of broad weather indices that may not capture localized climate events (Okoffo et al., 2023). Studies from Malawi and Kenya have shown that when farmers suffer crop losses but receive no compensation, their trust in the insurance system erodes significantly (Karlan et al., 2014). Such experiences discourage both initial uptake and continued participation in WII programs (Carter et al., 2017). In Kenya, farmers have expressed a preference for insurance contracts that offer transparent communication of weather data, as this can increase their confidence in the system (Mutua et al., 2020).

Financial constraints also play a central role in limiting participation (Matsuda et al., 2019). Many smallholder farmers operate under tight budget constraints and view the insurance premium as an additional, often unaffordable expense (Okoffo et al., 2023). For instance, in northern Ghana, farmers cited high premiums as a key reason for their unwillingness to subscribe, even when they understood the potential benefits (Donkor et al., 2017). Similarly, in Kenya, the cost of premiums has been identified as a significant barrier, with many farmers unable to afford the insurance (Agricultural and Food Security, 2018). Studies in Kenya have also found that short rain seasons and household size influence participation, with larger households less likely to participate (Isaboke, 2020).

Gender disparities further compound the problem of low participation (Cole et al., 2013). Women farmers, in particular, face numerous socio-economic challenges that hinder their ability to engage with insurance schemes

(Belissa et al., 2019). These include lower access to credit, limited land ownership, and lower levels of education and financial literacy (Ali et al., 2020). In Ghana, it was observed that women were significantly less likely to participate in WII programs due to these constraints (Donkor et al., 2021). Research has shown that women often prefer standalone insurance products rather than bundled insurance-savings schemes, indicating the need for gender-sensitive product designs (Akter et al., 2016).

Institutional and infrastructural challenges also undermine the effectiveness and appeal of WII (Takahashi et al., 2020). Poor access to accurate and localized weather data, inadequate regulatory frameworks, and weak delivery channels hinder both the design and implementation of effective index insurance schemes (Carter et al., 2017). As noted by Hill et al. (2014), the lack of institutional support contributes to farmer skepticism, particularly when the product does not meet expectations or is perceived as externally imposed. In Kenya, factors such as the distance to weather stations and the availability of agro-veterinary services have been found to influence participation negatively (Isaboke, 2020).

Further, access to technology influences participation in WII schemes. Mobile phones, internet connectivity, and digital literacy are essential for receiving weather information, making payments, and accessing claims (Carter et al., 2017). In areas where these technologies are limited, farmers face greater barriers to engaging with WII (Isaboke, 2020). A study in Kenya revealed that farmers who owned mobile phones and lived near weather stations were significantly more likely to purchase index insurance (Mutua et al., 2020). In summary, low participation in Weather Index Insurance is driven by a

combination of informational, economic, social, and institutional factors. These barriers suggest that increasing uptake will require not only better product design but also robust educational campaigns, targeted subsidies, inclusive policies, and strong institutional frameworks to build trust and accessibility.

### **Impact of Climate Variability on Yield, Productivity, and Farmer's Income**

Climate change, characterised by increasingly erratic weather patterns, poses a significant threat to global food security (IPCC, 2021). At the heart of this challenge is the impact of climate variability on agricultural systems. Fluctuations in temperature and precipitation directly affect crop yields, livestock productivity, and ultimately the livelihoods of millions of farmers worldwide (FAO, 2019). The empirical literature consistently underscores the profound impact of climate variability on agricultural yields, productivity and, ultimately, farmers' incomes. Studies across different geographical contexts converge on the notion that variations in temperature and rainfall patterns have a significant impact on agricultural outcomes.

Adu-Boahen, Dadson, and Halidu (2019) highlight the direct link between erratic rainfall patterns and reduced food crop productivity in Ghana. The study's findings underscore how climate variability, manifested in increased dry spells, directly translates into lower yields and, consequently, potential income losses for farmers. Similarly, Asare-Nuamah (2021) shows that climate variability has a significant impact on subsistence agriculture, leading to reduced yields and subsequent food insecurity, a condition often correlated with lower household incomes.

Kyaw et al. (2023) provide detailed insights into the crop-specific impacts of climate variability. Their study shows that higher temperatures had a negative effect on longan yield, but a positive effect on maize production. This highlights the complex and often contradictory effects of climate change on different crops. Such differential impacts have important implications for farmers' income diversification and risk management strategies (Shumetie & Yismaw, 2017). Ochieng, Kirimi, and Mathenge (2016) further emphasise the crop-specific nature of climate change impacts. Their research in Kenya shows that while temperature has a negative impact on crop and maize yields, it has a positive impact on tea production. This finding highlights the importance of considering regional and crop-specific contexts when assessing the overall impact of climate variability on agricultural outcomes.

Beyond the direct impact on crop production, climate variability also affects farmers' adaptive capacity. Etwire (2020) found that Ghanaian farmers are responding to climate change by switching farm types to more resilient options. However, the transition to less profitable systems can have negative implications for overall agricultural output. Demem (2023) further underscored the importance of adaptive strategies, highlighting the various approaches employed by Ethiopian farmers to mitigate climate change impacts. These studies emphasize the need for targeted support to help farmers adapt to changing climatic conditions. Understanding these nuances is crucial for developing effective adaptation strategies and policies to support farmers in mitigating the negative consequences of climate change. In conclusion, the empirical evidence overwhelmingly supports the notion that climate variability is a major determinant of agricultural yield, productivity, and farmer income.

The impacts are often complex, with varying effects across different regions, crops, and socioeconomic contexts. Understanding these nuances is crucial for developing effective adaptation strategies and policies to support farmers in mitigating the negative consequences of climate change.

### **Empirical Literature on Farmers Attitude towards Risk amidst Climate Variability and Change.**

Climate variability, characterised by fluctuations in temperature and precipitation patterns over time, has emerged as a critical challenge for many regions, particularly in sub-Saharan Africa (Ragatoa et al. 2018). Upper West Region (UWR) of Ghana, like many regions in sub-Saharan Africa, is heavily reliant on rain-fed agriculture (Kusakari et al., 2014). This makes it particularly vulnerable to the vagaries of climate variability and change (Kajtar et al., 2021). Studies such as Kusakari et al. (2014) and Subaar et al. (2018), have consistently shown that rainfall patterns in the region are becoming increasingly erratic, with prolonged dry spells, intense rainfall events, and overall declining trends in precipitation. Upper West Region is characterized by a bimodal rainfall pattern, with rainy seasons occurring from April to June and July to September. However, as highlighted by Ndamani and Watanabe (2014), there has been a growing incidence of rainfall anomalies, leading to frequent droughts in the Wa and Lawra districts. This irregularity in rainfall has been corroborated by other studies, which have documented decreasing trends in rainfall amounts for several months of the year (Issahaku et al., 2016; Quaye-Ballard et al., 2020).

Beyond the temporal variability, spatial patterns of rainfall are also complex (Klutse et al., 2020). Quaye-Ballard et al. (2020) found significant

spatial heterogeneity in rainfall across the Upper East Region, with the northeastern part exhibiting the highest variability. This spatial inconsistency underscores the challenges of developing region-wide agricultural strategies and highlights the need for localized adaptation measures. Temperature trends in the Upper West Region have also been on the rise, as evidenced by Issahaku et al. (2016) and Subaar et al. (2018). Increasing temperatures exacerbate the impacts of rainfall variability, leading to higher rates of evapotranspiration, increased water stress for crops, and heightened risk of heat-related stresses for both humans and livestock (Nyantakyi-Frimpong & Kerr, 2014). Rainfall variability and temperature patterns have profound implications for the agricultural sector in the region (Abbam et al. 2018). The negative correlation between rainfall and crop production, as reported by Ndamani and Watanabe (2014), underscores the vulnerability of farmers to rainfall variability.

As noted by Oduro et al. (2022) the erratic nature of rainfall makes it difficult for farmers to plan and implement appropriate agricultural practices, increasing the risk of crop failure and food insecurity. Moreover, the increasing frequency and intensity of extreme weather events, such as droughts and floods, further exacerbate the challenges faced by farmers (Boansi et al. 2017). Amoah et al. (2016) asserted that these extreme climate events can lead to significant crop losses, livestock deaths, and erosion of livelihoods. Given the high levels of climate variability and the consequent agricultural risks, farmers have developed various coping and adaptation strategies (Kumeh et al., 2022).

However, these strategies are often characterised by a high degree of uncertainty and risk. For instance, early planting to capitalize on early rains can be a risky strategy if subsequent dry spells occur. Similarly, relying on drought-

resistant crop varieties may not be sufficient if rainfall patterns become increasingly unpredictable (Dankwa et al., 2021). Qaisrani et al. (2021) asserted that the decision-making processes of farmers are influenced by a complex interplay of factors, including access to information, financial resources, social networks, and perceptions of climate change. Farmers with limited access to weather forecasts, extension services, and credit may be more vulnerable to climate shocks.

Upper West Region is experiencing significant climate variability, with implications for the livelihoods of its predominantly agrarian population (Klutse et al., 2020). Understanding the complex interactions between climate, agriculture, and farmer behavior is crucial for developing effective adaptation strategies. To understand these complex relationships, researchers have employed a range of statistical methods. For example, Quaye-Ballard et al. (2020) utilized cumulative residual analysis, Mann-Kendall, Sen's slope, wavelet transform, and principal component analysis to examine rainfall variability. Ndamani and Watanabe (2014) employed the coefficient of variation and precipitation concentration index to analyze rainfall characteristics. These methodologies have been instrumental in identifying trends, patterns, and the magnitude of climate variability.

Studies on farmer risk aversion amidst climate variability consistently reveal a predominant preference for risk mitigation strategies. A significant proportion of farmer's exhibit risk-averse behavior, as evidenced by a tendency towards full or partial insurance coverage (Janurati et al., 2019; Vassalos and Li, 2016). However, the extent of risk aversion varies across regions, crops, and socioeconomic contexts. Several studies such as (Janurati et al., 2019;

Senapati, 2020; Ngarava et al., 2018) has employed diverse methodologies to measure risk aversion, including multiple price lists, Likert scales, equal certainty equivalence, and experimental gambling. Also, factors such as sample characteristics, geographical location, and specific insurance program designs influence farmers' insurance preferences (Senapati, 2020).

For instance, Janurati et al. (2019) found a stronger inclination towards full insurance compared to Vassalos and Li (2016), potentially due to differences in the study contexts. Furthermore, Jirgi et al. (2016) also identified the impact of socio-demographic factors on risk attitudes. The result indicated that household size, off-farm income, and farming practices can influence farmers' risk preferences. Additionally, the type of crop cultivated can shape risk perceptions, with intercropping farmers often exhibiting higher risk aversion compared to mono-cropping farmers (Ngarava et al., 2018). While the majority of studies indicate risk-averse behavior among farmers, exceptions exist. Akinola (2014) found a surprising prevalence of risk-seeking behavior among poultry farmers in Nigeria, highlighting the potential influence of socio-economic factors and specific agricultural contexts.

### **Risk Optimality and Resource Allocation Pattern**

Farmers are confronted with a number of risks, including climatic, production and market risks, which can have a detrimental impact on their yield and investment in crop and livestock production (Mesfin, 2014). In terms of crop production, the majority of these farmers employ a strategy of diversifying their crops in order to mitigate this risk (Adewumi et al., 2021). In the northern part of Ghana, specifically the Upper West Region of Ghana, most farmers are faced with limited resources (Larkai, 2019). They rely on their experience,

intuition and often compare with neighbors in allocating these limited resources as well as choosing the best crops to produce so as to achieve optimality (Hakam, 2021). However, this does not guarantee optimal results and often leads to losses. It is therefore essential to develop a farm plan that demonstrates how resources can be allocated in order to achieve the greatest possible utility and returns. The Linear Programming model is an effective solution for addressing these complexities (Koufie, 2020).

Empirical studies on LP models, such as those by Antwi (2016), Drafor et al. (2013), Larkai (2019) and Koufie (2020), have typically employed conventional linear programming (CLP), which assumes that prices and resources used in building the model are mere estimates that can change. Furthermore, the CLP ignores the risk component of agriculture. The conventional linear programming model assumes that the individual utility function is linear, which implies that farmers are risk-averse. However, empirical evidence such as (Dadzie & Acquah, 2012; Kouame, 2017; Mitra & Sharmin, 2019) suggests that farmers are in fact more risk-averse and that their utility function follows the quadratic utility form. It is therefore appropriate to use a risk programming model to determine the optimal resource allocation for farmers. There are several risk programming models, including the quadratic risk programming model, MOTAD and Target MOTAD. The current study used the linear form of the quadratic programming model, known as Target MOTAD.

Studies consistently demonstrate the superiority of optimized farm plans over traditional practices in terms of income and resource efficiency. Udo et al. (2015) and Adewumi et al. (2021) highlight the potential for substantial

income gains through the adoption of normative or risk-efficient farm plans. However, a trade-off between profit maximization and risk minimization often emerges, as exemplified by Udo et al. (2015) and Osaki and Batalha (2014). The T-MOTAD model has proven to be a valuable tool for addressing this trade-off. By incorporating risk considerations into the optimization process, researchers have identified farm plans that balance profitability with risk reduction. Studies by Boustani and Mohammadi (2010), Sayed (2021), Kehkha et al. (2015), and Taverna et al. (2019) underscore the effectiveness of T-MOTAD in generating risk-efficient cropping patterns.

Several factors influence the optimal farm plan. Capital consistently emerges as a primary limiting resource, emphasizing the need for strategies to increase access to financial resources (Udo et al., 2015; Adewumi et al., 2021). Additionally, crop and livestock prices, as well as government policies, significantly impact farm decisions (Taverna et al., 2019). Climate variability is another critical factor. Lu et al. (2020) demonstrates the sensitivity of crop yields to temperature changes, highlighting the need for climate-resilient farm plans.

Komarek et al. (2015) also emphasize the importance of considering both price and climate variability in crop-livestock systems. The findings of these studies offer valuable insights for smallholder farmers and policymakers. By adopting optimized farm plans, farmers can potentially increase their incomes, improve resource efficiency, and mitigate risks. However, successful implementation requires access to information, credit, and extension services. Policymakers can play a crucial role by promoting the use of optimization tools, investing in agricultural research, and developing policies that support risk

management and climate adaptation. Additionally, fostering farmer organizations and cooperatives can facilitate knowledge sharing and resource mobilization.

### **Farmer's Preferences and their Willingness to Pay for Weather Insurance Index**

The concept of farmer's preferences for a particular product has been well-researched with different scopes. Some studies have measured farmers preferences using different analytical tool by capturing the most preferred products attribute and the values the farmers' place on these attributes using Kendall's coefficient of concordance, garret ranking formula etc and others have also looked at it from an econometric point of view using models such as Conditional logit model, Mixed logit model, Multinomial logit model etc.

Whiles others have combined both by first looking at the most preferred attributes by the farmers concerning a particular product (ie Crop insurance, Weather Index insurance, rice product and rainfall insurance) and after that looked at it from an econometric view point using econometric models to test the significant of these attributes to the preferences made by the farmers. Also, to estimate willingness to pay values, most studies have used econometric models such as the mixed logit model, multinomial logit model, Random parameter model, and the conditional logit model employing the Preference space approach or the Willing to pay space approach.

Several studies have explored consumer preferences for specific agricultural products. Ehiakpor et al. (2017) found that Ghanaian consumers prioritize visual appeal, packaging quality, and product purity when selecting local rice. Owusu and Dekagbey (2020) identified price as a primary

determinant of consumer choice for edible mushrooms, while Owusu (2019) highlighted gender-based differences in preferences for biofortified foods. These findings underscore the importance of tailoring product attributes and marketing strategies to specific consumer segments. Studies consistently show that factors like income, education, and farm size influence farmers' decisions to purchase insurance. For instance, Akter et al. (2016) found gender disparities in insurance preferences among Bangladeshi farmers, with women exhibiting higher insurance aversion. Farmers prioritize insurance attributes such as claim payouts, subsidized premiums, access to extension services, and clear information about compensation packages (Ali et al., 2020).

Mishra and Joshi (2018) noted the importance of understanding these preferences to design effective insurance programs. Their study highlights the role of information in shaping farmer preferences. Ali et al. (2020) asserted that access to extension services, weather information, and media can positively influence WTP for insurance. Therefore, there is the need to integrate insurance with other initiatives to enhance its appeal.

The current study employed the Kendall's coefficient of concordance to examine farmers' preferred weather attributes and used an advanced discrete choice experiment to evaluate farmers' preferences and willingness to pay estimate for weather index insurance policy. Thus, the study employed the Mixed logit model as an advancement to the multinomial logit model to generate willingness to pay (WTP) estimates using willingness to pay space (WS) method. By combining these advanced techniques, this study aims to provide a more nuanced understanding of farmer preferences for WII attributes and their corresponding WTP, addressing the limitations identified in prior

research. This contribute valuable insights for designing WII programs that are more targeted, relevant, and appealing to smallholder farmers.

### **Influence of Risk Aversion Levels and Risk Optimum Income on Subscription and Subscription Intensity of Weather Index Insurance**

Farmers' decisions to adopt weather index insurance (WII) are not solely shaped by product characteristics or external shocks but are significantly influenced by underlying risk preferences and income-related considerations. While the literature has long acknowledged the socio-economic determinants of WII adoption, recent empirical studies have expanded this focus to investigate how varying degrees of risk aversion and the concept of risk-optimal income affect both the decision to subscribe and the intensity of subscription to insurance products. These dimensions are crucial for understanding not just whether farmers participate in WII schemes, but also the extent to which they engage with them.

A consistent theme in the literature is the strong linkage between risk aversion and WII uptake. Hill et al. (2013) argue that traditional models of technology adoption can inform WII program design when modified to include farmers' risk tolerance, particularly through the lens of a "risk-optimal farm plan." This approach highlights how insurance design must be sensitive to the risk profiles of target farmers. Supporting this, Lyer et al. (2019) and Fonta et al. (2018) find that both farm vulnerability to climate events and the farmer's own risk aversion jointly influence the demand for WII. Shrum and Travis (2022) provide further nuance by showing that while risk-averse farmers are more likely to adopt WII, the insurance does not necessarily encourage greater risk-taking in their farming practices. This suggests a complex feedback loop

where risk-averse individuals adopt WII as a protective measure, but the availability of insurance does not substantially alter their conservative behavior.

Methodologically, researchers have employed a range of econometric tools to analyze both the decision to adopt WII and the intensity of adoption.

Johansson and Djehiche (2014) evaluated several count data models and determined that the Negative Binomial Hurdle model provided the best fit for analyzing both adoption and intensity. Similarly, Addey et al. (2021), focusing on rice farmers, compared two double-hurdle models to address overdispersion and non-normal residuals in their data. Their results indicated that the complementary log-log truncated Poisson model was superior, especially in capturing nuanced variations in subscription intensity. The careful selection of statistical models based on data characteristics such as the presence of excess zeros or overdispersion has emerged as a crucial factor in accurately analyzing WII adoption, as emphasized by Workie and Azene (2021) and Sarul and Sahin (2015).

The interplay between socio-economic factors and risk preferences is also central to the literature. Studies by Lichtenberg and Iglesias (2022) and Ali et al. (2021) show that risk and ambiguity aversion significantly shape willingness to pay (WTP) for crop insurance, with demographic variables such as age, income, gender, and education amplifying these effects. Similarly, Wang et al. (2018) and Jin et al. (2016) find that risk aversion positively influences WTP and participation in WII, underscoring the need for tailored premium pricing that reflects farmers' psychological and economic constraints. Notably, Haile et al. (2020) found that farmers purchasing WII in Ethiopia were

less risk-averse and more inclined to engage in risky farming behaviors after insurance adoption, suggesting that WII can, under certain conditions, incentivize bolder decision-making.

Beyond individual behavior, the adoption of WII is influenced by contextual and farm-level factors. For example, Mthethwa et al. (2022), using a probit hurdle model, found that household income, size, and education level significantly influenced both the decision to adopt climate-smart agriculture practices and the intensity of their adoption, which bears conceptual similarities to WII engagement. Nyarindo (2021), applying Cragg's Double Hurdle model in Kenya, revealed that while variables such as land size, household size, and income positively affected the decision to participate in WII, they had mixed or even negative effects on the extent of participation. These findings indicate that the determinants of initial adoption may differ significantly from those influencing adoption intensity, highlighting the need for policies that address both dimensions independently.

Further, the role of prior experience, market conditions, and policy design emerges as a significant determinant of WII subscription. Garrido and Zilberman (2017) and Sibiko (2017) suggest that exposure to past insurance products and positive perceptions of insurance outcomes can increase adoption rates. Kagraoka (2015), using the negative binomial hurdle model, confirms that demographic factors such as age, gender, and time since initial policy exposure also shape subscription behavior. These insights reinforce the idea that WII adoption is not a one-time decision but part of a broader, dynamic process influenced by individual learning, risk experiences, and institutional trust. The literature reveals that the adoption and intensity of weather index

insurance are influenced by a complex set of interrelated factors, particularly farmers' levels of risk aversion and perceptions of optimal income. Advanced econometric models such as hurdle and zero-inflated models have been instrumental in disentangling these effects, especially in the presence of non-normal and zero-inflated data.

Moreover, socio-economic variables, prior experience, and behavioral traits interact in multifaceted ways to shape both the willingness to adopt and the level of engagement with WII. Understanding these dynamics is crucial for the design of targeted, effective insurance programs that can enhance farmers' resilience in the face of climate risks. The literature review confirms several established relationships between factors like farm income, socio-economic characteristics, and farmer decisions regarding weather index insurance (WII). These studies identify similar key determinants, highlighting the multifaceted nature of WII adoption. However, a crucial gap exists in the current research. Prior studies have not explored the potential influence of risk-optimal income and risk aversion levels on WII subscription and intensity. This is a key novelty of the present study. Additionally, no prior research has investigated the concept of a risk-optimal farm plan as a potential support plan alongside WII. By examining these factors, this study offers a more comprehensive understanding of WII subscription and proposes an innovative approach to enhance its effectiveness.

### **Conceptual Framework**

In the context of agricultural activities, the impact of climatic conditions cannot be underestimated. Fluctuations in climatic conditions, which are often instantaneous and difficult to predict, especially in most developing countries

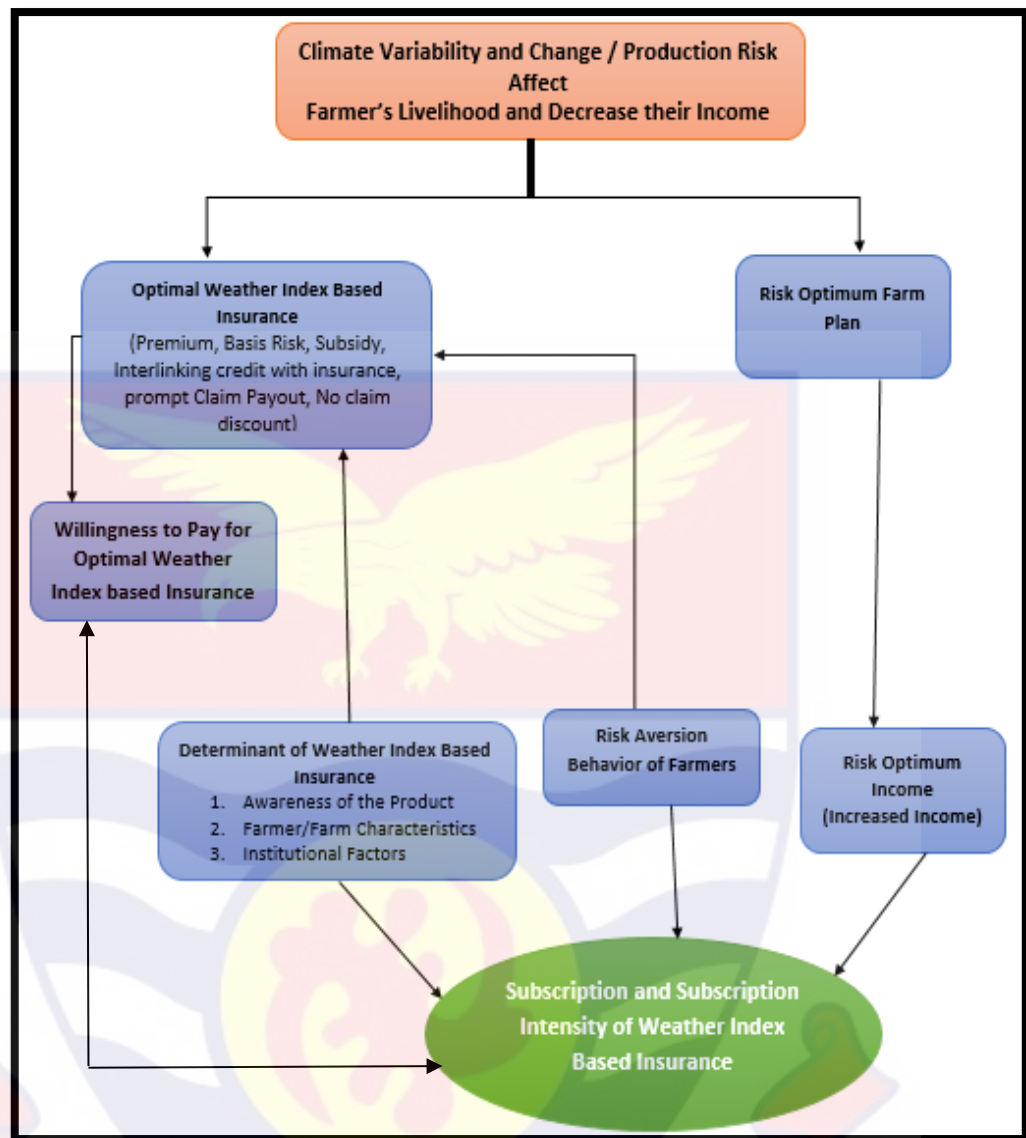
pose a significant threat and risk to farmers, investors, and stakeholders at large (Kouame, 2017). The adverse effects of climate variability and change, along with production risks, have a substantial negative impact on farmers' incomes and livelihoods (Mitra & Sharmin, 2019). Therefore, there is a persistent need to establish structures that serve as resilient mechanisms and safeguards to mitigate the risks prevalent in the agricultural sector.

In light of this, there is a need for an optimal weather index insurance policy that aligns with farmers' preferences, as well as a risk-optimal farm plan. Such a plan should aim to increase farmers' incomes and serve as a complementary support system to the optimal weather index insurance in the face of climate variability and change. This conceptualization is supported by the utility maximization theory and random utility theory, which postulate that farmers, as rational consumers, will choose a particular weather insurance policy and a risk-optimal farm plan that they perceive to deliver the highest level of satisfaction and income. Consequently, this approach helps to address the issues of climate and production risks faced by farmers.

The optimal weather index insurance encompasses attributes such as premium, basis risk, subsidy, interlinking credit to insurance, prompt payment of claims, and no-claims discount all of which are valued by farmers. This aligns with Lancaster's theory, which asserts that a consumer (in this case, the farmer) is drawn to a product (such as a weather index insurance product) not necessarily because of its name, but due to the attributes or characteristics it embodies. Thus, the optimal preferred weather index-based insurance product directly influences the farmer's willingness to pay. However, the preference for an optimal weather index insurance policy is further influenced by several

factors including product awareness, farmer and farm characteristics, institutional factors, and farmer risk aversion. These determinants, combined with risk-optimal income (i.e., increased income), shape farmers' decisions to either subscribe or not subscribe to weather index insurance, as well as the intensity of their subscription.

Given that both subscription and subscription intensity of weather index insurance are market behaviors, this study adopts them as proxies for farmers' willingness to pay. While the overarching research focus remains on willingness to pay, as indicated in the title of the study, both willingness to pay and subscription behavior were measured independently. However, for the purpose of empirical analysis, subscription and subscription intensity were used as the dependent variables, as they reflect actual adoption decisions and observable behavior. This approach reflects the understanding that subscription decisions are influenced by willingness to pay, while also serving as practical indicators of it. In the conceptual framework (Figure 2), this relationship is represented with a two-way linkage, acknowledging that willingness to pay informs subscription behavior, and subscription, in turn, serves as an empirical representation of willingness to pay.



**Figure 2:** Flow Chart of Weather Insurance Policy and Risk Optimum plan  
**Source:** Author's Construct, 2024

### Chapter Summary

The study chapter reviewed relevant literature on food crop farming systems in Ghana, crop mix enterprise and risk, balancing, risk and return in crop mix enterprise selection, weather index insurance, overview of weather index-based insurance in Ghana, risk estimation techniques for farm plan and risk attitude of farmers and theories such as random utility theory, utility maximization theory, and Lancaster theory that underpinned the study. The study reviewed empirical literature on risk attitude, preferences and willingness

to pay for weather index insurance, risk optimum farm plan as well as the factors (risk optimality, risk aversion levels, socio-economic characteristic) and its influence on farmer's subscription and subscription intensity of the weather index insurance policy.



## CHAPTER THREE

### RESEARCH METHODS

This chapter outlines the methodological approach employed to investigate risk aversion levels, risk optimality, and farmers' willingness to pay for weather index insurance in Ghana's Upper West Region. The structure of the methods section is as follows: research philosophy, research design, study area, population, sampling procedure, data collection instruments, data collection procedures, data processing, and analysis.

#### **Research Philosophy**

This study adopts the positivist research philosophy as it aligns with the nature and objectives of the research, which centers on quantifying farmers' willingness to pay for weather index insurance, assessing risk aversion levels, and determining risk-optimal decisions. These are inherently measurable constructs that require a structured and empirical approach. By adopting a positivist stance, the study treats farmer behaviour, risk attitudes, and insurance preferences as objective realities that can be observed, measured, and analysed statistically without researcher bias or subjective interpretation. Moreover, the key variables in this study which are willingness to pay, subscription behaviour, subscription intensity, risk optimality and risk aversion are quantifiable and lend themselves to hypothesis testing and model-based analysis. A positivist philosophy supports the use of econometric and mathematical models and statistical techniques, which are central to analysing relationships among these variables. This also allows the researcher to generalize findings from the sample to a broader population of farmers, an important goal of this study given the policy relevance of designing effective weather index insurance products.

This study seeks to establish cause-and-effect relationships between socio-economic and institutional factors and farmers' subscription decisions and willingness to pay. The positivist paradigm is well-suited to this purpose because it supports deductive reasoning and the testing of predetermined hypotheses using objective data. By applying this approach, the study ensures the reliability, validity, and replicability of its findings, which are critical in policy-oriented research aimed at reducing agricultural risk and improving farmer welfare. Therefore, the adoption of the positivist philosophy is not only appropriate but essential for achieving the aims of this study. It ensures that the research is rigorous, transparent, and based on observable evidence, which is particularly important in assessing economic behaviours related to insurance uptake and risk management under conditions of climate uncertainty.

### **Research Design**

A research design is a technique or approach for carrying out research in order to answer specific, testable research questions (Pandey, 2021). Depending on the objectives of the study, the study adopted quantitative research design and followed the positivist ideologies. The quantitative research approach was suitable for the study because it encompasses the application of mathematical and econometric models and follows procedures to test and verify the quantitative relationship between parameters or quantitatively measured variables. Also, the quantitative survey design was used because it allows the study to generalize the findings over the target population.

The study employed a cross-sectional design, utilizing data from 450 farmers to examine the current state of weather index insurance adoption and

related factors within the study area. Drawing upon previous research (Udo et al., 2015; Elis, 2016; Boateng-Gyambiby, 2019), the study aimed to describe the phenomenon and explore the relationship between farmers' risk aversion, optimal income levels, and their decisions regarding weather index insurance subscription and subscription intensity.

### **Study Area**

The Upper West Region of Ghana served as the chosen location for this research due to its significance in the country's food production and its concentration of food crop farmers (FOSTAT, 2018). This region also holds the distinction of being the birthplace of advocacy and pilot programs for weather index insurance (Hakeem et al., 2019; Sibiko, 2017). The Upper West Region borders Burkina Faso to the north and west, neighboring Ghana's Upper East and Northern Regions to the east, and sharing a southern border with the Northern Region (GSS, 2017). Its geographical coordinates lie between 9°35'N and 11°N latitude and 1°25'W and 2°50'W longitude (MoFA, 2015). According to GSS (2021), the population of Upper West Region is estimated to be about 901,502, with females constituting a slight majority (51.6%).

Geologically, the Upper West Region is part of Ghana's northwestern highlands (MOFA, 2017). The climate is characterized by a single, concentrated rainy season and a lengthy dry period spanning from October to April (MoFA 2015; Ellis, 2016). The region can be further divided into two agro-ecological zones based on rainfall patterns: the Guinea savannah zone in the south and the Sudan savannah zone encompassing the north and northeast (MoFA, 2017). A significant portion (roughly 70% or 12,933.2 square

kilometers) of the region's total land area of 18,476 square kilometers is classified as arable (GSS, 2017).

Agriculture forms the backbone of the Upper West Region's economy, with about 80% of the working population directly or indirectly involved in agricultural production and processing (MoFA, 2015). Other economic activities include trade, weaving with traditional textiles, basketry, some fishing, and, more recently, a growing mining sector (MoFA, 2017). The primary crops cultivated in the region are maize, millet, sorghum, groundnuts, and vegetables (MoFA, 2015). A map depicting the Upper West Region and the two districts chosen for the study is illustrated in Figure 3. Figure 3 below shows the map of Upper West Region and the two (2) districts selected for study.

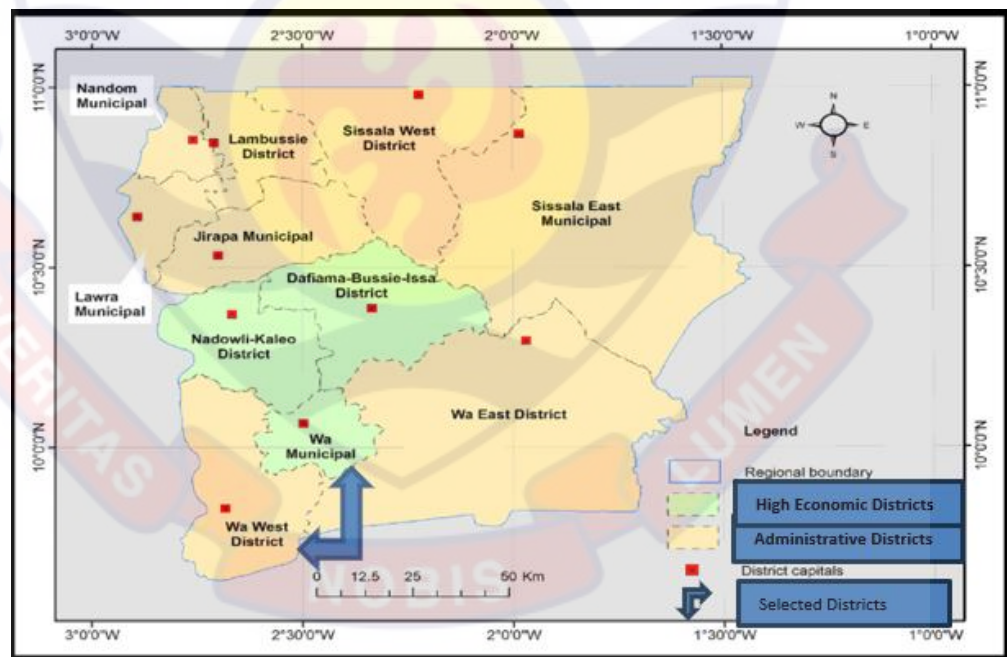


Figure 3: Map of the Upper West Region of Ghana

Source: Ghana Statistical Service (2018)

### Demographic Overview of Wa Municipal Assembly

The Wa Municipal Assembly is one within eleven districts comprising Ghana's Upper West Region. Located between latitudes 10°40' North and

2°0'45' North and longitudes 9°32' West and 10°0'20 West (MoFA, 2015), it covers an area of approximately 234.74 square kilometers, constituting roughly 6.4% of the entire region's landmass (GSS, 2017). The climate in Wa Municipality features a lengthy, hot, and windy dry season followed by a shorter rainy season with frequent storms (MoFA, 2015). With a total population of 87,245, the municipality experiences a higher population growth rate in urban areas (4%) compared to rural areas (2.7%) (GSS, 2017). Agriculture remains the main economic activity in the municipality (Twumasi, 2022). It contributes significantly to the local economy, employing more than 70 percent of the working population (FOSTAT, 2018; Antwi, 2016). Millet, sorghum, maize, soybeans, yam, rice, cowpea and groundnuts are the staple crops produced for subsistence in the area (MoFA, 2015).

### **Study Description of Wa West District**

The Upper West Region of Ghana encompasses nine districts, and Wa West District is one of them (Twumasi, 2022). Located in the region's western sector, the district falls roughly between longitudes 40°N and 45°N and latitudes 9°W and 32°W (MoFA, 2015). Wechiau and Dorimon serve as the district's primary townships. Wa West District borders the Savannah Region to the south, the Nadowli-Kaleo District to the north, the Wa Municipality to the east, and Burkina Faso to the west (MoFA, 2015).

The climate in Wa West District is characterized by two distinct seasons: a rainy season spanning from May to September and a dry season lasting from October to April (GSS, 2017; Twumasi, 2022). The average annual rainfall varies between 840 mm and 1400 mm (MoFA, 2015). With a population of approximately 69,170, the district has a slight female majority.

Agriculture forms the backbone of the district's economy, with majority of the population relying on subsistence farming (Antwi, 2016; MoFA, 2015). The farming system is heavily influenced by agro-ecological factors, particularly the unimodal rainfall pattern (MoFA, 2015). Maize, sorghum, groundnut, cowpea, soybean, and vegetables are the most commonly cultivated crops (GSS, 2017).

### **Study Population**

The population of interest consisted entirely of food crop farmers in the Upper West Region of Ghana. According to GSS (2021), the population of Upper West Region is estimated to be about 901,502. The target population for this study consisted of food crop farmers within the Wa West and Wa Municipality where advocacy, sensitisation and sale of weather index insurance has taken place. The population of the two selected districts is 297,629 and the estimated food crop farmer population for the two districts is about 5879 (GSS, 2022; MoFA, 2023). Based on crop production capacity, farm size and number of farmers, the Wa West has a total of 11 major food crop farming communities (ie. Nyoli, Gadi, Wechiau, Ga, Pognyamayiri, Domangili, Goyiri, Dornye, Bankpama, Veiri and Chogsia) while the Wa Municipality has 15 major food crop farming communities (ie. Guli, Chansa, Kagu, Zingu, Mangu, Charia, Nyagali, Sagu, Jonga, Chegli, Kperisi, Tabiehi, Boli, Sing, Kpongu (Sibiko, 2017; Hakam, 2021).

### **Sampling Procedure and Sample Size**

The sample size for the study was determined using the Yamane method (Yamane, 1967), which is considered particularly appropriate in situations involving large populations and unknown population size. The sample size of

450 was determined using Yamane formula for sample size determination, which is given below.

$$n = \frac{N}{1+N(e)^2} \quad (3.0)$$

Where;  $n$  = the sample size needed,  $e$  = confidence level (95%, which is 0.05 margin of error),  $N$  = Population size (which is 5879). The sample size is then calculated as:

$$n = \frac{5879}{1+5879(0.05)^2} = 374.52 \approx 375$$

Salkind (2020) recommends oversampling by 10-20% to increase the precision of estimation of unknown parameters, to improve the response rate and to account for outliers. The sample size was increased to 450 (which is 20% of  $375 = 75$ ). Therefore, 450 food crop farmers who are into cereal-legume crops such as maize, millet, rice, sorghum, soya bean, groundnut were interviewed to account for any outliers. The study employed a multistage sampling technique. The first step was to purposively select Wa Municipality and Wa West District. Wa Municipality and Wa West District were selected because they are the two major districts in the Upper West Region where advocacy and piloting of weather index insurance has taken place (Adiku et al., 2017; Sibiko, 2017). Based on total crop production, farm size, and number of farmers, the Wa West District has 11 major crop-based food communities, namely Nyoli, Gadi, Wechiau, Ga, Pognyamayiri, Domangili, Goyiri, Dornye, Bankpama, Veiri and Chogsia, while Wa Municipality has 15 major food crop farming communities which are Guli, Chansa, Kagu, Zingu, Mangu, Charia, Nyagali, Sagu, Jonga, Chegli, Kperisi, Tabiehi, Boli, Sing, Kpongu (Sibiko, 2017; Hakam, 2021) and these were the communities used for the study. A list

of food crop farmers in these two selected districts was obtained from the regional office of the Ministry of Food and Agriculture.

The second stage involves the process employed to arrive at the estimated sample size for each of the districts selected for the study. Thus, the researcher divided the population of farmers in each district by the total number of farmers in the two districts and multiplied by 100 to get the percentage of farmers to be selected from each district. Based on this, the researcher found that 45% of the estimated sample size had to come from the Wa Municipality while 55% was to come from the Wa West District. The 45% works out to 202 farmers for Wa Municipality to be distributed across the 15 farming communities. While the 55% for Wa West District gives 248 farmers to be distributed across the 11 farming communities in the district.

The third stage was to find out how many farmers have to be selected from each of the farming communities. In this stage, the proportionate stratified random sampling was used. Thus, for Wa Municipality, the researcher divided the population of each farming community by the total number of farmers in the municipality and multiplied by the expected sample from the municipality to arrive at the sample proportion of farmers to be selected from each farming community. For Wa West District, the researcher divided the population of each farming community by the total number of farmers in the district and multiplied by the expected sample from the district to arrive at the sample proportion of farmers to be selected from each farming community. Finally, respondents were randomly selected using the lottery method to arrive at a sample size of 450 food crop farmers. Table 1 below shows a summary of the farmers selected from each farming community in Wa Municipality/Wa West.

**Table 1: Sample Size Determination for the Selected Communities**

Wa Municipality			Wa West District		
Farming Communities	No. of Farmers	Sample Size	Farming Communities	No. of Farmers	Sample Size
Guli	97	7	Nyoli	261	20
Chansa	246	19	Gadi	312	24
Kagu	141	11	Wechiau	270	21
Zingu	193	15	Ga	324	25
Mangu	76	6	Pognyamayiri	316	24
Charia	331	25	Domangili	183	14
Nyagali	306	23	Goyiri	355	27
Sagu	194	15	Dornye	368	28
Jonga	63	5	Bankpama	259	20
Chegli	162	12	Veiri	318	24
Kperisi	99	8	Chogsia	270	21
Tabiehi	177	14		-	-
Boli	124	9		-	-
Sing	156	12		-	-
Kpongu	278	21		-	-
TOTAL	2643	202		3236	248

Source: Author's Construct, 2024

## Background of the Study Respondents

### Socio-Economic Characteristics of Farmers in the Upper West Region

Based on Table 2, farmers in the Upper West Region of Ghana appear to be relatively young, with an average age of 33.26 years. The youngest farmer in the study was 20 years old, and the oldest was 72. This trend of younger individuals participating in agriculture could be linked to the region's high unemployment rate and the fact that a substantial portion of farmers lack formal education, potentially limiting their employment options outside of agriculture.

From Table 2 the results indicate that the average number of years of farm experience among farmers is 16.39. The minimum and maximum farm experience are 5 and 48 years, respectively. This may be attributed to the fact that farmers typically commence their farm enterprises at a younger age. Table 2 once again demonstrates that the average household size is 5.08, with a maximum of 14. Consequently, the majority of farmers interviewed had more

than one wife. This increases the number of children per household head, thereby increasing the number of household size. A larger household size is advantageous during periods of peak labour demand, such as sowing, fertiliser application, harvesting and threshing.

Conversely, smaller households are at a disadvantage because they are forced to rely on hired labour during these periods, which increases their production costs. This is consistent with the findings of Hakam (2021). Nevertheless, the mean value of 5.08 is somewhat higher than the regional mean household size of 4.7 reported by the Ghana Statistical Service (GSS, 2017). Table 2 further indicates that the average farm size cropped is 2.7 hectares, which is higher than the national average of less than 2.0 hectares and the regional average of 2.5 hectares (GSS, 2017). The average income generated by cropped farms is GHC 7,885.01, which is insufficient to support the livelihoods of farmers. Therefore, many farmers asserted that they supplement their income by engaging in off-farm activities, such as motorcycle riding, trading, butchery, and share picking, as well as hunting for firewood.

**Table 2: Summary Statistics of Some Selected Descriptive Variables**

Variable	Min.	Max.	Mean	Std. (Deviation)
Age of Farmer	20	72	33.26	9.48
Household (size)	1	14	5.08	2.50
Experience	5	48	16.39	3.32
Farmland size cropped (ha)	0.81	8.50	2.70	1.40
Farmland size owned (ha)	1	15	3.21	1.62
No.Ext.Service Access per season	1	8	3.80	1.54
Farm income per ann. (Ghc)	320	20,000	7885.01	1326.28
Off-Farm Income	0	7000	808.89	282.44
Distance to the farm (km)	0	25	10.53	4.32

Source: Field survey, Koufie (2024)

### Age of Farmer

The age of a farmer plays an essential role in farm production activity. “All other things being equal”, older farmers are more endowed than younger farmers. Thus, older farmers may be blessed with multiple wives and many children, which makes them have high household sizes and more hands available for farm activities that require more labourers. Hakam (2021) asserted that the age of a farmer positively correlates with farming experience and influences the decision-making processes of the household. With regard to this study, the results presented in Table 3 indicate that 2% of the farmers are between the age brackets of (20-29years), with the majority of farmers (64%) in the middle age, ranging between the ages of 30 and 49 years. This implies that the younger generation is now involved in farm production activities. Intuitively, this suggests that farmers will be able to adopt and use different farm technology with ease.

**Table 3: Distribution of the Age of Farmers in the Upper West Region**

Age	Number of Respondents	Percentage (%)
20 – 29	9	2
30 – 39	135	30
40 – 49	153	34
50 – 59	108	24
60 +	45	10

Source: Field Survey, Koufie (2024)

### Sex of Farmer

Figure 4 illustrates that approximately 66.2% of farmers in the Upper West Region are male, while approximately 33.8% are female. This suggests that farming in the Upper West Region is predominantly male-dominated. This finding is consistent with previous studies, such as those by Hakam (2021) and Twumasi (2022), which have demonstrated that in the three northern

regions of Ghana, men tend to have greater access to land and other agricultural inputs for farm production than women.

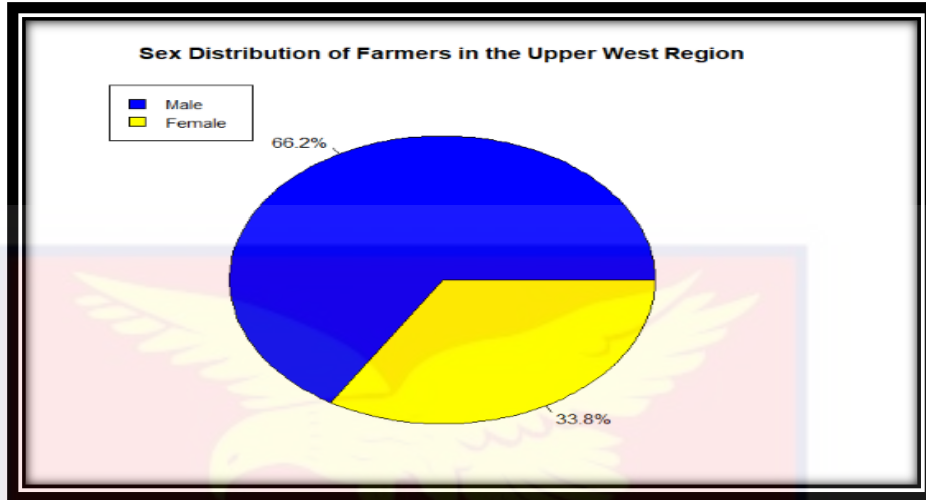


Figure 4: Sex Distribution of Farmers in the Upper West Region  
Source: Field survey, Koufie (2024)

### Marital Status

Figure 5 indicates that the majority of farmers (65.8%) are married, while 14% are divorced and 11.3% are single, with 8.9% being widowed. This may be attributed to the fact that agricultural activity in the Upper West Region is predominantly undertaken by men. Consequently, a married woman is more likely to be granted access to farmlands for agricultural production. It is intuitive that a greater proportion of women will be married in order to have access to their agricultural inputs for their survival.

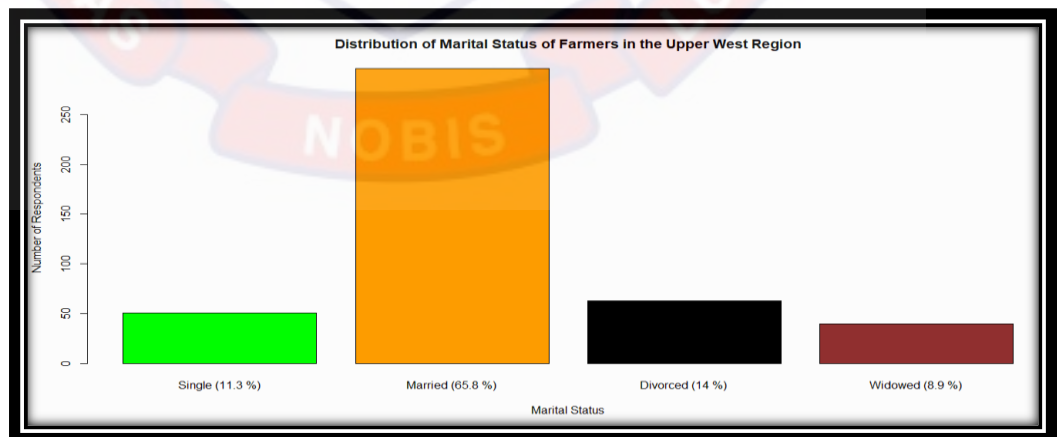


Figure 5: A Distribution of Marital Status of Farmers in Upper West Region  
Source: Field Survey, Koufie (2024)

### Level of Education of Respondents

Figure 6 illustrates that approximately 53.3% of farmers lack any form of education. This is a typical farming setting in the three northern regions of Ghana, where the majority of farmers have no education (Hakam, 2021). However, only a small proportion of farmers have completed primary education (25.3%), MSLC/JHS (8.9%) or SHS/vocational training (7.8%), with only 4.7% having completed tertiary education. This may be associated with government policies such as the Youth in Agriculture (YIA) initiative, government posting's to the region, and the Planting for Food and Jobs (PFJ) initiative, which have influenced graduates from high school, vocational schools, and tertiary institutions to pursue farming as an occupation. This study is consistent with previous studies such as those conducted by Antwi (2016) and Dogee (2021).

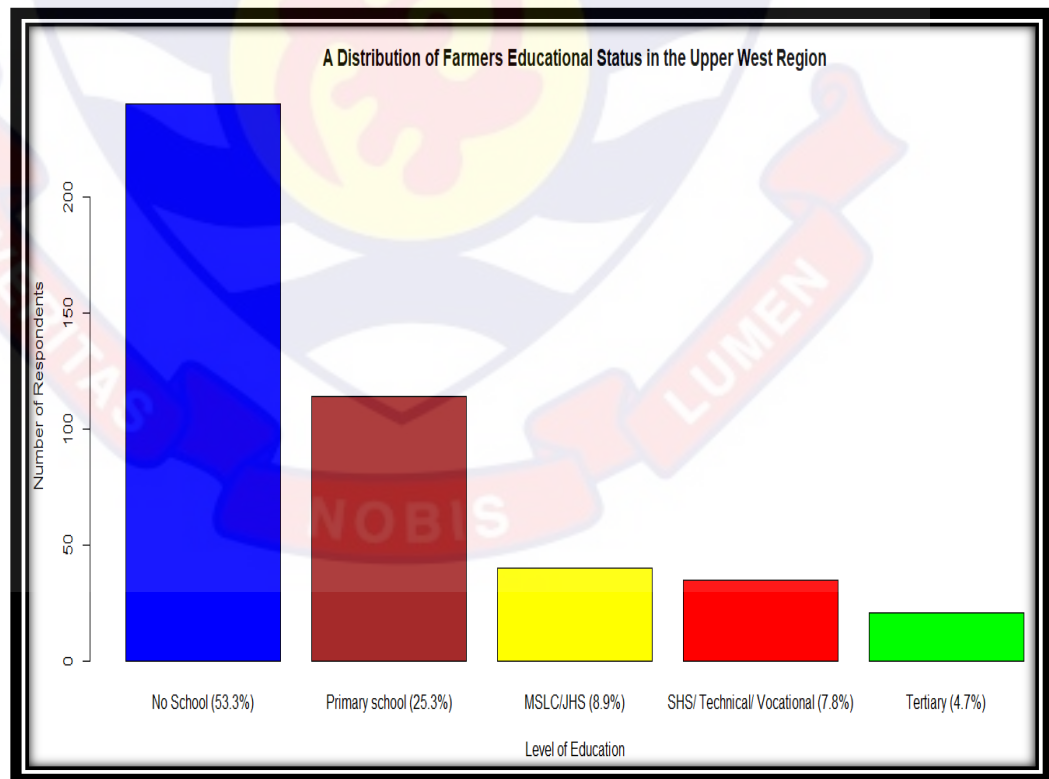


Figure 6: A Distribution of Farmer’s Educational Status in the UWR  
Source: Field Survey, Koufie (2024)

## Household Size

The size of a farmer’s household is an essential component in farm production activities. This entails members of the nucleus family and the extended family living with the farmer and eating from the same food pot. There is a positive correlation between farmer household size and the number of children and wives a farmer has, as they assist in labour-intensive activities (Hakam, 2021). Figure 7 of the study revealed that approximately 46.2% of farmers are adult males, 34% are adult females, and 19.8% are children. This indicates that there are more adult males and females in the household, which means that they are available to provide family labour for farm production activities.

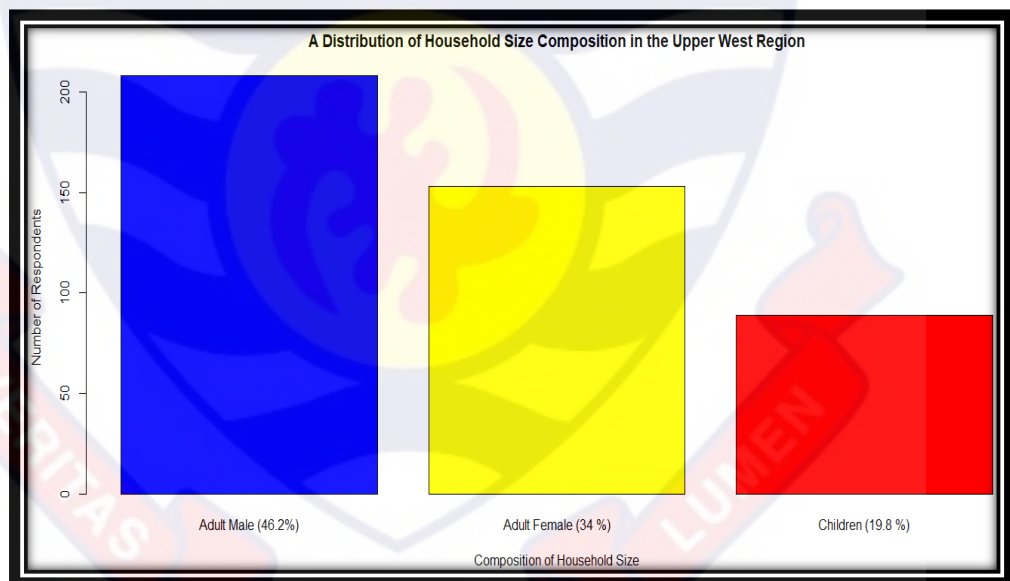


Figure 7: Distribution of Household Size Composition of Farmers (UWR)  
Source: Field Survey, Koufie (2024)

## Farming Experience

Table 4 indicates that approximately 67.8% of farmers have between 10 and 19 years of experience in farm production. The next largest group of farmers has 20 to 29 years of experience. This suggests that the majority of farmers have at least 10 years of farming experience. This implies that most

farmers begin farming at an early age. This finding is consistent with the results of previous studies, including those by Adiku et al. (2017), and Sibiko (2017), which similarly indicate that the majority of farmers in farming communities begin their farming careers at an early age.

**Table 4: Distribution of Respondents Farming Experience in Years**

Farming Experience	Number of Respondents	Percentage (%)
0 – 9	13	2.9
10 – 19	305	67.8
20 – 29	110	24.4
30 – 39	13	2.9
40+	9	2

Source: Field Survey, Koufie (2024)

### Farmland Size

The size of a farm determines the scale of production and also influences the number of crops rural farmers grow. Table 5 shows that the majority of farmers, approximately 68.9%, cropped between 1 and 2.99 hectares. This is inconsistent with the fact that in Ghana smallholder farmers cultivate on less than 2 hectares of farmland. The reason is that the region is endowed with a lot of farm lands for cultivation. However, most of the farmers are not able to increase their cropped farm size capacity. In response to the question of why they are unable to increase their cropped farm size, the respondents indicated that the costs associated with expanding their farmland are significant. Additionally, the lack of access to working capital to hire machinery or labour further constrains the expansion of farmland size for farm production.

**Table 5: Distribution of Farmland Size by Farmers in the UWR**

Farmland Size	Number of Respondents	Percentage (%)
0 – 0.99 ha	19	4.2
1 – 1.99 ha	134	29.8
2 – 2.99 ha	176	39.1
3 – 3.99 ha	48	10.7
4 ha +	73	16.2

Source: Field Survey, Koufie (2024)

### Cross Distribution of Gender and Farm Size by farmers in the UWR

In the context of agricultural inputs, women are constrained by a lack of resources. In the northern region of Ghana, women are frequently excluded from decision-making processes related to agricultural production and have limited access to resources such as land (Hakam, 2021). Table 6 reveals that the majority of female farmers (128 out of 152, representing 84.2%) own between 0 and 2.99 hectares for cultivation, which is less than 3 hectares. This corroborates the assertion made by Hakam (2021) that female farmers in Northern Ghana have less access to farmlands.

Conversely, the results presented in Table 6 indicate that male farmers tend to cultivate larger farmlands, with sizes ranging from 2 to 3.99 hectares and even exceeding 4 hectares. This is due to the fact that in Northern Ghana, male farmers are responsible for production decisions and often possess the farmlands. Female farmers who have access to farmlands are often in smaller sizes (less than 3 hectares) and are mostly from their husbands (Antwi, 2016; Hakam, 2021). The results of the Pearson chi-square test ( $\chi^2 = 21.954$ ,  $p$ -value =  $9.585e-08$ ) indicate that there is a statistically significant relationship between gender and farmland size in the Upper West Region of Ghana.

**Table 6: Cross Distribution of Gender and Farm size by Respondents**

Gender	Farm Size Cropped (Hectares)					Total
	0-0.99ha	1-1.99ha	2-2.99ha	3-3.99ha	4ha+	
Male	11	84	106	36	61	298
Female	8	50	70	12	12	152
Total	19	134	176	48	73	450

Pearson's Chi-square test

$$x^2 = 21.954 \quad df = 4 \quad p - value = 9.585e-08$$

Source: Field Survey, Koufie (2024)

### Data Collection Instrument

A structured questionnaire, content validated and pre-tested, was used to collect data. The structured questionnaire was designed according to the objectives of the study and the literature review. The questionnaire contained both open-ended and multiple choice questions. The structured questionnaire was used because of its carefully predetermined nature, which increases credibility, reliability and validity, and its fixed nature, which reduces contextual effects and other biases (Tegan & Merkus, 2022). These questions were divided into five sections (A, B, C, D and E). Section A looked at socio-economic characteristics such as age, gender, marital status, educational background, farm size, occupation, years of farming, etc., while section B looked at attitude of farmers amidst climate variability and change.

Section C looked at farmers' insurance attributes preferences and the values they place on these preferences as well as choice experiment questions which was used to determine the most preferred attributes by the farmers and also to estimate the willingness to pay for the weather index insurance policy. Section D looked at the production information of the farmer such as inputs items use, rental cost, farm equipment's used and their cost, crop yield and

benefit for past production etc. Section E looked at subscription and subscription intensity of the weather index insurance policy.

### **Validity and Reliability**

To ensure the instrument accurately measured the intended construct of interest, the researcher sought feedback from his supervisor(s). This involved reviewing the instrument's content and the types of questions to assess if they effectively captured the relevant construct. Thirty (30) food crop farmers were interviewed as a sample for the pre-test; however, these farmers were not included in the main data collection and this served the purpose of face and content validity. The pre-test carried out using the structured questionnaire lasted for a week prior to the actual administration of the structured questionnaire. With regard to the reliability of the instruments, a reliability analysis was carried out from the pre-test exercise using Cronbach's alpha in SPSS version 25. The results from the Cronbach's alpha for this study was 0.8, which means that the instrument is reliable and can be accepted for data collection. The problems with the survey instrument were identified during the pre-testing process and the necessary changes were made. Therefore, the final changes to the survey instrument were made before the final data collection.

### **Ethical Issues**

To ensure ethical research practices, the researcher obtained clearance from the University of Cape Coast's Institutional Review Board. This review process safeguards the rights of research participants, as emphasized by McClelland and Burnham (2008). Fontana and Frey (2000) highlight three core ethical considerations in questionnaire administration: informed consent,

privacy, and protection from harm. Adhering to these guidelines, participation in the study was entirely voluntary.

Before data collection began, all participants received a statement as part of the questionnaire explaining the research goals and how the collected information would be used. The researcher ensured complete confidentiality throughout the process. The questionnaires used were designed to not include names for identification of any individual participant. This was done to ensure that a specific response will not be linked to a particular person.

Following the University of Cape Coast's plagiarism guidelines, the researcher maintained a word similarity index below 20% in the final report. Turnitin software was employed to verify the originality of the final report.

#### **Data Collection Procedure**

Once the research instruments gained approval from the supervisor (s) and ethical clearance was also obtained from the University of Cape Coast Institutional Review Board (UCC-IRB) with reference ID (UCC/CANS/2023/28), the data collection phase commenced. To assist with administering the structured questionnaires, the researcher recruited a team consisting of four well-trained enumerators. These enumerators received comprehensive training on the study's objectives and the proper methods for administering the questionnaires. The selected enumerators were trained for a week. The content of their training covered various aspect of field work, including data collection techniques, explanations of the validated research instruments in both English and local dialects as well as safety protocols.

Their training also incorporated ethical Issues such as confidentiality, informed consent, cultural sensitivity, impartiality and objectivity. For

instance, the field assistants were trained to understand the need to obtain informed consent from participants before any data collection and the implication of not doing so. Also, they were trained on respecting cultural norms and practices while interacting with the local communities to avoid unintentional harm and offense, and the need for unbiased and impartial data collection.

The data collection process spanned a maximum of one month, occurring between March and April 2024. Questionnaires were distributed across various locations: respondents' homes and farms, and community centers where weather index insurance awareness programs were held. The enumerators provided assistance to respondents as they completed the questionnaires. For those unable to write themselves, the enumerators filled out structured questionnaire forms capturing their responses. In addition, secondary data (time series data) from Ghana Meteorological Agency on climate variables such as rainfall, maximum and minimum temperature ranging from 1976 to 2023 was also taken to analyse climate trends or variability in the Upper West Region.

### **Data Processing**

The research data was processed using a combination of statistical software packages: R (version 4.4.1), IBM SPSS (version 25.0), and LiPs. The specific software used for each step depended on the nature of the data and the analysis being conducted. The data analysis procedures used is as follows.

### **Data Analysis**

#### **Multiple Price List Elicitation Method for Estimating Risk Aversion**

To investigate the risk aversion of farmers in the face of climate variability and change. First, trend analysis was conducted using climate

variables to establish the fact that farmers in the region are actually faced with climate variability and change (see details in page 111-114). The study then used the Multiple Price List elicitation method to estimate the risk aversion levels of farmers. Apart from the MPL, there are other elicitation methods such as the bisection method and the trade-off method that could be used to estimate risk aversion levels (Filippin & Crosetto, 2016). However, the advantage of the multiple price list method is that it can be used even if the respondent has no knowledge of probability (Berry et al., 2020).

Another advantage of the multiple price list method is that it is transparent to the respondent and provides simple incentives for truthful preference disclosure (Allcott & Kessler, 2019). Therefore, it is relatively easy for respondents to see that truthful revelation is in their best interest and it is easy to explain to respondents and implement. The study adopted the multiple price list as used by (Vassaol & Li, 2016; Yanuarti, Ali & Rondhi, 2019) with some slight modifications to suit the attitudes of farmers' decision to purchase weather index insurance in the Upper West region.

In order to measure the risk aversion of the food crop farmers using the MPL approach, a tailor-made question was asked. Thus, the farmers were asked to consider their decision based on the possibility of disaster (such as drought, pest attack and flood) and different economic benefits. As a farmer, Table 7 shows that you have five (5) plots of land for maize production, each plot having an area of 0.25ha. Therefore, you have the option to insure or not insure the land.

However, if you choose to insure the land, you will have to pay a premium of Gh¢60 per hectare for one planting season, but your land will be

guaranteed against losses due to the disaster. Thus, the guarantee in this case means that the insured land would receive a compensation of Gh¢1450 per hectare. Conversely, if you do not take out insurance, you do not have to pay premiums, but your land is not guaranteed against losses due to disasters. Given that there is a 50% chance of no disaster affecting the crops. In this case, each plot could have yielded a profit of Gh¢498, resulting in a total profit of Gh¢2490 for five plots. However, if a disaster struck, there would be no profit (Gh¢0).

Table 7 presents questions used to assess farmers' risk aversion. These options range from "A (extreme)" to "F (neutral to negative)" with corresponding levels of risk aversion ("A" being the most risk-averse and "F" being the least risk-averse). Before the analysis was done, these ordinal categories (A-F) were converted into numerical values using a method called the method of successive intervals (MSI).

**Table 7: Cross Distribution of Gender and Farm size by Respondents**

Choice	Insured Farm Plot	Uninsured Farm Plot	If Disaster Doesn't Happen (Probability 50%; GH¢)	If Disaster Happens (Probability 50%; GH¢)	Risk Aversion Levels
A	5	0	2415	1812.5	Extreme
B	4	1	2430	1450	Severe
C	3	2	2445	1087.5	Intermediate
D	2	3	2460	725	Moderate
E	1	4	2475	362.5	Slightly to Neutral
F	0	5	2490	0.00	Neutral to Negative

Source: Field Survey, Koufie, 2024

### Discrete Choice Experiment Design

Discrete choice experiments (DCEs) rely on presenting respondents with a series of hypothetical scenarios where they must make trade-offs. In each

scenario, they choose between different options for a service or product, with each option offering varying levels of specific features (attributes). By analyzing these choices, researchers can understand what aspects of the service are most valued and how much individuals are willing to compromise on less-desired features (Campbell, & Erdem, 2020). This approach is valuable for exploring the potential impact of different features on the adoption of a new intervention or program (Santeramo, 2018).

Essentially, DCEs function as a quantitative tool to reveal individual preferences (Senapati, 2020). Researchers use DCEs to ask respondents to choose between various hypothetical options, thereby uncovering how individuals value specific features of a program, product, or service. There are two main categories of choice experiments: labelled and unlabelled (Cantillo et al., 2020). Labelled options use descriptive names (e.g., "Best Point Weather Index Insurance Policy"), while unlabelled options use generic names (e.g., "Weather Insurance Option A"). The number of options presented can theoretically be unlimited in either case (Hensher et al., 2014).

In general, there are two types of discrete choice experiments, namely stated preference and revealed preference. In the stated preference discrete choice method, respondents are asked directly about their preferences, which are then typically translated into their willingness to pay (WTP) (Surminski, 2016). Thus, respondents do not actually change their behaviour, but simply state that they would behave in a certain way. The stated preference method is best suited for estimating non-use values for which no market actually exists (Coletta et al., 2019).

Revealed preference discrete choice methods, also known as indirect methods, use actual choices made by consumers in real market transactions to develop models of choice (Ben-Akiva et al., 2019). They are called indirect because they typically use the costs incurred by consumers in consuming the good or service as a means to reveal/infer their preferences. In the current study, the stated preference discrete choice method was used. Designing a DCE involves a systematic approach with four key stages. The first step focuses on identifying the relevant attributes – the specific features that will be varied across the different options presented to respondents. The second stage involves defining the different levels for each attribute. The third stage tackles how to create the choice sets – how the various options with different attribute levels will be grouped for respondents to consider. Finally, the fourth stage involves generating the actual experiment and pre-testing it to ensure clarity and effectiveness before deploying it to a wider audience.

### **Establishing Attributes**

A key component in the design of a discrete choice experiment is the choice of attributes and levels. Presenting respondents with a choice set of hypothetical products requires some variation in the design (Harrison, 2024). In the design of the DCE, the variation is usually achieved through the use of different attributes that act as elements of the product (Fifer et al., 2020). According to Lancaster and Louviere (2018), the attributes are assigned with different levels and these levels influence the preferences of individuals to make the choice decision. Thus, a respondent is usually given a variety of choice tasks to make a decision, at least two choice tasks at the same time, where he has to choose his most preferred.

In the context of this study, the attributes of weather index insurance that were included in the hypothetical weather index insurance policies were premium, base risk, subsidy, prompt payment of claims, linking of credit to insurance and payment of no-claims discount. These were adopted from Boateng-Gyambiby (2019) and slightly modified to include prompt payment of claims. Further literature aside Boateng-Gyambiby (2019) were reviewed on the selected attributes to affirm its relevance. For instance, studies such as (Clarke et al., 2012) and (Miranda & Nadolnyak, 2023) found that poor households are reluctant to take out weather index insurance unless it is subsidised or bundled with other benefits. Also, studies such as (Vyas et al., 2021), (Elabed et al., 2013) and (Jensen et al., 2017) have also identified basis risk as one of the main problems of weather index insurance rebates, which also contributes to the low uptake of index-based insurance. A study by Serfilippi et al. (2015) also found that non-payment of insurance rebates contributes to the low uptake of index-based insurance. These reasons form the basis for selecting the attributes.

In order to know whether the selected attributes were preferred and relevant to the food crop farmers in the study area, and also to know whether any relevant attributes were excluded from the discrete choice experiment, an in-depth face-to-face interview with the farmers was also conducted to confirm the relevance of the selected attributes. This was done to ensure that no relevant attributes were left out.

### **Ways of Presenting a Choice Experiment Design**

There are three main ways to present choice experiments to participants: verbal descriptions, paragraph descriptions, and pictorial

representations (Acheampong, 2015). Verbal descriptions use cards with brief descriptions of each attribute level. Paragraph descriptions provide more detailed explanations for each level. Pictorial representations, on the other hand, use images to convey the different attribute levels. Studies have shown that visual aids can improve how respondents process information, leading to more accurate interpretations and easier evaluation of the options presented (Achnicht & Osberghaus, 2019). Recognising the high illiteracy rates and language variations within the study communities, this research adopted a combined approach using both paragraph and pictorial presentations (see Appendix Cii) for the weather index insurance options.

#### **Assigning of Attributes Levels**

Manganyi (2022) emphasize the critical role of assigning appropriate attribute levels in DCE studies. These levels significantly influence the overall validity of the research. Furthermore, ensuring the levels are both realistic and relevant to the target population enhances the accuracy of the parameter estimates obtained (Hall, 2004; Boateng-Gyambiby, 2019). For this study, the weather attributes and their corresponding levels were adapted from Boateng-Gyambiby (2019). These were then carefully modified to better reflect the specific preferences of farmers within the study area. For instance, the premium levels were modified. There was an engagement with a number of insurance companies to have an insight or a semblance on how much they charge for selling such an insurance product to the farmers and based on the engagement the study came across the average price to be approximately GH¢60 and this became the first attribute level for premium. The study also had a face-to-face interview with the farmers to infer from them on how much they are willing to

pay for such an insurance product and then the average price was approximately GH¢50 and this also became the second attribute level for the premium. Table 8 below presents the attributes and attribute levels of the weather index insurance products used for the study.

**Table 8: Attributes and Attribute Levels of Hypothetical WII**

ATTRIBUTES	LEVELS
Premium	1. GH¢60 2. GH¢50
Basis Risk	1. Data (Rainfall) from GMet Weather Station 2. Data (Rainfall) from a Satellite
Prompt Claim Payment	1. Bank Payment 2. Non-Bank Payment
Inter Linking Credit and Insurance	1. Credit Inter Linked with Insurance 2. Credit not Inter Linked with Insurance
“No” Claim Discount Payment	1. End of Next Season Payment 2. Next Seasons Reduction in Premium
Subsidy.	1. Agricultural Inputs (Subsidy) 2. Weather Index Insurance Policy Premium (subsidy)

Source: Adopted and Modified from (Boateng-Gyambiby, 2019)

### Experimental Design of the Choice Sets

The experimental design stage focuses on creating different scenarios (choice sets) that will be presented to the respondents. A critical aspect of this stage is ensuring sufficient variation in the levels of the relevant attributes, both within each scenario and across all the scenarios presented (Johnson et al., 2013). This variation is essential for researchers to be able to accurately identify

the effects of interest in the study. Johnson et al. (2013) noted that in order to analyse the data to obtain unbiased parameter estimates for each parameter in the model, the correct design must be identified. Therefore, a combination of six (6) attributes, each with two (2) levels, will result in a very large questionnaire that will take a long time to complete if all possible combinations are used. This is known as a full factorial. Thus, a full factorial allows for the calculation of main effects and interaction effects that are independent of each other and includes all possible combinations of an attribute and its levels (Lancsar & Swait, 2014). The main effect is known as the direct independent effect on the choice variable (dependent variable), while the interaction effects are the effects on the choice variable obtained by varying two or more attribute levels together (Manganyi, 2022).

Full factorial estimation is of the form  $A^n$ . Where 'A' denotes the levels of the weather index insurance attributes, while 'n' denotes the number of attributes. The experimental design for this study had (6) attributes, each with (2) levels. This resulted in sixty-four possible alternatives ( $(2^6)= 64$ ) as a full factorial. However, in order to avoid respondent fatigue, to save time, to avoid inconsistent choices, to limit respondent cognitive load and to avoid lexicographic choice behaviour, the fractional factorial design was used for the study.

### **Characteristics of an Efficient Choice Experiment Design**

A fractional factorial experimental design of choice should have both orthogonal and balanced properties (Conradt et al., 2015). These two properties in the fractional factorial design make it perfectly efficient as its attributes are statistically independent (Santeramo, 2018). A balanced design means that each

level appears equally, often within each attribute, and an orthogonal design means that each pair of levels appears equally, often across all pairs of attributes in the design (Johnson et al., 2013). The most efficient design can also be obtained using the D-efficiency measure (Street et al., 2019). Another property that characterises efficient choice designs is minimal overlap (Rao et al., 2019).

This means that each attribute level is only meaningful in comparison to others within the choice set.

In this study, the fractional choice set used by Boateng-Gyambiby (2019) was adopted and modified. The fractional choice set adopted had a total of six choice sets, with each choice set having two policy options or alternatives. Therefore, the respondent was free to choose any of the hypothetical policies within the choice set. However, the respondent can decide not to choose any of the policies within the choice set. The reason for this is that in the real market, customers or buyers have the free will to choose the type of policy that gives them maximum satisfaction and if they are not satisfied with the policy options, they can decide not to take out the policy.

Therefore, the decision not to choose any of the hypothetical policies within the choice set was considered as a third hypothetical policy option. Each respondent selected one policy option per choice set. After the experiment, a respondent is required to select six (6) weather index insurance policies that provided maximum utility or optimal satisfaction. Table 9 below shows the hypothetical optimal weather index insurance policies used for this study.

**Table 9: Hypothetical Weather Index Insurance Policies**

Choice set	Premium	Basis Risk	Prompt mode Claim Payment	Inter Linking Credit with Insurance	“No Claim Discount” Payment	Subsidy
1	GH¢60	Rainfall date from a satellite.	Non-bank payment.	Credit not interlinked with insurance.	Reduction of next season’s premium.	Subsidy on weather index insurance policy premium.
1	GH¢50	Rainfall date from the GMet weather station	Bank payment	Credit interlinked with insurance.	Payment at the end of the next season.	Subsidy on agricultural input.
2	GH¢50	Rainfall date from the GMet weather station	Bank payment	Credit not interlinked with insurance.	Payment at the end of the next season.	Subsidy on weather index insurance policy premium.
2	GH¢60	Rainfall date from a satellite.	Non-bank payment	Credit interlinked with insurance.	Reduction of next season’s premium.	Subsidy on agricultural input.
3	GH¢50	Rainfall date from the GMet weather station	Non-bank payment	Credit not interlinked with insurance.	Reduction of next season’s premium.	Subsidy on agricultural input.
3	GH¢60	Rainfall date from a satellite.	Bank payment	Credit interlinked with insurance.	Payment at the end of the next season.	Subsidy on weather index insurance policy premium.
4	GH¢50	Rainfall date from a satellite.	Bank payment	Credit interlinked with insurance.	Reduction of next season’s premium.	Subsidy on weather index insurance policy premium.
4	GH¢60	Rainfall date from the GMet weather station	Non-bank payment	Credit not interlinked with insurance.	Payment at the end of the next season.	Subsidy on agricultural input.

5	GH¢60	Rainfall date from the GMet weather station	Bank payment	Credit interlinked with insurance.	Reduction of next season's premium.	Subsidy on weather index insurance policy premium
5	GH¢50	Rainfall date from a satellite.	Non-bank payment	Credit not interlinked with insurance.	Payment at the end of the next season.	Subsidy on agricultural input.
6	GH¢60	Rainfall date from a satellite.	Bank payment	Credit not interlinked with insurance.	Reduction of next season's premium.	Subsidy on agricultural input.
6	GH¢50	Rainfall date from the GMet weather station.	Non-bank payment	Credit interlinked with insurance.	Payment at the end of the next season.	Subsidy on weather index insurance policy premium.

Source: Adopted and Modified from Boateng-Gyambiby (2019)

### Econometric Modelling Technique

The econometric basis of the discrete choice experiment is based on the framework of random utility theory. Over the years, the multinomial logit model has been one of the most commonly used methods to analyse consumer preferences and willingness to pay for product attributes (Owusu, 2019). However, due to its inadequacies in accounting for preference heterogeneity among individuals as well as preference variations, the mixed logit model serves as an evolution of the multinomial logit model (Greene, 2024; Owusu & Dadzie, 2021).

The mixed logit model avoids the three limitations of the standard multinomial logit by allowing for random preference variation, unrestricted substitution patterns, and correlation in unobserved factors (Campbell, 2007). Based on random utility theory, the utility that an individual  $n$  derives from choosing an alternative is made up of the sum of two components (Greene,

2024). These are the systematic and random components. The systematic component,  $V(X_{nit}, \beta)$ , is specified as a function of the alternative attributes  $i$  and  $X_{nit}$ , which includes a cost or price attribute (Owusu Coffie et al., 2016). The second component, known as the random component,  $\varepsilon_{nit}$ , represents an unmeasured variation in preferences (Hole & Kolstad, 2012). Therefore, the theoretical model could be extended to capture the socio-economic characteristics,  $S_n$ ; hence, the resulting equation is given as:

$$U_{ni} = V_{ni}(X_{ni}, \beta, S_n) + \varepsilon_{ni} \quad (4.0)$$

Where  $U_{ni}$  is the utility of the  $n^{th}$  farmer choosing the  $i^{th}$  weather index insurance alternative. The random utility model can be specified based on the distribution of the error term. Assuming that the error terms are drawn independently and identically drawn (iid) from an extreme value distribution, there is the multinomial logit model. In the multinomial logit model, the probability that an individual  $n$  chooses alternative ( $i$ ) among a set of ( $j$ ) alternatives are given by (Hanley & Czajkowski, 2019) as:

$$P_r(i) = \frac{\exp(\beta'_n x_{ni})}{\sum_{j=1}^J e^{\beta'_n x_{nj}}} \quad (4.1)$$

To account for preference heterogeneity and to address the independence from the irrelevant alternative (IIA) shortcoming of the MNL, the mixed logit model (MIXL) was applied. The MIXL model is the integral of the standard logit probability over a probability density (Greene, 2024). Within the mixed logit model, the utility that an individual  $n$  derives from choosing alternative  $j$  ( $U_{nj}$ ) is given by Eq 4.2 as:

$$U_{nj} = \beta'_n x_{nj} + \varepsilon_{nj} \quad (4.2)$$

where  $\beta'_n$  is a vector of coefficients of observed variables for individual  $n$ ,  $x_{nj}$  denotes observed variables relating to individual  $n$  and alternative  $j$ , and  $\varepsilon_{nj}$  represents the unobserved utility for individual  $n$  and alternative  $j$  or the random term which includes *i. i. d.* extremes. The mixed logit model is written as:

$$P_{ni} = \int L_{ni}(\beta_n) f(\beta_n) d\beta \quad (4.3)$$

$L_{ni}(\beta_n)$  is known as the logit probability function conditioned on  $\beta_n$ ,  $f(\beta_n)$  is also known as the density function, which can be either discrete or continuous.  $L_{ni}(\beta_n)$  is given mathematically as:

$$L_{ni}(\beta_n) = \frac{e^{(\beta'_n x_{ni})}}{\sum_{j=1}^J e^{(\beta'_n x_{nj})}} \quad (4.4)$$

Since  $\beta_n$  is unconditional on  $\beta$ , and utility is assumed to be linear in parameters, the integral of  $L_{ni}(\beta_n)$  over all possible  $\beta'_n$  becomes the unconditional choice probability. The unconditional probability integrated over the distribution of  $\beta$  is given as:

$$P_{ni} = \int \frac{e^{(\beta'_n x_{ni})}}{\sum_{j=1}^J e^{(\beta'_n x_{nj})}} f(\beta_n) d\beta \quad (4.5)$$

Estimating the mixed logit model requires assumptions to be made about the  $f(\beta_n)$  coefficients over the population (Train, 2009). The assumption about the distribution of  $f(\beta_n)$  coefficients can be either log-normal, normal, non-stochastic or triangular, among others (Greene & Hensher, 2010). In this study, a normal distribution was assumed for all attributes. There is a need to account for conditional heterogeneity; therefore, an extension of the model is required to include the socio-economic characteristics of the respondents

(Owusu, 2019). Therefore,  $S_n$  is included in the model specification to capture the socioeconomic characteristics of the respondents, which is expressed as:

$$P_{ni} = \int \frac{e^{(\beta_n' x_{ni} + S_n)}}{\sum_{j=1}^J e^{(\beta_n' x_{nj} + S_n)}} f(\beta_n) d\beta \quad (4.6)$$

The parameters in the model have already been explained. The study, in an attempt to account for heterogeneity, used a maximum likelihood estimation. The idea behind maximum likelihood estimation is to find a solution by simulating ( $n$ ) draws from distributions with given means and SDs (standard deviations) (Greene, 2024; Owusu Coffie et al., 2016). To perform simulation estimation, the standard method known as random draws is usually used. However, when dealing with sophisticated models and large sample sizes, relying on the random draws can be very time consuming (Owusu & Dadzie, 2021). Therefore, the Halton draws serves as a better alternative with an advantage of speed gain and also has no degradation when performing the simulation estimation (Revelt & Train, 2000). In this study, Halton draws were adopted as the simulation estimation approach.

### **Estimating Farmer's Preferences and the Value They Place on Insurance Policies**

This study used Kendall's Coefficient of Concordance to rank the preference for weather index insurance attributes. Food crop farmers rated the importance of the weather attributes in their choice of a particular weather index insurance product. The attributes were given a score (i.e. from 1 to 6), with 1 being the most preferred attribute and 6 being the least preferred attribute. The total rank score for each attribute was calculated and the attribute with the lowest score was ranked as the most preferred attribute, while the attribute with the highest score was ranked as the least preferred attribute.

Kendall's Coefficient of Concordance was chosen because it is a robust non-parametric statistical tool that measures the degree of agreement among raters (in this case, farmers) when ranking multiple items. It is particularly suited for ordinal data and helps assess the consistency of preferences across a group. This makes it highly appropriate for determining the level of consensus in farmer rankings of insurance attributes, especially when working with rural populations where numerical rating or utility-based responses may not be feasible. While Kendall's W was used in this study, other ranking techniques such as Garrett Ranking and Spearman's Rank Correlation were also considered.

Garrett Ranking is a widely used method in agricultural research that converts ranks into scores using a conversion table, providing a more direct measure of the perceived importance of each attribute. However, Garrett Ranking does not offer a statistical measure of concordance or agreement among respondents, which is critical when assessing collective preference consistency. Similarly, Spearman's Rank Correlation can be used to assess the relationship between two sets of rankings—typically between individual respondents or between attributes. However, unlike Kendall's W, it does not provide a single measure of agreement across multiple raters and attributes simultaneously. Therefore, Kendall's W was considered more suitable for this study's objective: to determine the degree of agreement among many farmers ranking the same set of insurance attributes.

The Kendall's coefficient of concordance is given as follows:

$$W = \frac{12[\sum T^2 - (\sum TP)^2/n]}{nm^2(n^2-1)} \quad (5)$$

The Kendall's Coefficient of Concordance ( $W$ ) statistic represents the coefficient itself,  $T$  signifies the sum of ranks assigned to a particular product attribute,  $m$  represents the total number of farmers participating in the survey, and  $n$  represents the total number of product attributes being ranked. Following the calculation of  $W$ , it was then used to test the significance of agreement among farmers' preferences using the F-distribution. The formula for the F-ratio is presented below:

$$F = [(m - 1)W / (1 - W)] \quad (5.1)$$

From Edwards (1964), the numerator's degrees of freedom are given as:

$$\frac{(n-1) - (2/m)}{m-1[(n-1) - 2/m]} \quad (5.2)$$

From an econometric perspective, the MNL model and the mixed logit model were employed to empirically model the choices made by farmers in response to a choice experiment. In this context, samples of individuals were asked to select their preferred alternatives from a sequence of grouped options pertaining to different weather index insurance (WII) options. Each option was described in terms of WII attributes and the monetary price (premium) to be paid for the option by the respondents. Consequently, each individual was presented with six (6) choice experiment questions, which they were asked to answer. Therefore, the respondent is at liberty to select any of the hypothetical policies within the choice experiment that gives them the optimal satisfaction. The empirical model for the study was specified in such a way that the probability of selecting a particular weather index insurance option is a function of the attributes of that weather index insurance option. The indirect utility from the WII insurance attributes takes the form:

## Empirical Model Specification

### Multinomial Logit Model (MNL)

$$\begin{aligned}
 Preferences_{nj} = & \beta_0 + \beta_1 Premium_i + \beta_2 Bas\ Risk_i + \beta_3 ClaPamt_i + \\
 & \beta_4 Interlink\ Credit.Insu_i + \beta_5 Non\ Claim\ Dis + \beta_7 Subsidy_i + \varepsilon_i \quad (6)
 \end{aligned}$$

$\beta_{1-7}$  represent the coefficient of the attributes describing the weather attributes preferred by farmers.  $Preferences_{nj}$  denotes to individual  $n$  choosing the  $j^{th}$  alternative from a choice set, with the value of (1 if the respondent chooses any of the alternatives and (0) if the respondent decides not to choose anything (opt-out)). All farmers share the same  $\beta_i$  coefficients preferences are assumed homogeneous.

### Mixed Logit Model (MIXL)

$$\begin{aligned}
 Preferences_{nj} = & \beta_{0n} + \beta_{1n} Premium_i + \beta_{2n} Bas\ Risk_i + \\
 & \beta_{3n} ClaPamt_i + \beta_{4n} Interlink\ Credit.Insu_i + \beta_{5n} Non\ Claim\ Dis + \\
 & \beta_{7n} Subsidy_i + \varepsilon_{in} \quad (6.1)
 \end{aligned}$$

### Interactive Form:

$$\begin{aligned}
 Preferences_{nj} = & \beta_0 + \beta_{1n} Premium_i + \beta_{2n} Bas\ Risk_i + \beta_{3n} ClaPamt_i + \\
 & \beta_{4n} Interlink\ Credit.Insu_i + \beta_{5n} Non\ Claim\ Dis + \beta_{7n} Subsidy_i + \\
 & \partial_1 (Premium_i * Age_n) + \dots \partial_7 (Subsidy_i * Age_n) + \dots \partial_n (Subsidy_i * \\
 & \text{last. soecon. characteristics}) + \varepsilon_i \quad (6.2)
 \end{aligned}$$

In the context of choice models, various social and economic factors influence farmers' preferences and decision-making behavior. Equation 6.2 represents an advanced model that incorporates these factors into the utility function, specifically accounting for interaction effects observed in the choice experiment data. NB: Each farmer has their own coefficients drawn from a distribution, capturing preference heterogeneity.

### **Willingness to Pay for Hypothetical Weather Index Insurance Policy**

The study employed the discrete choice experiment approach. The discrete choice experiment framework assumes that respondents select the alternative that provides the greatest utility for them (Tzemi & Breen, 2019). Santeramo (2018) highlights that the choices made by participants in a DCE experiment provide valuable insights into the features (attributes) that most significantly influence their decisions. These choices also reveal their willingness to compromise on certain features in favor of others. Critically, if price is included as an attribute, researchers can estimate how much farmers are willing to pay for changes in the other (non-monetary) attributes (Hynes et al., 2016). Train (2009) emphasizes that responses to DCE questions can be analyzed using specific models called discrete choice models. These models are built upon the foundation of Random Utility Theory. This theory suggests that individuals choose an option from a set based on the perceived value (utility) they associate with each option in the set.

In estimating willingness to pay in the discrete choice experiment approach, the standard approach is to estimate willingness to pay in preference space (PS), where marginal utility coefficients are first estimated, followed by the calculation of WTP values (Owusu, 2019). An alternative approach is to estimate Willingness to Pay Space (WS), which addresses the challenges associated with WTP in Preference Space (PS) by reformulating the Preference model so that the estimated coefficients directly represent the WTP values for the attributes (Greene, 2024; Owusu Coffie et al., 2016). In order to estimate the WTP within the Preference Space model, it is necessary to distinguish

between the monetary and non-monetary attributes and this is specified as follows:

$$U_{nj} = \beta_{np} P_{nj} + \sum_{i=1} \beta_{nj} X_{nj} + \varepsilon_{nj} \quad (7)$$

$\beta_{np}$  and  $\beta_{nj}$  represent the monetary and non-monetary attributes, respectively. In order to estimate the WTP Space (WS) model, the PS model must be reformulated in such a way that the direct coefficients can be obtained as WTP values (Owusu Coffie et al., 2016). This is given as:

$$U_{nj} = \beta_{np} [P_{nj} + \sum_{i=1} \beta_{nj}^* X_{nj}] + \varepsilon_{nj} \quad (7.1)$$

$\beta_{np}$  represents a normalising constant.  $\beta_{nj}^*$  is a vector of WTP values obtained.  $\beta_{np}$  is the coefficient of the price attribute, while  $\beta_{nj}$  is a vector of the coefficients of the non-price attributes.  $P_{nj}$  represents the price attribute, while  $X_{nj}$  denotes the non-price attributes. It is anticipated that the utility derived from the price will be negative, thereby indicating that as the price increases, the utility derived from it will decrease.

### **Determining the Risk Optimum Farm Plan that Maximizes Returns in the Face of Production and Climatic Risk**

In areas prone to drought, such as the Upper West Region of Ghana, studies on farm planning analysis must explicitly incorporate the risk and uncertainty associated with the drought-prone area by building a Stochastic Linear Programming Model (Koufie, 2020). Despite the infinite number of alternative combinations, there is one that maximises the utility of income. As stated by Udo et al. (2015), when more than one crop is cultivated, a strategy for allocating resources to each crop in order to achieve the maximum gross margin with associated risk should be followed. The traditional linear programming approach is frequently used by agricultural economists to assist

farmers in choosing the best farm layout that would produce the highest form of utility (Hakam, 2021). One limitation of this model is that it assumes farmers to be risk-neutral, whereas in reality, they are known to be risk-averse (Koufie, 2020).

A more suitable alternative, the Target-MOTAD model, is preferred to the conventional LP model because it provides solutions that comply with the Second-order Stochastic Dominance (Kaseva et al., 2017). In this study, the Target-MOTAD was employed. The objective function of the Target-MOTAD for this study was to maximise the returns of food crop production. The resource constraint in this study included the land constraint, capital constraint, labour constraint, fertilizer constraint and the non-negativity constraint. The study incorporated risk constraint into the LP model (Target-MOTAD analysis). Consequently, a Target-MOTAD with “ $n$ ” decision variables, “ $m$ ” constraints and a minimum food requirement is mathematically represented as follows:

$$\max Z = \sum_{j=1}^n c_j x_j \dots \dots \dots \text{(Objective function)} \quad (8.0)$$

**Subject to:**

$$\sum_{j=1}^m a_{ij} x_j \leq b_i \dots \text{(Resource constraint)} \quad \forall_i = 1, \dots m \quad (8.1)$$

$$\sum_{j=1}^m C_{rj} + y_r \geq T \dots \dots \text{(Risk Constraint)} \quad r = 1 \dots m \quad (8.2)$$

$$\sum_r p_r y_r \geq \lambda_r \quad \lambda = M \rightarrow 0 \quad (8.3)$$

$$\sum_{j=1}^n k_{ij} x_j \geq w_i \text{(Minimum Food Requirement)} \quad \forall_i = 1, \dots n \quad (8.4)$$

$$X_i \geq 0 \dots \dots \dots \text{(Non-negativity constraint)} \quad (8.5)$$

$Z$  represents the total value of the gross margin from the enterprise(s),  $x_j$  denotes the level of activity  $j$  where ( $j = 1 \dots, n$ ),  $c_j$ : performance measure coefficient for activity  $j$ ,  $b_i$ : amount of resource  $i$  available ( $i = 1 \dots, m$ ),

$a_{ij}$  : amount of resource  $i$  consumed by each unit of activity  $j$ . The decision variables are  $x_j$  and the parameters are  $c_j, b_i, a_{ij}, k_{ij}, w_i, p_r$ .  $Y_r$  represents the negative deviation in total net revenue in the  $r^{th}$  state of nature below the targeted net revenue level,  $T$  denotes the target net revenue level, and  $\lambda$  denotes the maximum amount of shortfall in net revenue permitted,  $C_{rj}$ : Revenue of the enterprise  $j$  in the state of nature or year ( $r$ ).

### **Target-MOTAD Estimation Technique**

The Target-MOTAD model was developed by Tauer (1983) and is similar to the MOTAD model. However, the Target-MOTAD model introduces a new constraint that sets a target level for total revenue (Hakam, 2021). With regard to this study, the objective function, which is also known as the goal of the Target-MOTAD model, was to maximize the expected returns from all food crop enterprises under study. The expected return, also known as the total gross margin, is defined as the overall gross margin from all crop enterprises. The Target-MOTAD model offers alternative farm plans that incorporate several crop combinations, each with their own returns and risks (Kaiser & Messer, 2011). Consequently, if the proposed plans are expected to yield greater returns, the associated return variance would also be expected to be greater. Conversely, lower returns are associated with a lower variance or deviation. Farmers tend to prioritize utility optimization over income maximization due to their risk aversion (Larkai, 2019).

In order to compute for the Target-MOTAD model, two distinct stages must be considered. The initial stage entails identifying a solution to the conventional linear programming model, which provides solutions that are not constrained by risk. Consequently, this provides a solution at the highest point

on the expected return and variance (EV) frontier. The second stage involves the identification of the risk element, which is formulated as a matrix of the gross margin deviation from expected returns. On the risk efficiency frontier, the points are derived by parametrically decreasing the value of  $T$  and  $\lambda$  in arbitrary reductions.

### Gross Margin Estimation

One of the principal components of a linear programming model is the gross margin per unit (acre/hectare). The gross margin is defined as the difference between farm revenue and total variable costs. Variable costs are the cost of production per output unit area during the season. Due to the inherent volatility of prices and the varying pricing of products and inputs based on each crop, gross margin differs amongst crop enterprises. The algebraic expression for gross margin is as follows:

$$GM = TR_i - TVC_i \quad (9.0)$$

$$TR_i = P_i \cdot Y_i \quad (9.1)$$

where  $Y_i$  denotes the output per hectare of crop enterprise (i),  $P_i$  represents the price of the outputs of crop enterprise (i),  $TVC_i$  denotes the Total Variable Cost for the crop enterprise (i).

### Farmland Constraint

The availability of farmland is a significant constraint for farmers, given the limited amount of land they typically have access to (Hakam, 2021). Consequently, it is imperative to optimise the scarce farmland available to the farmer. The farmer must then make a decision on how to apportion this limited land resource to his crop enterprise. In making this decision, it is necessary to ensure that the total area allocated for crops in the season is less than or equal

to the sum total of the farmland available for cultivation. In relation to this study, the farmland was measured in hectares. Mathematically, the land constraint is expressed as follows:

$$\sum_{i=1}^n l_i x_i \leq TL_i \quad (10)$$

$n$  denotes the number of crops cultivated,  $l_i$  represents the area of land apportioned to the  $i^{th}$  crop,  $x_i$  represents the decision variable or the  $i^{th}$  crop under cultivation.  $TL_i$  denotes the total area of land available for cultivation.

### Capital Constraint

The term "working capital" is used to describe the capital that is available for use in the production process. This capital is comprised of two distinct components: equity capital and borrowed capital. The working capital is the capital required to produce the  $i^{th}$  crop enterprise. Consequently, the sum of capital per hectare apportioned to the  $i^{th}$  crop enterprise should be less than or equal to the total sum of capital available to the farmer for production. Mathematically, the capital constraint is given by:

$$\sum_{i=1}^n WC_i x_i \leq TWC_i \quad (11)$$

$n$  denotes the number of crop enterprises,  $WC_i$  is the working capital required to produce the  $i^{th}$  crop,  $x_i$  denotes decision variable or the crop enterprise per hectare of the  $i^{th}$  person.  $TWC_i$  is the total working capital available to the farmer for production.

### Labor Constraint

Labour is a crucial component of crop production, serving as the driving force behind on-farm activities, harvesting and post-harvesting operations (Antwi, 2016). The quantity of labor employed in crop production is quantified in terms of man-days or man-hours (Larkai, 2019). In the context

of crop production, labour is sourced from either family labour or hired labour, or a combination of both. With regard to this study, the measurement of labour was conducted in man-days and represents the number of days required for land preparation through to the harvesting of crops. In the Target-MOTAD model of the study, the labour constraint was defined as the number of labour days per hectare apportioned to the  $i^{th}$  crop, which must be less than or equal to the total number of labour days available for farm production activity. The aforementioned sum total of labor days comprises both family and hired labor. The algebraic expression for the labour constraint is as follows:

$$\sum_{i=1}^n FamLab_i x_i + HiredLab_i x_i \leq TLab_i \quad (12)$$

Where  $n$  represents the number of crop enterprises,  $FamLab_i$  represents family labor required for both on-farm/off-farm activities for crop (i),  $HiredLab_i$  is known as hired labor.  $TLab_i$  denotes the sum total of the labor available for production activity,  $x_i$  denotes the decision variable of the  $i^{th}$  crop per hectare.

### **Risk Constraint**

Farmers modify their farming plans in accordance with their risk profiles. Consequently, profit-maximising models, which fail to account for risk preferences among farmers, have been unable to provide accurate normative or positive economic results when applied to a multitude of farming scenarios (Tzemi & Breen, 2019). Such models tend to overstate optimal output levels, exaggerate specialisation in cropping patterns, give biased estimates of supply elasticities, overvalue resources, and incorrectly predict technology choices on the part of producers (Hazell & Norton, 1986; Kaiser & Messer, 2011).

Consequently, in order to conduct a comprehensive analysis of farm-level decision-making processes, it is essential to incorporate risk and uncertainty as critical elements within the decision environment. With regard to this study, the Target-MOTAD model was employed as the risk programming model. The Target-MOTAD model incorporated risk into its analytical framework. The degree of risk was quantified in terms of the extent to which the target was exceeded. Consequently, a target income is established, which should be equivalent to the anticipated returns without the influence of risk. The target income is also known as the optimum income value, which is derived from the conventional linear programming. The deviation below the target should be confirmed to a specific value (Kaiser & Messer, 2011).

#### **Empirical Estimation of Target MOTAD Model for the Study**

In the context of this study, the actual Target-MOTAD problem is first formulated by analysing the LP problem of the study without including a risk constraint in the model. This was achieved by optimising the expected gross margin  $E(GM)$  of the decision variables ( $x_j$ ) subject to a resource constraint. In this study, the decision variables ( $x_j$ ) were defined as hectares of land to be allocated to the various food crop enterprises. The food crop enterprises considered in this study were maize, groundnut, soya bean and sorghum, as these are the major food crop enterprises produced in the study area (Hakam, 2021; Twumasi, 2022).

Consequently, the optimal income derived from the LP model serves as the target income for the Target-MOTAD model. The Target-MOTAD is analysed by including a risk constraint into the LP model and setting the Target income, which is the optimum income derived from the LP model without risk

constraint. Therefore, the mathematical expression of the Target-MOTAD for the purposes of this study is as follows:

$$\text{Maximize: } E(\text{GM}) = c_1x_1 + c_2x_2 + c_3x_3 + c_4x_4 \quad (13)$$

Subject to: Resource constraint

$$a_{1,1}x_1 + a_{1,2}x_2 + a_{1,3}x_3 + a_{1,4}x_4 \leq b_1 \text{ (Land constraint)} \quad (13.1)$$

$$a_{2,1}x_1 + a_{2,2}x_2 + a_{2,3}x_3 + a_{2,4}x_4 \leq b_2 \text{ (Labour constraint)} \quad (13.2)$$

$$a_{3,1}x_1 + a_{3,2}x_2 + a_{3,3}x_3 + a_{3,4}x_4 \leq b_3 \text{ (Capital constraint)} \quad (13.3)$$

$$a_{4,1}x_1 + a_{4,2}x_2 + a_{4,3}x_3 + a_{4,4}x_4 \leq b_4 \text{ (Fertilizer Constraint)} \quad (13.4)$$

Risk constraint

$$\sum_{j=1}^n C_{rj}x_j + y_r \geq T \quad \dots \text{ where } r = 1 \dots m \quad (13.5)$$

$$\sum_{r=1}^s p_r y_r = \lambda \quad (13.6)$$

$$x_1, x_2, x_3, \dots \geq 0. \text{ (Non-negativity constraint)} \quad (13.7)$$

where  $x_1$  = maize,  $x_2$  = groundnut,  $x_3$  = soyabeans,  $x_4$  = sorghum. ( $a_{1,1}$ ,  $a_{1,2}$ ,  $a_{1,3}$  and  $a_{1,4}$ ) are the hectares of land apportioned to maize, groundnut, soya bean and sorghum, respectively. ( $a_{2,1}$ ,  $a_{2,2}$ ,  $a_{2,3}$  and  $a_{2,4}$ ) represent the labor days (man-days) apportioned to maize, groundnut, soya bean and sorghum. ( $a_{3,1}$ ,  $a_{3,2}$ ,  $a_{3,3}$ , and  $a_{3,4}$ ) represent the amount of capital (GHS) apportioned to maize, groundnut, soya bean and sorghum, respectively. ( $a_{4,1}$ ,  $a_{4,2}$ ,  $a_{4,3}$  and  $a_{4,4}$ ) represent kg/hectare of fertilizer apportioned to maize, groundnut, soya bean and sorghum. Also,  $b_1$  represents the total hectares of land available to the farmer,  $b_2$  represents the total number of labor days (man-days) available to the farmer,  $b_3$  represents the total capital (GHS) available to the farmer for production activity and  $b_4$  represents the total quantity of fertilizer (Kg) available to farmer. ( $c_1$ ,  $c_2$ ,  $c_3$  and  $c_4$ ) represent the gross margin obtained from maize, groundnut, soya bean and sorghum enterprises.  $T$

represents the optimal income obtained from the LP model in the absence of risk constraint (Target gross margin).

The total number of time periods considered is represented by ( $s$ ). In this study, three time periods were considered: the 2021 farm season, the 2022 farm season and the 2023 farm season.  $p_r$  represents the probability of time period  $r$ . The probability of time period 2021 was assigned a value of 0.3, while that of time period 2022 was assigned a value of 0.3 and that of time period 2023 was assigned a value of 0.4. These values were then summed to yield a total probability of 1. This approach was informed by studies such as that of Kaiser and Messer (2011), which posited that in formulating a Target-MOTAD model, the current time period can be assigned a higher probability value distinct from the probability values of the previous time periods, provided that the sum of all probability values equals one.

$C_{rj}$  represents the expected gross margin of the  $j^{th}$  enterprise in the  $r$  time period or farming season.  $y_r$  is the deviation below the target income ( $T$ ) in time period  $r$ .  $\lambda$  is the maximum amount of shortfall in the gross margin permitted. In order to successfully solve the Target-MOTAD model of this study, it was necessary to vary  $\lambda$  from zero to a large number, given a target profit level. For example, as the value of  $\lambda$  was decreased, the level of risk tolerance also decreased (i.e. the farmer is said to be risk-averse in this situation). For each iteration,  $\lambda$  is set such that the target income constraint (equations 13.5 and 13.6) is no longer binding. Consequently, the model solution was deemed feasible, and risk-efficient plans (II and III) were generated.

## **Estimating the Influencing of Risk Optimality and Risk Attitude on WTP for Weather Index Insurance**

### **Count Regression Models**

The variable of interest in this study was the subscription intensity of weather index insurance. In order to increase the number of subscriptions for the weather index insurance policy, it is necessary to first determine whether to subscribe or not to subscribe to the weather index insurance. Once a decision has been made to subscribe to the weather index insurance, the first hurdle has been overcome. At this point, the decision can be made as to whether to increase the subscription from (1 to n) number of subscriptions permitted. Consequently, when the variable of interest (dependent variable) exhibits a count nature, it becomes necessary to utilise count models based on non-normal distributions, such as the Poisson or negative binomial distributions, in order to elucidate the relationship between the dependent variable and a set of independent variables.

The Poisson regression model was selected as the base count model for the study, with the negative binomial hurdle model and zero-inflated negative binomial model considered as advanced count models due to their advantage of addressing overdispersion and excess zeros in a count data set (Fernandez & Vatcheva, 2022). Among the three count models considered for the study, the zero-inflated negative binomial is considered to be the optimal model (Sarul & Sahin, 2015; Feng, 2021; Sharker et al., 2020). Nevertheless, other studies, such as those by (Skevas, Massey & Grashuis, 2022; Amponsah, Mensah & Ampaw, 2018 and Addey, Jatoe & Kwadzo, 2021), have also asserted that the negative binomial hurdle model and Poisson regression model are the most

appropriate models for count data. In light of the preceding literature, the study proceeded to empirically test the suitability of the three advanced count models for the study, employing statistical indicators such as AIC, BIC, the log-likelihood ratio test and the Vuong statistical test. The count models were mathematically specified as follows:

**Poisson Regression Model (PRM)**

A Poisson regression model with a response variable  $y$  has a distribution given as:

$$P(Y_i = y_i) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}, y_i = 0,1,2,3 \dots \dots \quad (14)$$

Given the above equation,  $\mu_i$  represents the parameter of the Poisson distribution. The mean of the Poisson distribution is equal to the variance, and as such, the Poisson regression model is given as:

$$\log(\mu_i) = \beta_0 + \beta_1 X_1 + \dots \dots \dots + \beta_p X_p = X_i^T \beta \quad (14.1)$$

Where  $\beta$  is given as the vector coefficient of  $X_i^T$ .

**Zero-inflated Negative Binomial Model:**

$$p(y; \mu, \theta) = \frac{\Gamma(y+\theta)}{\Gamma(\theta)y!} \frac{\mu y \theta^\theta}{(\mu+\theta)^{y+\theta}}, \theta > 0, \mu > 0 \quad (15)$$

In the event that there are ( $p$ ) predictor variables for both the probit model and the negative binomial function, then, the zero-inflated negative binomial regression is specified as follows:

Probit Model (First stage):

$$probit(EY) = \beta_0 + \beta_1 X_1 + \dots \dots \dots + \beta_p X_p = X_i^T \beta \quad (15.1)$$

Negative Binomial Model (Second stage):

$$\log(\mu_i) = \gamma_0 + \gamma_1 G_1 + \dots \dots \dots + \gamma_p G_p = G_i^T \gamma \quad (15.2)$$

### Negative Binomial Hurdle Model

The probability density function for negative binomial hurdle regression, derived from the probability law of total, is as follows:

$$f_{NBHM}(y_i) = \begin{cases} 1 - P_i, & y_i = 1, 2, 3, \dots, p \\ \frac{P_i}{1 - (1 + a\mu_i)^{-a-1}} \frac{\Gamma(y_i + a^{-1})}{\Gamma(y_i)\Gamma(a^{-1})} \left(\frac{a^{-1}}{\mu_i + a^{-1}}\right)^{a-1} \left(\frac{\mu_i}{\mu_i + a^{-1}}\right)^{y_i} \end{cases} \quad (16)$$

$P_i$  is known as the probability of count variable having a value other than zero (0).  $a$  is known as the dispersion parameter.  $\mu_i$  denotes the mean of positive counts, and  $\Gamma(\cdot)$  represents the Gamma function. Binomial model with Probit link function was used in the first process of the binary stage to show the relationship between the binary variable and the  $p$  predictor variables. This is mathematically defined as follows:

$$\text{Probit link function: } \text{probit}(EY) = \Phi^{-1}(p) = \Phi^{-1}(P|Y = 1) \quad (16.1)$$

The expectation of the binary dependent variable was transformed using the link function. Consequently, the Probit model may be expressed as a linear combination of the regressors and this is expressed as follows:

$$\text{probit}(EY) = \beta_j X_{ji} = X_i^T \beta \quad (16.2)$$

$$\text{probit}(EY) = \beta_0 + \beta_1 X_{1j} + \dots + \beta_n X_{in} = X_i^T \beta \quad (16.3)$$

Where  $X_{ji}$  represents the value of the  $j^{\text{th}}$  predictor variable (*where*  $j = 0, 1, 2, \dots, n$ ) of the  $i^{\text{th}}$  observation (*where*  $i = 1, 2, \dots, n$ ), with  $X_{i0} = 1$ .  $\beta_j$  represents the  $j^{\text{th}}$  regression coefficient of the probit model, where ( $j = 0, 1, 2, \dots, n$ ). Zero-truncated negative binomial regression model was used in the second stage to model the relationship between the count variable and the  $k$  predictor variables. This is mathematically expressed as:

$$\log(\mu_i) = \gamma_k G_{ki} = G_i^T \gamma \quad (16.4)$$

$$\log(\mu_i) = \gamma_0 + \gamma_1 G_{i1} + \dots + \gamma_m G_{im} = G_i^T \gamma \quad (16.5)$$

Where  $(\gamma_k)$  is the  $k^{th}$  regression coefficient of zero-truncated negative binomial regression model, with  $(k)$  ranging from  $(0 \text{ to } m)$ ;  $G_{ik}$  is the  $k^{th}$  predictor variable of the zero-truncated negative binomial model, where  $(k)$  ranges from  $(0 \text{ to } m)$  and  $(G_{i0} = 1)$ . The explanatory variables used in both the probit model and the zero-truncated negative binomial model can differ.

However, in this study, the explanatory variables were the same. Thus,  $(k = j)$  predictor variables.

### **Study Variable (Dependent Variable)**

The dependent variable was a continuous variable. The dependent variable was quantified as the ratio of the area of land insured (ha) to the total area of cultivated land (ha). Consequently, for the purpose of estimation, the dependent variable was converted into a count variable  $(0, 1, 2, 3, \dots, 10)$ , as proposed by Kalmijn (2013). This was achieved by first multiplying the dependent variable, which is a ratio, by 10 (for example,  $0.25 \times 10 = 2.5$ ). The second step is to approximate the continuous values to the nearest whole number. For instance, 2.5 can be approximated to 3, while 2.2 can be approximated to 2. Consequently, the dependent variable is now a count variable and thus requires the use of count models for its estimation.

### **Explanatory Variables**

A detailed breakdown of the count regression model, which explains the explanatory factors and their respective a-priori expectations, is presented in Table 10. Table 10 presents the explanatory variables, their description, measurement, and a priori expectations.

**Table 10: Explanatory Variables for the Count Regression Models Empirical Model Specification**

Variables	Description	Measurement	A-priori Expectation
Sex	Sex of the farmer	Male=1, Female=0	+
Age	Age of Farmer	Years	-
Marital Status	Married or Single	Married=1 Single = 0	+
Education	Years of education	Years	±
Household Size	Number of persons in the household	Number	±
FBO	Access to farmer Based Organisation	Yes = 1 No = 0	+
Experience	Years of Experience in farming	Years	+
Risk Efficient Income	Income from the Risk optimum farm plan	Target MOTAD (Amount)	+
Weather Information	Access to weather information	Yes= 1 No = 0	±
Insurance Awareness	Awareness of the weather index insurance policy	Yes = 1 No = 0	+
Extension Service	Access to Extension service	Yes=1 No=0	+
Insurance prompt payout	Prompt insurance payout compensation through the bank	Yes = 1 No = 0	+
Credit Access	Access to credit facilities	Yes= 1 No = 0	+
Risk Aversion	Risk behavior Towards the WII	Risk averse=1 Not Risk averse= 0	±

The study employed the count regression model to analyse the risk-efficient income and risk aversion of farmers with regard to their subscription and subscription intensity of weather index insurance. The count model comprises two component modelling processes. The first is the binary stage,

which employs the binary model, and the second is the truncated stage, which utilises the truncated model. In the initial stage, which is the binary stage, the respondent is presented with the option of subscribing to weather index insurance products or not. Given that the initial stage is the binary decision stage, the probit model was employed. With regard to the second stage, the study employed the zero-truncated negative binomial model to analyse the intensity of subscription. The number of subscriptions in question determines the number of hectares of land insured using weather index insurance products. The empirical model for this study is specified as follows:

**Poisson Regression Model (Count Model)**

$$\begin{aligned} Subscription_i = \exp(\beta_0 + \beta_1 Age_i + \beta_2 Sex_i + \beta_3 Edu_i + \beta_4 Maritalstatus_i + \\ + \beta_5 Farmsize_i + \beta_6 Experience_i + \beta_7 FBO_i + \beta_8 HHsize_i + \\ \beta_9 Ins. Prompt paytm_i + \beta_{10} Ins. Awarnes_i + \beta_{11} Weather. info_i + \\ \beta_{12} Ext. Serv_i + \beta_{13} CreditAccess_i + \beta_{14} RAVL_i + \beta_{15} RiskEf. Inc_i) \end{aligned} \quad (17.0)$$

**Negative Binomial Double Hurdle Model (Count Model)**

**Binomial model with Probit Link Function:**

$$\begin{aligned} Subscription_i = \beta_0 + \beta_1 Age_i + \beta_2 Sex_i + \beta_3 Edu_i + \beta_4 Maritalstatus_i \\ + \beta_5 Farmsize_i + \beta_6 Experience_i + \beta_7 FBO_i + \beta_8 HHsize_i + \\ + \beta_9 Ins. Prompt paytm_i + \beta_{10} Ins. Awarnes_i + \beta_{11} Weather. info_i \\ + \beta_{12} Ext. Serv_i + \beta_{13} CreditAccess_i + \beta_{14} RAVL_i + \beta_{15} RiskEf. Inc_i \end{aligned} \quad (17.1)$$

**Truncated Negative Binomial Model:**

$$\begin{aligned} Sub. Intensity_i = \beta_0 + \beta_1 Age_i + \beta_2 Sex_i + \beta_3 Edu_i + \beta_4 Maritalstatus_i \\ + \beta_5 Farmsize_i + \beta_6 Experience_i + \beta_7 FBO_i + \beta_8 HHsize_i + \\ + \beta_9 Ins. Prompt paytm_i + \beta_{10} Ins. Awarnes_i + \beta_{11} Weather. info_i \\ + \beta_{12} Ext. Serv_i + \beta_{13} CreditAccess_i + \beta_{14} RAVL_i + \beta_{15} RiskEf. Inc_i \end{aligned} \quad (17.2)$$

**Zero Inflated Negative Binomial Model (Count Model)**

$$\begin{aligned} Pr(Zero_i) = \sigma(\beta_0 + \beta_1 Age_i + \beta_2 Sex_i + \beta_3 Edu_i + \\ \beta_4 Maritalstatus_i + \beta_5 Farmsize_i + \beta_6 Experience_i + \beta_7 FBO_i + \\ \beta_8 HHsize_i + \beta_9 Ins. Prompt paytm_i + \beta_{10} Ins. Awarnes_i + \\ \beta_{11} Weather. info_i + \beta_{12} Ext. Serv_i + \beta_{13} CreditAccess_i + \beta_{14} RAVL_i + \\ \beta_{15} RiskEf. Inc_i) \end{aligned} \quad (17.3)$$

$$\text{Subscription}_i | \text{Subscription}_i > 0 = \text{NB}(\beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{Sex}_i + \beta_3 \text{Edu}_i + \beta_4 \text{MaritalStatus}_i + \beta_5 \text{FarmSize}_i + \beta_6 \text{Experience}_i + \beta_7 \text{FBO}_i + \beta_8 \text{HHSize}_i + \beta_9 \text{Ins. Prompt paytm}_i + \beta_{10} \text{Ins. Awarne}_i + \beta_{11} \text{Weather.info}_i + \beta_{12} \text{Ext. Servi}_i + \beta_{13} \text{CreditAccess}_i + \beta_{14} \text{RAVL}_i + \beta_{15} \text{RiskEf.Inc}_i) \quad (17.4)$$

## Definition of Some Variables Used in the Regression Models

### Age of Farmers

The Age of Farmers was measured in years. It is hypothesised that age can negatively influence a farmer's decision to subscribe to weather insurance and the intensity of their subscription. Consequently, older farmers are less likely to subscribe to weather insurance than younger farmers. This is due to the fact that older farmers tend to gather experience from farming and adhere to traditional methods of production, and are therefore less inclined to adopt new technology (Baidu-Forson, 2016).

### Gender of Farmer

Gender was operationalized as a dichotomous variable, with male farmers coded as 1 and female farmers coded as 0. It was hypothesized that gender would be positively associated with the outcome variable. This was based on the assumption that male farmers possess greater access to resources, such as land, than their female counterparts. Consequently, male farmers were expected to be more likely to subscribe to weather insurance and to increase their intensity of subscription.

### Marital Status

The marital status of farmers was measured as a dummy variable, with married farmers coded as 1 and single farmers coded as 0. It is hypothesised that marital status is positively associated with the willingness of farmers to subscribe to and increase their intensity of subscription for weather insurance

policies, given that married farmers are more likely to consider the survival of their family in the event of any uncertainty (Danso-Abbeam et al., 2018). Consequently, it can be reasonably assumed that a greater proportion of the population would be willing to subscribe to and increase their level of subscription for the weather insurance policy.

### **Education of Farmers**

It is assumed that a farmer who has gained formal education is able to critically analyse and make independent decisions between technologies (Obayelu et al., 2019). Consequently, a farmer who has gained formal education is more likely to subscribe to weather insurance and even increase their intensity of subscription.

### **Household Size**

It is postulated that household size can have a positive or negative influence on a farmer's decision to subscribe to a weather insurance scheme, as well as on the intensity of their subscription. This is due to the fact that a farmer with a large household size may be reluctant to spend their income on other activities, preferring to use it to cater for their household. Conversely, a farmer may subscribe to the weather insurance scheme in order to mitigate the risk of losing his farm and, consequently, his household in the event of a disaster.

### **Risk Optimum Income**

It is postulated that an optimal level of income can positively influence a farmer's decision to subscribe to a weather insurance policy and also increase the intensity of their subscription. This is because, once a farmer's income

exceeds their existing income, they will be willing to purchase insurance products, provided that all other factors remain constant.

### **Risk Attitude**

The risk attitude of a farmer can influence their decision in a positive or negative manner. The rationale for this is that risk behaviour of a farmer can influence the decision as to whether to subscribe to the weather index insurance scheme or not.

### **Model Selection Method**

In order to assess the performance and identify the optimal model for the study, the study employed the traditional Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC) and log-likelihood ratio test. Furthermore, the study employed the Vuong statistical test, given the count data, to ascertain which of the three count models is capable of correcting over-dispersion or under-dispersion, as well as excess zeros in the data. Mathematically, the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Vuong statistical test are expressed as follows:

#### **Akaike Information Criteria (AIC)**

AIC is a statistical measure of the relative quality between two or more models, given a particular data set. Consequently, in the context of multiple models for a given data set, the Akaike Information Criterion (AIC) is employed to assess the quality of each model under consideration. This enables the identification of the optimal model, defined as the one with the smallest AIC value. The Akaike information criterion is estimated using the relations, as this is mathematically given as follows:

$$AIC = -2\text{Log}(L) + 2p \quad (18)$$

Where  $p$  is defined as the number of parameters in the model and  $L$  is the maximised value of the likelihood function. The model with the least  $AIC$  value is known as the model that best-fit the data. In relation to this study, among the three count models under study, thus, negative binomial hurdle model, zero-inflated negative binomial model and Poisson regression model, the one with the smallest  $AIC$  value was concluded as the best fit model.

### **Bayesian Information Criteria**

BIC is closely related to AIC, as it is also a statistical measure used to identify the optimal model in relation to other models that are most suitable for a specific data set. Consequently, the Bayesian information criterion is an asymptotic estimate derived under the assumption that the distribution of the data is in the exponential family. The Bayesian information criterion is defined mathematically as:

$$BIC = -2\text{Log}(L) + \log(n)p \quad (19)$$

Where  $n$  the total number of observations,  $p$  is defined as the number of parameters in the model and  $L$  is the likelihood function. The model with the least  $BIC$  value is known as the model that best fits the data. Consequently, in the context of this study, among the three count models under study, thus, negative binomial double hurdle model, zero-inflated negative binomial model and Poisson regression model, the one with the smallest  $BIC$  value was concluded as the best fit model.

### **Vuong Statistical Test**

The Vuong test is a non-nested statistical measure used to compare the predicted probabilities of two non-nested models (Harrison, 2024). Therefore,

in relation to this study, the Vuong statistical test was used to find the count model relative to other count models that are capable of dealing with overdispersion, underdispersion and excess zeros in the count data of the study. The count regression models considered were NBHM, PRM and ZINBM. These models were paired against each other.

### Hypothesis Test for Vuong Statistical Test for the Study

Poisson regression model Vs Negative binomial double hurdle model:

$$H_0: LLR_{PRM} = LLR_{NBDHM} \quad (20)$$

$$H_1: LLR_{PRM} \neq LLR_{NBDHM} \quad (20.1)$$

Poisson regression model Vs Zero-inflated negative binomial model:

$$H_0: LLR_{PRM} = LLR_{ZINBM} \quad (21)$$

$$H_1: LLR_{PRM} \neq LLR_{ZINBM} \quad (21.1)$$

Zero-inflated negative binomial model Vs Negative binomial double hurdle model:

$$H_0: LLR_{ZINBM} = LLR_{NBDHM} \quad (22)$$

$$H_1: LLR_{ZINBM} \neq LLR_{NBDHM} \quad (22.1)$$

The decision criteria are as follows: if a paired model exhibits a positive value of test statistic in the Vuong test, it can be inferred that the first model is more suitable for dealing with overdispersion and excess zeros than the second model. Consequently, the first model is statistically superior. However, if the Vuong statistical test yields a significantly negative result, then the second model is more suitable for dealing with overdispersion and excess zeros than the first model. Consequently, the second model is the preferred option.

### Trend Analysis Method

Non-parametric statistical techniques were employed to identify significant trends within the rainfall and the temperature datasets which was taken from the Ghana Meteorological Agency in the Upper West Region. The Meteorological data ranges from 1976 to 2023. The data was first subjected to exploration involved assessing data normality using the Shapiro-Wilk test. This step was crucial for selecting appropriate analytical methods for both the rainfall and temperature datasets. The Shapiro-Wilk test was chosen due to its reliability and widespread use in normality testing (Mishra, 2019). Mathematically, the Shapiro Wilk test is given as:

$$\text{Shapiro-Wilk (W)} = \frac{(\sum_{i=1}^n a_i x_i)^2}{\sum_{i=1}^n (x_i - \bar{X})^2} \quad (23)$$

$x_i$  represents the ordered sample value,  $a_i$  represents a constant obtained from the means, variances and co variances, and covariance of the ordered statistics,  $n$  is the number of observations and  $\bar{X}$  is the sample mean.

### Homogeneity Test

Subsequently, homogeneity test was conducted to assess data consistency prior to trend analysis. The Standard Normal Homogeneity (SNHT) was employed to determine if the data exhibited homogeneity. The null hypothesis was evaluated at a significance level of 0.05. Mathematically the SNHT, it is given as:

$$P_y = y * \bar{z}_1 + (n-1) \bar{z}_2, \text{ where } y = 1, 2, 3 \dots n \quad (24)$$

$$\bar{z}_1 = \frac{1}{y} \sum_{i=1}^y \frac{y_i - \bar{y}}{s} \text{ and } \bar{z}_2 = \frac{1}{n-y} \sum_{i=y+1}^n \frac{y_i - \bar{y}}{s} \quad (24.1)$$

Where  $\bar{z}_1$  is defined as a test statistic comparison of the mean of the first ( $y$ ) years with the last years of  $(n - y)$  using  $P_y$ . NB: The year ( $y$ ) is consisted of a break if value of  $P$  is a maximum. Thus, the null hypothesis is rejected if

$$P_0 = \max_{0 \leq y \leq 1} P_y \quad (24.2)$$

NB: see appendix (i) for the results of the SNHT. Out of the 47 data points studied just one was significantly inhomogeneous, for rainfall it was 1992, for maximum temperature it was 2000 and for minimum temperature it was 1999. Since majority of the data points were found by the test to be homogenous, this was useful for trend analysis irrespective of the change point (Asamoah & Ansah-Mensah, 2020). The study proceeded with the Modified Mann-Kendall Trend Test.

#### **Modified Mann-Kendall Trend Test and Sen's Slope Test**

The Modified Mann-Kendall test was employed to identify trends in rainfall, maximum temperature (Tmax), and minimum temperature (Tmin). As a non-parametric method, it does not necessarily require normally distributed data since it uses the ranks rather than the actual values. Thus, it can be used for both normally distributed or non-normally distributed data. The test assesses the null hypothesis of no trend against the alternative of an increasing or decreasing trend. Sen's slope estimator was used to quantified the rate of change. To account for potential autocorrelation, which can influence trend analysis, a lag-1 serial correlation test was conducted prior to the Modified Mann-Kendall test. The lag-1 autocorrelation coefficient ( $r_1$ ) was calculated to assess the presence of autocorrelation at a 5% significance level.

$$r_1 = \frac{\sum_{i=1}^{n-1} (X_i - \bar{X})(X_{i+1} - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (25)$$

The autocorrelation coefficient was calculated using the sample mean ( $\bar{X}$ ) and sample size  $n$ , where  $X_i$  represents an individual observation of time series data. The autocorrelation coefficient values were tested against the following equation:

$$r_1 \text{ vs } 95\% = \frac{-1 \pm 1.96\sqrt{(n-2)}}{n-1} \quad (26)$$

The meteorological data (time series data) on rainfall, maximum and minimum temperature ranging from 1976 to 2023 obtained from the Upper West Region were considered serially correlated, when  $r_1$  lies between the upper and lower limit of the confidence interval (see Appendix (i) for the results). Therefore, a Modified Mann-Kendall trend test, which is robust to autocorrelation was used to analyse the data. Thus, the Modified Mann-Kendall test is a robust tool for trend analysis in time series data with autocorrelation. This was followed by the Sen's Slope Estimation. The study used the "modifiedmk" and "Trend" packages in R software version 4.4.5 to perform the Modified Mann-Kendall trend test and the Sen's slope test respectively.

### Chapter Summary

This chapter presents the detailed methodology employed in the study. The study demonstrated that a multistage sampling procedure was employed to select the sample. The first objective of the study was estimated using multiple price lists, Modified Mann-Kendall trend test and Sen's slope test. The software employed was MSI and R software version 4.4.5. Objective two was analysed using the Target-MOTAD and the linear programming model to obtain the risk-optimal farm plan. The LiPs software and the R software version 4.4.5 were employed for this purpose. Objective three was analysed using the Kendall's Coefficient of Concordance, the Multinomial Logit Model,

and the Mixed Logit Model. SPSS and R software were employed for this purpose. The final objective was analysed using count regression models to determine the influence of risk-optimal income and risk aversion of farmers on their subscription and subscription intensity of weather index insurance. The R software version 4.4.5 was employed to analyse this objective (objective four).



## CHAPTER FOUR

### RISK AVERSION LEVELS AND RISK EFFICIENT FARM PLANS OF FARMERS IN THE UPPER WEST REGION

#### **Introduction**

This chapter presents and discusses the findings of farmers' attitude towards risk amidst climate variability and the risk-efficient plans that give them a maximum expected income. It addresses the first and second objectives of the study. The chapter is divided into eleven sections. The first section discusses descriptive on rainfall, max and min temperature data from 1976 to 2023. The second section presents the summary results of Modified Mann-Kendall and Sen's slope test on climate variables. The third and fourth section illustrates the Trend of Rainfall and, maximum and minimum temperatures respectively. The fifth section discusses the findings of risk aversion levels of farmers amidst climate variability and change.

The sixth section discusses the results of the food crop mix enterprises operated by the farmers in the study area. The seventh section presents and discusses the findings of the farmer's plan, the risk-efficient plans and the optimum plan. The eighth section presents the results of the resource allocation and utilisation by the LP/T-MOTAD model in obtaining the risk-efficient plans and the optimum plan. The ninth section presents and discusses the crop mix requirement that helps the farmers to meet their subsistence needs alongside the optimum plans and the income penalties that come with it. The tenth section presents the significance of the aforementioned plans (I, II, III and IV) using a T-test. The final section presents a summary of the chapter.

## **Trends in Climate Data from Recorded Meteorological Data**

### **Descriptive on Rainfall Data and, Max and Min Temperature Data**

Table 11 indicate the descriptive analysis of rainfall data and, maximum and minimum temperature. The results show an average rainfall amount of 990.40mm/year over the 47 years' period under review, with a coefficient of variation of 0.168. This implies that the variation in rainfall pattern is about 16.8% which is significant to note. The observations of variation in the rainfall pattern are also backed by the wide range of minimum rainfall amount of 522.9mm to a maximum rainfall amount of 1292.3mm. This implies high fluctuations above and below the average rainfall amount that might give an indication of complex extreme event such as drought and floods. The results in Figure 8 helps to throw more light on the fluctuations and trend in the rainfall pattern over the years studied (ie.1976-2023).

Accordingly, Table 11 shows that over the 47 years' period under review, the maximum temperature recorded was as low as 32.68°C and as high as 34.59°C, while the minimum temperature recorded was as low as 21.50°C and as high as 23.60°C. Table 11 show an annual average maximum temperature of 33.68°C and the minimum temperature of 22.48°C, with a coefficient of variation of 0.013 and 0.022 respectively. This implies that there is 1.3% and 2.2% variation in maximum and minimum temperature respectively. Although, the temperature variability is low, it is possible it can still influence the severity and frequency of extreme events. For instance, higher temperatures can increase evaporation rates, potentially exacerbating droughts.

**Table 11: Descriptive Analysis of Annual Rainfall and Temperature Data from (1976-2023)**

Statistic	Meteorological Variables		
	Rainfall (mm/year)	Max. Temperature (°C)	Min. Temperature (°C)
Mean	990.40	33.68	22.48
Standard Dev.	166.13	0.45	0.49
Maximum	1292.3	34.59	23.60
Minimum	522.9	32.68	21.50
Coef. Of Var	0.168	0.013	0.022

Source: Secondary data from GMS, 1976-2023

### Summary of Modified Mann-Kendall and Sen's Slope Test on Climate Variables

Trend analysis for annual rainfall, maximum temperature and minimum temperature was performed using the Modified Mann Kendall trend test, and Sen's slope estimator. The Modified Mann-Kendall test was used to detect trends in the time series data, and the Sen's slope estimator was employed to estimate the magnitude of the trend. Given the presence of significant lag-1 serial correlation for rainfall (0.15), maximum temperature (0.46), and minimum temperature (0.65), as shown in Appendix (i), these non-parametric methods were chosen for their robustness to autocorrelation. The results from Table 12 indicate that there was an increasing or upward trend in rainfall, but this was not significant at the 5% level. This means that the rainfall trend appears to be increasing over the years, but there is no clear increase that is significant (Figure 8 sheds more light on this). Sen's slope estimator also showed that the magnitude of the change in the annual average rainfall trend was 3.432 units per year. This is in line with a study by Abbam et al. (2018),

who also noted that there is no significant upward trend in rainfall in the Upper West Region, Upper East Region and the border districts of the Northern Region, which are adjacent to the Upper West and Upper East. Therefore, there is a need for targeted interventions to address the climatic risks faced by farmers.

From Table 12, the result show that there was significant increasing trend in both the maximum and minimum temperature at 1% level. This implies that the region is experiencing a period of intense heat which could pose threat of climate risk to farmers. The Sen’s slope estimator also revealed that the rate of increase of both the maximum and the minimum temperature trend were 0.017°C and 0.025°C per year respectively. The findings are consistent with a study by Kusakari et al. (2014) and, Nyantakyi-Frimpong and Kerr (2014) who also noted that is a significant increasing trend in both maximum and minimum temperature in the Wa West district of the Upper West Region of Ghana.

**Table 12: Summary of Modified Mann-Kendall and Sen’s Slope Test**

Climate Variable	Modified Mann-Kendall Test		Sen’s Slope Test	
	Mk (Z Test)	P-Value	Estimate	Trend (↑ or ↓)
Rainfall (mm/yr)	1.911	0.0560	3.432	(↑) Trend
Max.Temp (°C)	5.483***	1.482e-05	0.017	(↑) Trend
Min.Temp (°C)	6.234***	4.531e-10	0.025	(↑) Trend

Source: Secondary data from GMS, 1976-2023

**Trend in Rainfall Data from Meteorological Data (1976-2023)**

Figure 8 shows the annual rainfall trend in the Upper West Region of Ghana between 1976 and 2023, based on meteorological data. The results from Figure 8 show that the rainfall trend (represented by the green line) appears to

have an increasing trend, but there is no clear increase in the trend. This is supported by the results of the Modified Mann-Kendall test for rainfall trend, which shows that rainfall has an increasing trend over the years, but the trend is not statistically significant at the 5% level (see Table 12). The results from Figure 8 also show that there is a high degree of variability in the rainfall patterns which poses a threat of climate risk to the farmer. From Figure 8, the high variations above the average rainfall observed in 1980, 1999, 2008 and 2018 can be considered as outliers, indicating years with potentially higher rainfall amounts. Conversely, years such as 1983 and 1986 show a significant dip below the average, indicating a period of lower rainfall.

These observations are consistent with the findings of previous studies in the region. For example, a study by Nyantakyi-Frimpong and Kerr (2014) also identified 1986 as the year that recorded the lowest amount of rainfall below average in the region with 1999 and 2008 as the years with potentially higher amount of rainfall in the region. A study by Abbam et al. (2018) also identified 1980 and 2008 as the years that recorded higher rainfall amount, with 1983 as the year with potentially lower rainfall amount in the region. In addition, Ndamani and Watanabe (2014) noted that the Upper West Region has higher rainfall variability, which is in line with the present study and this poses a threat of climate risk to farmers in the region.

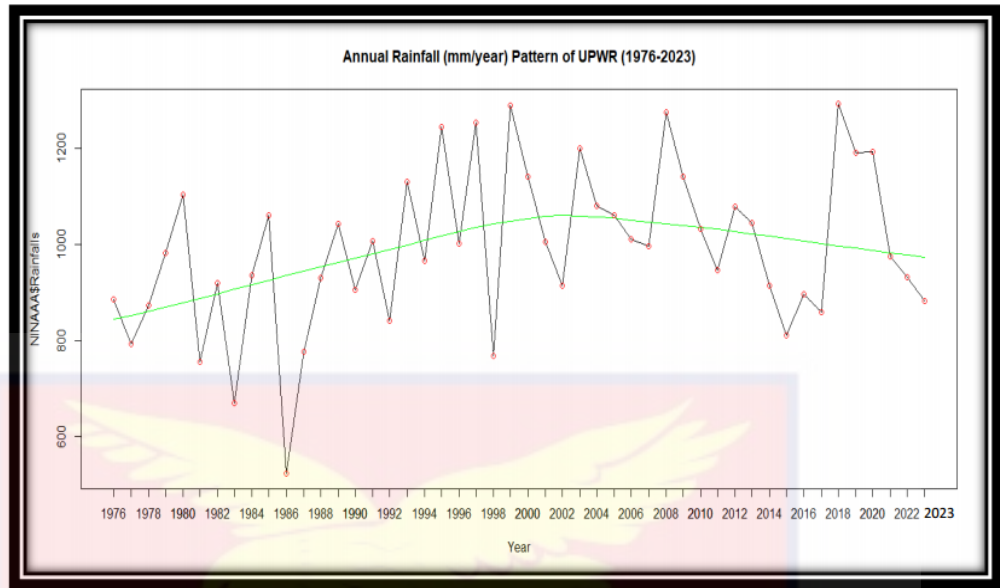


Figure 8: *Trend in Rainfall Data of UPWR (1976-2023)*

Source: Secondary data from GMS, 1976-2023

A moving average test was conducted to provide further insight into the visual trend of rainfall data. This process helps to smooth out short-term trends in the original data, thereby making the underlying rainfall trend more apparent. By integrating the visual inspection of the rainfall graph with the moving average, a comprehensive understanding of the rainfall trend can be gained, as demonstrated in Figure 9.

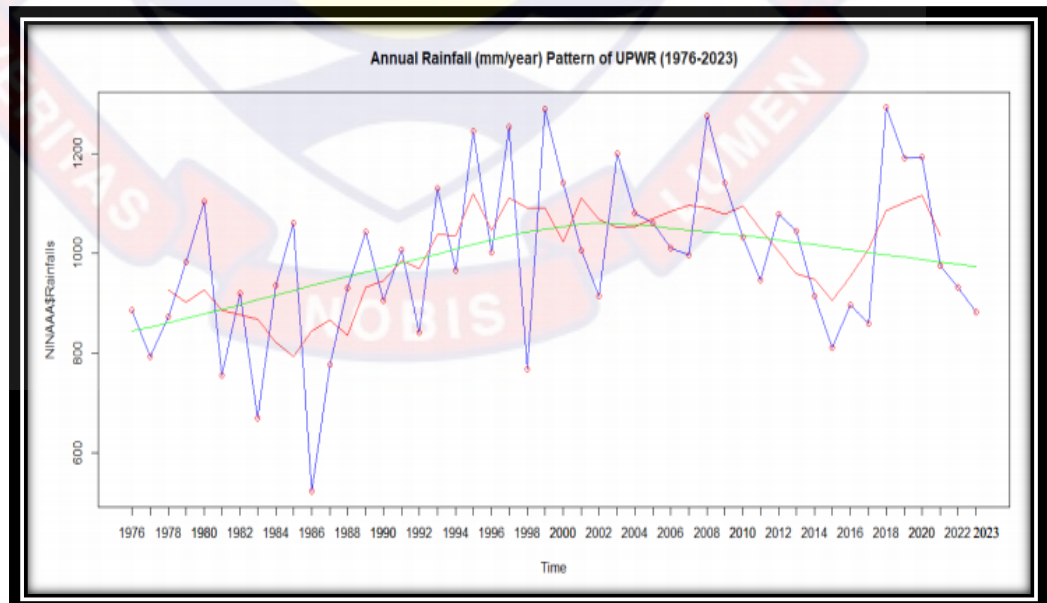


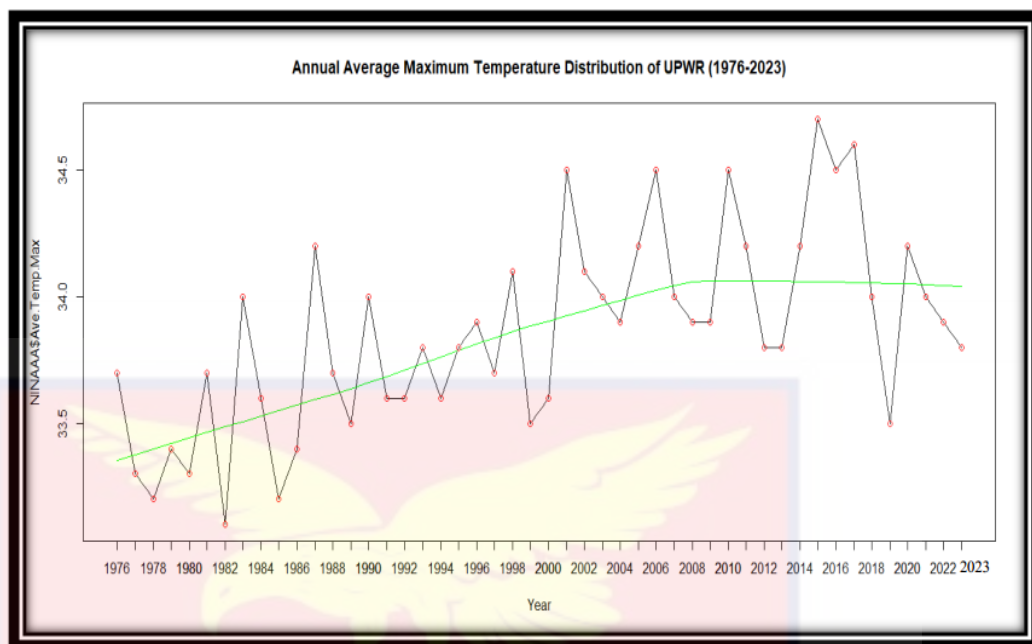
Figure 9: *Moving Average Trend in Rainfall Data of UPWR (1976-2023)*

Source: Secondary data from GMS, 1976-2023

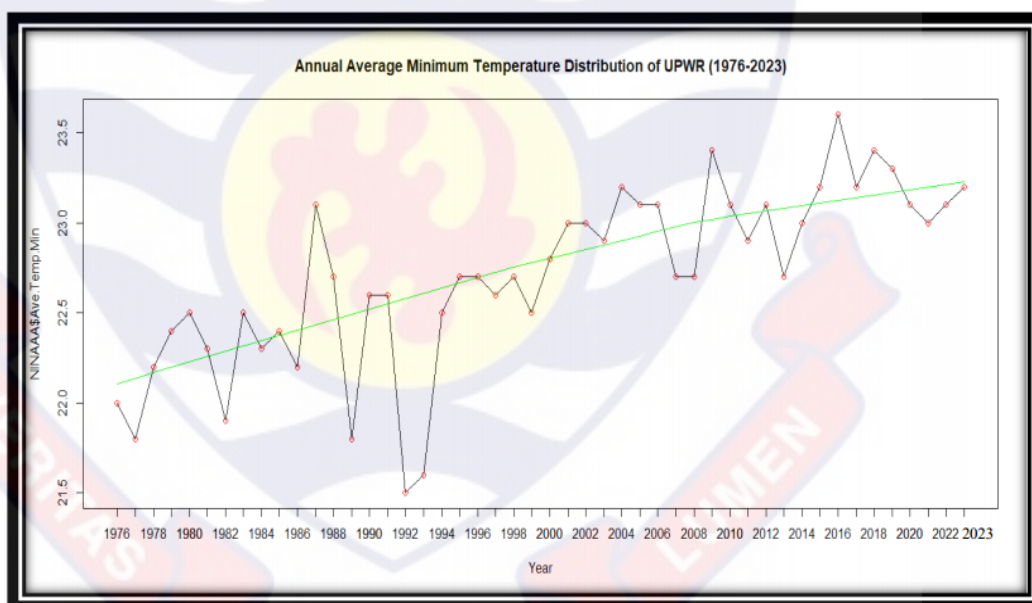
### **Trend Analysis in Max. and Min Temperature Data (1976-2023)**

Figures 10 and 11 show the maximum and minimum temperature trends from 1976 to 2023-time period. The results show an increasing significant trend in maximum and minimum temperature data. From Figures 10 and 11, the upward trajectory of the green line indicates a warming effect, with annual maximum and minimum temperatures rising steadily. However, this warming is not uniform. While the trend suggests an overall increase in both maximum and minimum temperature, there are significant year-to-year fluctuations. This highlights the inherent variability in annual maximum and minimum temperatures, even within a warming trend.

Interestingly, in Figure 10, some years stand out as clear outliers, such as 2001, 2006, 2010, 2015 and 2017, with exceptionally high recorded maxima. These years may represent extreme weather events that punctuate the overall warming pattern. The rising maximum temperature mirrors global climate change patterns which could lead to a cascade of environmental and societal challenges, including heat waves, droughts, disruptions to agricultural practices and adverse health impacts. This is consistent with a study by Subaar et al. (2018) who also recorded 2001, 2006, and predicted 2015 and 2017 as years that recorded exceptionally high temperature and further noted that there is an increasing trend in maximum temperature in the Upper West Region. This poses a climate risk to farmers in the region.



*Figure 10:* Trend in Maximum Temperature Data of UPWR  
Source: Secondary data from GMS, 1976-2023



*Figure 11:* Trend in Minimum Temperature Data of UPWR  
Source: Secondary data from GMS, 1976-2023

### **Risk Aversion Level Classification of Farmers in the Upper West Region of Ghana in the Face of Climate Variability**

It is inevitable that farmers will face risks in their farm production. Their attitudes towards risk and their approaches to dealing with risky events vary. Weather index insurance is seen as an important mitigation measure used

by farmers in the Upper West Region (Adiku et al., 2018; Hakam, 2021), given the region's climate variability and change (see Table 11-12; Figure 8-11). In order to assess farmers' attitudes towards risk in the context of climate variability and change, a multiple price list elicitation method was employed. This involved asking a tailored question using a questionnaire. Maize, a staple food crop produced by almost every household in the Upper West Region (Larkai, 2019), was used for the multiple price list elicitation procedure. With regard to the MPL procedure, farmers were asked whether they would insure five plots of land for maize production, each with an area of 0.25 ha, using a weather index insurance. This was done in order to ascertain their risk aversion levels amidst climate variability and change. Further details can be found in Chapter 3, pages 75-76 (Table 7).

Table 13 indicates that approximately 65.65% of farmers (Choice A) prefer to insure their entire farmland against climate variability and change with a weather index insurance product. Meanwhile, approximately 22.67% of farmers (Choice B) and 6.00% of farmers (Choice C) prefer to insure the majority of their farmland amidst climate variability and change with a weather index insurance product. Additionally, approximately 2.00% (Choice F) of the farmers indicated that they do not wish to insure their farmland against climate variability and change. This suggests that the farmers are highly risk averse. Consequently, they are likely to avoid risk at all costs, which may influence their decision to participate in a weather index insurance scheme or other agricultural insurance schemes to mitigate the risk of crop failure and climate variability. This finding is consistent with the results of previous studies, including those by Dadzie and Acquah (2012), Vassalos and Li (2016), and

Yanuarti, Aji and Rondhi (2019), who found that the majority of farmers have a highly risk averse attitude.

**Table 13: Result of Risk Aversion Level Classification of Farmers**

Choice	Insured Plot	Uninsured Plot	MSI Value	No. of Choices	(%)	Risk Aver. Level
A	5	0	1.00	295	65.56	Extreme
B	4	1	2.32	102	22.67	Severe
C	3	2	2.93	27	6.00	Intermediate
D	2	3	3.26	11	2.44	Moderate
E	1	4	3.50	6	1.33	Slightly to Neutral
F	0	5	4.00	9	2.00	Neutral to Negative
Total	-	-	-	450	100	-

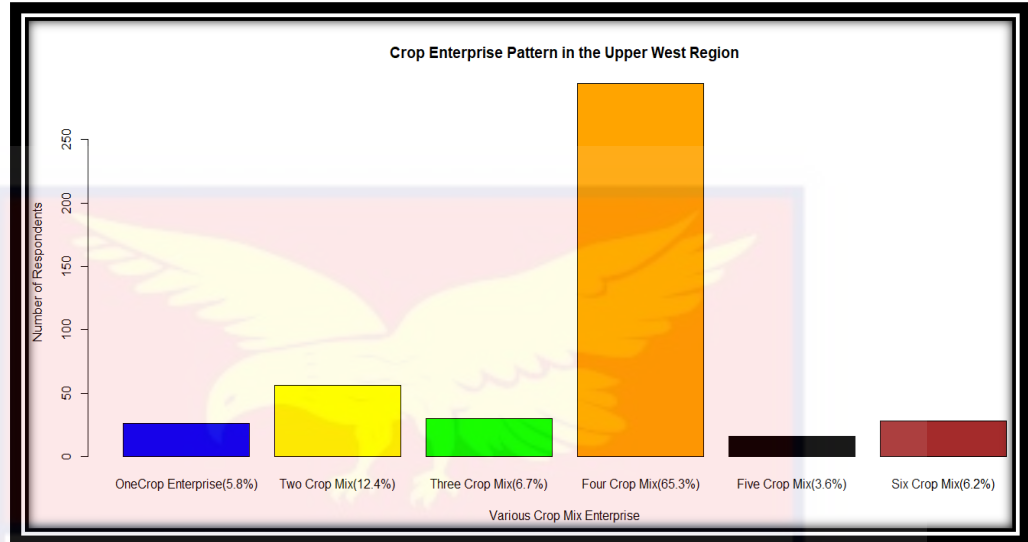
Source: Field Survey, Koufie (2024)

### **Cropping Patterns of Farmers in the Upper West Region**

In the Upper West Region of Ghana, most farmers produce a variety of crops such as maize, groundnut, sorghum, soybean, rice and millet (MoFA, 2015). Figure 12 shows the food crop enterprise patterns that farmers in the Upper West Region operate on their farms. Most of these farmers operate different crop mixes mainly to hedge against production and climatic risks (Hakam, 2021). Figure 12 shows that the majority of farmers (65.3%) operate mainly four-crop enterprise mix, with (maize, soybean, groundnut and sorghum) being the dominant four-crop enterprise mix.

The study shows that the cereal-legume cropping system is the most common among farmers, with maize, sorghum, soybean and groundnut being the main crops. This is because most of the farmers interviewed indicated that these crops serve as both cash crops and food security crops. Previous studies such as those by Lakai (2019) and Twumasi (2022) found two crop mix and three crop enterprise mix, respectively, as the crop pattern in their study area.

These differences in crop pattern are as a result of individual crop strength, culture, agronomic factors as well as climatic conditions of a particular area of study.



*Figure 12: Crop Enterprise Mix Pattern of Farmers in Upper West Region*  
Source: Field Survey, Koufie (2024)

### Existing Plan, Optimum Plan and Risk Efficient Farm Plans on Crops

In the Upper West Region, four crop enterprise mixes are identified as the most dominant crop enterprise patterns operated by farmers. These include maize, sorghum, soya bean and groundnut, which are the most dominant among the four enterprise patterns (see discussion in Figure 12). These four major crop enterprise mixes became the basis for the farmers' plans and the LP/Target-MOTAD selected crop mixes used for the farm plan scenarios in this study. Table 14 presents the results of the farmer's plan (I), the risk-efficient farm plans (II and III) and the profit maximisation plan (IV). Given the limited resources available to the farmer, such as land, labour, fertilizer and capital, the farmer's plan is to combine the selected crops in order to obtain an expected income.

Table 14 indicates that the farmer's plan (I) involves the production of maize (0.54 hectares), soyabean (1.00 hectares), groundnut (0.56 hectares) and

sorghum (0.5 hectares) with the objective of generating an expected income of GH¢7412.97. This income figure represents the expected income generated by the farmer from their own farm plan. The farmers interviewed for the study asserted that their income is still low, which affects their livelihood. This concurs with previous studies such as Hakam (2021), Twumasi (2022) and Degee (2022), who also noted that farmers in the Upper West Region are faced with low income and resource allocation problems, which affect their livelihood. Consequently, an optimal farm plan through an LP/T-MOTAD approach is required to enable farmers to achieve a higher income, given the same available resources for production.

A number of studies have employed the LP model to identify strategies for optimising farmers' incomes. These include (Igwe et al., 2011 ; Ogunbo, 2015 ; Osama et al., 2017; Haq et al., 2020; Koufie, 2020). The findings of these studies indicate that the LP model is an effective tool for achieving this objective. Consequently, the present study employed the LP model to identify the optimal profit-maximisation plan. Table 14 indicates that the profit maximisation plan (IV) derived from the conventional LP model would result in an optimal income of GH¢11168.10.

To achieve this optimum income, the farmer should produce 1.50 hectares of soya bean and 0.74 hectares of groundnut. In comparison, the profit maximisation plan (IV) yields a profit of approximately GH¢3755.13 ( $\text{GH¢}11168.10 - \text{GH¢}7412.97 = \text{GH¢}3755.13$ ), representing a 33.62% increase in income compared to the farmer's plan (I). Notwithstanding the fact that the optimal income obtained by the farm plan (IV) is high, additionally, this

strategy is associated with a high level of risk, which may appeal to those who are risk-loving.

The majority of farmers in the Upper West Region exhibit a high degree of risk aversion amidst climate variability (see Table 13). This finding is consistent with previous studies such as those conducted by Larkai (2019), and Hakam (2021). Consequently, it is essential to develop a risk-efficient farm plan that aligns with their specific needs and attitudes. In light of the aforementioned considerations, the study employed the Target MOTAD model to identify risk-efficient crop enterprise combinations by varying the degree of reduction in a target expected income level and its associated risk. Thus, farmers are primarily concerned with achieving a maximum income from their farming activities and also with ensuring that their returns do not fall below certain income levels (Kaiser & Messer, 2011).

Table 14 indicates that the risk-efficient farm plans (II and III) include the production of soya bean and sorghum in respective hectares (1.50ha and 0.33ha, Plan II) and (1.50ha and 0.42ha, Plan III) to yield a risk-efficient income of GH¢9403.42 and GH¢9835.10, respectively. The risk-efficient income obtained by the risk-efficient farm plans (II and III) is higher than the farmer's income by 24.04% (equivalent to  $\text{GH¢}9403.43 - \text{GH¢}7142.97 = \text{GH¢}2260.46$ ) and 27.37% (equivalent to  $\text{GH¢}9835.10 - \text{GH¢}7142.97 = \text{GH¢}2692.13$ ), respectively. This implies that, given the same available resources, the farmer can obtain an increased income with a reduced level of risk for both risk-efficient plans (II & III).

From an economic standpoint, it is also logical for the Target-MOTAD model to transition from groundnut cultivation to less risky crops such as

sorghum and soybeans (for Plans, II and III), which are more resilient to market fluctuations. However, a comparison of the risk-efficient plans (II and III) with the profit-maximisation plan (IV) reveals a reduction in income of 15.80% (equivalent to GH¢11168.10-GH¢9403.42=GH¢1764.68) for plan (II) and 11.94% (GH¢11168.10-GH¢9835.10=GH¢1333) for plan (III). It is well established that the reduction in risk-efficient farm income (II and III) represents the risk premium for avoiding a riskier plan and moving towards a risk-efficient plan with a reduced risk probability. Consequently, a farmer may decide to pursue risk-efficient plans (II and III), if he/she is willing to forego the additional income (risk premium) that is assured in the profit maximisation plan (IV).

**Table 14: Farmer’s Plan, Optimum and Risk Efficient Plan of Crops**

	<b>Farmer’s Plan (I)</b>	<b>Risk Efficient Plan (II)</b>	<b>Risk Efficient Plan (III)</b>	<b>Profit Maximization Plan (IV)</b>
Optimal Value (GH¢)	7412.97	9403.42	9835.10	11168.10
<b>Enterprises</b>				
Maize (ha)	0.54	0.00	0.00	0.00
Groundnut (ha)	0.56	0.00	0.00	0.74
Soyabean (ha)	1.00	1.50	1.50	1.50
Sorghum (ha)	0.50	0.33	0.42	0.00
<b>Total Crop Area</b>	<b>2.60</b>	<b>1.83</b>	<b>1.92</b>	<b>2.24</b>

Source: Field survey, Koufie (2024)

**Resource Utilization Under Optimal and Risk Efficient Plans (II, III, IV)**

Table 15 illustrates the resource utilization patterns under the optimum farm plan and the risk-efficient farm plans. The results from Table 15 demonstrate that land, labour and capital were underutilized under the risk-efficient farm plans (II and III), while fertiliser was fully utilized under the risk-efficient plans. This implies that land, labour and capital were in excess of what was actually needed by the farmers in their food crop production.

Consequently, the risk-efficient plans (II and III) will not be affected if these unused resources were discarded. This is logical, given that the Upper West Region is endowed with farmlands for cultivation and that the majority of residents engage in farming, which is a significant occupation in the region (Antwi, 2016; Hakam, 2021). This corroborates the findings of the study that some of the labour and land will be left unused.

Furthermore, it is economically rational that a certain amount of capital will be left unused, given that the risk-efficient crops (soya bean and sorghum under plan II & III) are not particularly capital-intensive. However, fertilizer was fully utilized, as evidenced by the fact that in practice, the majority of farmers apply a small amount of fertilizer to these risk-efficient crops (soya bean and sorghum) in order to achieve higher yields. This corroborates the findings of the study that the limited available fertilizer will be fully utilized.

The profit maximisation farm plan (IV) utilized capital and fertiliser to their fullest extent. The land size under this farm plan (IV) was greater than that of the risk efficient farm plans and groundnut, which is a crop under this farm plan, is also capital-intensive (see Table 14). This will require a significant amount of capital to meet production expenses in order to attain the optimum expected income. Therefore, it was economically rational that this plan (IV) utilize capital to its fullest extent. However, the land and labour inputs under this plan (IV) were found to be in excess of what was actually needed by the farmer. This implies that in a situation where these resources are used for purposes other than crop production, there will be no effect on the profit maximisation farm plan (IV). This corroborates the findings of Udo et al. (2015) and Poonia et al. (2022), who also reported that in optimising farm plans

for arable crop farms under the profit maximisation plan, capital and labour were found to be fully utilized.

**Table 15: Resource Utilization under Optimal Farm Plans (II, III, IV)**

Resource	Land (hectare)	Labour (Man- days)	Capital (GH¢)	Fert. (KG)	Resource fully used	Resource not Fully used
<b>Activity</b>				<b>Plan II</b>		
Available	2.70	240	4565	150	Fertilizer	Land
Usage	1.83	177.88	3883.52	150		Labor
% Usage	67.78	74.12	85.08	100		Capital
Left Over	0.87	62.12	681.48	0.00		
% Left over	32.22	25.88	14.92	0.00		
<b>Activity</b>				<b>Plan III</b>		
Available	2.70	240	4565	150	Fertilizer	Land
Usage	1.92	185.77	4039.36	150		Labour
% Usage	71.11	77.40	88.49	100		Capital
Left Over	0.78	54.23	525.64	0.00		
%Left over	28.89	22.60	11.51	0.00		
<b>Activity</b>				<b>Plan IV</b>		
Available	2.70	240	4565	150	Fertilizer	Land
Usage	2.24	206.20	4565	150	Capital	Labour
% Usage	82.96	85.92	100	100		
Left Over	0.46	33.80	0.00	0.00		
%Left over	17.04	14.08	0.00	0.00		

Source: Field Survey, Koufie (2024)

#### **Trade of between Crop Mix Requirement and Income (II, III and IV)**

In Ghana, farmers cultivate food crops not only for commercial purposes (Frimpong, 2014). Indeed, the majority of farmers produce primarily for consumption, with some also selling surplus crops. Consequently, scenarios involving the production of groundnut and soya bean solely for-profit maximisation or sorghum and soya bean solely for risk minimisation would not fully satisfy the purpose of production. It is therefore necessary to include a food consumption constraint in the programming model. To illustrate this point, almost every farmer interviewed grows maize, which they regard as the most important crop.

In Ghana, maize is regarded as a major staple crop (Oppong, Onumah & Asuming-Brempong, 2014; Ghana Statistical Service, 2017; Obour, Arthur & Owusu, 2022). If a farmer wishes to produce a staple food for consumption, it is logical to allocate a portion of the resources to maize and sorghum production, in addition to the profit-maximising crops or maize and groundnut production, in addition to the risk-efficient crops. However, it should be noted that if certain food crops are forced into the model, the expected gross margin will be reduced due to income penalties (Koufie, 2020).

Table 16 presents the non-basic activity (crop mix conducted by the researcher), their income value, and their corresponding percentage trade-off. Table 16 indicates that, in order to satisfy the consumption requirements, a hectare of maize and a hectare of groundnut were incorporated into the model in conjunction with the risk-efficient crops. This was done in accordance with the risk-efficient plans (II and III). Table 16 reveals that the crop combination with the lowest income among the risk-efficient farm plans (II and III) is identified as maize/sorghum/soyabean/groundnut, with an expected income of GH¢9005.68 and GH¢9437.36, respectively, and a percentage income trade-off as 4.23 and 4.04, respectively. Comparably, this is still higher than the farmer's expected income of GH¢7412.97. Consequently, the farmer is more economically advantageous to pursue risk-efficient plans (II and III) despite the desire to meet subsistence needs.

With regard to the profit maximisation plan (IV), to satisfy the consumption requirement, a hectare of maize and a hectare of sorghum were incorporated into the model in interaction with the profit-maximisation crops. The results of Table 16 revealed that the combination of maize, sorghum,

soyabean and groundnut had the highest percentage income trade-off (3.56) and the lowest expected income of GH¢10770.36. This implies that the greater the diversification of crops through the optimal approach, the lower the income obtained by the farmer and the higher the income trade-off. This confirms the assertion made by Koufie (2020) that optimal income is reduced when other crops, in addition to the optimal crops, are forced into the model. These findings are consistent with those of previous studies conducted by Udo et al. (2015) and Twumasi (2022). These studies also observed that the optimal income declines when additional crops are introduced, due to the income penalties associated with these crops.

**Table 16: Crop Mix Trade off Requirements and Income (II, III and IV)**

<b>Risk Efficient Plan (II)</b>		
<b>Non-Basic Activity</b>	<b>Income (GH¢)</b>	<b>% Trade Off (Income)</b>
Soya Bean/Sorghum (Risk Eff. Crops)	9403.42	-
Groundnut/Soya Bam/Sorghum	9346.97	0.60
Maize/Soya Beans/Sorghum	9062.13	3.63
Maize/Groundnut/soya Bean/Sorghum	9005.68	4.23
<b>Risk Efficient Plan (III)</b>		
<b>Non-Basic Activity</b>	<b>Income (GH¢)</b>	<b>% Trade Off (Income)</b>
Soya Bean/Sorghum (Risk Eff. Crops)	9835.10	-
Groundnut/Soya Bam/Sorghum	9778.65	0.57
Maize/Soya Bean/Sorghum	9493.81	3.47
Maize/Groundnut/soya Bean/Sorghum	9437.37	4.04
<b>Optimum Farm Plan (Plan IV)</b>		
<b>Non- Basic Activity</b>	<b>Income (GH¢)</b>	<b>% Trade Off (Income)</b>
Soya Bean/ Groundnut (Optimal Crops)	11168.10	-
Groundnut/Soya Bean/Sorghum	11111.65	0.51
Sorghum/Soya Bean/ Groundnut	10826.81	3.06
Maize/ Sorghum/ Soya Bean/ Groundnut	10770.36	3.56

Source: Field Survey, Koufie (2024)

### **Test Significant Differences between the Farm Plans (I, II, III and IV)**

It is of great importance to test the significant difference between the farmer's plan (I) and the optimized farm plans (II, III and IV). This is because it helps to determine how statistically useful it is for the farmer to shift to the optimized farm plans. Table 17 presents a comparison between the farmer's existing plan, the profit maximisation plan and the risk-efficient plans in terms of the expected income generated by each plan. Table 17 reveals a significant difference between the farmer's plan (I) and the risk-efficient plan (II). This is evidenced by the mean income difference of GH¢1791.58 and a p-value of 0.0002. This implies that the farmers are losing their investment with their current plan because they could earn more returns with the same resources.

A comparison of the farmer's plan (I) and the optimum farm plan (IV) from Table 17 reveals a significant difference between the two. This is evidenced by a p-value of 0.0000, which is significant at 1% level and substantiated by the mean income difference of GH¢3556.26. Consequently, the farmer is demonstrably better off adopting the optimum farm plan (IV) than his own plan (I) in terms of income.

A comparison of the risk-efficient plan (II) and the optimum plan (IV) reveals a significant difference between the two. This is evidenced by the mean income difference of GH¢1764.68 and a p-value of 0.0000 (significant at 1% level). In essence, the optimal plan (IV) represents a superior option for the farmer if their objective is to achieve the highest possible profit, which is associated with a higher degree of risk. Conversely, by adopting the optimal plan (IV), the farmer is at a heightened risk of losing their investment.

However, risk-averse farmers may find greater benefit in adopting the risk-efficient plan (II), which is associated with a lower degree of risk.

Table 17 presents a comparison between the risk-efficient plan (II) and the risk-efficient plan (III). The results indicate a significant difference between the two plans, as evidenced by the mean income difference of GH¢431.68 and a p-value of 0.0223, which is statistically significant at the 5% level. This indicates that a less risk-averse farmer will opt for plan III and receive an additional income of GH¢431.68 compared to a more risk-averse farmer who will adopt risk-efficient plan (II), which is associated with less risk. Therefore, since the farmers in the study area are highly risk averse, it is important for them to go in for risk efficient plan (II).

**Table 17: T-test Results of Differences between the Farm Plans (I, II, III and IV)**

<b>Farmer’s Plan (Plan I) vs Risk Efficient Plan (Plan II)</b>		
Mean Income Difference GH¢	t-value	p-value
1791.58***	17.9410	0.0002
<b>Farmer’s Plan (Plan I) vs Optimum Farm Plan (Plan IV)</b>		
Mean Income Difference GH¢	t-value	p-value
3556.26***	35.6120	0.0000
<b>Risk Efficient Plan (Plan II) vs Optimum Farm Plan (Plan IV)</b>		
Mean Income Difference GH¢	t-value	p-value
1764.68***	12.2443	0.0000
<b>Risk Efficient Plan (Plan II) vs Risk Efficient Plan (III)</b>		
Mean Income Difference GH¢	t-value	p-value
431.68**	3.0567	0.0223

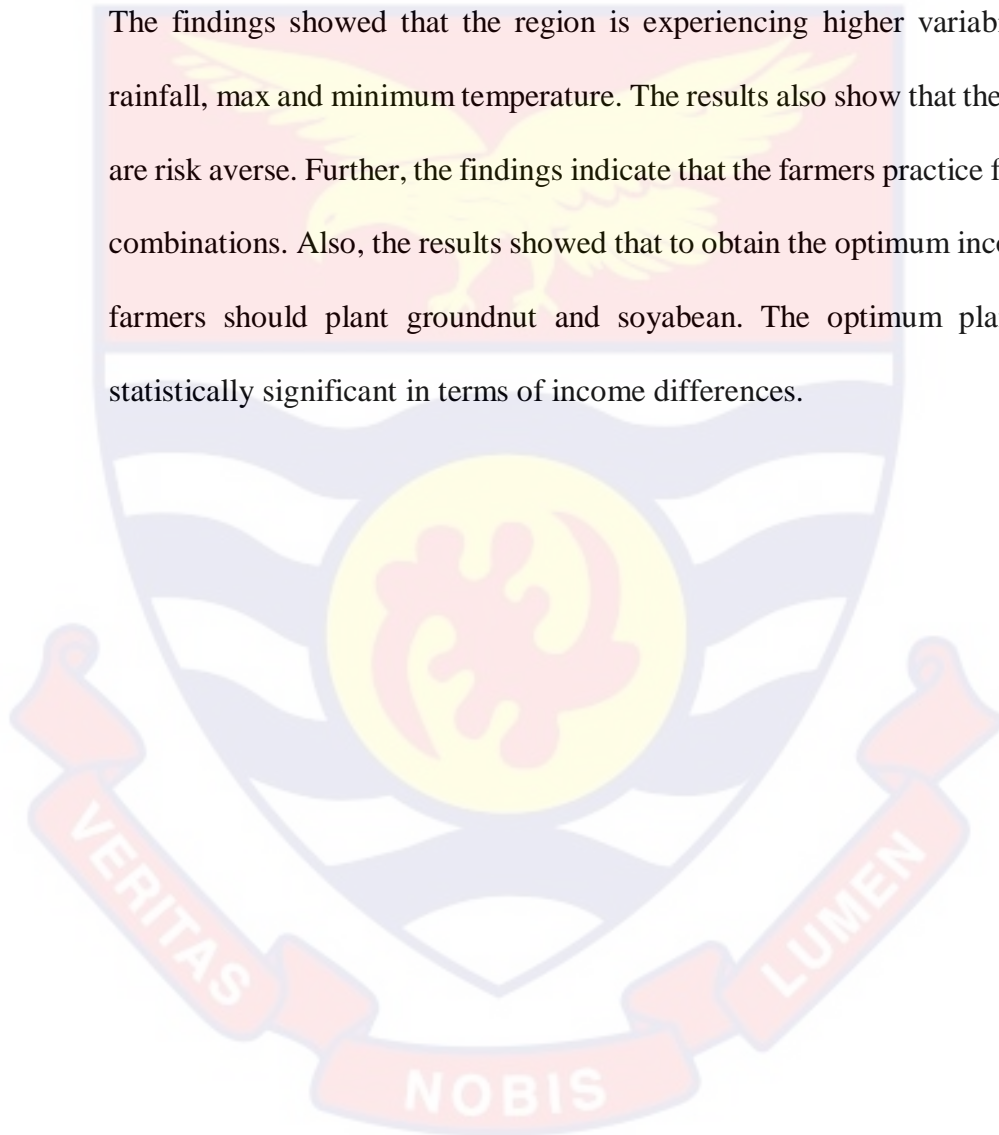
Source: Field Survey, Koufie (2024)

### Chapter Summary

The preceding chapter presented the findings of objective one and objective two. The chapter looked at climate trends using climate variables such as rainfall, maximum and minimum temperatures. The chapter also looked at the risk aversion levels of farmers amidst climate variability and

change as well as the crop enterprise patterns operated by the farmers. The study also presented and discussed the optimum farm plan that gives the farmer the highest income as well as the farmer's plan and the risk efficient plans. The study went further to look at resource utilization as well as tradeoff between the crop mix and the significant differences between the different farm plans.

The findings showed that the region is experiencing higher variabilities in rainfall, max and minimum temperature. The results also show that the farmers are risk averse. Further, the findings indicate that the farmers practice four crop combinations. Also, the results showed that to obtain the optimum income, the farmers should plant groundnut and soyabean. The optimum plans were statistically significant in terms of income differences.



## CHAPTER FIVE

### FARMER'S VALUE ON WEATHER INDEX BASED INSURANCE ATTRIBUTES AND THEIR WILLINGNESS TO PAY FOR THE WEATHER INDEX BASED INSURANCE POLICY

#### Introduction

This chapter presents the findings of the value placed by farmers on the weather index insurance (WII) and their willingness to pay for the WII policy. This chapter addresses the third objective. The chapter is divided into six sections. The first section discusses the value that farmers place on the WII attributes using the Kendall's coefficient of concordance to rank the attributes in order of importance. The second section presents the results of the estimates of farmers' preference for the WII insurance policy. The third section presents the findings of the comparison between the multinomial logit model and the mixed logit model used in estimating the interaction between the socio-economic characteristics of the farmers and the attributes of the weather index insurance. The fourth section presents and discusses the results of the interaction between the socio-economic characteristics of the farmers and the attributes of the weather index insurance. The fifth section presents and discusses the results of the farmers' willingness to pay for the WII insurance products using the willingness to pay space approach. Finally, the chapter concludes with a summary of the key findings.

#### The Value Farmers Place on the Weather Index Insurance Attributes

Knowing the right kind of attributes of weather index based insurance needed by the farmers and the value they place on the insurance policy is a key factor to implementing the right kind of WII insurance policies. The weather

index based insurance attributes which were premium, basis risk, prompt claim payout, interlinking credit with insurance, subsidy and “No discount claim” were ranked by the farmers from the most important preferred attributes to the least important preferred attributes. Scores were assigned to the ratings of the responses. That’s with (1) being the most important preferred attribute and (6) being the least important preferred attribute. The Kendall’s coefficient of concordance was used to analyze the rankings.

The result from Table 18 show that prompt claim payout was rated as the most important preferred WII attribute that farmers consider when making the decision to choose a particular set of weather index insurance policies and was ranked as 1<sup>st</sup> with a mean rank of 2.62. Intuitively, what it means is that, for a farmer to make a rational decision to purchase a particular weather index insurance policy, the first thing he/she looks out for is prompt claim payout. This makes economic sense because practically most of the farmers interviewed indicated that they pay attention to when and which medium they will be paid as that is a paramount concern to them. This is consistent with the findings of Cole et al. (2013) and Dercon et al. (2014), who emphasized that timely and transparent payout mechanisms significantly affect farmers’ trust and willingness to participate in weather index insurance schemes.

This was followed by the premium, with a mean rank of 2.68. The reason is that for a farmer to make a rational decision to purchase an insurance product, it is of essence that the premium (either low or high) to be paid is taken into consideration. Similar conclusions were drawn by Giné and Yang (2009), who observed that the cost of the premium is often a major determinant of uptake in developing countries, where farmers operate under tight liquidity

constraints. Farmers tend to evaluate whether the cost of coverage is justified by the perceived benefit, which reinforces the role of premium affordability in insurance demand.

Subsidy, basis risk and interlinking credit with insurance took the 3<sup>rd</sup>, 4<sup>th</sup> and 5<sup>th</sup> position with a mean rank of (3.08), (3.51) and (4.47) respectively.

“No discount claim” was rated last and the least important preferred attribute. This implies that, once the respondents are satisfied with the premium and the other attributes, “all other things being equal”, a reduction of the next seasons premium (no discount claim) will be the least important attribute to them. This is consistent with studies by Clarke and Dercon (2019) who noted that no-claim bonuses are often less valued by farmers in low-income settings.

Table 18 reveals that the results of the Kendall’s W test show that an agreement exists among the farmers regarding the ranking of the WII attributes, which is statistically significant at the 1% level. The Kendall’s W of 0.220 indicates that approximately 22% of respondents concurred that the attribute “prompt claim payout” is the most important preferred weather index insurance attribute, with the least important preferred attribute being “no discount claim”.

**Table 18: Value Farmers Place on the Weather Insurance Attributes**

Weather Insurance Attributes	N	SD	Mean Ranking	Rank
Claim Payout	450	1.55	2.62	1 <sup>st</sup>
Premium	450	1.74	2.68	2 <sup>nd</sup>
Subsidy	450	1.13	3.08	3 <sup>rd</sup>
Basis Risk	450	1.41	3.51	4 <sup>th</sup>
Int.linking Credit	450	1.35	4.47	5 <sup>th</sup>
No Claim Discount	450	1.76	4.63	6 <sup>th</sup>
Kendall’s Test of Concordance				
Kendall’s $W^a$			0.220	
Chi-Square			495.814	
Degree of freedom, df			5	
Asymp. Sig			0.000	

Source: Author’s Compilation, 2024.

### Parameter Estimate for Weather Index Insurance Attributes

This section presents the findings of the econometric estimations of farmer's choice behavior and their preference for weather index insurance attributes. Table 19 presents the results of the estimates of farmer's preference for weather insurance attributes from multinomial logit and mixed logit model.

The multinomial logit model serves as the base model in this analysis. The models were estimated in R using 10 000 Halton draws and all the parameters were assumed to be normally distributed. The results (Table 19) show that the parameters in both models (MNL and MIXL) were statistically significant. This implies that the WII attributes selected for the choice experiment survey are exactly what the farmers will look out for when making the decision of purchasing the weather insurance policy.

From Table 19, the coefficient for premium, no claim discount and subsidy were all negative and statistically significant at 1% level in both models (MNL and MIXL). Table 19 shows that both MNL and MIXL models indicate that premium as an attribute for a weather insurance policy (with attribute level of GH¢60) has a negative coefficient and is statistically significant at 1% level. This implies that farmers will prefer to purchase a lower price weather index insurance policy rather than a high price weather index insurance policy. This makes economic sense, because "all other things being equal", farmers utility decrease when price of a particular product increases. This is consistent with Cole et al. (2013) who also found that higher insurance premiums deter participation among smallholder farmers, especially those with limited liquidity.

Table 19 show that both models (MNL and MIXL) indicate that the attribute “no claim discount” (with attribute level as, payment at the end of the next season) had a negative coefficient value and is statistically significant at 1% level. By implication, farmers will prefer to receive their claim payout promptly rather than wait for the end of the next season. The plausibly reason is that; most of food crop farmers are risk averse in nature and may prefer the certainty of immediate payment since delayed payout often breeds uncertainty. It is also likely, that payout at the end of the next season could affect the liquidity needs of the farmers. In a sense that, the farmers may need the payout to purchase inputs for the next planting season, cover living expenses or even manage cash flow. This is in line with findings from Dercon et al. (2014), who emphasized that immediate payouts are essential for building trust in index insurance, especially in regions where farmers rely on timely capital for seasonal agricultural decisions.

Table 19 show that both MNL and MIXL models indicate that subsidy (with an attribute level as, subsidy on agricultural inputs) has a negative coefficient value and is statistically significant at 1% level. This implies that subsidizing agricultural inputs as an attribute when included in WII insurance policy will decrease the utility farmers derive from the policy which could lead to a lower likelihood of farmers not purchasing the WII policy. The plausibly reason is that; the farmers may prefer subsidy on weather index insurance policy premium or probably cash payout. This aligns with Mobarak and Rosenzweig (2022), who found that the form in which subsidies are provided significantly affects insurance uptake decisions for which many farmers prefer direct premium subsidies or cash transfers over input-based support.

From Table 19, both MIXL and MNL models indicate that the WII attribute basis risk (with attribute level, rainfall data from the GMet weather station) has a positive coefficient value and is statistically significant at 1% level. This implies that, farmers are likely to prefer rainfall data from the GMet weather station as an attribute in their WII insurance policy. The plausible reason is that; farmers may have previously utilised the GMet data in order to inform their decision-making processes and are more likely to prefer it for insurance purposes. Also, it is possible that farmers may find it easier to interpret and apply GMet data because they are accustomed to its format and terminology. This concurs with a study by Atiah et al. (2020) who tested the validity and reliability of rainfall data from GMet stations and the results showed that at least there is a 70% probability that rainfall over the country has been adequately reproduced by GMet stations. Therefore, the rainfall data from GMet is reliable and valid to be used for climate impact studies. This is also consistent with the findings of Jensen, Barrett, and Mude (2018), who stressed that reducing basis risk by using locally trusted data sources enhances farmers' confidence in index-based insurance schemes.

Both Models (MNL and MIXL) from Table 19 indicate that, interlinking credit with insurance as an attribute (ie. with attribute level as, credit interlinked with insurance) has a positive coefficient value and is statistically significant at 5% level. This implies that farmers will prefer credit interlinked with insurance as an attribute in their weather index insurance policy. The plausible reason is; it is likely farmers will be able to secure a loan by using the insurance as a collateral when they interlink their credit with WII insurance policy. This is supported by Carter et al. (2016), who found that

bundling insurance with credit helps to reduce lending risks and can incentivize both credit uptake and insurance subscription, especially where formal collateral is lacking.

Also, a significantly positive prompt mode of claim payout (prompt bank payment) from both MNL and MIXL models implies that this attribute has a positive effect on farmers' utility towards the WII policy. This is because most of the farming communities are now having rural banks and other banks not far from the communities making it easy for farmers to have access to banks for business. Intuitively, farmers will feel safe taking their money through the banks. This differs from the findings of Ellis (2016) and Boateng-Gyambiby (2019) who noted that there is a negative relationship between mode of claim payout of insurance and farmer's preference for weather index insurance.

The ASC (opt-out variable) which measured the opting out in the choice experiment was significantly negative at 1% for both models (MNL and MIXL). This implies that farmers benefit from choosing an alternative rather than opting out. Also, in MIXL model it can be seen that almost all the standard deviations were significant implying that there is an unobserved heterogeneity present in the farmer's preference for WII insurance policy. This supports findings by Train (2009), who indicated that significant standard deviations in MIXL models signal the presence of varied individual preferences that cannot be captured by observable characteristics alone, suggesting that personalized or targeted insurance designs may yield better uptake.

**Table 19: Parameter Estimate for Weather Index Insurance Attributes**

Variable	Multinomial Logit Model (MNL)		Mixed Logit Model (MXL)	
	Coef.	SE	Coef.	SE
Premium	-0.025***	0.008	-0.039***	0.009
Basis Risk	0.234***	0.067	0.304***	0.078
Claim Payout	0.099**	0.049	0.200***	0.063
Int.linking Credit	0.164**	0.064	0.158**	0.074
No claim Discount	-0.494***	0.046	-0.513***	0.057
Subsidy	-0.151***	0.049	-0.142***	0.058
ASC	-1.716***	0.447	-2.790***	0.538
SD Basis Risk	-	-	0.087	0.203
SD Claim Payout	-	-	0.714***	0.067
SD Int.linking Credit	-	-	-0.394***	0.063
SD No Claim Disc.	-	-	0.532***	0.089
SD Subsidy	-	-	0.408***	0.080
Log-Likelihood	-	-1895.865	-	-1833.092
Null Log-Likelihood	-	-2934.393	-	-2934.393
AIC	-	3805.729	-	3690.185
BIC	-	3846.961	-	3760.867
McFadden $R^2$	-	0.354	-	0.375
Adj. McFadden $R^2$	-	0.352	-	0.371
No. of Observations	-	2671	-	2671

NB: ASC= Alternative Specific Constant, SD= Standard Deviation, AIC= Akaike Information Criterion, BIC = Bayesian Information Criterion

Source: Author's Compilation, 2024.

### **Best Fit Model between Multinomial Logit Model (MNL) and Mixed Logit Model (MIXL)**

In order to account for preference heterogeneity in the parameter estimates of the weather index insurance attributes. The interaction between farmers' socio-economic characteristics and the weather index insurance attributes was performed using both the multinomial logit model (MNL) and mixed logit model (see Table 21 for the full model estimation). Table 20 shows the results for the best fit model between MNL and MIXL for the study and that could also statistically account for preference heterogeneity. This was done using certain key components such as Akaike Information Criteria (AIC),

Bayesian Information Criteria (BIC), Adjusted McFadden ( $R^2$ ), from the model estimations in Table 21.

From Table 20, the results show that the Mixed Logit Model (MIXL) has AIC and BIC values comparatively smaller than that of multinomial logit model (MNL) (i.e.  $3714.342 < 3808.857$  for AIC and  $3816.026 < 3884.539$  in the case of BIC). As the model with the minimum computed AIC and BIC, MIXL appears to have empirical superiority than MNL. Also, log-likelihood results in the Table 20 also portray that MIXL has the biggest log likelihood value of -1841.227 compared with -1892.928 for MNL. This also suggests that MIXL has empirical superiority for the data set than MNL.

Consequently, the model that has best fit for the data set for this study is the mixed logit model since it has a minimum AIC and BIC values as wells as maximum log likelihood value than its competing model (MNL). The  $(BIC_1 - BIC_2)$  value of 68.513 also shows that the mixed logit model is statistically preferred as it accounts for preference heterogeneity in estimating farmers' preferences for weather index insurance attributes.

**Table 20: Comparing Multinomial logit Model and Mixed logit Model**

	MNL	MIXL	Diff. in BIC ( $BIC_1 - BIC_2$ ) (Preferred)	Remarks
Log-likelihood	-1892.928	-1841.227		
Null LL	-2935.393	-2935.393		
AIC	3808.857	3714.342		
BIC	3884.539	3816.026		
Adj. McFadden $R^2$	0.350	0.366		
MNL Vrs MIXL	-	-	68.513	MIXL

Source: Author's Compilation, 2024

NB: ASC= Alternative Specific Constant, SD= Standard Deviation, AIC= Akaike Information Criterion, BIC = Bayesian Information Criterion. Decision Criteria: If  $BIC_1 - BIC_2 < 0$ , then MNL model is preferred and if  $BIC_1 - BIC_2 > 0$ , then the MIXL model is Preferred.

## **Interaction of Socio-Economic Characteristics and the Choice of Attributes**

The study interacted several socio-economic characteristics with the weather index insurance attributes. This was done in order to account for an observed heterogeneity in the preference estimate (Owusu & Dadzie, 2021).

Thus, advanced discrete choice models like the mixed logit model are able to account for unobserved heterogeneity but fails to account for the sources of heterogeneity (Owusu, 2019). Therefore, the need for the interaction. After several interactions between the socio-economic characteristics and the weather index insurance attributes, the results are presented in Table 21 by removing the insignificant interaction terms as revealed by their p-values and only reporting the significant interaction term.

In reference to Table 20 which present the results of AIC, BIC, Log-likelihood test and Adjusted McFadden  $R^2$  of both the multinomial and mixed logit model in estimating the interaction between socio-economic variables and the preference for the weather index insurance attributes, all showed that the mixed logit model is the best fit model for the study. Therefore, the study discussed the results of the mixed logit model presented in Table 21. From Table 21, unlike, the mixed logit model without interaction, basis risk was found not to be significant under the mixed logit model with interaction. However, all the other attributes were statistically significant.

Table 21 show that a risk averse farmer has a statistically positive attitude towards WII's premium and is significant at 5% level. This implies that a risk averse farmer is likely to pay an extra amount of premium to be insured in order to avoid risk of crop failure or losses regarding any unforeseen event.

This supports the findings of Liu et al. (2013), who indicated that risk-averse farmers are more willing to invest in risk mitigation strategies such as insurance. Table 21 indicate that there is a positive and statistically significant relationship between risk averse farmer and basis risk at 5% level. This implies that, given the lack of transparency regarding rainfall measurement, a risk averse farmer is likely to rely on rainfall data from GMet weather station. This is consistent with a study by Shee et al. (2021) who also noted that a risk averse farmer has a positive attitude towards rainfall data from GMet as an attribute in WII.

Table 21 show that there is a statistically positive relationship between extension service access and basis risk (rainfall data from GMet weather station) and is significant at 5% level. This implies that farmers who have more access to extension service in terms of training and learning the importance of rainfall information on weather index-based insurance policy are likely to rely on rainfall information from GMet weather station. The plausible reason is that; it provides accurate rainfall data which is easy to interpret and apply as well as frequent update from the station which allows farmers to adjust their practice accordingly. Therefore, it is more likely famers will prefer it for insurance purpose. This aligns with Dercon et al. (2024), who found that extension services improve farmers' understanding and trust in insurance products and the data underlying them.

Table 21 show that extension service has a negative relationship with credit interlinked with insurance and is statistically significant at 10%. By implication, more access to extension service is likely to influence the farmers not to interlink their credit with insurance. The plausible reason is that; it is

likely that the farmers will be educated on the loss of assets if they default payment which may deter them from interlinking their credit with insurance. This finding is supported by Carter et al. (2011), who noted that information access can change perceptions of financial risk and influence insurance-credit adoption decisions.

From Table 21, the results indicate that there is negative relationship between age of a farmer and interlinking credit with insurance as WII attribute and is statistically significant at 10% level. This implies that older farmers are less inclined to combine their credit facilities with their insurance policies. The reason is that the interlinking of credit with insurance may necessitate more complex administrative processes or the use of technology, which may present challenges for older farmers compared to their younger counterparts. Also, older farmers are known to be more risk averse and maybe concerned about the potential complexities or risks associated with interlinked products. This is similar to the findings of Giné and Yang (2019), who observed lower participation in complex insurance-linked products among older farmers.

The results from Table 21 indicate that there is a statistically positive relationship between education and claim payout (prompt bank payment) which is significant at 5% level. This implies that educated farmers will prefer to receive their indemnity from the bank promptly than non-bank payment. It can be posited that those with a higher level of education may be more financially literate, which in turn may lead to a greater comfort and trust in banking systems for financial transactions. As also noted by Hill et al. (2013), higher education levels correlate positively with uptake of formal financial services in rural areas.

Table 21 indicate that there is a significantly negative relationship between age and basis risk at 10% level. This implies that older farmers may not want to use information from GMet weather station for their insurance. The plausible reason is that; older farmers may encounter difficulties in accessing or interpreting data from modern weather stations such as GMet. Consequently, they may opt for traditional methods or local knowledge rather than data from weather stations, particularly if they have encountered discrepancies between reported data and actual weather outcomes. This is consistent with the work of Patt et al. (2019), who found that older farmers often rely on traditional knowledge over technical data sources.

From Table 21, the results show that there is statistically positive relationship between education and basis risk and is significant at 10% level. This implies that educated farmers are likely to use data from GMet weather station for their insurance decisions. The reason is that educated farmers are likely to be more comfortable interpreting and utilising data from sources such as the GMet weather station in order to make insurance-related decisions. This concurs with the findings of Cole et al. (2012), who indicated that education enhances comprehension of probabilistic information, which is key in understanding basis risk. Similarly, studies in rural Ethiopia and Kenya have found that higher education levels significantly increase the likelihood of adopting weather index insurance, as educated farmers are better equipped to understand and manage basis risk associated with such insurance products (Hill et al., 2011; Fukumori et al., 2022). Additionally, research by Darkoh et al. (2024) also indicates that farmers with higher educational attainment are more willing to pay for weather index insurance, suggesting a positive relationship

between education and the adoption of insurance products that may involve basis risk.

**Table 21: Interaction of Socio-Economic Characteristics and the Farmer’s Choice of WII Attributes**

Variable	Multinomial Logit Model (MNL)		Mixed Logit Model (MXL)	
	Coef.	SE	Coef.	SE
Premium	-0.009	0.010	-0.020*	0.012
Basis Risk	0.039	0.109	0.121	0.131
Claim Payout	0.096**	0.049	0.231***	0.066
Int.linking Credit	0.211***	0.092	0.329***	0.113
No claim Discount	-0.546***	0.083	-0.620***	0.104
Subsidy	-0.151***	0.049	-0.142**	0.058
ASC	-1.757***	0.450	-2.368***	0.522
Observ.Heterogeneity				
Premium*RiskAtt.	0.010**	0.004	0.012**	0.005
Basis Risk*RiskAtt.	0.127**	0.058	0.158**	0.070
Basis Risk*ExtServ.	0.226**	0.087	0.247**	0.104
Int.linkCredit*ExtServ.	-0.145*	0.065	-0.183*	0.108
Age* Int.linkCredit	-0.097*	0.048	-0.125*	0.109
Age*Basis Risk	-0.021**	0.009	-0.042*	0.020
Edu*Claim Payout	0.035**	0.018	0.230**	0.067
Edu* Basis Risk	0.445*	0.260	0.019*	0.011
SD Basis Risk	-	-	0.292***	0.109
SD Claim Payout	-	-	0.767***	0.075
SD Int.linking Credit	-	-	0.317**	0.126
SD No Claim Disc.	-	-	0.486***	0.092
SD Subsidy	-	-	-0.545***	0.069
Log-Likelihood	-	-1892.928	-	-1841.227
Null Log-Likelihood	-	-2935.393	-	-2935.393
AIC	-	3808.857	-	3714.342
BIC	-	3884.539	-	3816.026
McFadden $R^2$	-	0.354	-	0.373
Adj. McFadden $R^2$	-	0.350	-	0.366
No. of Obs.	-	2671	-	2671

NB: ASC= Alternative Specific Constant, SD= Standard Deviation, AIC= Akaike Information Criterion, BIC = Bayesian Information Criterion

Source: Author’s Compilation, 2024

### **Estimating Willingness to Pay for Weather Index Insurance Attributes**

The study used the willingness to pay space model approach of the mixed logit model to estimate the willingness to pay values. This approach involves estimating willingness to pay values directly (Owusu, 2019). The results from Table 22 show that there is a statistically positive relationship between basis risk and farmer's willingness to pay and is significant at 1% level. This implies that farmers are willing to pay GH¢ 5.38 pesewas on the premium for a weather index insurance policy that uses rainfall data from GMet weather station to determine their indemnity payout. This concur to the findings of (Jensen et al., 2017; Boateng-Gyambiby, 2019) who asserted that farmers are not willing to pay for a weather index insurance product that uses rainfall data from satellite but rather GMet station. The reason was that, farmers are unable to appreciate how the satellite operations work but rather are familiar and prefer a GMet weather station that is closer to their area to determine their indemnity payout.

Table 22 indicate that there is a statistically positive relationship between subsidy (with a coefficient of 6.669) and farmers' willingness to pay for WII policy and is significant at 1% level. This show that farmers are willing to pay GH¢ 6.669 pesewas on subsidy of agricultural input as an attribute for weather index insurance. By implication, this suggests that incorporating input subsidies into WII packages can enhance their attractiveness and perceived value, potentially increasing adoption rates among smallholder farmers. Interestingly, in Table 19, preference estimate for subsidy on agricultural inputs showed a negative coefficient. However, the results in Table 22 show that farmers are willing to pay for it. The plausible reason is that; farmers

evaluate various attributes of insurance policies, and while they may prefer a policy without a subsidy on agricultural inputs, they are not opposed to paying for a policy that includes it if other attributes align with their needs. This illustrates the significance of considering the entire bundle of attributes and the trade-offs that farmers are willing to make. This is consistent with Farrin and Miranda (2015) who also found that subsidizing insurance premiums significantly increases demand for weather index insurance among smallholders, particularly in low-income settings. Similarly, Jin et al. (2016) also reported that input subsidies coupled with index insurance enhanced uptake in rural China by making the insurance package more cost-effective for farmers.

From Table 22, the results show that “No claim discount (ie. Payment at the end of the next season), has a positive coefficient of 13.911 and indicate a positive relationship with farmer’s willingness to pay for the WII policy and is statistically significant at 1% level. This implies that farmers are willing to pay GH¢13.911 for payment to be deferred to next season. Interestingly, Table 19 indicated a negative preference estimate for payment at the end of the next season. The plausible reason for this counterintuitive is; it is likely farmers recognise the value of having the option to receive payment at the end of the next season and are willing to pay a higher premium for it, even if it is not the most preferred option when compared to others available to them (this is reflected in Table 18). This could indicate that the farmers might use the deferred payment as a form of savings or investment for the next planting season.

Table 22 indicate that interlinking credit with insurance has a coefficient of 3.82 and shows a positive statistical relationship with farmers' willingness to pay for WII policy and is significant at 1% level. This implies that farmers are willing to pay GH¢3.82 pesewas for their insurance to be linked with credit facilities. The possible reason is that insurance may act as a form of collateral or risk mitigation for lenders, which could potentially improve farmers' access to credit. From Table 22, the results indicate that prompt claim payout (prompt bank payment) with a coefficient as -4.509 has a statistically negative relationship with farmer's decision to pay for weather index insurance policy.

**Table 22: Willingness to Pay Estimates Using the Willingness to Pay Space Approach**

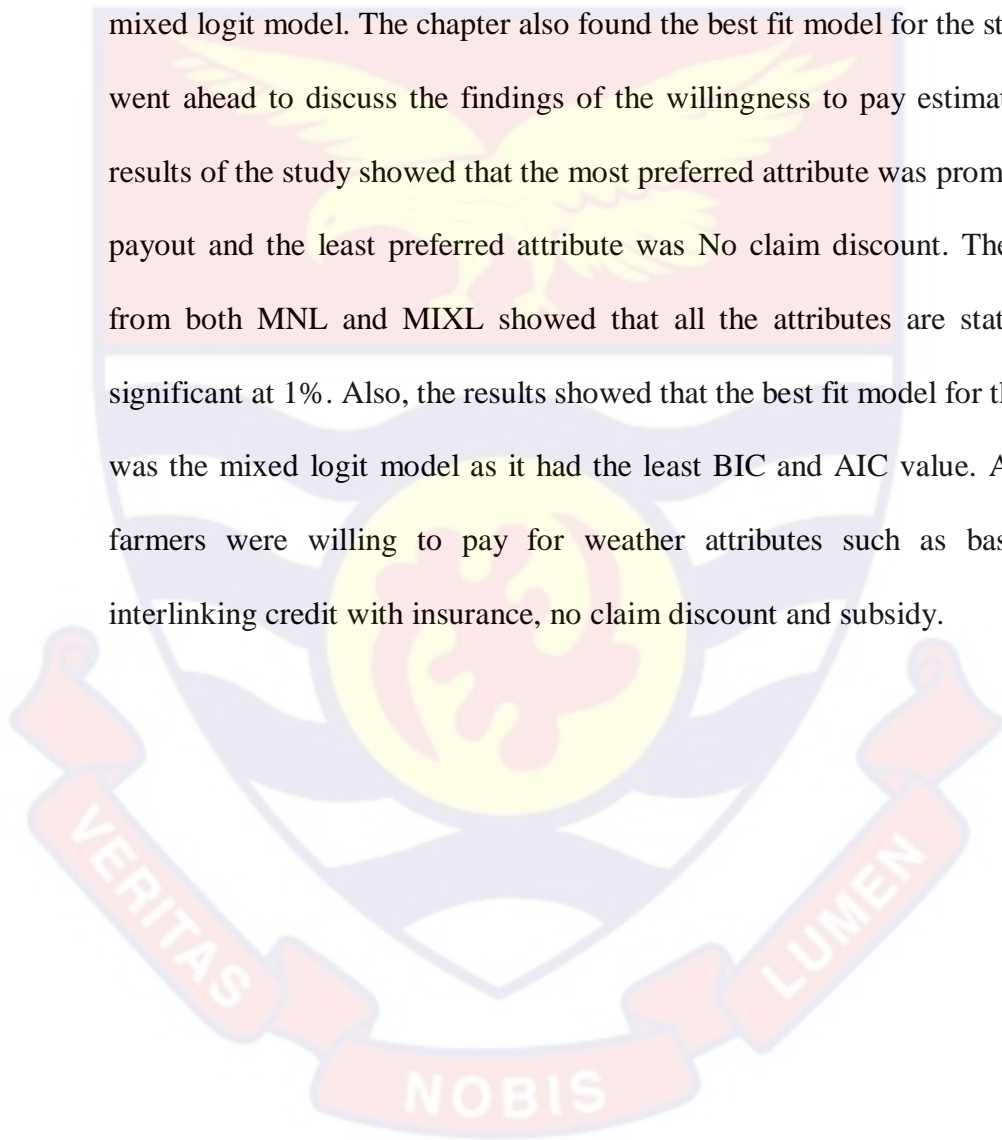
Variable	Coef.	Std.Error
Basic Risk	5.376***	0.984
Prompt Claim Payout mode	-4.509***	1.427
Int.linking Credit	3.816***	1.458
No Claim Discount	13.911***	2.272
Subsidy	6.669***	1.465
Premium	Fixed	-
ASC	5.979***	2.069
SD Basis Risk	2.684	2.297
Sd Claim Payout	11.984***	1.315
SD Int.linking Credit	6.818***	1.554
SD No Claim Disc. Payment	9.142***	1.278
SD Subsidy	7.608***	1.251
Log-Likelihood	-1857.724	
Null Log-Likelihood	-2934.393	
AIC	3739.448	
BIC	3810.131	
McFadden $R^2$	0.367	
Adjusted McFadden $R^2$	0.363	
No. of Obs.	2671	

NB: ASC= Alternative Specific Constant, SD= Standard Deviation, AIC= Akaike Information Criterion, BIC = Bayesian Information Criterion

Source: Field survey, Koufie (2024)

## Chapter Summary

The preceding chapter presented the findings of the objective three. Thus, the chapter presented the preferred attributes by the farmers using the Kendall's coefficient of concordance and went further to measure the preferences from an econometric point of view using the multinomial logit and mixed logit model. The chapter also found the best fit model for the study and went ahead to discuss the findings of the willingness to pay estimates. The results of the study showed that the most preferred attribute was prompt claim payout and the least preferred attribute was No claim discount. The results from both MNL and MIXL showed that all the attributes are statistically significant at 1%. Also, the results showed that the best fit model for the study was the mixed logit model as it had the least BIC and AIC value. Also, the farmers were willing to pay for weather attributes such as basis risk, interlinking credit with insurance, no claim discount and subsidy.



**CHAPTER SIX**  
**THE INFLUENCE OF RISK OPTIMUM INCOME AND RISK**  
**AVERSION OF FARMERS ON SUBSCRIPTION AND**  
**SUBSCRIPTION INTENSITY OF WEATHER INDEX-BASED**  
**INSURANCE POLICY**

**Introduction**

I wish to state that this empirical chapter has gone through the peer review process and has been accepted for publication by Agris on-line Papers in Economics and Informatics Journal. This chapter presents and discusses the findings of risk optimum income and risk aversion on subscription and subscription intensity of the weather index insurance. It addresses the fourth objective of the study. The chapter is divided into six sections. The first section presents the results of farmers' subscription of weather index insurance. The second section discusses the findings of farmers' subscription intensity of weather index insurance.

The third section presents and discusses the findings of the best fit model between Poisson regression, negative binomial hurdle and zero-inflated negative binomial models in analysing the weather data of the study. Thus, the study presents the results of the AIC, BIC and log-likelihood ratio of the selected models. The fourth and fifth sections present and discuss the findings of the Vuong statistical test and rootogram in identifying the optimal model between the selected models for the study. The sixth section presents and discusses the influence of risk efficient income and risk-averse of farmers on farmers' subscription and subscription intensity of weather index-based insurance. The final section presents a summary of the chapter.

### Subscription of the Weather Index Insurance Product

Figure 13 indicates that of the 450 food crop farmers interviewed, 287 (63.8%) have subscribed to the weather index insurance policy. The remaining 163 farmers (36.2%) have not subscribed to the weather index based insurance policy. The farmers interviewed indicated that their low income, lack of preferred attributes, and prompt payments, among other factors, are the primary constraints preventing them from subscribing to the weather insurance.

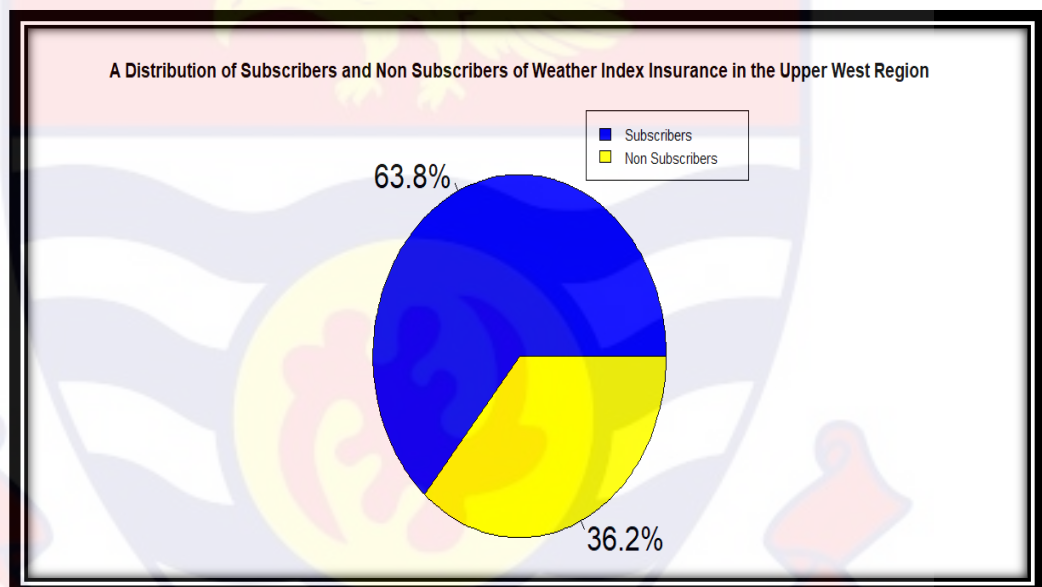


Figure 13: Distribution of Subscribers and Non-Subscribers of WII in UWR  
Source: Field Survey, Koufie (2024)

### Subscription Intensity of the weather Index Insurance Product

Table 23 indicates that the average land size owned by farmers in the study area is approximately 3.21ha. Additionally, the mean farm size cultivated was approximately 2.70 ha. The plausible reason is that farmers lack sufficient income and access to credit, which limits their ability to expand their farm production activities. Further, the farmers interviewed indicated that they are confronted with climate extremes, which also impairs their farming operations. Consequently, there is a clear need for weather index insurance.

Table 23 indicates that the average land size insured against climate variability and change using weather index insurance was 1.05 ha out of the 2.70 ha used for cultivation. The subscription intensity of weather index insurance is 0.39 (area of land insured per land cultivated). This implies that, for every hectare of cultivated farmland, the farmer insures 0.39 ha. The most probable explanation is that the majority of farmers interviewed stated that they are financially constrained, which makes it challenging for them to expand the land area insured.

**Table 23: Subscription Intensity of Weather Index Insurance Policy**

<b>Agricultural Activity</b>	<b>Mean</b>	<b>Subscription Intensity</b>
Area of land insured using WII (Hectares)	1.05	
Area of land cultivated (Hectares)	2.70	
Area of land owned (Hectares)	3.21	
Subscription Intensity of Weather Index Insurance		0.39

Source: Field Survey, Koufie (2024)

### **A Frequency Distribution of Subscription Intensity of Farmers in the Upper West Region**

Figure 14 presents the frequency distribution of the subscription intensity of food crop farmers in the Upper West Region. The distribution exhibits a minimum value of 0.24 ha and a maximum value of 0.60 ha. From Figure 14, the histogram for the variable subscription intensity of the weather index insurance demonstrates a slight rightward skew. This indicates that the majority of values are greater than the mean score of 0.39 ha. Furthermore, the data exhibit a deviation from the mean score of 0.09 (standard deviation = 0.09).

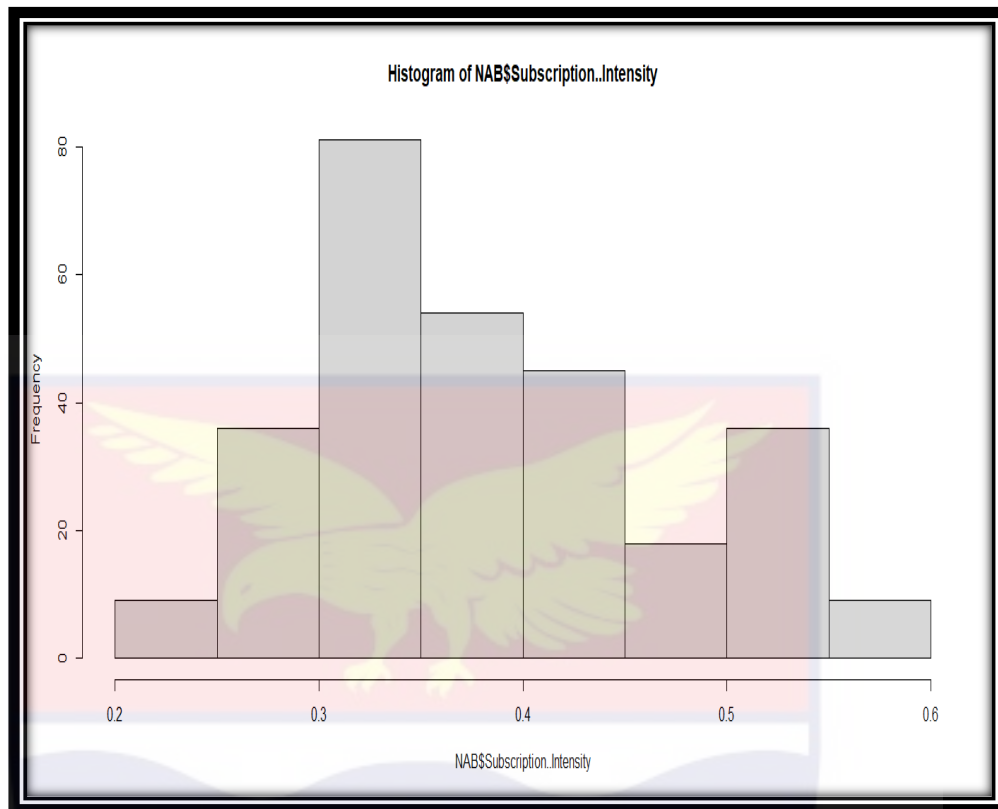


Figure 14: Distribution of Crop farmers' WII Subscription Intensity

Source: Field Survey, Koufie (2024)

#### Best Fit Model between PRM ZINBM NBDHM using AIC, BIC, LL

In light of the findings of studies such as those by Sarul and Sahin (2015) and Addey, Jatoo and Kwadzo (2021), it can be concluded that the negative binomial hurdle model is the optimal model for analysing count data. It is noteworthy that studies such as those by Workie and Azene (2021), Mthethwa et al. (2022) and Lee et al. (2023) have also challenged the assertion made by previous studies, which found the zero-inflated negative binomial to be the optimal model for analysing count data. The current study empirically verified either of the above assertions by employing three different count models that follow Poisson or negative binomial distributions to the data set used in the study and testing for their superiority.

The count models employed were the Poisson Regression Model (PRM), Negative Binomial Hurdle Model (NBHM) and Zero-Inflated Negative Binomial Model (ZINBM). The Akaike Information Criterion (AIC), Bayesian Information Criteria (BIC) and log likelihood (LL) values have been computed for each model in order to assist in determining which model estimates are most appropriate for the data set used in the study.

In reference to Table 26, which presents the results of the PRM, NBHM and ZINBM in estimating the effect of risk optimum income and risk aversion on subscription and subscription intensity of the WII. The AIC, BIC, and LL from the three count models (PRM, NBHM and ZINBM) presented in Table 26 have been presented in Table 24. The results presented in Table 24 demonstrate the performance of all three count models employed in the study. The results show that NBHM has AIC and BIC values comparatively smaller than that of ZINBM which values are also smaller than that of PRM (i.e.  $2557.469 < 2559.325 < 10851.4$  for AIC and  $2693.074 < 2694.930 < 10917.15$  in the case of BIC). The model with the lowest computed AIC and BIC, NBHM, appears to have empirical superiority over ZINBM, which in turn has empirical superiority over PRM.

Further, the log-likelihood results in the Table 24 also portray that NBHM has the biggest log likelihood value of -1246 compared with -1247 for ZINBM and that of PRM which is -5410. This also suggests that NBHM has empirical superiority for the data set than ZINBM and PRM respectively. Consequently, the model that has best fit for the data set for this study is the Negative Binomial Hurdle Model since it has a minimum AIC and BIC values as wells as maximum log likelihood value than its competing models. This

confirms the assertion made by previous studies such as (Sarul & Sahin, 2015; Addey, Jatoe & Kwadzo, 2021; Yildirim, Kaciranlar & Yildirim, 2022) that the NBHM is the best fit model in analysing count data.

**Table 24: Best Fit Model between PRM ZINBM NBDHM using AIC, BIC, Log-likelihood**

Count Models	AIC	BIC	Log-likelihood
PRM	10851.40	10917.15	-5410
ZINBM	2559.325	2694.930	-1247
NBHM	2557.469	2693.074	-1246

Source: Field survey, 2024

**Vuong Test Results Based on Pair Comparisons of PRM, NBHM and ZINBM**

In an attempt to find the count model that is suitable in dealing with underdispersion, overdispersion and excess zeros in the weather index insurance, the study further employed the Vuong statistical test. In employing the Vuong test, the three selected count models (PRM, NBHM and ZINBM) have to be paired. The decision criterion was that if a paired model yielded a positive value of the test statistic in the Vuong test, then the first model was deemed to be more suitable in dealing with overdispersion and excess zeros than the second one (Pittman et al. 2020; Yildirim, Kaciranlar & Yildirim, 2022).

In this study, PRM was paired as the first model with NBHM and ZINBM, respectively. Furthermore, the ZINBM was paired as the first model with the NBHM. The results are presented in Table 25. The results in Table 25 show that all the computed Vuong test z-statistic values are negative and highly significant. The Vuong test result of -20.2716\*\*\* between the Poisson Regression Model (PRM) and the Negative Binomial Hurdle Model (NBHM)

implies that the NBHM is statistically preferred to the PRM. Similarly, the test result of -20.2669\*\*\* between the Poisson Regression Model (PRM) and the Zero-Inflated Negative Binomial Model (ZINBM) indicates that the ZINBM is statistically preferred to the PRM.

Further, the Vuong test result of -2.3414\*\*\* between the Negative Binomial Hurdle Model (NBHM) and the Zero-Inflated Negative Binomial Model (ZINBM) indicates that the NBHM is statistically preferred to the ZINBM. In light of these findings, the Negative Binomial Hurdle Model (NBHM) is deemed to be the best count model for addressing excess zeros and overdispersion in the weather index insurance data set. This corroborates the findings of Table 24, which indicate that the Negative Binomial Hurdle Model (NBHM) is the best fit count model for this study and is also capable of addressing excess zeros, under- and over-dispersion in the WII data set of the study.

**Table 25: Vuong Test on Pair Comparisons of PRM, NBHM, and ZINBM**

Count Regression Models	Vuong test z-statistic	p-value
PRM vs NBHM	-20.2716***	2.22e-16
PRM vs ZINBM	-20.2669***	2.22e-16
ZINBM vs NBHM	-2.3414***	0.0026

Source: Field Survey, Koufie (2024)

### **Hanging Rootogram of the PRM, NBHM and ZINBM for the Study's**

#### **Count Data**

Following the discussions in Tables 24 and 25, the best count model for addressing the issue of excess zero, under and over dispersion in the WII data set was identified. This study went further to use a hanging rootogram to show

which of the three count regression models best fits the study's count data, addresses excess zeros, and treats over and under dispersion in the count data.

Figure 15 displays the three count regression models, with the Poisson Regression Model (PRM) located at the top-left, the Negative Binomial Hurdle Model (NBHM) at the top-right, and the Zero-Inflated Negative Binomial Model (ZINBM) at the bottom left. The rootogram for PRM (top-left) indicates that the counts (1 and 2) are overfitted, while zero (0) and the majority of counts from 3 and above are underfitted. This clearly demonstrates overdispersion and a high number of underdispersion in the data. Therefore, a clear lack of fit for the zero count indicates that there is still a possibility of excess zeros in the study's count data.

Also, the rootogram for ZINBM (bottom-left) shows that there is underfitting of the zero count and counts (3 and above), indicating the presence of excess zeros and underdispersion in the count data. Comparably, the Zero-Inflated Negative Binomial Model (ZINBM) is a much better fit than the Poisson Regression Model (PRM). However, the rootogram for NBHM (top-right) shows that the model perfectly fits the count zero (0). This clearly indicates that NBHM effectively addresses the issue of excess zeros

Further, the deviations between the observed frequencies and the predicted frequencies are quite small for most of the positive counts. Therefore, the NBHM is the best fit model for this study. This concurs with the findings presented in Tables 24 and 25, as well as those of other studies, such as those by (Hu, Pavlicova & Nunes, 2011; Sarul & Sahin, 2015), who similarly confirm that the Negative Binomial Hurdle Model is a best fit count regression model for addressing excess zeros, under- and over-dispersion in count data.

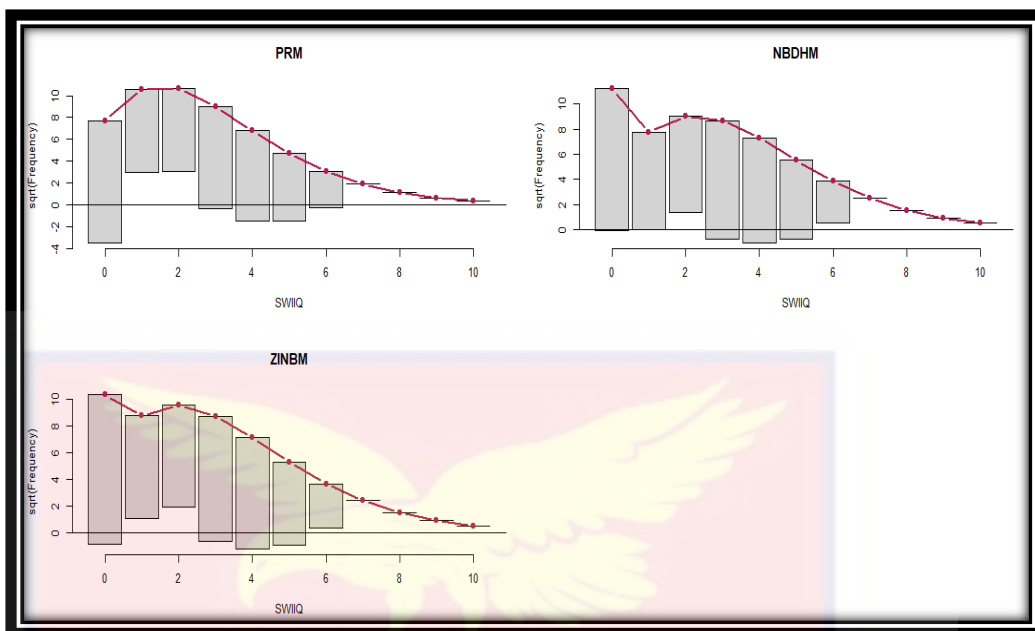


Figure 15: Hanging Rootogram of Different Count Models for the study's Count data (0,1,2,3,4,.....10)

Source: Field Survey, Koufie (2024)

### **Risk Aversion Levels and Risk Efficient Income on Subscription and Subscription Intensity of Weather Index Based Insurance**

In reference to Table 24 which presents the results of (AIC, BIC, and Log-likelihood), Table 25, which shows the results of the Vuong statistical test and Figure 15, which illustrate the results of the rootogram, all results show that the Negative Binomial hurdle model is the best model for this study in comparison to its competing models (PRM and ZINBM). The results of the NBHM on the effect of risk aversion behavior and risk-efficient income on subscription and subscription intensity, as presented in Table 26, will now be discussed. From Table 26 the results of the Negative Binomial Hurdle Model (NBHM) indicate the estimate with their associated standard errors in bracket.

In the first regression stage of the NBHM (Zero-hurdle model), the results show that variables such as the age of a farmer, sex, farm size, insurance prompt payment, extension service, credit access, risk aversion behavior and

risk efficient income are statistically significant in influencing food crop farmer's decision to subscribe to the weather index insurance. In the second regression stage of the NBHM (Count model), the results show that age, sex, education, farm size, experience, FBO, household size, insurance prompt payment, insurance awareness, credit access, risk aversion behavior and risk efficient income are the variables that are statistically significant in influencing the intensity of farmers' subscription to the weather index insurance.

From Table 26, the results of zero hurdle and count model of the NBHM show that the age of a farmer has a negative relationship with subscription and subscription intensity and is significant at 1% and 10% respectively. By implication, older food crop farmers have extensive knowledge and skills, have dealt with many crop failures and losses, and have gained a lot of experience dealing with risky situations such as climatic or production risk. Therefore, they are more likely not to subscribe to the weather index insurance, let alone increase the number of subscriptions. This finding highlights the need for age-sensitive policy interventions. This is consistent with studies such as (Hill et al., 2013; Sujarwo & Rukmi, 2018; Addey, Jatoo & Kwadzo, 2021), who also found that the age of a farmer has a negative effect on agricultural insurance as this makes them not willing to subscribe as well as intensify the subscription of agricultural insurance products.

The results of the zero-hurdle model of the NBHM from Table 26 show that farm size has a negative effect on the subscription for WII insurance and is statistically significant at 5%. This implies, it is more likely that a hectare increase in farm size will reduce the number of people who will subscribe to the weather insurance policy. The plausible reason is that; it is likely they may

not have the financial capacity to pay the subscription fee (premium) for an additional hectare of farm land. Interestingly, farm size was positive for subscription intensity in the count model of the NBHM from Table 26. This implies that, farmers with large farm size are more likely to insure a greater percentage of the farm lands available to them. The plausible reason is that; since farm size serves as proxy for wealth and collateral, farmers with large farm size could lease a portion of the land to raise money to purchase the insurance policy. This contradicts studies such as (Ntukamazina et al., 2017; Boateng-Gyambiby, 2019). However, this is in line with a study conducted by Haruna (2015) who also noted that there is a positive relationship between farm size and subscription intensity.

Also, the results of the zero-hurdle model of the NBHM show that access to extension services is found to have a positive effect on the subscription of WII and is statistically significant at 5% level. This implies that increasing extension service access to farmers is more likely to increase the number of farmers who will subscribe to the weather insurance policy. This is consistent with a study by Ankrah et al. (2021). From Table 26, the results of the count model of NBHM show that education have a positive relationship with subscription intensity of weather insurance and is statistically significant at 1%. This means that since education and training are mostly used as a proxy for understanding agricultural insurance policies. An educated farmer is more likely to appreciate the WII insurance contract and increase the proportion of the farm land insured.

Accordingly, from Table 26, the results of the count model of NBHM, show that insurance awareness was found to have a negative relationship with

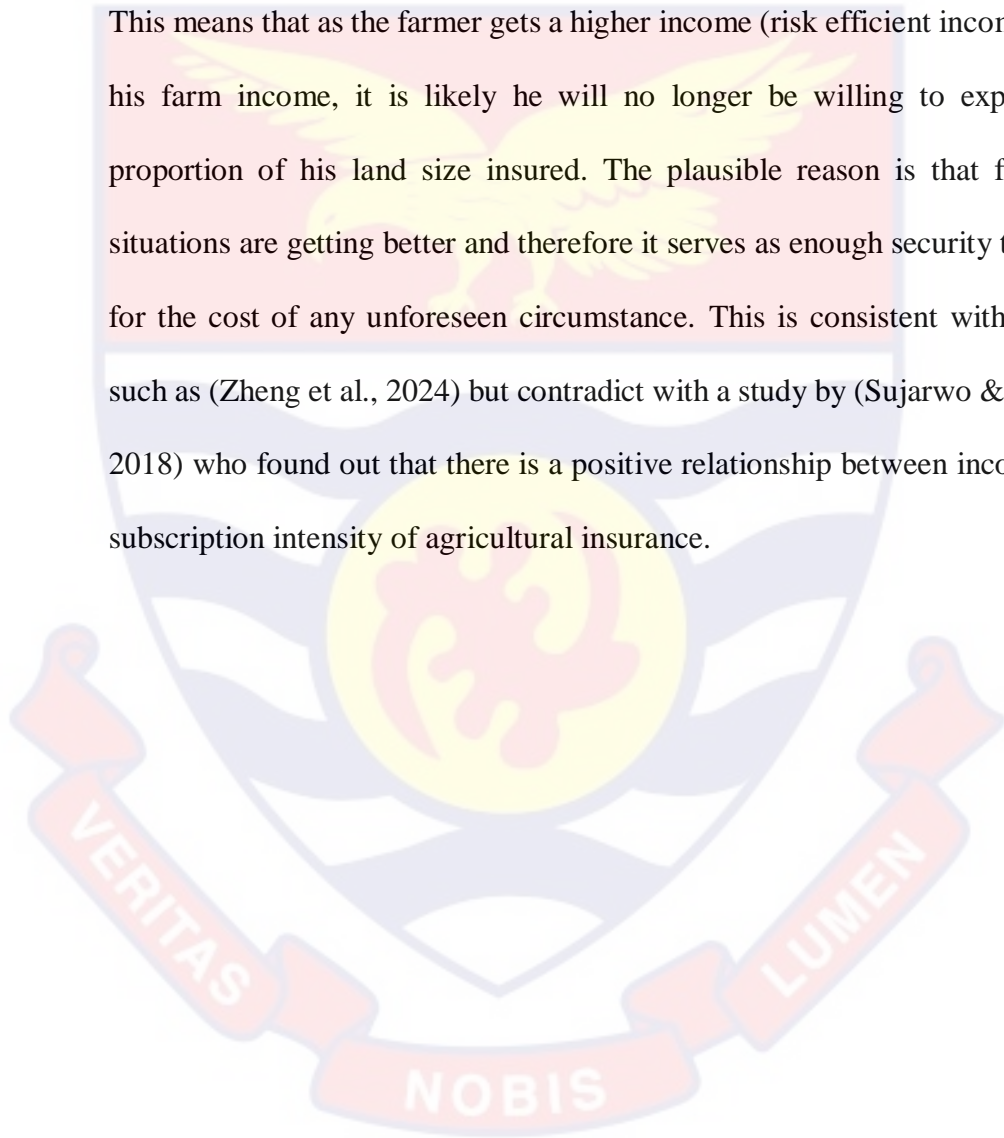
subscription intensity of WII and is statistically significant at 1% level. This implies that, it is likely they may be aware of the WII but do not have the purchasing power to increase their subscription intensity. This differs from studies such as (Akinola, 2014; Duhan & Dhingra, 2018), who found insurance awareness to be positively related to subscription and subscription intensity of weather index insurance. Insurance prompt payment have a positive effect on subscription and subscription intensity of the WII and is significant at 5% and 10% respectively. This means, it is likely that immediate payment of insurance compensation will attract food crop farmers to subscribe and increase the proportion of the land size insured. Access to credit was found to have a positive relationship with subscription and subscription intensity, and is statistically significant at 1% and 5%, respectively. This implies that making credit available to the farmers to be able to access is likely to increase subscription as well as the number of farm lands insured.

From Table 26, the results from the count model of the NBHM showed that, risk aversion behavior of farmers have a positive and statistically significant effect on subscription intensity of WII at 10% level. This implies that farmers with high risk aversion are more likely to increase proportion of their farm land insured. This confirms the assertion that the risk aversion behavior of a farmer is a key determinant when it comes to subscription intensity of weather insurance policy. This is consistent with studies such as Ali et al. (2020) who noted that risk averse farmers are more likely to increase the proportion of the land size insured than risk loving farmers.

From Table 26, the results of the zero-hurdle model of NBHM show that risk efficient income has a positive and statistically significant effect on

subscription of weather index insurance policy at 1% level. This implies that an increase in the income of the farmer (Risk efficient income) is likely to increase the number of farmers who will subscribe to the insurance policy. Interestingly, the count model results of the NBHM shows a negative coefficient for risk efficient income and is statistically significant at 10% level.

This means that as the farmer gets a higher income (risk efficient income) than his farm income, it is likely he will no longer be willing to expand the proportion of his land size insured. The plausible reason is that financial situations are getting better and therefore it serves as enough security to carter for the cost of any unforeseen circumstance. This is consistent with studies such as (Zheng et al., 2024) but contradict with a study by (Sujarwo & Rukmi, 2018) who found out that there is a positive relationship between income and subscription intensity of agricultural insurance.

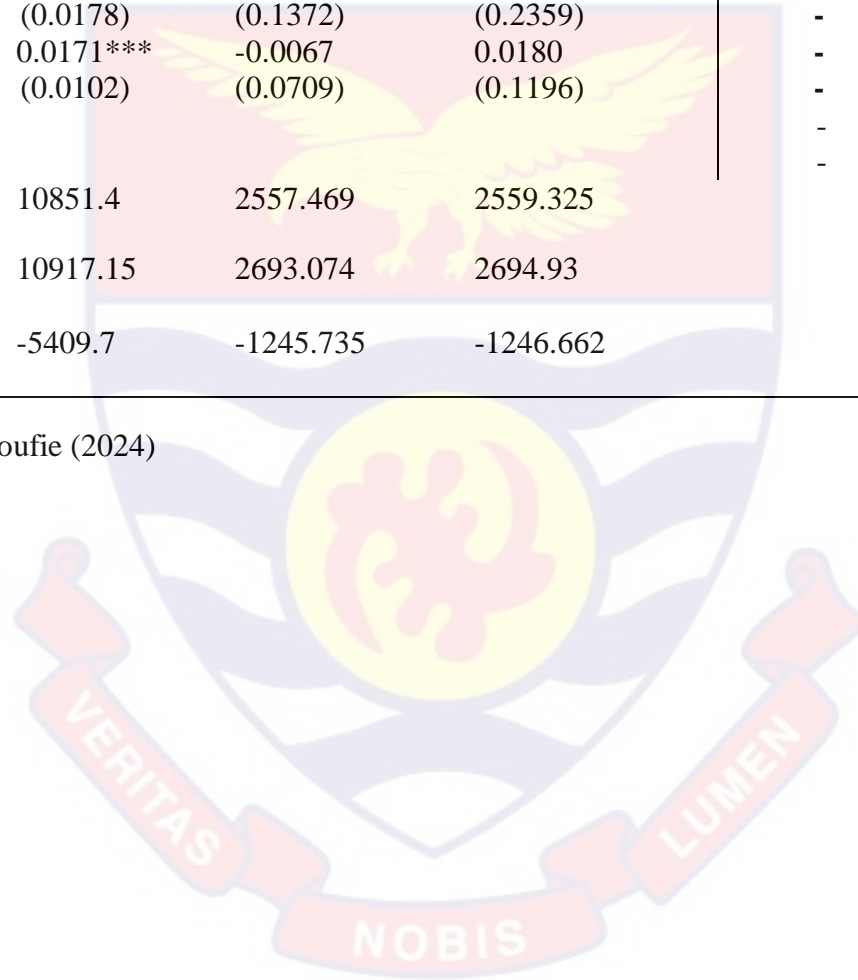


**Table 26: Risk Efficient Income and Risk Aversion on Subscription and Subscription Intensity Weather Index-Based Insurance**

Variable	Subscription of Weather Index-Based Insurance			Subscription of Intensity Weather Index-Based Insurance		
	PRM	NBHM (Zero Hurdle)	ZINBM (Zero Model)	PRM	NBHM (Count Model)	ZINBM (Count) Model)
Intercept	6.9861*** (0.1808)	7.9162*** (1.3987)	-12.8891*** (2.4122)	-	3.9678*** (0.2479)	3.9679*** (0.2479)
Age	-0.0316*** (0.0017)	-0.0467*** (0.0113)	-0.0777*** (0.0190)	-	-0.0046* (0.0027)	-0.0046* (0.0027)
Sex	-0.3563*** (0.0230)	-0.6582*** (0.1798)	1.1078*** (0.3093)	-	-0.0522* (0.0317)	-0.0522* (0.0317)
Education	0.0490*** (0.0116)	-0.0487 (0.0806)	0.0822 (0.1378)	-	0.0784*** (0.0159)	0.0784*** (0.0159)
Farm Size	-0.0202*** (0.0051)	-0.0938** (0.0406)	0.1478* (0.0672)	-	0.0220** (0.0068)	0.0220** (0.0068)
Farm Experience	0.0122*** (0.0027)	0.0044 (0.0176)	-0.0087 (0.0294)	-	0.0118** (0.0039)	0.0118** (0.0039)
FBO	0.0744** (0.0240)	0.0021 (0.1596)	-0.0289 (0.2681)	-	0.0724* (0.0313)	0.0724* (0.0313)
Household Size	-0.0177*** (0.0043)	-0.0265 (0.0280)	0.0407 (0.0476)	-	-0.0109* (0.0061)	-0.0109* (0.0061)
Insurance Prompt	-0.0848*** (0.0215)	0.3191** (0.1485)	0.5356* (0.2493)	-	0.0565* (0.0279)	0.0565* (0.0279)
Insurance Awareness	-0.1308*** (0.0210)	-0.0726 (0.1443)	0.1105 (0.2397)	-	-0.1374*** (0.0292)	-0.1374*** (0.0292)
Weather Information	0.1272*** (0.0206)	0.3386** (0.1474)	-0.5164* (0.2473)	-	-0.0316 (0.0296)	-0.0316 (0.0296)
Extension Service	0.1910*** (0.0211)	0.2925** (0.1442)	- 0.5021* (0.2418)	-	0.0255 (0.0275)	0.0255 (0.0275)

Credit Access	0.3328*** (0.0220)	0.5372*** (0.1560)	-0.8782*** (0.2602)	-	0.0638** (0.0287)	0.0638** (0.0287)
Risk Efficient Inc.	-0.2872* (0.0178)	0.5209*** (0.1372)	0.8430*** (0.2359)	-	-0.0602* (0.0246)	-0.0602* (0.0246)
Risk Aversion	0.0171*** (0.0102)	-0.0067 (0.0709)	0.0180 (0.1196)	-	0.0308* (0.0141)	0.0308* (0.0141)
Log (Theta)				-	4.1618*** (0.2170)	4.1618*** (0.2170)
AIC	10851.4	2557.469	2559.325			
BIC	10917.15	2693.074	2694.93			
Log-likelihood	-5409.7	-1245.735	-1246.662			

Source: Field survey, Koufie (2024)



## Chapter Summary

The preceding chapter presented the results of the fourth objective. The chapter presented and discussed the findings of subscription and subscription intensity of weather index insurance. Again, the chapter also presented and discusses the best fit model among the three selected count models (PRM, NBHM and ZINBM) using indicators such as AIC, BIC, Log-likelihood ratio test, Vuong statistical test and rootogram. The chapter goes further to look at the influence of risk efficient income and risk aversion behavior on subscription and subscription intensity of weather index insurance. This was done using Poisson regression model, negative binomial hurdle model and zero-inflated negative binomial model to analyse the weather insurance data of the study.

The results showed that majority of the farmers have subscribed to the weather index insurance. However, out of a hectare of available land for cultivation, only 0.39ha is insured. Also, from all the indicators employed showed that the best fit model for the study's count data (WII data set) is the negative binomial hurdle model and is able to address excess zeros, overcome under and over dispersion in the study's count data. The results further showed that factors such as age of a farmer, sex, farm size, insurance prompt payment, extension service, credit access and risk efficient income influences subscription of the weather index insurance policy. Also, factors such as age, sex, education, farm size, experience, FBO, household size, insurance prompt payment, insurance awareness, credit access, risk aversion behavior and risk efficient income influences subscription intensity of weather index insurance.

## CHAPTER SEVEN

### SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

#### Introduction

This chapter summarizes the key findings, conclusions, and recommendations based on the objectives of the study. The chapter also offers recommendations for further research and elaborates on the study's importance to knowledge.

#### Summary

This study primarily aimed to identify a risk-optimal farm plan that ensures a risk-efficient income for farmers, which could serve as a supportive plan for weather index-based insurance policy. Specifically, the study assessed the farmers' attitude towards risk amidst climate variability and change, their preferences and willingness to pay for the preferred weather index insurance policy. The study also looks at the effect of risk efficient income and risk averse behavior of farmers on their subscription and subscription intensity of the weather index insurance policy. A quantitative research method was utilized, adhering to the positivist research paradigm. The research design was cross-sectional. A multistage sampling technique was employed to select the 450 food crop farmers. At the end of the sampling, 202 farmers were selected from Wa Municipality and 248 farmers were selected from Wa West district.

A structured questionnaire, validated by research supervisors, was used to collect cross-sectional data from the 450 food crop farmers who agreed to participate in the survey. The data were processed using LIPS and R statistical software. Data analysis was conducted using descriptive statistics, the multiple price list elicitation method, Modified Mann-Kendall trend test, Sen's slope test, the Target-MOTAD model, Kendall's coefficient of concordance, the

multinomial logit model, the mixed logit model, the Poisson regression model, the negative binomial hurdle model, the zero-inflated negative binomial model, the Vuong statistical test, and the rootogram.

The Modified Mann-Kendall trend test and the Sen's were used to detect the trend in climate variables and test the magnitude of the trend. The multiple price list elicitation method was used to measure the risk aversion levels of the farmers. The Target-MOTAD model was applied to determine the risk-optimal income. Additionally, Kendall's Coefficient of Concordance was employed to gauge the WII attributes preferred by the farmers. Econometric models such as the multinomial and mixed logit models were utilized to assess the significance of these preferred attributes and to estimate the farmers' willingness to pay for the preferred weather index insurance attributes.

Furthermore, to ascertain the effect of risk-optimal income and risk aversion behavior on the subscription and intensity of subscription to weather index insurance, three selected count models were employed. However, based on the Vuong test, rootogram, and traditional indicators such as AIC, BIC, and log-likelihood, the Negative Binomial Hurdle Model (NBHM) was identified as the best fit for the study. Therefore, its results were discussed in preference to its competing models (Poisson Regression Model and Zero-Inflated Negative Binomial Model). Based on the objectives of the study, the significant findings are as follows:

### **Risk Attitude of the Farmers amidst Climate Variability and Change**

The findings indicate that rainfall, maximum temperature and minimum temperature have an increasing trend but for rainfall the increasing trend is not statistically significant at 5%. Also, the rate of change was 3.432, 0.017, and

0.025 for rainfall, maximum and minimum temperature, respectively. The maximum and minimum rainfall values were 1292.3mm and 522.9mm respectively. The maximum temperature ranges from 32.68°C to 34.59°C and the minimum temperature ranges from 21.50°C to 23.60°C. The findings of the climate variables (ie. rainfall, maximum and minimum temperatures) indicated that farmers in the study area are faced with climatic risk. The findings for this objective further indicated that approximately 68.56% of the farmers preferred to insure their entire farmland against climate variability and change using the weather index insurance policy. Additionally, about 29% of the farmers chose to insure most of their farmland in the face of climate variability and change using weather index insurance. Meanwhile, roughly 2.44% of the farmers preferred not to insure their farmland against climate variability at all.

#### **Risk Optimum Farm Plan that the Farmers Should Operate in Order to Get the Maximum Return in the Face of Production and Climatic Risk**

The findings of the study revealed that the farmers' plan (I) was to produce maize (0.54 ha), groundnut (0.56 ha), soybean (1.00 ha), and sorghum (0.50 ha) to obtain an income of GH¢ 7,412.97. The risk-efficient plan (II) involved the farmer producing soybean (1.50 ha) and sorghum (0.33 ha) to achieve a risk-efficient income of GH¢ 9,403.42. For risk-efficient plan (III), the farmer was to cultivate soybean (1.50 ha) and sorghum (0.42 ha) to obtain a risk-efficient income of GH¢ 9,835.10. Additionally, the optimum plan (IV) entailed producing soybean (1.50 ha) and sorghum (0.74 ha) to achieve an optimum income of GH¢ 11,168.10. Fertilizer was fully utilized in all the optimum plans, followed by capital. Moreover, the risk-efficient plans were statistically significant at the 1% level. The study also found that a combination

of maize, sorghum, soybean, and groundnut could be used to address the subsistence needs of the farmer. However, it should be noted that this combination comes with a high-income penalty.

### **Farmers' Preferences and Willingness to pay for Weather Index Based Insurance**

The findings of the study indicated that the most preferred attribute was prompt claim payout, with a mean rank of 2.62, followed by premium (mean rank of 2.68), subsidy (mean rank of 3.08), basis risk (mean rank of 3.51), and interlinking credit with insurance (mean rank of 4.47). The least preferred attribute was “no discount on claim payment”, with a mean rank of 4.63. The study also revealed that approximately 22% of the farmers concurred with the rankings of the preferred attributes.

All these preferred attributes were statistically significant, and the farmers were willing to pay for all the attributes. Thus, in relation to subsidy on agricultural inputs, they were willing to pay GH¢6.67. For rainfall data from the GMet weather station, they were willing to pay GH¢5.38. Also, for no claim discount payment, they were willing to pay GH¢ 13.91; for prompt non-bank payout, GH¢4.51; and GH¢3.82 for interlinking their credit with insurance. The findings of the study further showed that risk averse attitude positively influences premium and basis risk, education positively influence claim payout and basis risk. Meanwhile, age and extension services negatively influence basis risk and the interlinking of credit with insurance.

## **Effect of Risk Optimum Income and Risk Attitude of Farmers on their Subscription and Subscription Intensity of the Weather Index Based Insurance Policy**

The study results indicated that the majority of the farmers have subscribed to weather index insurance. However, out of every hectare of farmland available for cultivation, only 0.39 ha is insured. Furthermore, the results revealed that among the three count regression models the negative binomial hurdle model, the zero-inflated negative binomial model, and the Poisson regression model used to analyze the weather index insurance data, the negative binomial hurdle model was the best fit for the study. This was determined by it having the lowest AIC value, BIC value, and log-likelihood ratio test.

The results of the Vuong statistical test and the rootogram also confirm that the negative binomial hurdle model is statistically preferred over the Poisson regression model and the zero-inflated negative binomial model, as it addresses the issues of excess zeros and overdispersion in the study's count data. Consequently, the negative binomial hurdle model's results indicated that household size, farm size, age, sex, prompt insurance payment, extension service, Farmer-Based Organizations (FBOs), insurance awareness, access to credit, risk-efficient income, and risk aversion behavior were statistically significant factors influencing food crop farmers' decisions to subscribe to weather index insurance, as well as their subscription intensity.

### **Conclusions**

Based on the findings of the research questions, the following conclusions were drawn from the study.

Upper West Region is facing high climate variability and change which could lead to flood or drought which affect farmers in the region. Food crop farmers in this region, especially maize farmers, are highly risk-averse in the midst of climate variability and change. These farmers are willing to make certain managerial decisions to mitigate both climatic and production risks using weather index insurance. Thus, a risk-averse farmer is likely to make such decisions even at the expense of earning a lower income. Farmers are inherently risk-averse and may be inclined to use weather index insurance as a strategy to reduce both their production and climatic risks.

In the midst of this climate variability and change, four crop enterprise pattern is the dominant enterprise operated by the farmers in the region, with maize, groundnut, sorghum and soya bean being the four dominant crops. However, these crop enterprise combinations give the farmer a lower income. Therefore, there is a need for a risk-efficient plan that will address the resource allocation problems faced by farmers and ensure that subsistence needs of the farmer is met as well as increased the farmers' income. To achieve this, the study suggests that food crop farmers should produce soybean and sorghum, as this will enable them to utilize their limited available resources to obtain a risk-efficient income. The risk-efficient income obtained was higher than what the farmers were initially earning from their farms. Having achieved such an increase in their income will help improve their livelihood.

weather index insurance is needed amidst climate variability and change. However, the food crop farmers preferred certain attributes in their weather insurance policy. These attributes included prompt claim payouts through the bank, reduced premiums for the next subscription season when no

claim is paid, credit interlinked with insurance, subsidies on the weather insurance premium, and rainfall data from the GMet weather station to determine the payment of their compensation. The farmers concurred that these stated preference attributes were what they actually desired in the weather index insurance policy. Based on the results estimating the willingness to pay for weather index insurance, the food crop farmers were willing to pay at least GHS 3.81 for their preferred weather insurance attributes to be on their weather insurance policy. Which are rainfall data from the GMet weather station, subsidized agricultural inputs, credit interlinked with insurance, reduced premiums in the subsequent subscription when no claim payout is made, and prompt non-bank payout.

Most of the farmers had subscribed to weather index insurance (64%), but out of every hectare of land cultivated, the area of land insured by the subscribers is 39%. The age of a farmer, sex, farm size, prompt insurance payment, extension services, access to credit, and risk-efficient income were found to be statistically significant in influencing food crop farmers' decisions to subscribe to weather index insurance. However, regarding subscription intensity, age, sex, education, farm size, experience, Farmer-Based Organizations (FBOs), household size, prompt insurance payment, insurance awareness, access to credit, risk aversion, and risk-efficient income were the variables that significantly influenced farmers' subscription intensity to weather index insurance. Methodologically, the study revealed that based on indicators such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), log-likelihood ratio, Vuong statistical test, and rootogram, the negative binomial hurdle model is the best fit for analyzing the

subscription and subscription intensity of weather index insurance data of the study.

### **Recommendations**

The policy recommendations below are in line with the stated research objectives for the study.

#### **Objective One**

1. The Ghana Meteorological Agency (GMA) should enhance its early warning systems to provide timely and accurate weather forecasts, enabling farmers and communities to prepare for and respond to impending climate risk.
2. The Ministry of Food and Agriculture through Parliament, should incorporate agricultural insurance into the Insurance Act to safeguard the welfare of farmers and sustainable agricultural productivity.

#### **Objective Two**

1. The Ministry of Food and Agriculture should integrate the Risk-Efficient Farming Plan into the content of extension training to help extension workers to get more information on risk efficient crops so that they can educate farmers on the need to adopt the Risk-Efficient Farming Plan.

#### **Objective Three**

1. The Ghana Agricultural Insurance Pool should intensify its work with farmers and agricultural insurance providers to develop more affordable and attractive weather insurance policies tailored to the specific needs of farmers in the Upper West Region.

2. The Ministry of Food and Agriculture should also integrate agricultural insurance (weather index based insurance) into agricultural programmes such as Feed Ghana Programme. This integration will increase the acceptability and awareness of weather index insurance.

#### **Objective Four**

1. The Ghana Agricultural Insurance Pool should consider the risk-efficient farm plan as a support plan for the weather index base insurance policy. This approach will grant farmers a higher income, enabling them to afford the subscription fee.
2. The Ministry of Food and Agriculture, together with agricultural insurance providers, should intensify education on weather index insurance, and integrate indigenous knowledge into weather index insurance education.

#### **Contribution to Literature, Methodological and Knowledge Gap**

The study contributed to literature and methodological in the following ways;

1. This study contributes to the literature by adding to the limited number of studies on subscription, subscription intensity, and willingness to pay for weather index based insurance as well as trends in rainfall, maximum and minimum temperature.
2. The study contributes to the limited body of research on risk optimization for food crops. Furthermore, it employs a risk programming model, known as the Target-MOTAD model, instead of the conventional linear programming model, to analyze the risk-efficient farm plan of the study.

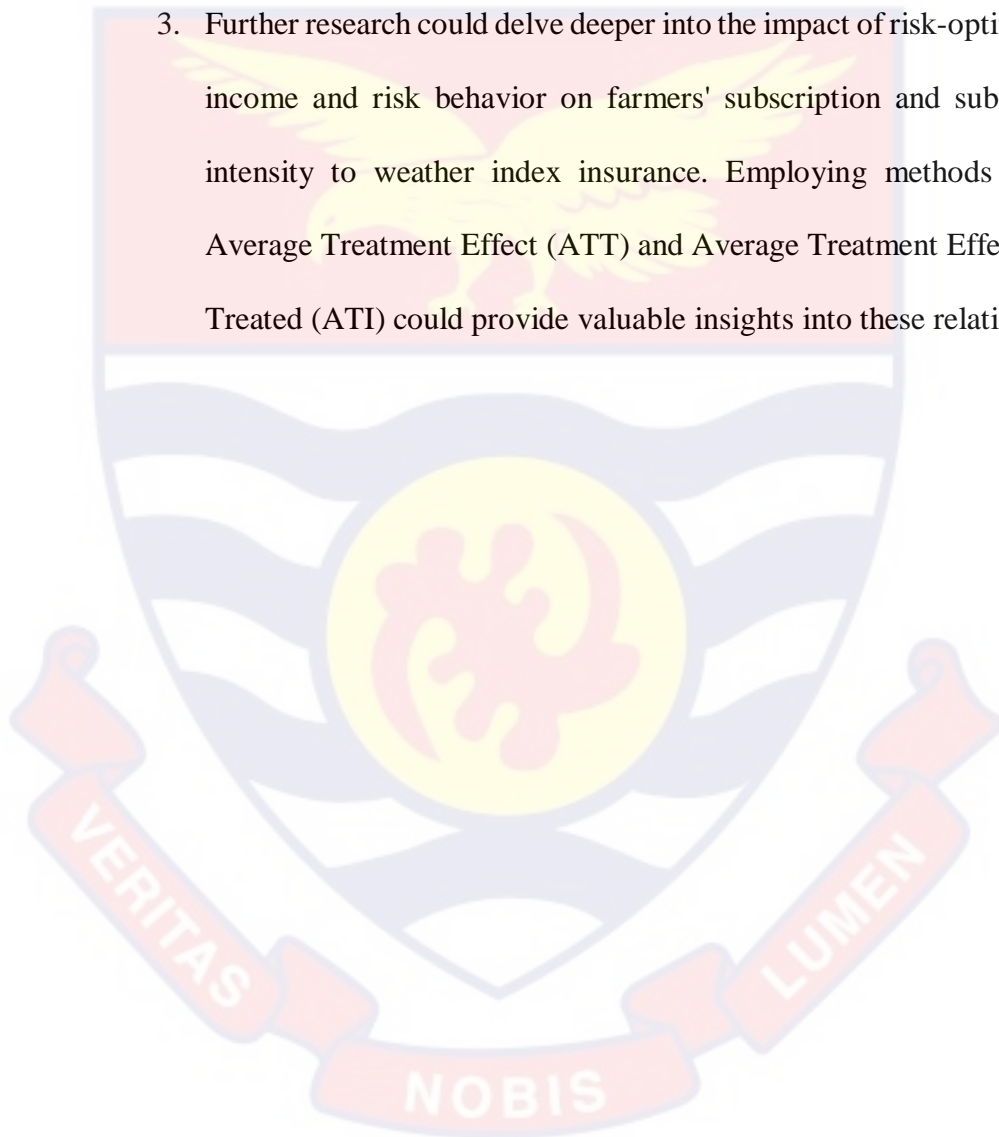
3. This study also integrates a risk-efficient farm plan with the weather index insurance policy as a support plan, marking the first initiative of its kind in the Ghanaian context.
4. To bridge the methodological gap, a discrete choice model such as the mixed logit model, which serves as an advanced model to the multinomial logit model, was used to determine the farmers' willingness-to-pay estimates for weather index based insurance. Thus, the mixed logit model, through the willingness-to-pay space approach, was used to directly estimate the farmers' willingness to pay for weather index insurance values.
5. Additionally, the study examined the influence of risk-efficient income and risk aversion behavior of farmers on the subscription to, and the intensity of subscription for, weather index based insurance.
6. The study bridged the methodological gap by testing the empirical superiority of the negative binomial hurdle model and the zero-inflated negative binomial model as advancements over the Poisson regression model in analyzing the study's count data.

#### **Suggestion for Further Studies**

1. Further study can also look at the effect of risk aversion behavior, risk optimum income, and socio-economic characteristics as well as interaction between these variables on willingness to pay for the preferred weather index based insurance.
2. While this study used a count model approach to analyse subscription intensity, it is important to note that alternative modelling strategies could be explored in future research. Treating subscription intensity as

a continuous variable and using models such as beta regression and fractional regression model could provide additional insights into the factors influencing WII insurance take-up. A comparative analysis of the results obtained from count and continuous models could provide on the impact of transformation on the results.

3. Further research could delve deeper into the impact of risk-optimal farm income and risk behavior on farmers' subscription and subscription intensity to weather index insurance. Employing methods such as Average Treatment Effect (ATT) and Average Treatment Effect on the Treated (ATI) could provide valuable insights into these relationships.



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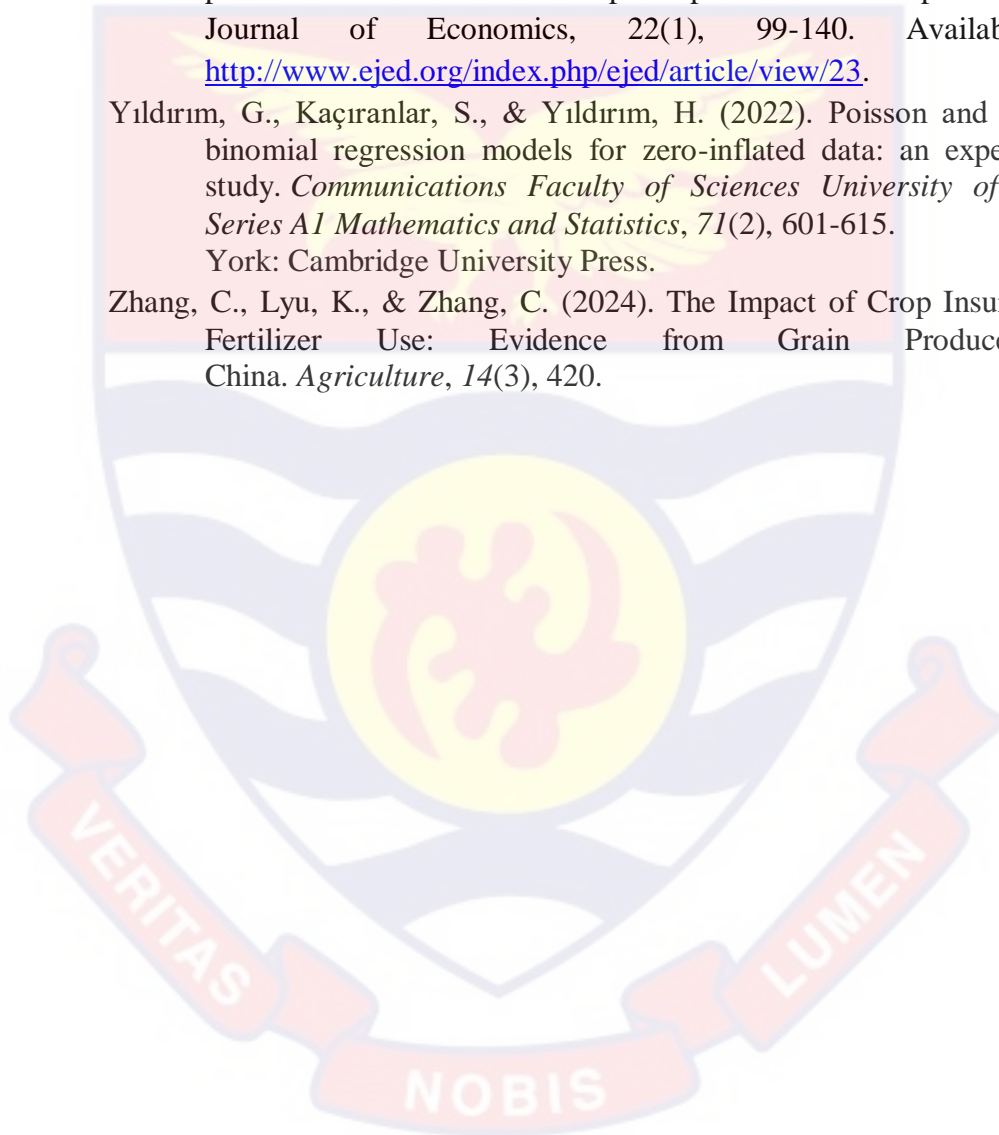
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## APPENDICES

UNIVERSITY OF CAPE COAST  
COLLEGE OF AGRICULTURE & NATURAL SCIENCES  
SCHOOL OF AGRICULTURE

DEPARTMENT OF AGRICULTURAL ECONOMICS & EXTENSION

Questionnaire No. .... Serial No.....

Name of District.....Town/Village:.....

Tel. Number.....

### THE PURPOSE OF THE QUESTIONNAIRE AND CONSENT

This questionnaire is designed to assess information from farmers in the Upper West Region of Ghana on their risk aversion levels, willingness to pay for weather index insurance, subscription and subscription intensity of the WII, and their production information. This is to help develop a risk efficient farm plan to serve as a support policy option to the weather index insurance policy. Therefore, any information you enter will only be used for educational reasons. Information gathered about respondents' profiles is kept strictly secret and will only be shared with the survey team and the Department. I would be very much appreciative of your participation in this survey. Participation in this survey is voluntary and you can choose not to answer any individual question or all of the questions. However, I hope that you will participate in this study since your views are important.

**Consent Information:** Please do you want to proceed to answer these questions? Yes [ ] No [ ]

**SECTION A**

**SOCIOECONOMIC CHARACTERISTICS OF THE FARMER**

1. Age (as at last birthday) ..... years

2. Sex of farmer

a. Male [ ]

b. Female [ ]

3. Marital status

a. Single [ ]

b. Married [ ]

c. Divorced [ ]

d. Widowed [ ]

e. Separated [ ]

f. Others (specify).....

4. Educational Level

a. No school [ ]

b. Primary school [ ]

c. MSLC/JHS [ ]

d. SHS/Technical/Vocational [ ]

e. Tertiary [ ]

f. others (specify) .....

4ii. Years of formal education completed.....

5. How many people make up the household? .....

6. Composition of Family

a. Adult Males [ ]

b. Adult Females [ ]

c. Children (under 18) [ ]

7. Is farming your major occupation?

a. Yes [ ]

b. No [ ]

8. Number of years in farming ..... (Number)

9. Aside farming, what other economic activity do you engage in? .....

10. Do you belong to any farmer-based organization (s) in the area?

a. Yes [ ]

b. No [ ]

11. Do you have access to credit?

a. Yes [ ]

b. No [ ]

12. . If Yes, select the source of your credit? (Tick (✓)all the apply)

a. Money Lenders [ ]

b. Cooperative society [ ]

c. Family Members [ ]

d. Banks [ ]

e. . Others .....

13. Do you have access to extension service?

a. Yes [ ]

b. No [ ]

14. If Yes, how often do you receive extension service in a production year?

.....

15. Do you engage in any off -farm activities?

a. Yes [ ] b. No [ ]

16. What is your total income per month?.....

17. If yes to Q16, how much of the total income of your household comes from outside the farm? (indicate percentages) .....

18. What is the approximate distance between your house and your farm?.....km



## SECTION B

### RISK ATTITUDE/ RISK AVERSION LEVELS

#### Instructions for the Risk Attitude or Risk Aversion Level Experiment

As a farmer, Table 1 indicates that you have five (5) plots of land for maize production, each plot has an area of 0.25ha. Therefore, you have the opportunity to insure the land or decide not to insure. However, if you choose to insure the land, there is a premium to be paid in the amount of Gh¢ 60 per hectare for a planting season but your land is guaranteed from losses due to the disaster. Thus, the guaranteed in this case means that the land insured will get a compensation of Gh¢1450 per hectare. Conversely, if you do not take the insurance, you do not need to pay premiums but your land is not guaranteed from losses due to disasters. With a 50% probability, if there is no disaster each plot will generate a profit of Gh¢498, so the total profit that can be obtained (from five plots) is Gh¢2490. However, if a disaster occurs, then the profit is Gh¢0, i.e. there is no profit. Kindly select one choice (circle) based on your risk aversion level.

**Table 1: Risk Aversion Elicitation Method Using Multiple Price List**

Choice	Insured Farm Plot	Uninsured Farm Plot	If Disaster Doesn't Happens (Probability 50% GH¢)	If Disaster Happens (Probability 50%GH¢)
A	5	0	2415	1812.5
B	4	1	2430	1450
C	3	2	2445	1087.5
D	2	3	2460	725
E	1	4	2475	362.5
F	0	5	2490	0.00

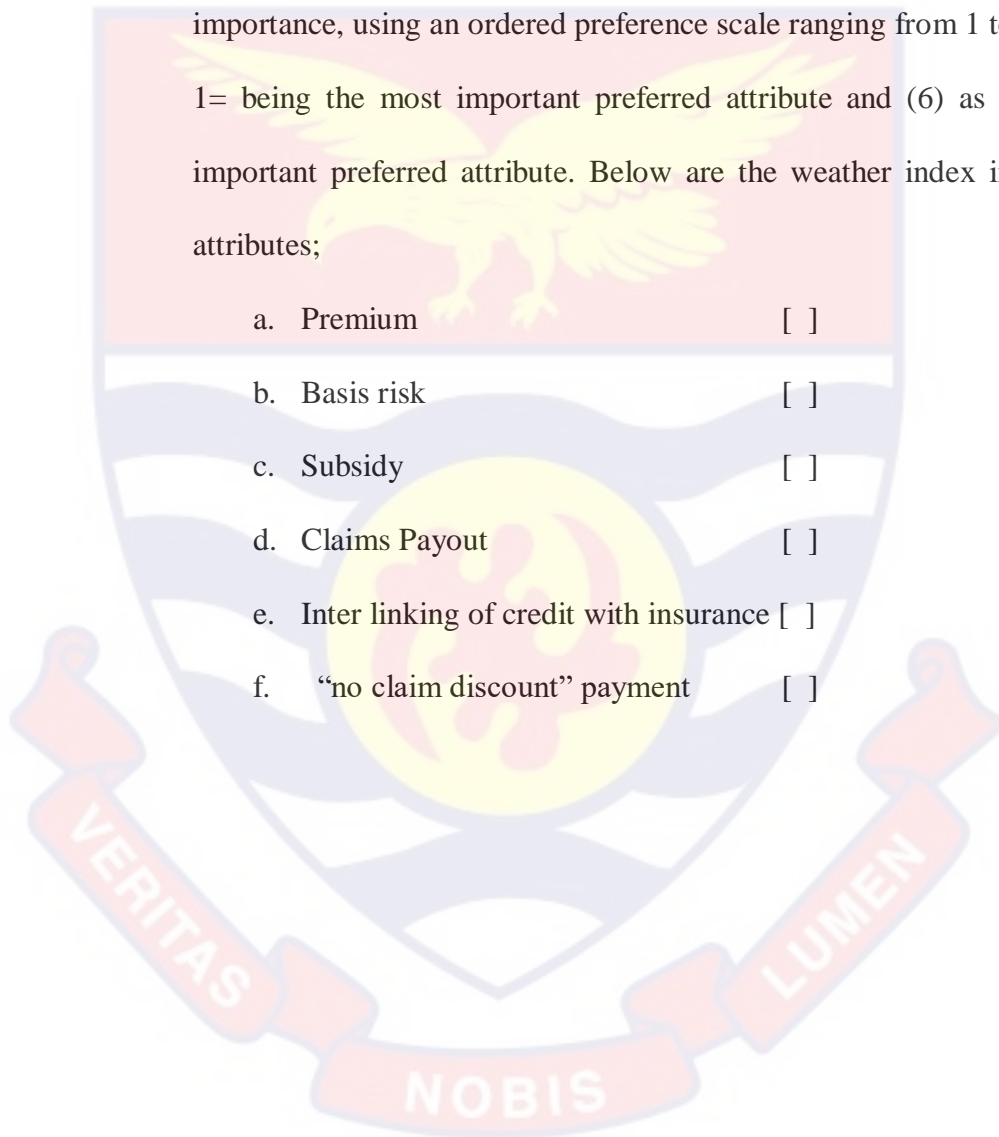
**SECTION C (i)**

**PREFERENCES AND WILLINGINGS TO PAY FOR WEATHER**

**INDEX INSURANCE**

19. Please rank the following weather index insurance attributes in order of importance, using an ordered preference scale ranging from 1 to 6, with 1= being the most important preferred attribute and (6) as the least important preferred attribute. Below are the weather index insurance attributes;

- a. Premium [ ]
- b. Basis risk [ ]
- c. Subsidy [ ]
- d. Claims Payout [ ]
- e. Inter linking of credit with insurance [ ]
- f. “no claim discount” payment [ ]



## SECTION C (ii)

### CHOICE EXPERIMENT QUESTIONS

#### Instructions for Choice Experiment

There are six (6) hypothetical questions that we will like you to answer. Please remember that all decision taken will be kept confidential as described in the participant consent forms. In each decision you will see two alternative weather index insurance policy decisions that you might subscribe to. The weather index insurance policies will differ based on the weather index-based insurance policy attributes to the food crop farmer. Thus, whether or not you will pay Ghc 60 as a premium, receive rainfall data from a satellite, whether they will receive claim pay-out via bank payment, credit interlinked with an insurance policy, reduction of next seasons premium in the situation where claim is made and finally subsidy on weather index insurance policy premium.

For each decision, you will also have the option to choose neither of the weather index insurance policy option. Please choose the alternative- weather index policy option (1), option (2) or neither of the policy option based on the one that you most prefer. Although, the decision is hypothetical, kindly make your decisions as best as you can. Below is a choice card which will indicate your choice by placing a check mark in the appropriate box in the last column.


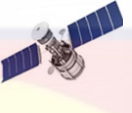










CHOICE CARD ONE 1							
	Premium.	Basis risk	Prompt Mode Claims payout	Inter Linking credit with insurance	“No” Claim Discount” payment	Subsidy	I would Select
Weather Index Insurance Policy (Option 1)	 GHc 60	 Data (Rainfall) from a satellite	 Nonbank payment	 Credit not Inter Linked with insurance	 Next seasons premium’s reduction	 Subsidy on weather index insurance policy premium	○
Weather Index Insurance Policy (Option 2)	 GHc50	 Data (Rainfall) from the GMet weather station	 Bank payment	 Credit Inter Linked with insurance	 Payout at the end of the next season	 Subsidy on agricultural inputs	○
None of the policy option							

Figure 1: Hypothetical Weather Index Insurance Policy Options on Choice Card 1








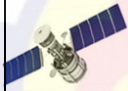




CHOICE CARD 2							
	Premium	Basis risk	Prompt mode Claims payout	Inter Linking credit with insurance	“No” Claim Discount” payment	Subsidy	I would Select
Weather Index Insurance Policy (Option 1)	 GHc50	 Data (Rainfall) from GMet weather station	 Bank Payment	 Credit not interlinked with insurance	 Payout at the end of the next season	 Subsidy on weather index insurance policy premium	<input type="radio"/>
Weather Index Insurance Policy (Option 2)	 GHc60	 Data (Rainfall) from a satellite	 Non-Bank payment	 Credit Inter linked with insurance	 Next seasons reduction in premium	 Subsidy on agricultural inputs	<input type="radio"/>
None of the police option							

Figure 2: Hypothetical Weather Index Insurance Policy Options on Choice Card 2








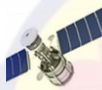




CHOICE CARD THREE (3)							
	Premium	Basis risk	Prompt mode Claims payout	Inter Linking credit with insurance	“No” Claim Discount payment	Subsidy	I would Select
Weather Index Insurance Policy (Option 1)	 GHc 50	 Data (Rainfall) from the GMet weather station	 Non-Bank Payment	 Credit not interlinked with insurance	 Next seasons reduction in premium	 Subsidy on agricultural inputs	<input type="radio"/>
Weather Index Insurance Policy (Option 2)	 GHc60	 Data (Rainfall) from a satellite	 Bank payment	 Credit interlinked with insurance	 Payout at the end of the next season	 Subsidy on weather index insurance policy premium	<input type="radio"/>
None of the policy option							

Figure 3: Hypothetical Weather Index Insurance Policy Options on Choice Card 3


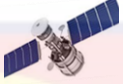










CHOICE CARD FOUR (4)							
	Premium	Basis risk	Prompt mode Claims payout	Inter Linking credit with insurance	“No” Claim Discount payment	Subsidy	I would Select
Weather Index Insurance Policy (Option 1)	 GHc 50	 Data (Rainfall) from a satellite	 Bank Payment	 Credit Inter Linked with insurance	 Next seasons reduction in premium	 Subsidy on weather index insurance policy premium	○
Weather Index Insurance Policy (Option 2)	 GHc60	 Data (Rainfall) from the GMet weather station	 Non-Bank payment	 Credit not interlinked with insurance	 Payout at the end of the next season	 Subsidy on agricultural inputs	○
None of the policy option							

Figure 4: Hypothetical Weather Index Insurance Policy Options on Choice Card 4













CHOICE CARD FIVE (5)							
	Premium	Basis risk	Prompt mode Claims payout	Inter Linking credit with insurance	“No” Claim Discount payment	Subsidy	I would select
Weather Index Insurance Policy (Option 1)	 Ghc 60	 Data (Rainfall) from the GMet weather station	 Bank Payment	 Credit Inter Linked with insurance	 Next seasons premium Reduction	 Subsidy on weather index insurance policy premium	<input type="radio"/>
Weather Index Insurance Policy (Option 2)	 GHc50	 Data (Rainfall) from a satellite	 Non-Bank payment	 Credit not Inter Linked with insurance	 Payout at the end of the next season	 Subsidy on agricultural inputs	<input type="radio"/>
None of the policy option							

Figure 5: Hypothetical Weather Index Insurance Policy Options on Choice Card 5













CHOICE CARD SIX (6)							
	Premium	Basis risk	Prompt mode Claims payout	Inter Linking credit with insurance	“No” Claim Discount payment	Subsidy	I would Select
Weather Index Insurance Policy (Option 1)	 GHc 60	 Data (Rainfall) from a satellite	 Bank Payment	 Credit not interlinked with insurance	 Next seasons Reduction in premium	 Subsidy on agricultural inputs	○
Weather Index Insurance Policy (Option 2)	 GHc50	 Data (Rainfall) from the GMet weather station..	 Non-Bank payment	 Credit Inter Linked with insurance	 Payout at the end of the next season	 Subsidy on weather index insurance policy premium	○
None of the policy option							

Figure 6: Hypothetical Weather Index Insurance Policy Options on Choice Card 6

**SECTION D**

**PRODUCTION INFORMATION**

20. Land Ownership: What type of land ownership do you have

- a. Own [ ]
- b. Lease [ ] (Acres/Hectares)
- c. Share Production [ ].....(Acres/Hectares)
- d. Rented [ ].....(Acres/Hectares)

21. Total Land size owned ..... (Acres/Hectares)

22. Land size Cultivated ..... (Acres/Hectares)

23. Amount paid for using rented land for production (GHS)

.....

24. Crop Produce by the farmer?

<b>Crops Produced by the Farmer</b>	<b>Land Area Under Cultivation (Acres/Ha)</b>
Rice	
Millet	
Sorghum	
Soyabeans	
Maize	
Groundnut	
Others...	

25. Complete the Table below for 2023 Production Season

Crops Produced by the farmer	Share of Labour (No of worker)		No. of Hours per Day	No. of days per week	Cost per Day GHS	Total Amount per month
	Family	Hired				
Rice						
Millet						
Maize						
Sorghum						
Soyabeans						
Groundnut						
Others.....						

26. Complete the Table below for 2022 Production Season

Crops Produced by the farmer	Share of Labour (No of worker)		No. of Hours per Day	No. of days per week	Cost per Day GHS	Total Amount per month
	Family	Hired				
Rice						
Millet						
Maize						
Sorghum						
Soyabeans						
Groundnut						
Others.....						

27. Complete the Table below for 2021 Production Season

Crops Produced by the farmer	Share of Labour (No of worker)		No. of Hours per Day	No. of days per week	Cost per Day GHS	Total Amount per month
	Family	Hired				
Rice						
Millet						
Maize						
Sorghum						
Soyabeans						
Groundnut						
Others.....						

28. Complete the Table below

Season	2021	2022	2023	2021	2022	2023	2021	2022	2023
Input use	Kind			Quantity			Value (GHS)		
Fertilizer									
Herbicide									
Weedicide									
Seed									

29. Complete the Table below

<b>Inputs</b>	<b>Replies</b>
Animal drawn power	01 = Yes [ ] 02= No [ ]
Tractor	01 = Yes [ ] 02= No [ ]
Hand hoe	01 = Yes [ ] 02= No [ ]
Cutlass	01 = Yes [ ] 02= No [ ]
Knapsack Sprayer	01 = Yes [ ] 02= No [ ]
Sickle	01 = Yes [ ] 02= No [ ]
Thrasher	01 = Yes [ ] 02= No [ ]
Sheller	01 = Yes [ ] 02= No [ ]
Others (Specify):	01 = Yes [ ] 02= No [ ]

30. Complete the Table below

<b>Inputs</b>	<b>Quantity Used</b>	<b>Cost/Price</b>	<b>Date Purchased</b>	<b>Duration (year)</b>	<b>Scrape Worth (GHS)</b>
Tractor					
Hand hoe					
Cutlass					
Knapsack Sprayer					
Animal drawn power					
Sickle					
Thrasher					
Sheller					
Others(Specify)					
.....					

31. Complete the Table below.

Inputs	Quantity	Rental Cost (GHS)		
		2021	2022	2023
Tractor				
Animal drawn power				
Cutlass				
Knapsack Sprayer				
Sheller				
Thrasher				
Sickle				
Hoe				
Others.....				

32. Complete the Table below.

Crops Produced	Land Cultivated (Acres/Ha)	Amount Harvested (Bags/Kg)	Amount Sold (Bags/Kg)	Amount Consumed (Bags/Kg)	Price Unit (GHS)
Rice					
Millet					
Sorghum					
Soyabeans					
Groundnut					
Others					

33. What is the total amount of fertilizer used for the 2023 production season.....?

34. Complete the Table below.

Crop Mix Produced	Amount of Fertiliser Applied
Rice	
Maize	
Millet	
Sorghum	
Soybeans	
Groundnut	
Others.....	

35. What is the total capital used for these crop production seasons

- a. GH¢..... (2021),
- b. GH¢..... (2022)
- c. GH¢ .....(2023)

36. Complete the Table below.

Crops Produced	Amount of Capital Used for 2021/2022 and 2023		
	2021	2022	2023
Rice			
Maize			
Millet			
Sorghum			
Soybeans			
Groundnut			
Others			

**SECTION D (II)**

**RISK CONSTRAINT**

37. From your experience, for the past five years which of the major crop(s) is/are susceptible to drought .....

38. Please tell me on your targeted yields and the actual yields for the 2023 cropping season.

Crops	Target Yield	Actual Yield
Rice		
Millet		
Maize		
Sorghum		
Soya bean		
Groundnut		

39. Please fill the Table below on yields for the past three years.

Crops	2021 Crop Season (with units attached)			2022 Crop Season (with units attached)		
	Acres / Ha	Target	Actual	Acres / Ha	Target	Actual
Rice						
Millet						
Maize						
Sorghum						
Soya bean						
Groundnut						
Others						

40. What did you think caused the yield deviations?

- a. Periodic drought [ ]
- b. Low use of fertiliser [ ]
- c. Untimely machine services [ ]
- d. Low rains [ ]

**SECTION E**

**SUBSCRIPTION OF WEATHER INDEX INSURANCE**

41. Are you aware of an insurance product called weather index insurance

- a. Yes [ ]
- b. No [ ]

42. Have you received any training on weather index insurance?

- a. Yes [ ]
- b. No [ ]

43. If (Yes), which organization conducted the WII insurance training? (**Tick all that apply**)

- a. Farmer Based Organisation [ ]
- b. Banks [ ]
- c. Microfinance scheme [ ]
- d. Cooperative Society [ ]
- e. Religious group [ ]
- f. Others.....

44. Have you experience any crop failure due to drought?

- a. Yes [ ]
- b. No [ ]

45. Have you ever subscribed to a weather index insurance policy to cover your crops?

- a. Yes [ ]
- b. No [ ]

46. If No to Q44, why haven't you subscribed to the weather index policy?

**Tick [✓] all that apply**

- a. Do not like the policy [ ]
- b. Have No Knowledge on how it works [ ]
- c. Delay in Payment [ ]
- d. Lack of funds to subscribe [ ] e. Others.....

47. Did you choose the crop (s) that you wanted the WII to cover?

- a. Yes [ ]
- b. No [ ]

48. Which of the crop(s) did you purchased the Weather Insurance to cover?

- a. Sorghum [ ]
- b. Soya bean [ ]
- c. Millet [ ]
- d. Maize [ ]
- e. Other.....

49. Did you insure your farmland during the 2023 production season?

- a. Yes [ ]
- b. No [ ]

If Yes, how many acre(s) / hectares of your farm land was insured during the 2023 farm production Season?.....

50. Have you received an insurance pay out from the insurance company?

a. Yes

b. No

51. If Yes, was the pay-out paid promptly?

a. Yes

b. No



Appendix (i)

Table 27: Normality test, Homogeneity Test and Autocorrelation Test

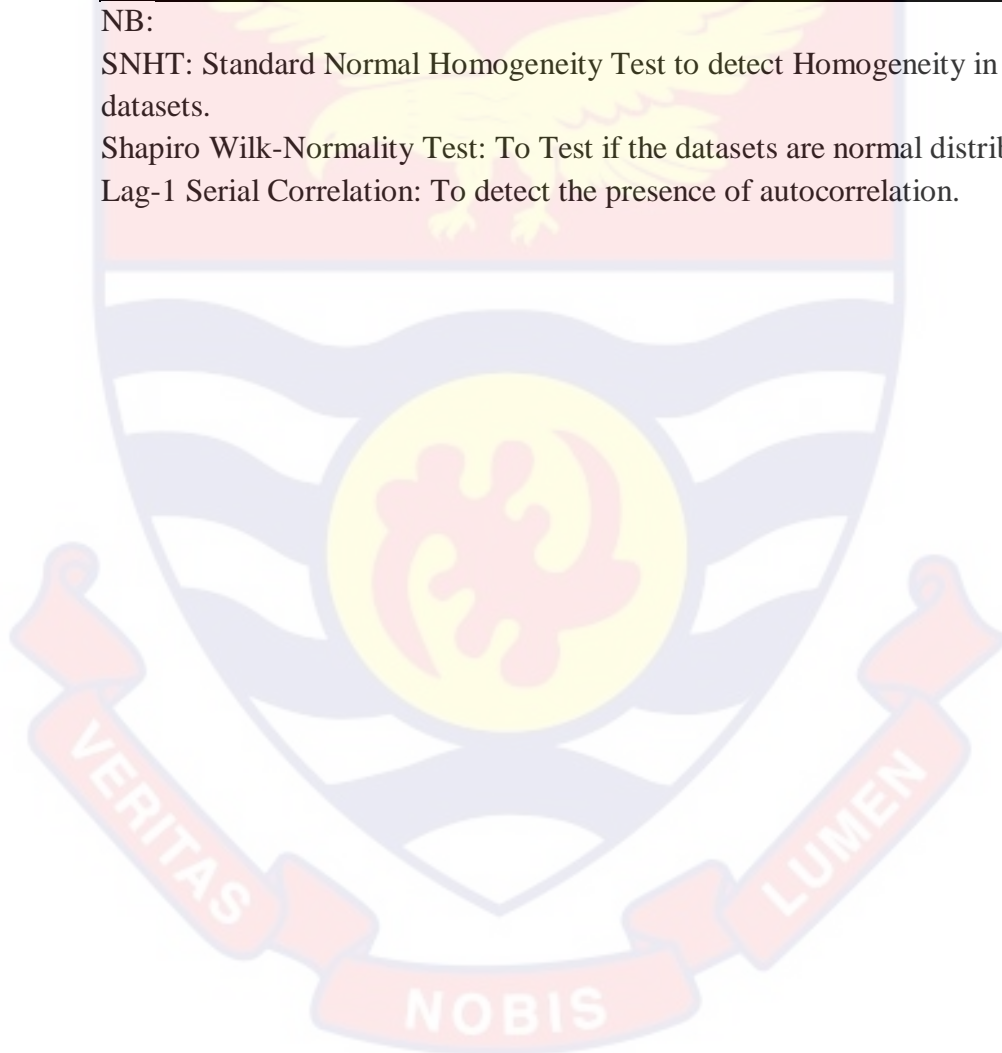
Meteorological Variable	SNHT		Shapiro Wilk-Normality Test		Lag-1 Serial Corr. Coe
	T	Sig.	W	Sig.	
Rainfall	1992	0.013	0.982	0.6294	0.15
Max.Temperature	2000	0.000	0.977	0.4771	0.46
Min.Temperature	1999	0.000	0.955	0.0657	0.65

NB:

SNHT: Standard Normal Homogeneity Test to detect Homogeneity in the datasets.

Shapiro Wilk-Normality Test: To Test if the datasets are normal distributed.

Lag-1 Serial Correlation: To detect the presence of autocorrelation.



## ETHICAL CLEARANCE FORMS

UNIVERSITY OF CAPE COAST

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IORG #: IORG0011497



19<sup>TH</sup> MARCH 2024

Mr Augustine Koufie  
Department of Agricultural Economics and Extension  
University of Cape Coast

Dear Mr Koufie,

#### **ETHICAL CLEARANCE – ID (UCCIRB/CANS/2023/28)**

The University of Cape Coast Institutional Review Board (UCCIRB) has granted Provisional Approval for the implementation of your research **Risk Aversion Levels, Risk Optimality and Willingness to Pay for Weather Index-Based Insurance Among Food Crop Farmers in the Upper West Region of Ghana**. This approval is valid from **19<sup>th</sup> March 2024 to 18<sup>th</sup> March 2025**. You may apply for an extension of ethical approval if the study lasts for more than 12 months.

Please note that any modification to the project must first receive renewal clearance from the UCCIRB before its implementation. You are required to submit a periodic review of the protocol to the Board and a final full review to the UCCIRB on completion of the research. The UCCIRB may observe or cause to be observed procedures and records of the research during and after implementation.

You are also required to report all serious adverse events related to this study to the UCCIRB within seven days verbally and fourteen days in writing.

Always quote the protocol identification number in all future correspondence with us about this protocol.

Yours faithfully,

Kofi F. Amuquandoh  
Ag. Administrator

SECRETARY  
INSTITUTIONAL REVIEW BOARD  
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