Reinforcing Sustainability through Agricultural Insurance: Models, Innovations, and Challenges in Building Climate-Resilient Agri Food Systems

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Abstract. Agricultural insurance is proven to be one of the tools that can help improve the climate resilience for sustainable agricultural development and the financial security of farmers. In spite of its potentiality there are still many developing regions where adoption is limited due to understand this. The present study systematically reviews 73 peer-reviewed articles following the PRISMA protocol, and the results are synthesized through the TCCM (Theory-Context-Characteristics-Methodology) framework. Many studies concentrate on a limited set of developing regions chiefly China, India, and parts of Sub-Saharan Africa and predominantly examine crop and weather-index insurance schemes. Evidence shows that adoption is influenced not only by income and exposure to climate risk but also by institutional trust, social networks, previous claim experience, insurance literacy, and product design. The increasing use of digital and climate-smart technologies mobile platforms, satellite monitoring, remote sensing, and artificial intelligence has improved transparency, reduced basis risk, and expanded coverage. Agricultural insurance supports income stability, climate adaptation, risk mitigation, and more resilient farming systems. Nevertheless, widespread uptake remains constrained by affordability, delayed payouts, low awareness, and weak institutional coordination. This study contributes to the literature by integrating behavioural, institutional, sustainability, and technological perspectives into a cohesive synthesis of agricultural insurance adoption.

Keywords: Agricultural Insurance, Weather Index Insurance (WII), Climate-Smart Agriculture (CSA), Sustainable Agriculture, Technology-Enabled Risk Management.

1 Introduction

Agriculture continues to be the backbone of livelihoods globally, especially in developing countries, where it is the primary source of income for millions of people who live in poverty and hunger. (Gates Foundation, n.d.; H. Williams, 2024). Farming is a source of economic activity and household security for rural communities. But this sector is under increasing pressure from climate variability and production risks that threaten agricultural systems (P. A. Williams et al., 2018). There are different climate change risks in different regions. Farmers in Uzbekistan face climatic and commercial shocks such as market volatilities (Nosurullaev, 2025). The climate-sensitive economies and their low adaptive capacity make sub-Saharan Africa vulnerable to increasing temperatures and unpredictable rainfall patterns. (Chatsiwa, 2024). The same

H. L. Chidananda et al. (eds.), *Proceedings of the 2nd International Conference on Innovations and Challenges in Financial Technology (ICICFT 2025)*, Advances in Economics, Business and Management Research 398,
https://doi.org/10.2991/978-94-6239-772-9_10

conditions are observed in Machakos county in Kenya, where temperature and rainfall are increasing. (M.K. Nyamai et al., 2024). In addition, climate change contributes to outbreaks of pests and diseases, droughts, floods and crop failures (Harvey et al., 2014). Smallholder farmers who form most of the world's rural poor bear the brunt of these risks due to limited resources and coping capacity (Cohn et al., 2017; Harvey et al., 2014). In places like Madagascar, Cyclones directly impact food security, income and well-being (Harvey et al., 2014). The combination of poverty, marginalisation, and climate stress makes effective risk-transfer mechanisms essential (Nosurullaev, 2025). However, access to affordable financial services such as credit, savings, and insurance remains limited (Negera et al., 2025). Social protection initiatives are helping bridge this gap by offering stability during crises and linking farmers to financial inclusion pathways (Joep Roest, 2025). Within this context, agricultural insurance has emerged as a vital tool for resilience and inclusion (Agri-PDB Platform, 2025). It protects farmers from income losses, facilitates access to credit, and supports investment and adoption of improved practices (Nosurullaev, 2025). When bundled with credit, digital platforms, or advisory services, insurance enhances productivity and adaptation (Agri-PDB Platform, 2025). For instance, Its effect is massive, with more than 57 million farmer applications covered, like in the Pradhan Mantri Fasal Bima Yojana (PMFBY) scheme in India (Joep Roest, 2025) While benefits of agricultural insurance have been observed in many developing regions, take-up of agricultural insurance is still limited. High premiums, liquidity constraints, poor awareness in and low trust with the insurance industry are barriers (Cole et al., 2017; Hill et al., 2016). Moreover, the reduced demand is driven by a number of behavioural factors, including loss aversion, ambiguity, and mistrust (Bryan et al., 2014; Clarke, 2016), while institutional inefficiencies and payout delays confidence (Cai, 2016; Carter et al., 2017).

Although research on agricultural insurance has expanded, it remains fragmented. The majority of research is concentrated on a few countries, particularly those located in China, India and parts of Sub-Saharan Africa, and other countries and product areas (e.g. digital insurance, livestock) are under-researched (Greatrex et al., 2015). There are relatively few studies that incorporate a behavioural or economic approach and only a few show methodological diversity (Norton et al., 2012). As this study reviews 73 peer-reviewed articles using the PRISMA technique and the Theory-Context-Characteristics Methodology (TCCM) framework. Using this combined approach, Researcher also look at the research techniques used, the factors driving insurance uptake, the farming and geographic settings of the authors' work, and their theoretical underpinnings. By arranging the literature according to the TCCM framework, This investigation may map known findings, draw attention to discrepancies in earlier findings, and identify significant gaps that call for additional investigation.

Applying TCCM, the review makes several contributions: it maps the theoretical bases used in adoption studies and underscores the limited deployment of formal behavioural and economic models; it documents geographical concentrations and varying interest across farming systems; it synthesises determinants into meaningful clusters socioeconomic, behavioural, institutional, financial, and product-design factors; and it traces methodological evolution from conventional econometrics to discrete-choice, causal, and experimental approaches. Collectively, these findings clarify priorities for future scholarship and provide actionable direction for policy and innovation in agricultural risk management.

1.1 Objectives of the Study

The purpose of this review is to accomplish four goals:

1. To Identifying and synthesizing of systematic reviews of peer-reviewed research on agricultural insurance adoption by transparent and replicable process, following the PRISMA 2020 protocol..
2. To analyse the literature using the TCCM or Theory–Context–Characteristics – Methodology framework which allows for structured evaluation of the theoretical basis, geographical and farming context, determinants of adoption, and methodology.
3. To map patterns, gaps, and trends in existing research by examining how farmers' behavioural, socioeconomic, institutional, and financial factors have been studied in relation to insurance uptake.
4. To build a unified knowledge of the mechanisms affecting agricultural insurance uptake and to gain clues from the knowledge to guide the future agendas for research, policy design and innovation in climate-risk management.

2 Methodology

This study used a systematic review approach per the PRISMA 2020 guidelines, which ensure transparency and replicability. The review process consisted of four main stages identification, screening, eligibility assessment, and inclusion. Scopus was chosen as the only one because it covers all peer-reviewed literature related to agricultural sciences, development economics and the study of climate risks. A structured search strategy was developed to identify studies related to the relationship between agricultural insurance (crop, micro, weather index) and farmer behaviours, participation decisions, willingness for payments for insurance and risk-management considerations. The exact search string used in Scopus was:

(TITLE-ABS-KEY(("agricultural insurance" OR "crop insurance" OR "weather index insurance" OR "index-based insurance" OR "microinsurance" OR "farm insurance" OR "livestock insurance" OR "climate risk insurance") AND ("adoption" OR "uptake" OR "participation" OR "demand" OR "willingness to pay" OR "perception" OR "behaviour" OR "decision-making" OR "farmer behaviour" OR "risk management") AND ("farmer" OR "smallholder" OR "rural household" OR "agricultural household" OR "farming community")))

The initial search yielded 1,548 records. During the identification stage, 386 non-journal and non-English items, including book chapters, conference papers, reports, and editorials, were excluded. The remaining 1,162 records were then screened by title/abstract, with 1,006 discarded due to their lack of relevance to agriculture, insurance, or farmer behaviour. At full text assessment stage 156 articles were considered in detail, 83 of which were excluded because they were not open access, not farmed context, or not relevant. As a result, 73 studies were included and these studies were retained for final synthesis.

The studies chosen if they met the following criteria: if they are peer-reviewed English-language journal articles, on the topic of farmers' / rural households' relationship with agricultural insurance, and on the factors influencing the farmers' adoption of agricultural insurance – behavioural, socioeconomic, institutional, or methodological. Studies were omitted if they were grey literature (thesis, reports, policy briefs), in a language other than English, were not available in full-text (either originally or as an adaptation), or only included actuarial pricing models, non-agricultural insurance products or macro-level insurance system studies. Grey literature was not included thus focusing on peer-reviewed, high quality empirical and conceptual studies. No additional databases (such as Web of Science or AGRIS) were used to maintain consistency in indexing and metadata structure.

A structured Coding matrix was developed as a guide for data extraction of knowledge related to information about the authors of the articles, publication year, country of origin, journal from where the article was published, type of insurance (crop, livestock, weather index, microinsurance), type of study design (econometric, experimental, or mixed-method), the theory the article draws from (Expected Utility Theory, Prospect Theory, Technology Adoption) as well as the behavioural and contextual determinants, and some key findings. A narrative synthesis framework (Theory–Context–Characteristics–Methodology) was used in the analysis process for identifying theoretical patterns, contextual differences, and methodological changes within studies. The PRISMA flow diagram was used to summarise the overall workflow, from the initial 1548 records to the final 73 studies used for analysis (Fig. 1).

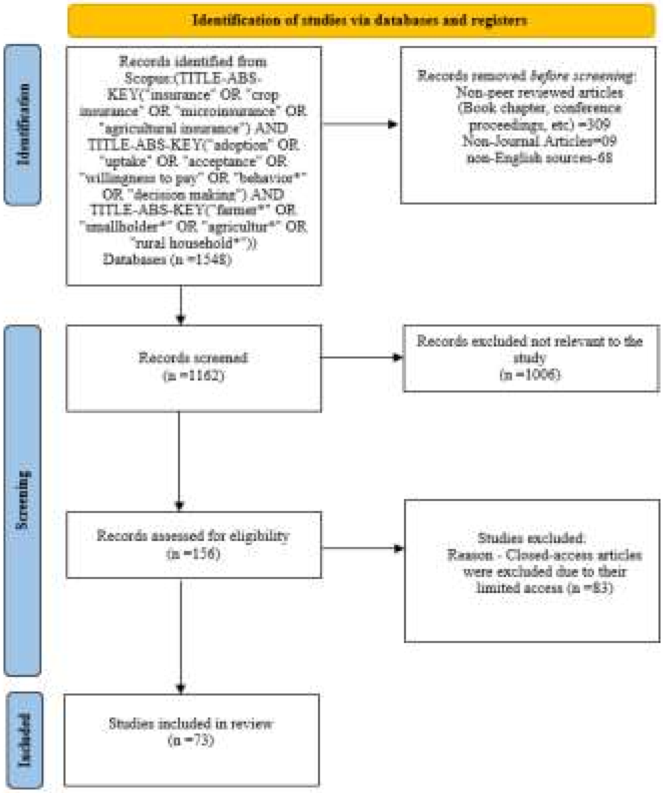

Fig. 1 PRISMA Flow Diagram

2.1 Theoretical perspectives

The PRISMA-based review revealed only several studies that explicitly used formal theoretical frameworks to explain farmers' behaviour, risk management and insurance acceptance, as presented in table 1.

Table 1: Comparison of all the theories highlighted in the literature

Theory	**References**
Cumulative Prospect Theory (CPT) framework	(Visser et al., 2020)
Random Utility Model (RUM)	(Doherty et al., 2021)
Dynamic model (Gollier & De Nicola)	(Aina et al., 2024)
Lancaster's characteristics model	(Ghosh et al., 2021)
Expected Utility Maximizing Nonlinear Program or DEMP	(Capitanio & Adinolfi, 2009)

Multiple equilibrium model	(Liao et al., 2019)
Behavioural insurance demand model	(Lampe & Würtenberger, 2020)
Certainty equivalent (CE) method	(Islam et al., 2021)

Source: Authors work

The studies are all theoretically grounded and provide a good representation of the diversity of analytical approaches used to capture risk, uncertainty and decision making process in the context of agricultural insurance. (Visser et al., 2020) employs the Cumulative Prospect Theory (CPT) framework as the core analytical tool to examine behavioural factors influencing farmers' decisions under risk in South Africa. The study offers a broad description of such experiments and a short review of the literature about the Tanaka, Camerer, and Nguyen experimental design. It estimates the major behavioural parameters, risk aversion, loss aversion and probability weighting, to provide some indication about the joint influence of psychological biases and insurance mechanisms on technology adoption and financial inclusion. In a similar study (Doherty et al., 2021) applies the Random Utility Model (RUM) to analyse data from a Discrete Choice Experiment (DCE) among Irish farmers, using Conditional and Mixed Logit models to estimate preferences for various design attributes of publicly backed climate risk insurance schemes.

Following intertemporal analysis, the study by (Aina et al., 2024) quantifies farmers' consumption, investment, and insurance decision making over time in the presence of stochastic production shocks and presents a Dynamic Model adapted from (Gollier, 2003) and (De Nicola, 2015) to demonstrate the long-term welfare effects of index insurance access. (Ghosh et al., 2021) argues against the use of DCEs, but also uses the Lancaster Characteristics Model to assign utility functions to certain aspects of crop insurance, such as coverage period, loss assessment method, and indemnity timing. The study by (Capitanio & Adinolfi, 2009) provides a normative optimization framework that combines risk preferences into the nonlinear programming model for farm decision-making under uncertainty to highlight the influence of risk aversion on input deployment and willingness to participate in insurance or environmental program.

It is interesting to see how (Liao et al., 2019) chooses to apply Multiple Equilibrium Model concepts at the system level to explain the emergence of poverty and prosperity equilibria in the context of agricultural risk, from which the long-term implications for welfare result, considering the interplay of three different factor endowments (capital, technology and insurance) involved. In (Lampe & Würtenberger, 2020) , another behavioral contribution introduces the Behavioural Insurance Demand Model (BIDM) based on Prospect Theory that takes into account both reference dependence and insurance literacy to develop the theory behind the heterogeneity in insurance demand, hypothesising that loss aversion is detrimental for insurance uptake for the "naïve farmer" but beneficial for the insurance "literate farmer." Finally, the (Islam et al., 2021) empirically derives farmers' risk attitudes through the Certainty Equivalent (CE) method, which identifies indifference points between risky payoffs, allowing the estimation of absolute risk aversion coefficients to indicate whether households are risk averse or risk seeking. These two theoretically grounded studies collectively constitute a conceptual foundation for the reviewed literature in terms of the conceptual shift from a classical expected utility and equilibrium-based approach to behavioural, dynamic and attribute-based approaches. Together, they draw attention to the importance of combining economic rationality with behavioural realism, intertemporal decision-making and contextual heterogeneity in the analysis of the adoption of agricultural insurance.

Theoretical Gaps and Critique

This is a comparison of the strengths and weaknesses, the assumptions and the omissions among the different theoretical and methodological approaches provided to analyse risk management and insurance demand sources from these sources solely.

Table 2: Strength and weakness of the most used Theories

Theory/Model	**Strengths**	**Weaknesses / Omissions**	**Key Assumptions**
Random Utility Model (RUM) (Doherty et al., 2021)	Dynamical Choice Experiments (DCEs), which allow researchers to investigate how various product qualities affect individual preferences, are theoretically based on the Random Utility Model. It makes it easier to identify respondents' Willingness to Pay (WTP) for changes in non-price features and	Restrictive assumptions like the Independence of Irrelevant Alternatives (IIA) are the cornerstone of conventional implementations, especially the Conditional Logit (CL) model. When decision alternatives are closely related, these presumptions may restrict the model's versatility and affect the	It is anticipated that people will choose the option with the most utility. Two components make up utility: a random component that captures unobserved influences on decision-making and an observable component that is explained by quantifiable features and respondent characteristics.

	to estimate trade-offs between attributes.	validity of policy outputs.	
Multiple equilibrium model (Liao et al., 2019)	Through identifying the groups of farmers most likely to gain from insurance interventions, this model adds to the analysis of agricultural insurance. It assesses the possibility of households experiencing long-term poverty using the ruin probability concept and shows that insurance is especially helpful for farmers whose capital levels are near or above a vital threshold.	The structure's ability to explain outcomes for households that are already living in extreme poverty is restricted because compensation might not be enough to lift them out of poverty. Additionally, because the model does not completely account for how risk aversion affects production decisions, such as decreased investment in productive inputs, it may underestimate the wider advantages of insurance.	In a rural economy with many equilibriums, poverty is conceptualised as a stable low-level equilibria. The model posits that the amount of capital accessible to individual households is the primary determinant of technology adoption and long-term economic results.
Expected Utility Maximizing Nonlinear Program (DEMP) (Capitanio & Adinolfi, 2009)	The mathematical programming approach allows for incorporating complex technical constraints (e.g., water scarcity, soil type) that are difficult to handle in econometric analysis. It enables researchers to maximize the utilization of known information about existing systems while	Nonlinear programming lacks a universal form, demands considerable experience and expertise to set up correctly, and is not as robust as linear programming for large-scale issues. There is no guarantee of	The representative farmer maximizes the expected utility of income (or wealth).

	incorporating new policies like crop insurance.	achieving global solutions.	
Cumulative Prospect Theory (CPT) framework (Visser et al., 2020)	A robust behavioural approach that accounts for risk aversion, loss aversion, and probability weighting, offering a more realistic view of decision-making under uncertainty than traditional expected utility.	Findings suggest that CPT alone may be insufficient to explain all uptake decisions, as insurance uptake was found to be inadequate to counter constraints related to asset accumulation and risk preferences among poorer farmers.	Decision-making is driven by three key prospect theory parameters: the coefficient of risk aversion (σ), the loss aversion parameter (λ), and non-linear probability weighting (α),.
Behavioural insurance demand model (Lampe & Würtenberger, 2020)	Offers an explanation for the puzzling low adoption rates of index insurance by integrating psychological factors like reference dependence and loss aversion, it predicts that the impact of loss aversion on demand varies systematically depending on the level of insurance understanding (or literacy),.	Model utility is highly sensitive to the choice of the appropriate reference point, which determines whether an outcome is perceived as a gain or a loss,. It predicts that "naïve" farmers (unaware of the loss-hedging benefit) will not demand insurance even if it is highly subsidized,	The model incorporates reference dependence and loss aversion, contrasting 'No Insurance Coverage' (for naïve farmers) versus 'Perfect Insurance Coverage' (for insurance-literate farmers) as reference points.
Certainty equivalent (CE) method	A clear methodological approach to quantify individual risk attitudes. It is used to	Primarily a measurement method for eliciting preferences rather than a predictive	The method assumes that individuals evaluate risky outcomes based on discrete payoffs and specified probabilities.

(Islam et al., 2021)	determine the financial value (Certainty Equivalent) that makes a farmer indifferent between a risky prospect and a certain outcome.	demand model. Results rely on fitting the CE data to an assumed utility function, such as a cubic utility function.	Risk-averse respondents have a positive coefficient for the absolute risk aversion measure

Source: Authors work

These theory and methods represent a range of theories and methods for conceptualizing risk and demand. Optimization models are based on the traditional rational choice models (RUM, DEMP, Dynamic Model), which assume the greatest satisfaction of utility given a known set of constraints, and whose big problems are complexity and psychological factors. Behavioral models (CPT, Behavioral Insurance Demand) more closely resemble the anomalies observed in the real world and trade away some mathematical simplicity for captured anomalies which are influenced by frames, reference points and risk perceptions (loss aversion). The Multiple Equilibrium model provides a nice structural bridge from the wealth level to the technology choice, provides a precise place where technology choice would become an intervention that is successful or not, the poverty trap critical value.

2.2 Context-Country, Types of Farming and Type of Insurance

Country

The geographical spread of the studies reviewed shows a high level of regional specialization in agricultural insurance research, not just in financial inclusion, but also in climate resilient insurance and innovation with technology. Comparative findings show that governance structures, financial infrastructure, and policy choices differentially affect insurer performance, farmer participation, and programme effectiveness across contexts. The agricultural insurance literature is tightly connected to wider development objectives poverty reduction, climate adaptation, livelihood protection, and inclusive rural growth especially in Asia and sub-Saharan Africa. The geographic concentration of studies underscores the role of agricultural insurance as a key policy instrument for strengthening the resilience of vulnerable and less-developed farming systems.

Type of Farming

The literature review found that an array of farming systems have been investigated in agricultural insurance research, with a few sectors treated with a significantly higher emphasis than the others. Maize based farming systems and smallholder or subsistence agriculture are the most extensively studied farming systems (12 papers, respectively) as illustrated in Fig. 2.

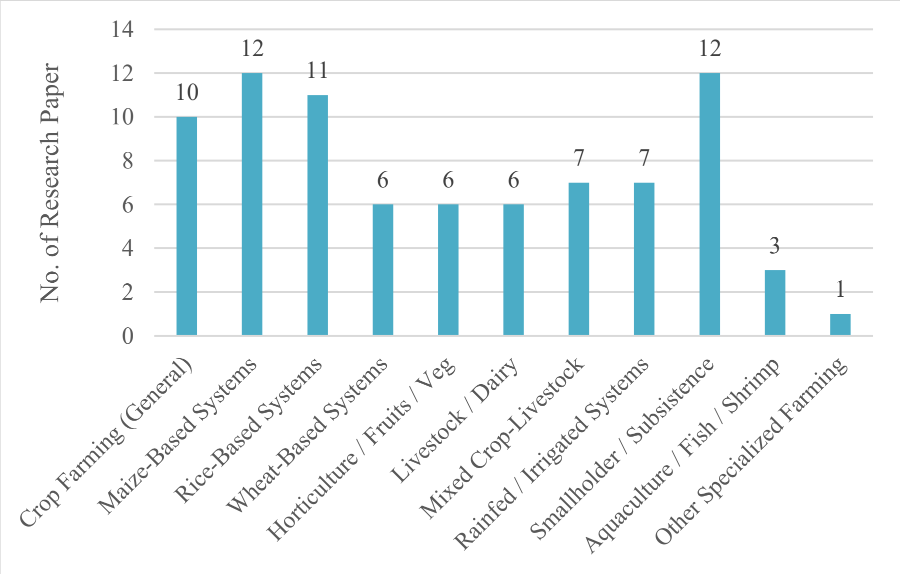

Fig. 2 Type of farming mentioned in the review papers

The reviewed studies indicate, however, that the bulk of agricultural insurance research still is concerned with general farming system and agricultural production that is climate-sensitive. Both general crop culture and cultivation of rainfed cropland and irrigated cropland have been looked at in terms of the effects of climatic variability on insurance demand and premiums, and both encounter strong impacts from climatic variability. Farming Systems

Environmental instability continues to shape farmers' assessments of agricultural risk and their choices about insurance participation throughout the farming systems studied in the literature. Agricultural productivity is still quite vulnerable to unpredictable rainfall, protracted droughts, flooding incidents, and variations in water supply, despite breakthroughs in weather forecasting that have made climate information more accessible. These environmental uncertainties have a significant impact on farmers' perceptions of the need for insurance and, ultimately, their decision to use the available insurance products.

The investigation also shows that work on livestock or dairy production and mixed crop-livestock systems acknowledges the complexity of integrated farming businesses, especially in rural areas where crop and animal production are closely related. This disparity shows that insurance solutions designed for non-traditional and growing agricultural sectors are still underdeveloped and constitute a significant gap in the literature.

When considered in its entirety, the available data shows that agricultural insurance research still focuses mostly on smallholder farming and cereal production, which mirrors larger policy concerns pertaining to food security, rural livelihoods, and vulnerability reduction.

Type of Insurance

A significant focus on products meant to mitigate climate-related production risks is seen in the distribution of studies across insurance categories, especially weather-based and crop insurance. Weather-index or parametric insurance constitutes the most widely examined category, accounting for 26 of the reviewed studies. Its relevance is a reflection of the increasing significance of climate risk management, particularly in developing nations where smallholder farmers continue to be extremely sensitive to extreme weather events and shifting climate conditions. The predominance of weather-index insurance in the literature is further explained by its broad implementation in both research and practice.

2.4 Methodology

The review of literature shows a highly varied methodological approach, as indicated in Fig. 4, particularly with regard to the use of econometric methods, statistical methods and regression methods and discrete choice modelling. This methodological diversity reflects a field's increasing focus on the farmer's behaviour and the economic drivers available for determining when farmers would or would not adopt agricultural insurance. CDEs, MLE (Mixed Logit or Random Parameter Logit) models and Conditional Logit models are some of the most common analytical tools among these preference-based approaches. Such techniques are often valuable for understanding farmers' willingness to pay (WTP) for particular features of available insurance products, including premiums, level of coverage, structure of payments, and contract flexibility. The advantage of looking at the relationship between different insurance attributes is that these models can yield more understanding of insurance preferences and insurance adoption behavior in the analysis of how farmers make trade-offs between attributes. Importantly, these approaches also reflect heterogeneity in farmer decision-making, acknowledging that risk perception and financial capability, and consequently also utility preference, vary among farmers, regions and farming systems.

This suggests a greater general trend in literature from using more generalized adoption analysis to micro-level behavioral modelling to better understand the complexity of choices made by farmers under uncertainty.

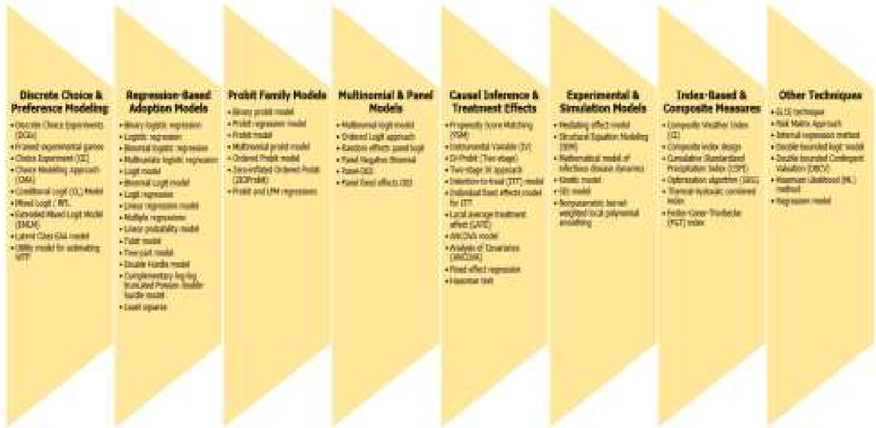

Fig. 4 Methodology used in the review papers

These techniques were applied to more than half the papers in the review to analyse farmers' insurance decisions. Logit models are also widely applied to model selection into binary outcomes, for example whether or not a farmer sells an insurance policy or probit models can be used to model the latent propensity of a farmer to adopt and for different probability distributions. More complex models such as the zero-inflated ordered probit and the doublehurdle can incorporate stochastic latent participation, sequential decision-making processes and, as well as based on the separation between access to insurance and its use, to censored determin behaviors. There is also an increasing interest in the use of panel data and the multinomial modelling framework, which corresponds to a rising demand for understanding what lead to insurance choices within a number of insurance alternatives over time. These methods enable more dynamic analyses of the changing decisions of farmers, unrestricted re-entry times, and heterogeneity in insurance choices. Indeed, the progressive sophistication of the field is also manifested in the increasing use of causal inference methods such as Instrumental Variable (IV) estimation, Propensity Score Matching (PSM), and Difference-in-Differences (DID) methodologies to address endogeneity concerns and establish stronger causal linkages. The literature shows a clear shift from simple descriptive correlations toward more rigorous quasi-experimental validation. At the same time, multidisciplinary syntheses are becoming more common, driven by experimental designs and structural modelling. These methods capture system-level dynamics that traditional econometrics often miss, incorporating factors such as risk perception, trust, behavioural mediation, and optimization of climate indices. The construction of composite measures—weather- or climate-based indices and multidimensional poverty metrics (for example, the Foster–Greer–Thorbecke index) exemplifies efforts to integrate multidimensional and climate-aware analysis. Optimization algorithms and simulation techniques further point to a move toward context-sensitive, data-driven, adaptive insurance solutions. The reviewed studies reveal a steady increase in methodological sophistication. Early work relying on binary regression to identify access determinants has given way to hybrid approaches that blend behavioural theory, causal inference, climate analytics, and simulation. This methodological diversification improves analytical precision and theoretical depth, yielding a richer, behaviourally informed, and data-intensive understanding of agricultural insurance adoption and its sustainability.

Sampling Method

There were considerable differences in the sampling designs reflected in the reviewed literature (Fig. 5), depending on both data availability and research context-specific objectives.

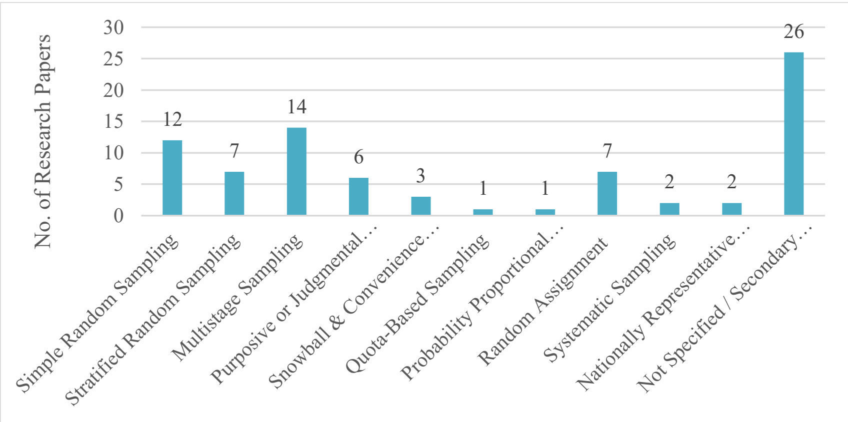

Fig. 5 Types of sampling method

Sampling is still used in the majority of agricultural insurance research. In the research examined, multistage random sampling was the most often employed approach (14), closely followed by basic random household sample (12). These methods have been commonly used because they increase representativeness and address the challenge of researching geographically separated farming populations scattered among villages and regions. The selection of farmers in seven studies relied strongly on stratified random sampling, which was particularly essential to account for the variation between agricultural climate zones, farm sizes, and socioeconomic groups all of which are factors that determine farmers' exposure to risk and access to standardised insurance services.

Reduced the number of possible responders. A more thorough qualitative investigation of behaviour in a restricted number of behavioral/micro level case studies was made possible by snowball and convenience sampling techniques, notwithstanding their limited statistical portability. Nonetheless, seven research used random assignment and experimental designs, indicating a growing curiosity in causal/impact-oriented studies, especially the insurance adoption experiment and the randomised controlled trial (RCT). 26 of the analysed studies were either dependent on secondary data or did not thoroughly specify how they sampled, which was a significant finding.

The evidence suggests that important gaps remain in agricultural insurance research, even as studies increasingly move toward standardized, national-level analyses. A growing but still limited set of papers use country-wide or census data, signaling a shift toward greater policy relevance and macro-level validation. Overall, the field is evolving from scattered, ad hoc investigations to more systematic applications of probabilistic, multistage, and experimental designs; many earlier studies relied on existing analytical tools rather than developing bespoke measures, while newer work shows greater methodological planning.

This progression reflects increasing methodological maturity and the availability of more reliable evidence to inform programmes and policy. The literature is predominantly quantitative: 65 of the 73 reviewed studies primarily employed quantitative methods (surveys, experiments) to examine farmer behaviour under risk, insurance adoption, and willingness to pay. Common techniques include panel analysis, logit and probit models, and causal-inference methods. By contrast, eight studies used mixed methods, combining quantitative analysis with qualitative data from focus groups, interviews, or participatory evaluation tools. These mixed approaches yielded richer insights into social dynamics, institutional trust, behavioural responses, and the usability of digital insurance mechanisms dimensions that econometric methods alone may miss. In sum, agricultural insurance research now rests on a strong empirical, quantitative base while increasingly integrating behavioural and social perspectives.

3. Discussion and Findings

The review's conclusions show that farm insurance is becoming more widely acknowledged as a crucial element for attaining agricultural sustainability and boosting climate resilience, in addition to being a vehicle for transferring financial risk. Adoption of agricultural insurance is linked to greater farmer willingness to invest in climate-smart practices and productivity-enhancing technologies, alongside improved income stability and resilience. Smallholder farmers in high-risk areas subject to extreme weather, floods, storms, pest and pesticide risks, and market swings stand to gain most, as insurance helps protect livelihoods and food security.

The review also highlights the growing role of digital innovation in strengthening agricultural insurance systems. Tools such as artificial intelligence, data-driven risk models, satellite and remote-sensing imagery, and mobile-based insurance platforms reduce transaction costs, increase operational efficiency, and enhance claims transparency. These technological advances are particularly relevant for Weather Index Insurance (WII), where timely and accurate data reduce basis risk and raise farmer confidence. By improving risk protection and predictability, such innovations encourage longer-term investments in sustainable agricultural practices. Farmers' decision-making skills can be further enhanced and sustainable resource management techniques can be encouraged by integrating insurance products with advisory services, climatic The paper finds that the sustainability effects of agricultural insurance vary by context, reflecting common constraints in many developing countries limited affordability, weak institutional capacity, low stakeholder awareness, and poor digital infrastructure. Robust compensation mechanisms and regulatory frameworks that incorporate biological knowledge, technical improvements, and climate-adaptation measures are essential for long-term viability. Building resilient agri-food systems therefore requires context-specific foundations supported by technology-enabled insurance approaches that explicitly priorities sustainability.

4. Conclusion

Encouraging regenerative farming, improving climate stability, and shielding rural communities from growing environmental and financial hazards are all made possible by agricultural insurance. Using the PRISMA practice and TCCM technique, this study shows that crop insurance uptake is influenced by social, institutional, cognitive, behavioural, and technological factors in plus to financial incentives. Resilient farming, financial inclusion, and environmental change adaptation can all be supported by well-designed insurance programs. So, implementation is hampered by issues such basis risk, delayed claims, low awareness, mistrust, and more expenses, remarkable among smallholder farmers in underprivileged regions. The research presents how digital technologies such as artificial intelligence, satellite monitoring, and mobile platforms are transforming agricultural insurance by improving risk assessment, reducing costs, and increasing transparency. These innovations are key to developing climate-smart, sustainable risk management systems. Future research should integrate behavioral and institutional insights alongside financial examin and see on different agricultural contexts using varied methodologies, including experimental and longitudinal studies.

Eventually, crop insurance is more than financial protection; it is a tool for fostering climate resilience and sustainability. Success needs good policies, farmer-centered products, ongoing technological advancement, and collaboration among governments, insurers, financial institutions, cooperatives, and tech providers. Such a whole approach is essential to build fair and durable agricultural systems capable of facing climate challenges.

5. Future Directions

The TCCM in sort identifies important priorities for upcoming agricultural insurance research and policy. Stronger theoretical frameworks are needed, incorporating behavioral and decision-making models to better understand how farmers respond to economic and climate challenges. Expanding research beyond staple crops and regions like Latin America, the Middle East, Central Asia, and the Pacific Islands is essential to capture diverse risks and insurance needs. Methodological spectrum is crucial; moving beyond cross-sectional studies to include mixed methods, longitudinal, and experimental designs will provide deeper insights into resilience and behavioral change over time. Technological advances such as AI risk scoring, blockchain, satellite monitoring, and mobile insurance offer promising ways to reduce risks and costs but need careful evaluation for bearing and fairness.

Finally, agricultural insurance should be studied as part of integrated resilience strategies that combine climate-smart farming, finance, stewardship, and advisory services, aiming to improve livelihoods, reduce poverty, and boost adaptability.

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