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Modeling of Crop Insurance and Risk in Stabilizing Crop Productivity and Income: A System Dynamics Study

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Abstract

The primary purpose the paper is to understand the dynamic complexity among the relationships of crop insurance, risk, crop productivity, and income of farmers. The study adopted a unique method i.e. system dynamics (SD) and causal loop diagram (CLD) methods to uncover the complexity. Further, with this method, the study examines the dynamic interrelationships among crop insurance, risk perception, productivity, and farm income. The developed model was later validated using the feedback from stakeholders. The results suggest that there are four important loops in the generic model of the system. They are: (R1) Loan and Investment Loop, (R2) Risk Perception Uncertainty Loop, and two balancing loops viz. (B1) Protection Failure Loop and (B2) Productivity Failure Loop. The generic model highlights that how timely credit and reduced uncertainly can create a virtuous cycle of higher input investments and crop productivity. The results also reveal that the external shocks and delay in claim settlement may generate adverse impact and can weaken income stabilization among farmers. The study provides a robust framework (generic model) which can guide various stakeholders (policymakers, decision makers, government, society, farmers, and local authorities) to evaluate and redesign crop insurance interventions under evolving climate risks.

Keywords: crop insurance, crop productivity, risk, system dynamics, CLD

Introduction

Agriculture remains an important and most risk exposed sectors of the Indian economic system. This is because crop outputs and farm income are jointly shaped the weather variability, pests and diseases, price fluctuations, etc. such as credit access and market linkages (IPCC, 2022; FAO, 2018; World Bank, 2011). These risks are consequential in India, where large share of farmer products are small and marginal (NABARD, 2024; IPCC, 2022). In this setting, the productivity and income are not only outcomes of agronomy but also they have dynamic results of how farmers manage their risks over time through various coping strategies (e.g., distress sales, reduced input use) and through formal risk-transfer and risk-reduction instruments (Dercon, 2002; Carter et al., 2018).

On a related note, in India, the crop insurance is seen as an important cornerstone of agricultural risk management as it can reduce the downside income volatility, protect creditworthiness, and encourage productive investment under uncertainty (Hazell, 1992; Barnett & Mahul, 2007). The Government of India schemes and programs such as Pradhan Mantri Fasal Bima Yojana (PMFBY), launched in 2016, was designed to provide "comprehensive risk cover" and stabilize farm income. The scheme also supports the adoption of modern agricultural practices and sustaining farmers' participation in cultivations. This scheme guideline explicitly acts as a catalyst for stabilizing income, creditworthiness, and reduce production risk in log run. Further, this scheme also emphasises on tech-based agricultural farming for improvement of yield.

In India, the crop insurance has a challenge for effective implementation that weakens the stabilizing effects of insurance. Government of India has highlighted many national-level concern on performance audits and reviews related to various scheme designs such as delay in farmers claim settlement, quality and timeliness of yield estimations, etc. Sectoral regulators also emphasize that crop insurance outcomes depend heavily on last-mile delivery, data systems, grievance redressal, and the integration of insurance with credit and extension systems (IRDAI, 2023; UNDP, 2023). In the same line, Indian rural financial survey report shows that show that household income structures and vulnerability profiles are very dynamic and change implying that the risk environment faced by farms is co-evolving.

The above discourse shows that a shift from viewing crop insurance as a standalone intervention to analizing it a complex process or system that integrate climate shocks, yield formation, farmer decision-making, credit cycles, and public-finance commitments. In practice, insurance could be a reinforcing factor and balancing feedback loops in the complex system. For example, timely claims can prevent distress borrowing, enabling continued input use and protecting subsequent-season yields. Conversely, delayed or unpredictable pay-outs can increase risk aversion, reduce fertilizer/seed expenditure, and depress productivity, thereby increasing the probability of future claims and fiscal pressure (Carter et al., 2018; Morduch, 1995). Insurance can also interact with moral hazard and adverse selection, especially when loss measurement is imperfect or when area-yield indices diverge from farm-level losses (i.e., basis risk) (Miranda & Glauber, 1997; Skees, 2008). These interactions are likely to intensify under climate change, which is already assessed as stressing food production systems and slowing agricultural productivity growth in many low and mid-latitude regions (IPCC, 2022; UNEP-FI, 2023).

From the above backdrop, the paper adopted a unique methodology of System Dynamics (SD) to study such interdependencies because it explicitly models feedback, time delays, nonlinearity, and accumulation processes that drive system behavior over time (Forrester, 1961; Sterman, 2000). In agricultural and climate-risk contexts, SD has been used to explore how policies perform under uncertainty, how behavioral responses amplify or dampen shocks, and how interventions can generate unintended consequences when implemented in complex socio-technical systems (Meadows, 2008; Ford, 2010). Applying SD to crop insurance in India enables integration of biophysical yield dynamics (rainfall/temperature shocks, pest incidence, technology adoption), institutional processes, and economic responses. Thus, the paper attempts to answers the following questions:

RQ1: What is the dynamic relationships between crop insurance, risk and productivity?

RQ2: How crop insurance, risk and productivity help stabilizing the crop productivity and income?

RQ3: How this dynamic relationship can help the various associated stakeholders in crop productivity?

The paper used the SD method to understand the complex phenomenon between various factors such as insurance and risk. The paper's contribution is to get the nuances of these relationships and finding out the role played by each interest variables in the system. The paper adopted the causal loop diagram (CLD) method to draw and understand the polarities between the variables. Further, all the identified loops were validated using the feedbacks from stakeholders. The developed generic CLD model would help the policy and decision makers to understand the system.

Literature Review

Previous work shows that crop insurance is not only a compensation mechanism but it also influences farmer behaviour over time i.e. input intensity, credit repayment, area allocation, and technology adoption (Table 1). It helps to shape subsequent yields and income stability. Further research stresses that results depend on scheme rules (area-yield approach, enrolment rules), governance capacity, and effective quality (timeliness and accuracy of loss assessment and claim settlement), which make feedback loops between trust, enrolment, fiscal burden, and scheme performance.

One major theme is the operational frictions that can erode trust, reduce voluntary participation, and push farmers back toward conservative, low-investment strategies weakening productivity and income stabilization goals. Many research in the field of crop revealed that the evolution and performance of agricultural insurance in India shows a concern of recurring implementation, administrative complexity, uneven state participation, delays, and awareness gaps. The constraints can boundary insurance's ability to defend livelihoods and catalyse speculation, even when best supports are high.

A comprehensive review in Risks (2021) evident that the policy shifts (e.g., making enrolment optional for loan farmers from Kharif 2020) can alter contribution dynamics which is an important SD modeling consideration. This is because it changes flows into/out of the insured population stock. Several studies reported the mixed welfare effects. The insurance may be associated with higher input spending (seed, weeding, pesticides, land preparation), but income effects may be weak or statistically insignificant in some settings suggesting that operational realities, local hazard profiles, and payout adequacy mediate the pathway from insurance → investment → yield → income. Government-commissioned evaluation on PMFBY awareness (Rabi 2022) reports sizeable improvements in awareness after campaigns and documents enrolment and claim-experience patterns—useful for parameterizing behavioural relationships (awareness → enrolment; enrolment → claim expectations) in SD. Official updates also show the rollout of technology/process reforms (e.g., DigiClaim module from Kharif 2022, integration with PFMS, penalties for delay in later seasons), underscoring that "claim settlement delay" is a policy lever that changes system behaviour over time.

The India literature strongly suggests modelling (a) trust/participation as endogenous (affected by delays/adequacy), (b) investment decisions as responsive to perceived protection, and (c) implementation capacity and timelines as structural constraints generating delays. Because PMFBY is largely implemented using an area-yield index approach, global and recent methodological literature on index design is directly relevant. A systematic review of index selection and yield–index modelling methods highlights rapid growth in methods that use satellites and crop models to improve index performance and reduce basis risk. A prominent line of work proposes improving index insurance through crop models and phenological monitoring, reinforcing the "data → accuracy → trust → participation" feedback loop that SD models can capture. Another systematic quantitative review (2025) documents the expanding use of satellite-based datasets for agricultural index insurance, useful for designing next-generation triggers and for monitoring yield estimation quality. Implication for System Dynamics: remote sensing and improved yield estimation reduce measurement error and settlement delays, which should increase perceived fairness and participation, potentially lowering long-term fiscal stress by stabilizing the system (fewer disputes, fewer exits, better targeting). While SD is widely used for complex agricultural systems and policy analysis, the direct SD modeling of crop insurance markets/policies is still relatively sparse in mainstream, peer-reviewed India crop-insurance work. The recent appearance of exploratory modeling focused on crop insurance market dynamics indicates growing interest, but the literature remains thin relative to econometric evaluations and descriptive performance studies. Clear gap for your study: integrate India-specific PMFBY processes (enrolment rules, CCE/yield estimation, claim workflow, subsidy timing) with farmer behavioural responses (input use, borrowing, risk aversion) and data/technology reforms (NCIP, DigiClaim), to test stabilization outcomes under alternative scenarios.

Table 1: Literature review on critical findings of earlier research in Crop management

Author(s)	**Year**	**Critical findings relevant to risk–productivity–income stabilization**
Singh & Agrawal	2020	Reviews India's agricultural insurance evolution; argues persistent operational/design defects limit effectiveness and coverage expansion.
Tiwari, Chand & Anjum	2020	Reviews PMFBY; highlights implementation and governance challenges that shape farmer outcomes and scheme credibility.
Kaur, Raj, Singh & Chattu	2021	Synthesizes crop insurance policies and PMFBY evidence; notes participation dynamics and implementation challenges; points to links between risk, food security, and farmer income.
Abdi et al.	2022	Systematic review of index selection and yield–index modelling; emphasizes basis risk reduction using new data sources (satellites) and improved methods.
Govt. of India / PMFBY, Evaluation of Mega Awareness Campaign	2022	Reports awareness increase after campaign (pre vs post), enrolment and claims-related patterns; useful for modelling awareness → enrolment dynamics.

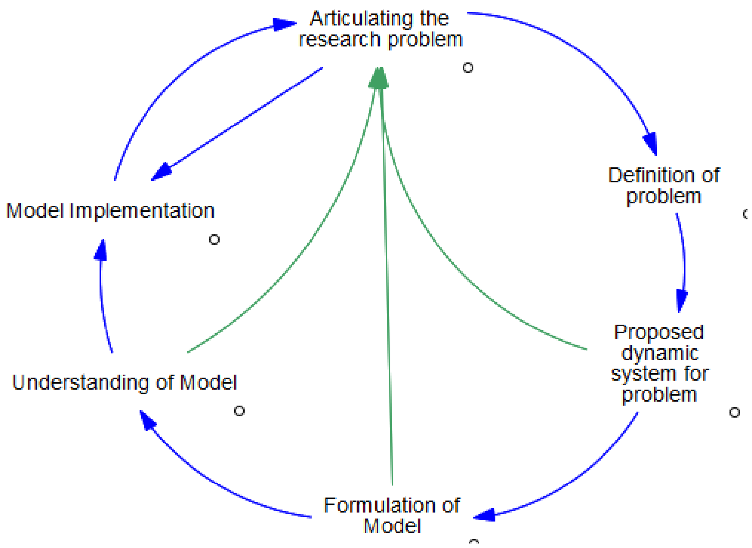
Agarwal & Dash	2023	Field study (tribal southern Rajasthan) argues PMFBY aims to stabilize income and enable investment/loan repayment; highlights awareness and operational issues in practice.
PIB/GoI press release on implementation	2025	Documents tech/process reforms (DigiClaim, NCIP–PFMS integration) and pending-claims reporting—key for modelling delay-reduction as a policy lever.
Crop Insurance in India and Its Impact on Crop Income, Bidar, Karnataka study	2025	Finds PMFBY associated with higher input costs (seed/weeding/pesticides/land preparation) but income/revenue effects may be insignificant—suggesting weak/mediated pathways.
Nguyen et al.	2025	Systematic quantitative review: satellite-based datasets increasingly used in index insurance; supports improving triggers/monitoring to reduce basis risk.
Afshar et al.	2021	Proposes improving index insurance performance using crop models and phenological monitoring—supports data-driven reduction of basis risk.
Stigler	2024	Develops methods for optimal index insurance and basis-risk decomposition; strengthens the analytical foundation for designing better indices.
PMFBY Admin Statistics Portal	2025	Provides season/year participation and administrative statistics—useful for calibrating SD stocks/flows (enrolment, states/districts notified, etc.).
Mahadik, D., Sahu, B., & Murmu, U. B.	2025	Illustrates emerging SD-style exploration of crop insurance market dynamics; signals research direction but limited mainstream empirical linkage.
Eneh et al.	2025	SD applied to agricultural practices and outcomes; supports SD suitability for feedback/time-delay policy analysis (even if not insurance-specific).

Methodology

System Dynamics and CLD

System Dynamics (SD) is a methodological approach for understanding and analysing complex systems (Arbnor & Bjerke, 1997). It enables researchers to clarify intricate system structures and interpret real-world problems more systematically (Sterman, 2000). The concept of SD was introduced by Jay W. Forrester at the Massachusetts Institute of Technology (MIT) and is prominently discussed in his foundational work Industrial Dynamics (Forrester, 1961). Forrester (1961) argued that business strategies, investment choices, and policy decisions are largely shaped by mental models. In SD, a mental model refers to the underlying assumptions, beliefs, and cause–effect perceptions that individuals hold about how a system functions over time. SD primarily seeks to represent the dynamic interrelationships among system variables and examine how these interactions influence managerial decision-making.

Figure 1: Process involved in an SD modeling



Source: Adapted from Roberts (1978)

Roberts (1978) outlined a structured SD modelling process that includes: identifying and defining the problem, developing causal loop diagrams (CLDs) to obtain a holistic understanding of the system, quantifying key variables, processing data for model development, validating the model, testing it under different scenarios or conditions, and finally using the results to support decision-making.

Table 2: Causal-loop modeling notations

CLD Arrow	Causality indication
Plus, sign (+)	Signifies positive effects between variables
Minus Sign (-)	Signifies negative effects between variables
Reinforcing loop polarity (R)	Signifies positive effects and feedback
Balancing loop polarity (B)	Signifies negative effects and feedback

Source: Researcher's explanation

Causal Loop Diagrams (CLDs) are a powerful visual tool in System Dynamics that help capture an initial understanding of complex system structures and facilitate interaction between model developers and policymakers. They are widely used to elicit and represent mental models by showing how key system variables are connected. These connections are expressed through causal relationships and feedback loops. A defining feature of CLDs is the feedback loop, where variables influence one another in a circular manner, producing dynamic patterns of behaviour over time. As shown in CLD analysis (Table 2), feedback loops are generally classified into two types: Reinforcing (R) and Balancing (B). A reinforcing loop is represented by a positive (+) polarity and indicates that changes in a cause lead to changes in the same direction in the effect—an increase in the cause increases the effect, and a decrease reduces it. In contrast, a balancing loop is represented by a negative (−) polarity and reflects a stabilising mechanism, where an increase in the cause leads to a decrease in the effect (and vice versa). A common rule of thumb in CLD interpretation is that any loop containing an odd number of negative links is classified as a balancing (negative) loop, while loops with zero or an even number of negative links are considered reinforcing (positive) loops.

Vensim PLE software is used to build a model showing cause and effect relationship in the study. Vensim is a potent tool for developing models and running simulations in different scenarios.

Data for Model Validation

The Model is validated using the data collected from reports extracted on various categories such as village type (Irrigated / Non-Irrigated), Farm size category (Small / Medium / Large), Pre-insurance production per farm/acres, Loss percentage, Claim or indemnity paid per farm/acres, and Post-insurance production per farm/acres. The method of regression and multiple regression were used to understand the relationship between two variables at initial stage. Further, the metrics such as path coefficient and p-values were being used to test the model variable relationships and different polarities.

Model Development

Answering RQ1 and RQ2, the study developed a unique model using the CLD method. There are various loops identified after the mental modelling is done on the interest variables. Table 3 illustrates the loop name, its label, and its significance. There are two reinforcing loops (R1-2) and two balancing loop (B1-2) in the CLD Model. Following are the loops:

R1: Loan and Investment Loop

R2: Risk Perception Uncertainty Loop

B1: Protection Failure Loop

B2: Productivity Failure Loop

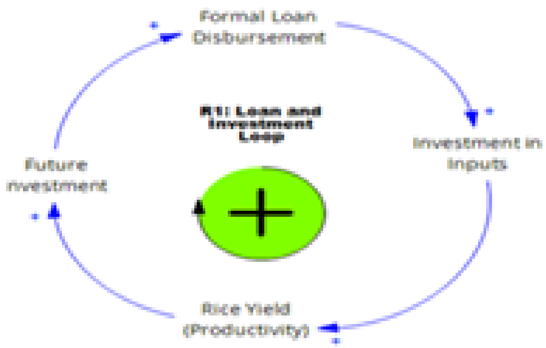
Table 3: Variables of the reinforcing and balancing loops in the CLD model of Crop Management

Reinforcing loop 1 (+)	Reinforcing loop 2 (+)	Balancing loop 1 (-)	Balancing loop 2 (-)
Formal Loan Disbursement	Risk Perception Uncertainty	External Shock	External Shock
Investment in Inputs	Future Investment	Actual Income Loss	Rice Yield (Productivity)
Rice Yield (Productivity)	Formal Loan Disbursement	Net Claim Deficit	Farmer Income Repayment Capacity
Future Investment	Investment in Inputs	Rice Yield (Productivity)	Formal Loan Disbursement
	Rice Yield (Productivity)		Investment in Inputs

R1: Loan and Investment Loop

Formal agricultural credit (from banks/cooperatives/MFIs) plays a vital role in reducing the reducing farmers' liquidity constraints at the beginning of the crop session. Further, when the credit is easily available for farmers, they are more likely to purchase productive items such as seeds, fertilizers, pesticides, irrigation services, and hired labour. It is experienced that the credit constraints hinder in the adoption of yield-enhancing technologies and input intensive agricultural practices (Feder et al., 1990). Similarly, the liquidity constraints can force farmers to underinvest in inputs, leading to low productivity outcomes (Carter & Barrett, 2006). Higher formal loan disbursement typically increases investment in inputs, especially during sowing and early crop growth stages when expenditure is highest. Thus, productivity of rice will also be boosted. R1 in the model shows this dynamic behavior of the variables associated in the loop formation.

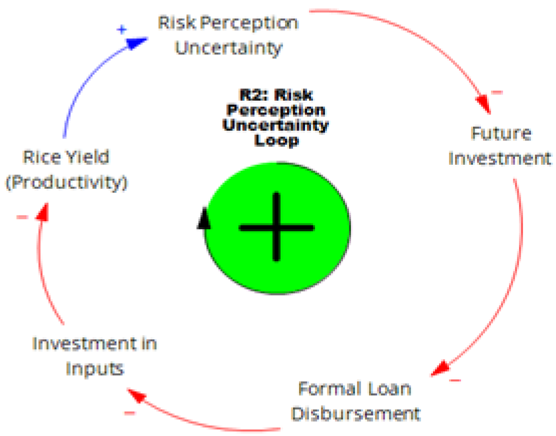
Figure 2: R1 Loop (Loan and Investment Loop)



R2: Risk perception uncertainty loop

R2 loop explains how risk perception and uncertainty can reduce agricultural growth through a chain effect. The loop says that when the farmers or investors feel insecure and uncertain about the future (such as weather conditions, market prices, or repayment pressure), their notion of risk increases, and hence they become less sure about the future investments. As future investment reduces, banks and financial institutions reluctant to facilitate loans to the farmers. Consequently, the farmers cannot invest properly in essential inputs like quality seeds, fertilizers, irrigation, and pesticides. As a result, the investment in inputs decreases**,** which directly lowers rice yield (productivity)**.** When productivity falls, it further increases uncertainty about future income, again raising risk perception and continuing the cycle. So, in order to strengthen this loop dynamic relationships, farmers have to take a calculated risk for agricultural activities. Banks and financial institutions should also extend their help in supporting the farmers to take risk in this regard.

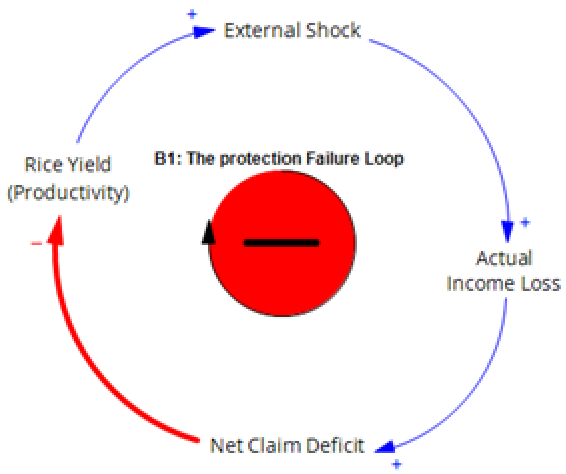
Figure 3: R2 Loop (Risk Perception Uncertainty Loop)



B1: The protection failure loop

B1 loop explains that the factors such as external shocks of drought, flood, pest attack, or a sudden fall in market prices can cause financial losses for farmers. This is because their crop output and earnings can be declined in due time. This in turn, impacts the farmer's dependency on the insurance claims, government compensations, or other financial supports as well. Also, if the farmers do not get the recovery from banks, they could not be able to invest properly in seeds, fertilizers, irrigation, and other farming requirements, which reduces **rice yield (productivity)**. Lower productivity then leads to further income loss and makes farmers even more vulnerable to future shocks. In order to balance this loop, the bank should give a financial guarantee to the farmers for compensation of the actual losses.

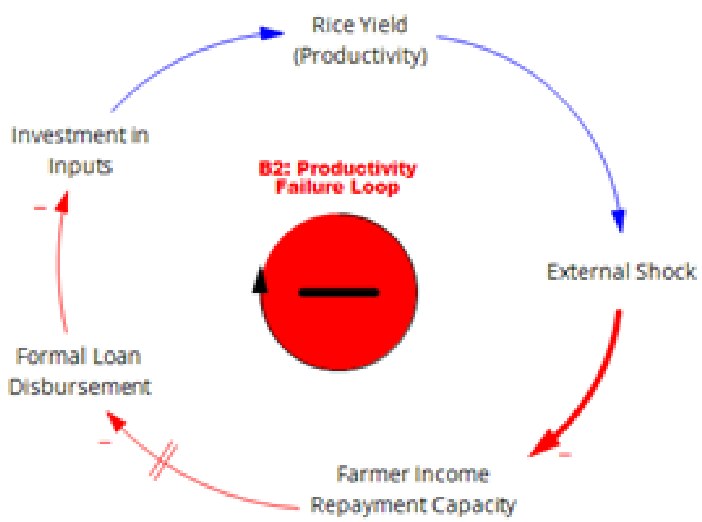
Figure 4: B1 Loop (The protection Failure Loop)



B2: The protection failure loop

B2 loop captures the dynamic relationships of the variables such as rice yield, external contingencies, farmer repayment capacity, formal loan disbursement, and investment in inputs. The Loop shows that when there is some external shocks experienced by farmers that can reduce farm productivity and weakens farmers' access to finance. Further, when these shocks happen such as drought, flood, pest attack, or a sudden market price fall occurs, it reduced the rice yield (productivity)**.** With this lower yield of the crops, it hampers the farmers' income and reduces the paying capacity again. Furthermore, when banks see feebler repayment ability, they reduce or delay formal loan disbursement because they consider loaning riskier. As a result, farmers receive less credit and cannot spend enough on essential inputs such as seeds, fertilizers, irrigation, and pesticides. This reduces investment in inputs**,** which further decreases rice yield, creating a negative cycle where productivity and income keep falling after the shock. So, in order to balance this loop, the yield has to be increased by using tech-based production system and processes.

Figure 5: B2 Loop (Productivity Failure Loop)



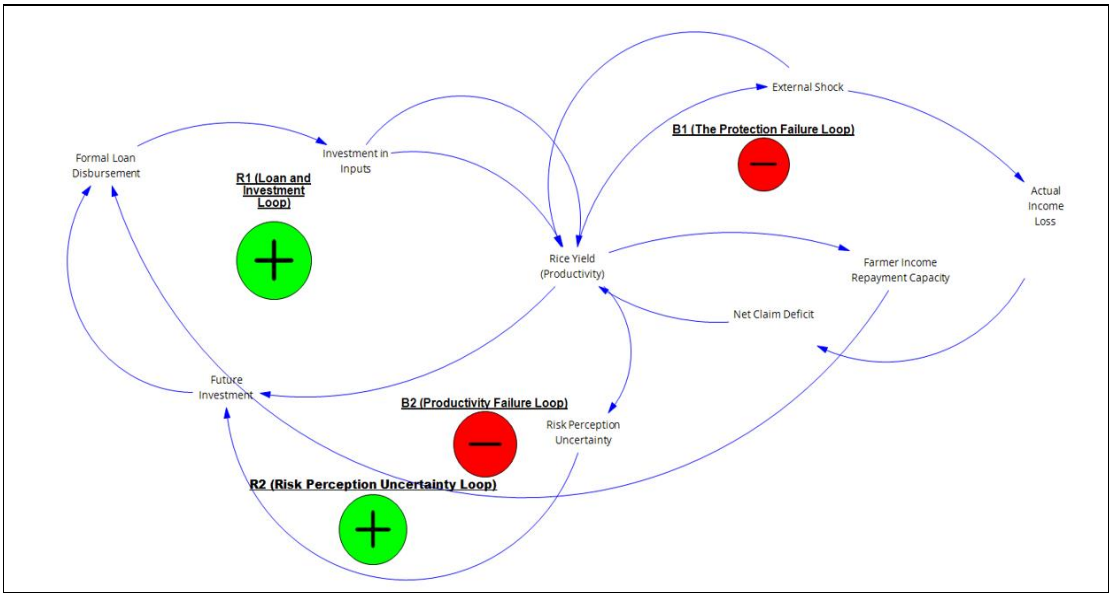


Figure 6: CLD Generic Model explaining the complex and dynamic relationships

Model Validation

The Model is validated using the feedback data from the stakeholders. The data was analysed using regression methods and the same results are corroborated with each loop which is developed using CLD method. Below table helps to understand the loop and its validation.

Table 4: Validation of Model using quantitative data

Loop	Regression Coefficient	Results
R1: Loan and Investment Loop	0.854	Validated as p-value is significant in the loop behaviour
R2: Risk Perception Uncertainty Loop	0.117	Validated as p-value is significant in the loop behaviour
B1: Protection Failure Loop	-0.923	Validated as p-value is insignificant in the loop behaviour
B2: Productivity Failure Loop	-0.623	Validated as p-value is insignificant in the loop behaviour

Table 4 captures how the loops are being validated using regression results and feedbacks from the stakeholders. The R1: Loan and Investment Loop has a path coefficient of **0.854**, and it is considered validated (coefficient greater than 0)**,** meaning the statistical relationship supports the loop behaviour. Similarly, R2: Risk Perception Uncertainty Loop has a path coefficient of **0.117**, and it is also validated**,** indicating that risk perception and uncertainty significantly influence the system dynamics. On contrary, B1: Protection Failure Loop has a regression value of **–0.923** and is marked as not validated (coefficient being negative), meaning the path coefficient is insignificant and the loop does not strongly explain the observed behaviour. Lastly, B2: Productivity Failure Loop shows a regression value of **0.623** and is also not validated, suggesting that this balancing loop does not have a statistically meaningful impact on the loop behaviour in the model.

Model Implication

Answering RQ3, the model results have significant implications for stakeholders involved in policy making, financial support, and agricultural development. Since R1 (Loan and Investment Loop) and R2 (Risk Perception

Uncertainty Loop) are validated, associated stakeholders should give importance to the factors such as formal credit facility, improvement in investments among farmers. This indicates that the banks and government agencies must focus on ensuring timely loan disbursement, plummeting procedural barriers, and promoting affordable credit so that farmers can invest in essential inputs and improve productivity. At the same time, the validation of the risk perception and indecision loop highpoints the need for stronger trust-building frameworks and guidelines such as clear communication, reliable market information, climate advisories, and financial literacy programs, which can reduce fear and hesitation in future investments. On the other hand, since B1 (Protection Failure Loop) and B2 (Productivity Failure Loop) are not validated, stakeholders should interpret these loops with caution and avoid relying heavily on them for decision-making at this stage. This suggests that protection mechanisms like insurance claims, compensation, or productivity failure controls may not be influencing the system as strongly as expected, or they may not be working effectively in practice. Therefore, stakeholders may need to re-examine these mechanisms, improve data collection, and redesign protection schemes to make them more responsive and impactful. Overall, the findings guide stakeholders to focus resources and strategies on credit-linked investment support and uncertainty reduction, while refining and strengthening protection and productivity-related interventions for better long-term resilience.

Conclusion, limitation and future research

This study shows that how crops insurance, risk and farmer behaviors interact and influence the crop productivity and income stability in Indian agricultural system. The study adopts a unique method of system dynamics to understand the complex dynamism among these variables. The CLD is used to understand the loop behaviours. The CLD generic model shows that there is a complex and dynamic influence of each factors on the overall crop management. The model depicts that the crop insurance can support a reinforcing cycle where formal loan disbursement upsurges investment in modern inputs, leading to enhanced rice yield and stronger repayment capacity. However, this intended growth cycle is often weakened by balancing loops driven by external shocks and protection failures. External shocks such as droughts, floods, pests, and price volatility reduce yield and income, lowering repayment capacity and restricting future credit and input investment. At the same time, delayed or insufficient claim payouts create a net claim deficit, increasing uncertainty and risk perception, which discourages future investment. Model validation using stakeholder feedback and regression results confirms the importance of credit–investment dynamics and risk perception in shaping system behaviour. Overall, the study determines that crop insurance alone cannot stabilize productivity unless it is strengthened through timely and adequate claim settlement, improved loss assessment, and complementary risk mitigation measures.

References

1. Abdi, A. M., et al. (2022). A systematic review of yield index selection and yield-index modelling methods for index-based insurance. Remote Sensing.
2. Agarwal, M., & Dash, B. (2023). PMFBY in tribal areas: Assessment and challenges. Journal of Rural Development / Case-based Journal Source.
3. Biswal, D. (2025). Demand for crop insurance in India: Evidence from Pradhan Mantri Fasal Bima Yojana (PMFBY). Human Values and Economics Journal, SAGE.
4. Debnath, N., & Giribabu, M. (2024). Evaluating the performance of Pradhan Mantri Fasal Bima Yojana (PMFBY) in India. Periodico di Mineralogia.
5. Keerthikumara, S. M., & Kumari, D. S. S. (2025). Crop insurance in India and its impact on crop income: Insights from pigeon pea farmers. Central University of Karnataka, Kalaburagi, India.
6. Kaur, S., Singh, H., Roy, D., & Chattu, V. K. (2024). Prospects of crop insurance for sustenance of farmers' livelihood during GM cotton crop failure in Indian Punjab. Journal of Agribusiness in Developing and Emerging Economies.

7. Parthiban, J. J., & Anjugam, M. (2023). A comparative study on the performance of various agricultural crop insurance schemes of India with special reference to Pradhan Mantri Fasal Bima Yojana (PMFBY). Asian Journal of Agricultural Extension, Economics & Sociology, 41(3), 145-153.
8. Radhika, R. R., & Rengarajan, P. (2024). Farmers' opinion on crop insurance scheme Pradhan Mantri Fasal Bima Yojana (PMFBY). Educational Administration: Theory and Practice, 30(5), 10744–10749.
9. Singh, P., & Agrawal, G. (2020). Development, present status and performance analysis of agriculture insurance schemes in India: Review of evidence. International Journal of Social Economics, 47(4), 461–481.
10. Tiwari, R., Chand, K., & Anjum, B. (2020). Crop insurance in India: A review of Pradhan Mantri Fasal Bima Yojana (PMFBY). FIIB Business Review, 9(4), 249–255.
11. Vanishree, K., Sharath Kumar, K. M., & Suresh, N. (2024). Analysis of agricultural insurance pertaining to PMFBY scheme: Exploring dynamics and future implications. Migration Letters, 21(S3), 1559-1568.

Reports and Government Sources

1. Government of India, Department of Agriculture & Farmers Welfare. (2022). Evaluation of mega awareness campaign on PMFBY (Rabi 2022). Government of India.
2. Government of India, Department of Agriculture & Farmers Welfare. (2023). PMFBY Operational Guidelines 2023 (effective from Kharif 2023 onwards). Government of India. (Unpublished Government Document).
3. PMFBY Administrative Statistics. (2020–2025). Administrative statistics and trends from PMFBY portal. Government of India.
4. Barnett, B. J., & Mahul, O. (2007). Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries. World Bank.
5. Carter, M. R., de Janvry, A., Sadoulet, E., & Sarris, A. (2018). Index insurance for developing country agriculture: A reassessment. Annual Review of Resource Economics, 10, 421–438.
6. CAG (Comptroller and Auditor General of India). (2017). Performance Audit of Crop Insurance Schemes (Report No. 7 of 2017).
7. Dercon, S. (2002). Income risk, coping strategies, and safety nets. World Bank Research Observer, 17(2), 141–166.
8. FAO. (2018). Climate Change and Food Security: Risks and Responses.
9. FAO. (2023). The State of Food and Agriculture 2023.
10. Ford, A. (2010). Modeling the Environment (2nd ed.). Island Press.
11. Forrester, J. W. (1961). Industrial Dynamics. MIT Press.
12. Government of India, Department of Agriculture & Farmers Welfare. (2021). Standing Committee on Agriculture (2020–2021): 29th Report on PMFBY.
13. Government of India, Department of Agriculture & Farmers Welfare. (2023). Operational Guidelines 2023 of PMFBY (effective from Kharif 2023 onwards).
14. Hazell, P. (1992). The appropriate role of agricultural insurance in developing countries. Journal of International Development, 4(6), 567–581.
15. IPCC. (2022). AR6 WGII—Impacts, Adaptation and Vulnerability (Chapter 5; Chapter 10).
16. IRDAI. (2023). Agriculture – Crop Insurance in India (Document download page).

17. Meadows, D. H. (2008). Thinking in Systems: A Primer. Chelsea Green.
18. Miranda, M. J., & Glauber, J. W. (1997). Systemic risk, reinsurance, and the failure of crop insurance markets. American Journal of Agricultural Economics, 79(1), 206–215.
19. Morduch, J. (1995). Income smoothing and consumption smoothing. Journal of Economic Perspectives, 9(3), 103–114.
20. NABARD. (2024). NAFIS 2021–22 highlights (press note / summary).
21. PIB (Press Information Bureau, Government of India). (2024). Empowering Rural India: NABARD Survey on Rural Financial Inclusion (NAFIS 2021–22).
22. Skees, J. (2008). Innovations in index insurance for the poor in developing countries. Agricultural and Resource Economics Review, 37(1), 1–15.
23. Sterman, J. D. (2000). Business Dynamics: Systems Thinking and Modeling for a Complex World. McGraw-Hill.
24. UNEP-FI. (2023). Agriculture Sector Risks Briefing: Climate Risks in the Agriculture Sector.
25. UNDP India. (2023). Access to Agricultural Credit and Insurance—Annual Progress Report 2023 (project page).
26. World Bank / GFDRR. (2011). National Agricultural Insurance Scheme in India: Making Insurance Markets Work for Farmers (referenced in World Bank technical documents).
27. World Bank. (2023). Disaster Risk Financing for Agriculture (index insurance overview).
28. Government of India (various). (2023). Agricultural Statistics at a Glance 2023 (alternative host PDF).