

Research Article

Application of Markov Model-Based IoT in Agricultural Insurance and Risk Management

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As the foundation of the national economy, agriculture is a high-risk, weak industry. Affected by many factors, agricultural production is subject to catastrophe risks from time to time. Agricultural production is mainly faced with two major threats, natural disaster risk and market risk. As an effective risk management tool, the production and promotion of agricultural insurance have played an essential role in guaranteeing the development of the agricultural industry in some developed countries and major agricultural countries in the world. This article combines the Internet of Things and Markov model for agricultural insurance risk management. First, we combine the structure of the Internet of Things and select relevant statistical data. Then, we build a panel data system, starting from two perspectives in different regions and analyze agricultural insurance's current development and characteristics at each stage. In addition, we use the Markov model to build a panel data model to explore the specific impact mechanisms deeply. We also study the effects of disaster risk levels in different regions on the development of agricultural insurance. After simulation verification, we believe that this model can effectively promote the balanced regional development of agricultural insurance.

1. Introduction

Policy-based agricultural insurance can protect the essential lives of poor people and prevent people from returning to poverty due to accidental disasters. This is the primary function of the insurance poverty alleviation system [1, 2]. However, with the deepening of poverty alleviation work, the insurance poverty alleviation mechanism has also evolved with time. It focuses on solving the funding bottleneck problems faced by poor areas, leveraging poverty alleviation funding resources, increasing credit and financing for the development of poor areas, and strengthening the industries [3].

Luz Maria Bassoco and others have conducted an in-depth study on the subsidy of agricultural insurance. Glauber and Collins have discussed the social welfare losses caused by the compulsory insurance. Some scholars in Canada have discussed the role of agricultural insurance in protecting farmers' income [3–5]. Most of these studies focus on the research of

state intervention theory and macrocontrol theory, emphasizing the use of economic, administrative, and legal means such as government fiscal policies and financial policies [4]. Kovacevic and Pflug pay attention to the role of property insurance in preventing families from falling into poverty. They established a random loss model of family assets with or without insurance based on the bankruptcy theory. The analysis results show that insurance can only reduce the assets of families with more assets than without insurance. The probability of falling into poverty has no significant impact on households with fewer assets [4]. Ahsan's research shows that the market is prone to failure in providing long-term insurance due to incomplete information. The main reason is to avoid the moral hazard and adverse selection problems of policyholders. Insurance companies should divide the risk units as accurately as possible and set the rate. Division subdivides the rate level, so the cost is relatively high for commercial insurance companies [5]. Shaik and Atwoo found that after farmers purchase agricultural insurance, they will

reduce the management level of agricultural production and reduce agricultural production factors such as pesticides and fertilizers. They ignore disaster prevention and mitigation, thus increasing the probability of agricultural production risk accidents [6]. The natural conditions for agricultural development in various regions are the same as the agricultural development structure. The poverty alleviation effects of agricultural insurance and credit guarantee insurance are complementary to a certain extent. They can form an overall promotion of regional insurance poverty alleviation.

In the context of the need to adjust the food price support policy letter and the lack of improvement of the farmers' interest protection mechanism, how to comprehensively and effectively manage the risks of farmers' income from growing grains, maintain the enthusiasm of farmers to engage in grain production and operation, and protect the interests of grain farmers and ensure national food security? Facing the two major threats of natural disaster risk and market risk [7, 8]. As an effective risk management tool, the production and promotion of agricultural insurance have played an essential role in guaranteeing the development of the agricultural industry in some developed countries and major agricultural countries in the world. This article combines the Internet of Things and Markov model for agricultural insurance risk management.

The rest of the paper is organized as follows: Section 2 provides the background and related work. The proposed agricultural insurance risk management using HMM is explained in Section 3. The results of related case test analysis are illustrated in Section 4, and the conclusion is given in Section 5.

2. Overview of Related Technologies

2.1. Agricultural Insurance. A complete agricultural risk management system includes different agricultural production and operation risks, different risk management strategies and tools that farmers can use, and government intervention in agricultural production and operation. The standard method for judging agricultural risk issues is a one-way analysis of the above three groups of elements [9–11]. First, measure the risks that need to be managed. Secondly, on this basis, select the best risk management tool for the farmer according to the risk preference and resources of the farmer [12]. Coble and Heifner's research on American corn producers shows that when futures market prices are used. Also, income insurance with the same level of protection faces less risk than production insurance [13]. The only thing that can be determined is that compared with other industries, the income risk of agriculture is greater. Finally, appropriate government policies are determined to improve risk management strategies. However, the relationship between the three agricultural risk management system elements is not linear, so linear analysis methods from risk sources to available risk management tools to government policies cannot be used [14–16]. The three sets of elements are interrelated and can extend in all directions. For example, policy measures to stabilize domestic prices may crowd out the development of the futures market. Figure 1 shows a schematic diagram of the organization of the government-sponsored agricultural insurance model.

As mentioned above, agriculture has natural reproduction and economic reproduction, biological reproduction, and social reproduction [17–19]. For an individual farmer, when he does not fully understand the market and the production of other farmers, his commercial production is blind behavior. This behavior will expose him to different risks, such as market conditions. Price risks and production risks caused by natural conditions may cause the farmer to “increase production but not income” [20]. The “cobweb theory” in economics tells us that production fluctuations often lead to price fluctuations because of the seasonality of agricultural production, thus, making it difficult for supply and demand to converge in equilibrium. Price fluctuations will affect farmers' income expectations and the next year—fluctuations in production decisions.

2.2. Internet of Things Technology. In order to count agricultural data, we combine the structure of the Internet of Things. We select relevant statistical data and build a panel data system, starting from two perspectives in different regions and analyzing agricultural insurance's current development and characteristics at various stages [21]. There are two ways of networking equipment nodes in the Internet of Things: wireless networking and wired networking; however, in some practical situations where there are long-distance transmission and complex wiring, wired networking for data transmission and remote network control is troublesome in wiring. It is also prone to lose delay phenomenon [22, 23]. Furthermore, it is much simpler and more reliable to use wireless networking to transmit data in the above cases. However, the farmland area is enormous, and the environment is complex. Therefore, wired networking is a waste of money and troublesome wiring, and wireless networking is used.

3. Agricultural Insurance Risk Management

3.1. Agricultural Insurance Subsidies. By comparing the aforementioned three major digital economy development indicator systems at home and abroad, it can be seen whether it is from the definition. Subsidies are a way of regulating economic entities through benefit subsidies. Therefore, it is a process of behavioral conversion, that is, through a certain intermediary through fiscal expenditure behavior, the behavior of the subsidized party is finally achieved [24]. Here, the first stage is how to choose how to pass the subsidy to the subsidized person and make it directly feel the benefits of the subsidy or get the benefits of the subsidy through adjustment behavior [25]. In the second stage, this subsidy enables the subsidized person to adjust their behavior. Figure 2 shows a diagram of the economic process of agricultural subsidies.

As the proportion of agriculture is scattered, the workload and costs are difficult to estimate. It is almost impossible to subsidize producers directly. Therefore, if there are too many links in the first stage, it will affect the role of financial subsidies [26]. As far as the second stage is concerned, the particularity of agricultural energy

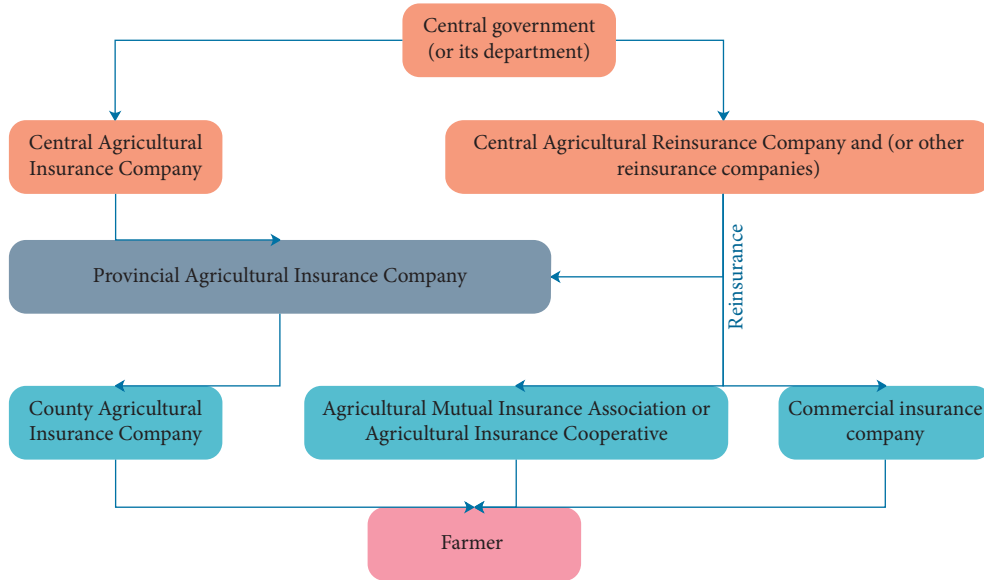


FIGURE 1: Schematic diagram of the organization of the government-sponsored agricultural insurance model.

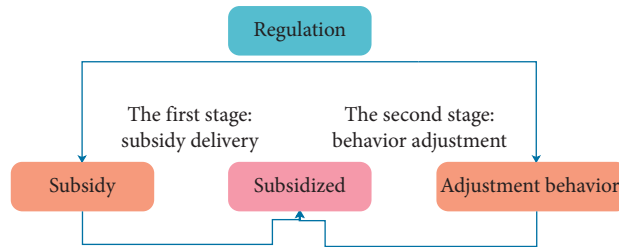


FIGURE 2: A diagram of the economic process of agricultural insurance subsidies.

production determines that financial subsidies to agriculture can enable the subsidized persons. The special conditions for farmers to adjust their economic behavior and the irresistible effect of natural forces make agricultural production always face natural risks. In the context of economic globalization, agricultural risks have become increasingly apparent and show complex trends. These have seriously affected the marketization process of agriculture, the growth of farmers' income, and the stable and healthy development of agriculture. Nevertheless, the main body of agricultural risk management has been at a low level.

3.2. *Agricultural Insurance Risk Management Based on Markov Model.* We use the Markov model to build a panel data model to deeply explore the specific impact mechanisms and effects of disaster risk levels in different regions on the development of agricultural insurance. The characteristic of the Markov process is that the future state is only related to the present and has nothing to do with history [27]. That is to say, the state of the system at time $t + 1$ is only related to the state it was in at time t and is not affected by the state it was in before time t [28].

Markovian testing is a necessary prerequisite for Markov probabilistic analysis. Markov chains of discrete sequences are usually tested with statistics [29].

$$\begin{aligned}
 & \sum_{i=1}^n y_{ij} \leq b_j x_j, \quad j = 1, 2, \dots, m, \\
 & \begin{cases} v_{ij}(t+1) = v_{ij}(t) + c_1 r_1(t)(p_{ij}(t) - x_{ij}(t)) + c_2 r_2(t)(p_{gj}(t) - x_{ij}(t)), \\ m_{ij}(t+1) = m_{ij}(t) + v_{ij}(t+1). \end{cases} \quad (1)
 \end{aligned}$$

For the transition matrix of the Markov model, its elements satisfy the following two basic properties:

$$\text{st. } \begin{cases} \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1 \quad (j = 1, \dots, n) \\ v_i \geq 0 \quad (i = 1, \dots, m), u_r \geq 0 \quad (r = 1, \dots, s), \end{cases} \quad (2)$$

$$t = \frac{1}{\sum_{i=1}^m v_i x_{ij}}, \quad w_i = tv_i, \mu_r = tu_r.$$

The clustering problem of the time series is transformed into the clustering problem of the Markov chain model, and the dynamic clustering algorithm is used. First, select a certain distance measure as the similarity measure.

$$\sum_{i=1}^n \sum_{j=1}^m y_{ij} \delta_{ir} \leq \sum_{j=1}^m x_j^r b_j, \quad r = 1, 2, \dots, l,$$

$$x_j^{r+1} x_j^r = 0, \quad j = 1, 2, \dots, m-1, r = 1, 2, \dots, l-1. \quad (3)$$

We can get the above definition and analysis: For a homogeneous Markov chain, its finite-dimensional probability distribution can be completely predicted and determined by the initial probability distribution and the one-step transition probability moment.

$$Q = \begin{cases} Y = a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + a_5 x_5, \\ a_1 + a_2 + a_3 + a_4 + a_5 = 1, \\ 0 < a < 1. \end{cases} \quad (4)$$

In order to represent the set of all other markers in the domain system adjacent to i . Markov characteristics describe the local characteristics of random fields.

$$Z_1 = -0.002Z_2 - 0.0869Z_3 + 1.6Z_4 + 0.385Z_5. \quad (5)$$

However, the Markov model is introduced to create a Markov chain model describing the dynamic characteristics of the sequence for each time series.

$$h_j = \frac{\sum_{r=1}^s u_r y_{rj0}}{\sum_{i=1}^m v_i x_{ij0}}. \quad (6)$$

In addition, we use the Markov model to build a panel data model to deeply explore the specific impact mechanisms and effects of disaster risk levels in different regions on the development of agricultural insurance.

4. Related Case Test Analysis

4.1. Model Test. In order to avoid the pseudoregression problem in panel data model estimation, ensure the validity of the estimation results. It also prevents the impulse response and the stability of the variance decomposition; the panel data stationarity must be tested. The most commonly used method to test the stationarity of the data is the unit root test [30]. Underestimated rates may stimulate

agricultural insurance demand, and one after another, chooses more expensive insurance schemes and higher levels of protection—target positioning of income insurance for food and agriculture. Income insurance for food and agriculture is an important policy tool for reforming food target prices at this stage. A variety of unit root test methods for panel data have certain limitations. In order to ensure the comprehensiveness and stability of the test results, this paper adopts LLC, IPS, and ADF, three test methods. The level value and the first-order difference value are tested for unit root. Table 1 shows the unit root test results of panel data.

Based on the above theoretical hypothesis and actual discussion, this chapter starts from the two perspectives of agricultural insurance development and regional disasters. Then, it uses empirical analysis methods to deeply explore the specific impact mechanism and effects of disaster risk level on the development of agricultural insurance [31]. In order to reduce the heteroscedasticity of the data when modeling, this paper takes the logarithm of the explanatory variable agricultural insurance depth and agricultural insurance density. Also, the core explanatory variables such as the proportion of the area are affected by the disaster and the severity of the disaster [32]. Figure 3 depicts the results of agricultural insurance samples and insurance density distribution.

The density and depth of insurance continue to decrease, and the development quality of agricultural insurance has gradually declined. In addition, the scope and severity of agricultural natural disasters have different impacts on the development of agricultural insurance. Generally speaking, the scope of agricultural natural disasters has a more significant impact on the development of agricultural insurance, which is a severe disaster. The degree of impact on agricultural insurance is about 5 times. Figure 4 shows the result of the proportion of affected areas in agricultural insurance.

Both core explanatory variables have a negative impact on the development of agricultural insurance. The variable used to measure the percentage of affected areas affected by agricultural disasters is negative for the coefficient of insurance density and depth of insurance for measuring the development of agricultural insurance. Both are significant at the level of 5%, indicating that the area affected by natural disasters in the previous year has a significant negative impact on the development of agricultural insurance this year. At the same time, the estimated value of the coefficient of agricultural insurance density and agricultural insurance depth, which reflects the extent of the impact of disasters in a region, is a negative number. Figure 5 depicts the coefficient estimates of the depth of agricultural insurance in different disaster areas.

Construct an agricultural income insurance pricing model based on the Copula model. The agricultural income insurance pricing model consists of two parts: one is the Copula model with double risk factors for price and yield. It is reflecting the joint distribution function of farmers' income from growing grain. The second is to use Monte Carlo simulation to generate random variables that imitate price and yield risk factors and bring into the dual risk factor Copula model. It brings an extensive sample sequence of

TABLE 1: Unit root test of panel data.

	Inoutput	Income	InNB	InXB
LLC	-8.159 (0.000)	-12.983 (0.001)	-7.271 (0.002)	-5.223 (0.000)
IPS	-8.159 (0.000)	-3.872 (0.000)	-2.463 (0.008)	-1.262 (0.068)
ADF	41.832 (0.004)	58.239 (0.000)	43.893 (0.001)	33.021 (0.050)

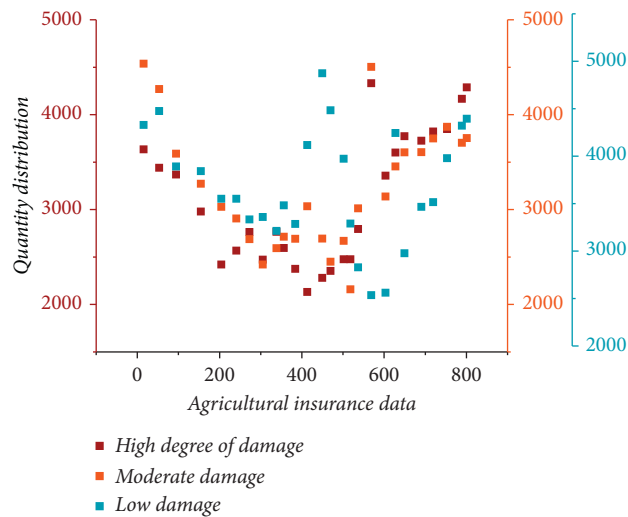


FIGURE 3: Agricultural insurance samples and insurance density distribution results.

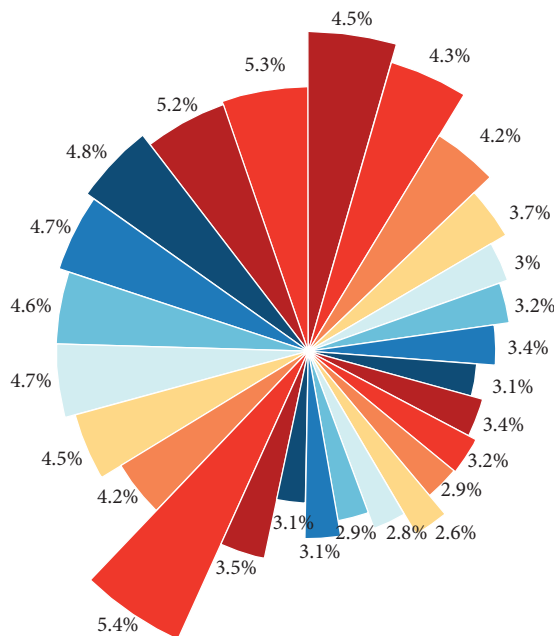


FIGURE 4: The proportion of affected area in the agricultural insurance.

simulated yield, price, and income into the income insurance pricing formula and determines the income insurance premium rate. Figure 6 shows the insurance payment price generated by the Monte Carlo simulation.

In the pursuit of effective allocation of resources, actuarial and fair insurance rates are essential. These are too low or too high rates that distort the agricultural insurance market and affect the acceptance of risk management policies and the economic sustainability of different types of insurance. These may also promote the introduction of inefficient public policies. On the other hand, underestimated rates may stimulate agricultural insurance demand. As a result, one after another chooses more expensive insurance schemes and higher levels of protection—target positioning of income insurance for food and agriculture. Income insurance for food and agriculture is an important policy tool for reforming food target prices at this stage. The organic combination of target price subsidies constitutes a new food safety net that focuses on subsidy efficiency and strengthened risk management. Compared with target price subsidies, target price insurance is more in line with international rules and can amplify the protection effect while reducing fiscal shocks. In the future, food and agriculture income insurance will play an increasingly important role in the grain risk management framework system.

4.2. Feedback Suggestions. The development of insurance poverty alleviation varies greatly in different regions. Agricultural insurance and credit guarantee insurance also play different roles. It is necessary to consider their own conditions and seek breakthroughs in insurance to help poverty alleviation in light of local conditions. On the one hand, local governments and relevant regulatory agencies should rationally allocate

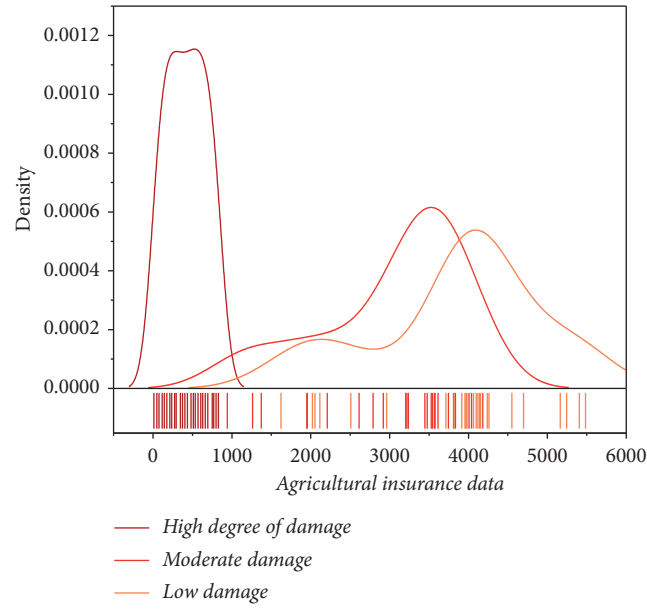


FIGURE 5: Coefficient estimates of agricultural insurance depth in different disaster areas.

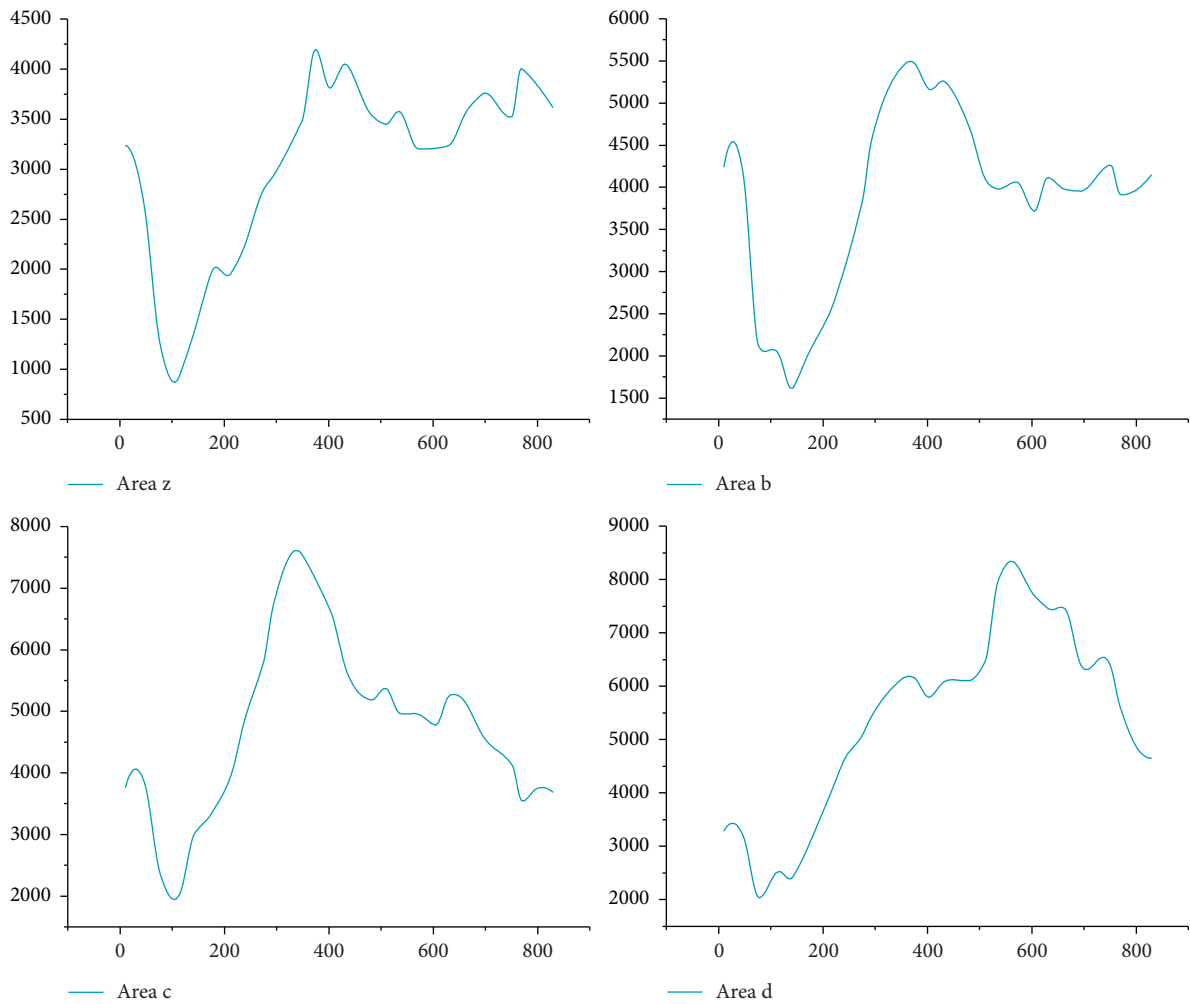


FIGURE 6: Insurance claim price generated by Monte Carlo simulation.

poverty alleviation resources according to the actual conditions of the region and formulate macroeconomic policies for regional assistance. While on the other hand, they should encourage insurance companies to establish different types of insurance poverty alleviation methods and products based on the poverty situation and characteristics of the region service. The natural conditions for agricultural development in various regions are the same as the agricultural development structure. The poverty alleviation effects of agricultural insurance and credit guarantee insurance are complementary to a certain extent. They can form an overall promotion of regional insurance poverty alleviation. Therefore, regional insurance poverty alleviation development should also be based on the region as a whole. The insurance business for regional poverty alleviation should be developed in a coordinated manner. First of all, the coordinated development of regional insurance poverty alleviation mechanisms requires the cooperation of various regional governments and insurance institutions.

On the one hand, regional governments must abandon traditional concepts. On the other hand, they should not only focus on developing poverty alleviation coordination mechanisms that require large financial funds so that they can fight for themselves or rely only on the leadership of other regional governments. These take into account the long-term poverty alleviation development goals, actively seek new development directions in the insurance poverty alleviation model. Also, these actively carry out information sharing on the regional insurance poverty alleviation situation and use insurance resources for poverty alleviation to achieve coordination across the region.

5. Conclusion

In economic globalization, agricultural risks have become increasingly apparent and show complex trends, which have seriously affected the marketization process of agriculture: the growth of farmers' income and the stable and healthy development of agriculture. The main body of agricultural risk management has been at a low level. Efficiency and lack of status make the research on agricultural risk management very urgent. Agricultural production is mainly faced with two major threats, natural disaster risk and market risk. As an effective risk management tool, the production and promotion of agricultural insurance have played an important role in guaranteeing the development of the agricultural industry in some developed countries and major agricultural countries in the world. This article combines the Internet of Things and Markov model for agricultural insurance risk management. From the previous analysis, it can be seen that the cooperative insurance system involving property rights is more in line with the characteristics of agricultural insurance development. The government should try to use fiscal, financial, taxation, legal, and other policy tools to formulate preferential policies to support the emergence actively. The government should perform the development of new farmer cooperative insurance organizations. Policy, starting with the organizational system, creating a new agricultural insurance business entity, expanding the scale of agricultural insurance development, forming a cooperative

agricultural insurance business model as soon as possible, and building a new agricultural natural risk management system.

Data Availability

The data of this article are obtained through public channels.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] B. Ramaswami, "Supply response to agricultural insurance: risk reduction and moral hazard effects," *American Journal of Agricultural Economics*, vol. 75, no. 4, pp. 914–925, 1993.
- [2] R. G. Chambers, "Valuing agricultural insurance," *American Journal of Agricultural Economics*, vol. 89, no. 3, pp. 596–606, 2010.
- [3] M. S. Kaylen, E. T. Loehman, and P. V. Preckel, "Farm-level analysis of agricultural insurance: a mathematical programming approach," *Agricultural Systems*, vol. 30, no. 3, pp. 235–244, 1989.
- [4] O. V. Arias, A. Garrido, M. Villeta, and A. M. Tarquis, "Homogenisation of a soil properties map by principal component analysis to define index agricultural insurance policies," *Geoderma*, vol. 311, pp. 149–158, 2018.
- [5] M. Hasdemir and H. Ozudogru, "Satisfaction levels of insured apricot producers towards agricultural insurance services," *Journal of Agricultural Science*, vol. 10, no. 3, 2018.
- [6] L. Xing and K. Lu, "The importance of public-private partnerships in agricultural insurance in China: based on analysis for Beijing," *Agriculture and Agricultural Science Procedia*, vol. 1, pp. 241–250, 2010.
- [7] R. G. Chambers, "Insurability and moral hazard in agricultural insurance markets," *American Journal of Agricultural Economics*, vol. 71, no. 3, pp. 604–616, 1989.
- [8] M. Miranda and D. V. Vedenov, "Innovations in agricultural and natural disaster insurance," *American Journal of Agricultural Economics*, vol. 83, 2001.
- [9] B. Müller and D. Kreuer, "Ecologists should care about insurance, too," *Trends in Ecology & Evolution*, vol. 31, no. 1, pp. 1–2, 2015.
- [10] T. W. Bank, "A workshop on disaster risk reduction and risk transfer: toward concrete action in south Asia and east Asia and the Pacific," *The Journal of Urology*, vol. 191, no. 4, p. e649, 2012.
- [11] K. H. Kahl, "A comprehensive assessment of the role of risk in U.S. agriculture," *American Journal of Agricultural Economics*, vol. 85, no. 4, pp. 1089–1091, 2002.
- [12] M. T. Fox, S. K. Godage, J. M. Kim et al., "Moving from knowledge to action: improving safety and quality of care for patients with limited English proficiency," *Clinical Pediatrics*, vol. 59, no. 3, 2020.
- [13] R. Spiewak, "Occupational dermatoses among polish private farmers, 1991–1999," *American Journal of Industrial Medicine*, vol. 43, no. 6, pp. 647–655, 2003.
- [14] B. K. Goodwin, "Problems with market insurance in agriculture," *American Journal of Agricultural Economics*, vol. 83, no. 3, pp. 643–649, 2001.
- [15] T. J. Lark, B. Larson, I. Schelly, S. Batish, and H. K. Gibbs, "Accelerated conversion of native prairie to cropland in

- Minnesota,” *Environmental Conservation*, vol. 46, no. 2, pp. 155–162, 2019.
- [16] Q. S. Wang, “The farmers behavior in agricultural insurance under the von-neuman-morgenstern utility model,” *Hydro-metallurgy*, vol. 1, pp. 226–229, 2010.
- [17] M. King and A. P. Singh, “Understanding farmers’ valuation of agricultural insurance: evidence from Vietnam,” *Food Policy*, vol. 94, Article ID 101861, 2020.
- [18] G. Bakoyannis, Z. Ying, and C. T. Yiannoutsos, “Nonparametric inference for markov processes with missing absorbing state,” *Statistica Sinica*, vol. 29, pp. 2083–2104, 2019.
- [19] P. L. Salemi, E. Song, B. L. Nelson, and J. Staum, “Gaussian markov random fields for discrete optimization via simulation: framework and algorithms,” *Operations Research*, vol. 67, no. 1, 2019.
- [20] C. Fabio, J. Alanko, and D. Belazzougui, “A framework for space-efficient variable-order Markov models,” *Bioinformatics (Oxford, England)*, vol. 35, no. 22, pp. 4607–4616, 2019.
- [21] F. Zheng, S. Derrode, and W. Pieczynski, “Parameter estimation in switching Markov systems and unsupervised smoothing,” *IEEE Transactions on Automatic Control*, vol. 64, no. 4, pp. 1761–1767, 2019.
- [22] T. X. Pham, P. Siarry, and H. Oulhadj, “Segmentation of MR brain images through hidden Markov random field and hybrid metaheuristic algorithm,” *IEEE Transactions on Image Processing*, vol. 29, pp. 6507–6522, 2020.
- [23] M. Vihola, J. Helske, and J. Franks, “Importance sampling type estimators based on approximate marginal Markov chain monte carlo,” 2020, <https://arxiv.org/abs/1609.02541>.
- [24] H. S. Jang and J. H. Baek, “Optimal TAL-based registration with cell-based central policy in mobile cellular networks: a semi-Markov process approach,” *The Journal of Supercomputing*, vol. 77, pp. 9172–9189, 2021.
- [25] Z. Zhou, X. Luan, S. He, and F. Liu, “High-order moment multi-sensor fusion filter design of Markov jump linear systems,” *IET Signal Processing*, vol. 14, no. 9, pp. 666–671, 2020.
- [26] X. Wang, I. C. Unarta, P. P.-H. Cheung, and X. Huang, “Elucidating molecular mechanisms of functional conformational changes of proteins via Markov state models,” *Current Opinion in Structural Biology*, vol. 67, pp. 69–77, 2021.
- [27] V. G. Yaji and S. Bhatnagar, “Stochastic recursive inclusions in two timescales with nonadditive iterate-dependent Markov noise,” *Mathematics of Operations Research*, vol. 45, no. 4, pp. 1405–1444, 2020.
- [28] S. Suwanwimolkul, L. Zhang, D. Gong et al., “An adaptive Markov random field for structured compressive sensing,” *IEEE Transactions on Image Processing*, vol. 28, no. 3, pp. 1556–1570, 2019.
- [29] P. M. Kumar and U. D. Gandhi, “Enhanced DTLs with CoAP-based authentication scheme for the internet of things in healthcare application,” *The Journal of Supercomputing*, vol. 76, no. 3, 2020.
- [30] O. Barker, “Realizing the promise of the internet of things in smart buildings,” *Computer*, vol. 53, no. 2, pp. 76–79, 2020.
- [31] D. A. d. Queiroz, C. A. d. Costa, E. A. I. F. d. Queiroz, E. F. d. Silveira, and R. d. R. Righi, “Internet of things in active cancer treatment: a systematic review,” *Journal of Biomedical Informatics*, vol. 118, Article ID 103814, 2021.
- [32] A. Manocha, R. Singh, and P. Verma, “An internet of things fog-assisted sleep-deprivation prediction framework for spinal cord injury patients,” *Computer*, vol. 53, no. 2, pp. 46–56, 2020.