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Enhancing the Effectiveness of Insurance Risk Management in the Agricultural, Livestock, and Fishery Sectors in Thailand

Thitivadee Chaiyawat
Chulalongkorn Business School, Chulalongkorn University, Bangkok, Thailand
E-mail: thitivadee@cbs.chula.ac.th

Samrieng Mekkriengkrai
School of Law, Sripatum University Khon Kaen, Thailand
E-mail: samrieng@yahoo.com

Supatra Phanwichit
School of Law, Sukhothai Thammathirat Open University, Thailand
E-mail: thailawresearch@gmail.com

In recent years, heightened attention has been directed towards evaluating the efficacy of risk management strategies, specifically within the agricultural sector, particularly in regions susceptible to various risks. This heightened interest has prompted increased scrutiny from both researchers and regulatory bodies. The current investigation endeavours to scrutinize the systematic procedural framework for formulating a pertinent crop insurance program tailored to distinct agricultural zones. Additionally, the study employs extreme value modelling to forecast daily maximum precipitation, facilitating the estimation of potential agricultural productivity diminution resulting from extreme precipitation events. Furthermore, the research underscores the pivotal role of governmental support in fortifying the implementation of a feasible and enduring agricultural insurance framework in Thailand. To amass pertinent data, the study involves stakeholders from public and private sectors in both the agricultural and agricultural insurance domains, employing methods such as questionnaire surveys, in-depth interviews, and public hearings. Moreover, this investigation employs machine learning methodologies to project potential Jasmine-105 rice yield losses in Ubon Ratchathani and Sisaket provinces. The acquisition of satellite data is integral for estimating long-term daily heavy rainfall in the aforementioned provinces. The study's revelations affirm the viability of area-yield crop insurance, utilizing machine learning to gauge rice production on a provincial scale, thereby bolstering the economic feasibility and sustainability of Thailand's rice industry. Notably, random forests demonstrate superior accuracy, particularly within specific rice farming locales. Furthermore, the research underscores the anticipated surge in heavy rainfall across Thailand over the next 10-100 years, attributable to climate change, underscoring the imperative for effective catastrophe risk financing and insurance risk management strategies. In summary, the research underscores the Thai government's dedication to advancing, endorsing, and implementing proficient and enduring agricultural insurance mechanisms. These mechanisms seek to incentivize farmers to safeguard their agricultural vulnerabilities through insurance products, fostering a more sustainable trajectory for the nation. The study imparts valuable insights into the critical role of insurance-based risk management in the agricultural sector, emphasizing the pivotal support required from the government for the successful implementation of such initiatives.

Keywords: Agricultural Insurance, Government Support, Area-Yield, Machine Learning, Extreme Precipitation

Introduction

Acknowledging the central importance of agriculture in supporting human sustenance and catalysing worldwide economic advancement, its historical significance is duly recognized. Unfortunately, agriculture continues to be vulnerable to risks associated with climatic variability. Effectively handling the agricultural risks proves to be a complex task, given their varied nature that spans from isolated incidents to intricately interconnected risks. Consequently, the compelling need for proficient risk management within the agricultural domain is unequivocal. This imperative has given rise to a spectrum of strategies formulated to address these complex challenges. Aquaculture insurance, crop insurance, and livestock insurance are crucial instruments. They enable the transfer of formidable risks faced by farmers to insurance markets. Rapidly gaining prevalence globally, these measures are potent tools for mitigating catastrophic risks, reducing vulnerabilities in agricultural practices, enhancing average productivity and income, fostering financial resilience for practitioners, and promoting social and environmental sustainability (Chatterjee & Oza, 2017). The agricultural sector in Thailand is currently confronted with increasing vulnerabilities attributed to rising temperatures and significant environmental hazards such as floods and droughts. This demographic represents approximately 30 percent of Thailand's total labour force (Musikawong et al., 2022). As per The World Bank (2022) report, a predominant portion of Thailand's impoverished population, comprising nearly 79 percent, is affiliated with agricultural households. The recurrent and severe incidence of floods and droughts has significantly impacted this substantial demographic, thereby placing considerable pressure on the government's financial resources dedicated to disaster relief endeavours over recent decades.

Recognizing Thailand's vulnerability to the impacts of climate change, anticipated to manifest in heightened frequency and severity of natural disasters, and acknowledging the imperative for transitioning towards an environmentally sustainable economy, the Thai government deems the progression of the agricultural sector as crucial. This recognition stems from the potential implications of global climate change on household welfare, agricultural output and agricultural income. Additionally, it includes the cost dynamics of production. Thailand integrated its commitments articulated in the United Nations 2030 Agenda for Sustainable Development and the Paris Agreement within its 20-Year National Strategy (Ministry of Foreign Affairs, 2022). Moreover, the insurance sector strategically prioritizes sustainability, utilizing insurance systems to mitigate risks, establish security, and contribute to the realization of a sustainable future (Intongpan, 2019). Considering the pressing need to systematically anticipate and mitigate the significant impacts of disaster risks, climate change, and other hazards, it is crucial for the Thai government to initiate the development of a comprehensive and systematic framework for risk management (Chainikom, 2022). Within this framework, it is crucial to prioritize appropriate agricultural insurance schemes and risk-financing solutions to protect vulnerable communities. Agricultural insurance and risk finance are essential components of Thailand's Integrated National Financing Framework (INFF). The goal is to strengthen the nation's ability to withstand impending shocks and promote inclusivity, with a specific focus on alleviating poverty among Thai farmers (Vuthipadadorn et al., 2023). The Thai government is confronted with the imperative of crafting and executing a financially robust budget capable of adeptly addressing unforeseen eventualities in the future. It is essential to prioritize the adoption of a comprehensive risk management strategy to effectively reduce and alleviate the negative effects on the Thai economy.

Consequently, to attain widespread sustainability in the agricultural sector, this investigation concentrates on examining an appropriate rice insurance framework, specifically the area-yield agricultural insurance, in Thailand. Through the application of machine learning techniques, this framework seeks to forecast the loss in yield production attributed to natural disasters, thereby facilitating the calculation of indemnity payments for rice crops. Moreover, the study employs extreme value modelling to anticipate daily maximum precipitation. This modelling aids in appraising the loss in agricultural productivity and underscores the imperative for proficient catastrophe management and transfer in the context of extreme precipitation events. Additionally, the research seeks to proffer a proficient instantiation of the agricultural insurance system in Thailand. Through the efficacious integration of risk management via insurance, Thailand can augment the resilience of its agricultural sector and assure the enduring sustainability of its farming communities.

Literature Review

Agricultural insurance is characterized as a quasi-public good, given its integration into broader governmental agricultural development initiatives. Policymakers strive to achieve their social and economic objectives by allocating resources to agricultural funding and insurance. The regulatory framework governing agricultural insurance holds crucial significance in articulating the government's intentions and aspirations in facilitating the provision of agricultural insurance. The prevalence of subsidy provision emerges as a shared characteristic in agricultural insurance endeavours across nations exhibiting diverse socioeconomic profiles (Nshakira-Rukundo et al., 2021). The development and enforcement of legislation significantly contribute to the progress of any society. Nations frequently contend with various natural and human-induced disasters, with the agricultural sector, in particular, being susceptible to their repercussions. In reaction to these disasters, countries promulgate legislation with the aim of mitigating immediate impacts and adeptly managing future ramifications. This legislative framework exerts substantial influence on the practices of risk management through insurance. Numerous investigations, such as those conducted by Gilissen (2015), Alnabhani et al. (2016), and Bang (2021), have examined the effectiveness of risk management in situations where legislation is grounded in public engagement. These investigations suggest that the application of suitable legal frameworks proficiently alleviates extant disaster risks by instituting regulations and acknowledging the engagement, responsibilities, and dedication of stakeholders. The hypothesis inferred from the aforementioned discourse is:

H1: *The Involvement of the public sector through crucial mechanisms in Thai agricultural insurance is essential for ensuring the effectiveness of insurance and risk management practices, thereby contributing to a more sustainable agricultural sector in Thailand.*

The disbursement of financial aid to farmers impacted by natural disasters in Thailand has predominantly been contingent upon the government's budgetary allocations. Nevertheless, this method has given rise to noteworthy oscillations in annual financial support, as previously underscored. As a result, the Thai government faces the challenge of prudently allocating fiscal resources and establishing a comprehensive strategy for managing risks within the agricultural sector (Muangmee et al., 2022). In response to the aforementioned challenges, the Ministry of Finance has implemented a crop insurance framework. The extant framework is centred on indemnity insurance based on damage, notably referred to as named peril crop insurance (NPCI). This insurance coverage is designed to address specific perils including floods, droughts, windstorms, frost, hailstorms, fires, elephant attacks, and pest infestations.

Within the spectrum of agricultural insurance categories in Thailand, rice insurance holds the foremost position in terms of the proportion of insured agricultural land. Nevertheless, the present rice insurance framework is confronted with inadvertent basis risk. As per the existing protocol, indemnity payments for rice insurance are triggered upon the provincial government's declaration of the insurance area as a disaster zone. Consequently, instances where rice crops sustain losses due to calamities and damage attributed to named perils are deemed total losses. However, criticism has been directed towards this calamity-based pay-out system, positing that it may engender a disconnection between the damage assessment and the actual losses incurred (Sethanand et al., 2023). This incongruity casts uncertainty on the efficacy of the prevailing crop insurance arrangement, as insured farmers in impacted regions may not receive the anticipated indemnification. Moreover, the rice insurance initiative based on NPCI in Thailand confronts challenges associated with adverse selection and moral hazard. These challenges assume significance due to their potential to impede the prospective expansion of the program. In contrast, index-based crop insurance is regarded as a more pragmatic alternative to indemnity-based insurance. Index-based insurance incorporates diverse factors influencing agricultural production losses, such as rainfall and yield, disbursing loss estimates when the specified index aligns with predetermined conditions (Biffis & Chavez, 2017). Several Asian nations, among them India and China, have effectively instituted programs for index-based crop insurance (Stutley, 2011).

Nevertheless, it is imperative to acknowledge that index-based crop insurance might not afford complete indemnification to farmers owing to the presence of basis risk, denoting the disparity between indexed pay-outs and actual losses. Despite this limitation, the basis risk associated with index-based crop insurance is notably diminished compared to provincial coverage, rendering the model particularly well-suited for dynamic weather conditions. The adoption of index-based crop insurance confers several advantages to both farmers and insurers, enhancing the cost-effectiveness of services. Through an index-based approach, insurers can streamline the claims process, as it obviates the need for post-loss verification, thereby reducing administrative burdens and expediting compensation for farmers (Biffis & Chavez, 2017; Dercon et al., 2014).

Area-yield index insurance represents a category of crop insurance contingent upon rainfall as the indexing parameter for indemnification assessment. The ascendancy of this insurance variant is attributed to its simplicity and the ready availability of pertinent data (Yoshida et al., 2019). Under area-yield crop insurance, farmers receive indemnity based on the average yield of the insured crop within a designated area, irrespective of the actual yield on their individual farms. The uniform compensation per unit area extended to all farmers within the insured region serves to diminish the prospects of moral hazard, wherein insured farmers might undertake greater risks given the security provided by insurance. Additionally, it alleviates adverse selection by encompassing all farmers in the area within the insurance pool, thereby minimizing the probability of selection bias by high-risk farmers (Chambers & Quiggin, 2002; Skees, 2008). Administrative costs are further reduced by obviating the necessity for individual claim adjustments and the verification of production histories (Deng et al., 2007). This enhances the cost-effectiveness of insurance for insurers (Choudhury et al., 2016; Miranda & Farrin, 2012). As posited by Nelson et al. (2014), precipitation has been established to exert a notable influence on crop productivity. Among diverse crops, rice cultivation is especially vulnerable to the adverse effects of flooding (Bailey-Serres et al., 2012). Prolonged periods of inundation and substantial flood depths have the potential to result in substantial reductions in rice production (Meng et al., 2022). Furthermore, the growth phase of rice, particularly during the periods preceding and succeeding the "booting stage," exerts an impact on its resilience to flooding. Consequently, comprehending the reaction of rice crops to inundation is imperative for gauging the prospective implications of forthcoming floods on rice production. This comprehension is fundamental for formulating appropriate rice crop insurance schemes that motivate farmers, private insurers, and the Thai government to engage in agricultural insurance initiatives, notwithstanding the inherent risks associated with weather and climate. The hypothesis inferred from the aforementioned discourse is as follows:

H2: *Area-yield crop insurance is a suitable model for insuring rice crops in Thailand, as it allows for accurate prediction of rice production yield loss resulting from floods.*

Climate change, particularly the phenomenon of global warming, constitutes a notable factor contributing to the escalation of extreme precipitation events and widespread flooding on a global scale (Tabari, 2020). This can be attributed to the direct influence of climate change on precipitation patterns and temperature, resulting in both water deficits and instances of flooding (Slettebak, 2012). The agricultural sector stands out as particularly susceptible to the impacts of climate change, given its heightened sensitivity to meteorological variations, and climate change exerts a direct influence on crop yields (Loi et al., 2022). Due to the effects of climate change, projections indicate an anticipated rise in both the frequency and intensity of extreme weather events, including but not limited to heat waves, droughts, and heavy precipitation (Zhu & Fan, 2021). In developing nations, particularly within the agricultural sector, the primary burden of economic repercussions stemming from extreme weather events is borne (Elahi et al., 2022). Projections suggest that climate change is poised to drive millions of people into a state of extreme poverty by the year 2030 (Jafino et al., 2020). The deleterious impacts of climate change on agriculture are conspicuous in the context of Thai farmers, who find themselves incapable of mitigating the consequences of increasingly severe climatic conditions (Felkner et al., 2009). The increase in global temperatures has been observed to influence the occurrence, severity, and duration of natural disasters, and these patterns are anticipated to persist as a consequence of climate change (Portner et al., 2022). This presents a challenge, as agricultural insurance becomes unattainable for low-income smallholder farmers in Thailand, amplifying their susceptibility. Furthermore, in the absence of efficient catastrophe management, private insurers may face the potential threat of insolvency, particularly within a risk-sensitive capital regime. The hypothesis inferred from the aforementioned discourse is as follows:

H3: *The impact of climate change in Thailand is evident in the increased intensity of extreme precipitation events and the heightened risk of flooding, which is further exacerbated by the correlation between increased precipitation and the rise in return levels.*

Research Methodology

The objectives of this study are threefold: (1) to proffer a proficient instantiation of the agricultural insurance system in Thailand to realize widespread sustainability, (2) to scrutinize the impact of rice crop area yield and forecast the level of rice production, and (3) to anticipate precipitation in the lower north-eastern provinces of Ubon Ratchathani and Sisaket.

To recommend the efficacious implementation of the agricultural insurance system in Thailand, this investigation employs a purposive sampling technique to identify participants comprising regulators, experts, individuals from both public and private sectors within the agriculture and agricultural insurance domains, as well as farmers. Purposive sampling, while acknowledging its limitations, is chosen deliberately to target sources rich in information concerning agricultural risk and insurance. This sampling approach is well-aligned with the goal of furnishing pertinent insights into the research's aims and objectives. A total of 40 in-depth interviews were conducted for comprehensive data collection. Furthermore, 397 questionnaire surveys were distributed, resulting in 308 valid responses (response rate: approximately 77.58%), to gather supplementary data on agricultural risk, insurance experience, literacy, demand, and farmers' willingness to participate. These surveys were administered to both public and private sector interviewees. In addition, in-depth interviews and group discussions were conducted in five distinct regions of Thailand. These regions include Surat Thani (shrimp farming), Sakon Nakhon (beef cattle production), Saraburi (dairy cow production), Ratchaburi (swine production), and Phitsanulok (rice cultivation). Additionally, the study employs a public hearing method to elucidate the perspectives and recommendations of stakeholders regarding the draft of agricultural insurance legislation. The initial session of public hearings transpired in Bangkok, followed by a subsequent session held in Khon Kaen. Both sessions garnered participation from over 200 experts and stakeholders. The feedback and opinions gathered during these public hearings were meticulously examined to iteratively revise, update, and ultimately refine the draft of agricultural insurance legislation prior to its formal submission to the cabinet for approval.

This research further seeks to scrutinize the impact of rice crop area yield and forecast the rice production level through the utilization of machine learning techniques designed for regression tasks. Specifically, three machine learning algorithms—multivariate polynomial regression, decision trees, and random forests—are deployed to predict the yield rate of the Jasmine-105 rice crop. The implementation of these algorithms is executed using the Python programming language. The inclusion of multivariate polynomial regression stems from its capacity to elucidate relationships among various factors influencing rice production. In line with previous research by Mısır and Akar (2022), the multivariate polynomial regression function is employed to formulate an equation, represented by equation (1), which encompasses three explanatory variables for each polynomial degree under consideration.

$$Y_p = \beta_0 + \sum_{i_1=1}^{3} \beta_{i_1} x_{i_1} + \sum_{i_1=1}^{3} \sum_{i_2=i_1}^{3} \beta_{i_1 i_2} x_{i_1} x_{i_2} + \cdots + \sum_{i_1=1}^{3} \sum_{i_2=i_1}^{3} \cdots \sum_{i_n=i_{n-1}}^{3} \beta_{i_1 i_2 \ldots i_n} x_{i_1} x_{i_2} \ldots x_{i_n} \quad (1)$$

where Y_p is production rate, x_1 is flood depth, x_2 is flood duration, x_3 is rice state, and β_0, β_{i_1}, β_{i_2}, … , β_{i_n} are coefficient parameters. Decision trees and random forests are prevalent non-parametric models in the domain of machine learning. Belonging to the supervised learning paradigm, these algorithms acquire patterns and generate predictions using labeled training data. Notably, decision trees and random forests exhibit versatility by adeptly handling both numerical and categorical data, rendering them suitable for diverse dataset structures. Furthermore, their interpretability stands out as a notable advantage, given that the decision-making process can be readily visualized and comprehended (Jensen, 2008). Nevertheless, decision trees are susceptible to overfitting, whereas random forests offer a highly effective means to mitigate overfitting concerns and furnish measures of feature importance (Cabras et al., 2016).

K-fold cross-validation facilitates the analysis of the most appropriate algorithm for the extant dataset. This investigation employs a 10-fold cross-validation approach (k = 10). A dataset comprising 150 observations is gathered from Jasmine-105 rice farming regions in the prominent rice-producing provinces of Ubon Ratchathani and Sisaket, along with data from the Office of Agricultural Economics under the Ministry of Agriculture and Cooperatives. These data encompass variables detailed in Table 1 for the purpose of predicting production rates.

Table 1. Variable definitions and summary statistics

Variable name	Variable definition	Mean	Min	Max	Stdev
Flood Depth	Average water height exceeds normal water level (centimeters)	170.20	60.00	400.00	76.55
Flood Duration	Time period while rice paddy encounters flood (weeks)	3.76	0.30	12.00	2.93
Rice State	Rice plantation phase classified as "before booting = 0" and "after booting = 1"	0.59	0.00	1.00	0.49
Production Rate	Percentage of Actual Production to Normal Production	0.25	0.00	0.95	0.28

This research also endeavours to assess long-term extreme precipitation employing the conceptual framework of Extreme Value Theory (EVT) outlined by Coles (2001). Concretely, the Peaks Over the Threshold (POT) methodology is employed to scrutinize the behaviour of precipitation surpassing a predefined high threshold. This approach facilitates the examination of all independent extreme data points by fitting the Generalized Pareto (GP) distribution. In the context of this study, the random variables $X_1 X_2, \ldots, X_n$ are presumed to be independent and identically distributed. The distribution function of these variables is considered to exhibit a peak over the threshold when X exceeds a specified threshold value, denoted as u. Mathematically, this can be expressed as $F_u(X) = Pr(X - u|X > u)$ where u is set to a relatively high value. For estimating the conditional distribution $F_u(X)$, the Generalized Pareto Distribution (GPD) is utilized. The GPD proves to be a fitting choice for extreme value analysis, especially when dealing with daily data. By isolating data points surpassing the threshold, the analysis focalizes on extreme events and their associated characteristics.

If X was designated as a random variable following the GPD, it was expressed as $X \sim \text{GPD}(\sigma, \xi)$,with σ as a scale parameter and ξ is the shape parameter. In the presence of a threshold, denoted as u, the cumulative distribution function (CDF) of x-u becomes conditional, meaning, $x > u,$ as outline in equation (2).

$$F(x-u) = H(x) = 1 - \left(1 + \frac{\xi x}{\tilde{\sigma}}\right)^{\frac{-1}{\xi}} \qquad (2)$$

where $x > 0$, $\tilde{\sigma} = \sigma + \xi(u - \mu)$ and μ is the location parameter.

In accordance with equation 2, the distribution fell into the same category as the GPD, Here, $\tilde{\sigma}$ represented a scale parameter corresponding to the specified value $u > u_0$, and $\tilde{\sigma} = \xi(u - u_0)$ is the scale parameter changing with the exception of where $\xi = 0$ the scale parameter was adjusted by $\sigma^* = \tilde{\sigma} + \xi u$. Furthermore, u_0 was chosen based on the minimum value of u where the estimators for $\sigma^*$and ξ remained constant. The probability distribution function (PDF) was then computed following the formula in equation (3).

$$h(x) = 1 + \xi\left[\left(\frac{x-u}{\sigma}\right)\right]^{-\frac{1}{\xi}} \text{where } \sigma > 0 \text{ and } -\infty < \xi < \infty \quad (3)$$

In the context where σ denotes a scale parameter and ξ denotes a shape parameter, within the Generalized Pareto Distribution (GPD), the scenario where $\xi \to 0$ is referred to as the exponential distribution. On the other hand, when $\xi > 0$ is greater than 0, it is termed as the Pareto distribution, and for $\xi < 0$ less than 0, it is identified as the gamma distribution.

The return level of GPD was calculated as in the following equation (4).

$$\hat{z}_p = u + \frac{\hat{\sigma}}{\hat{\xi}}\left[\left(T\eta_y\lambda_\mu\right)^{\hat{\xi}} - 1\right] \text{where } \hat{\sigma} > 0 \text{ and } -\infty < \hat{\xi} < \infty \quad (4)$$

where $\hat{z}_p$ refers to return level, $\hat{\mu}$ stands for the location parameter, $\hat{\sigma}$ represents scale parameter, $\hat{\xi}$ signify the shape parameter, T denotes the return period, η_y correspond to the average number of days per year and λ_μ denotes the estimated probability of the POT.

Data pertaining to the daily cumulative precipitation spanning the period from 2012 to 2022 is sourced from the satellite data provided by the NOAA Physical Sciences Laboratory (*https://psl.noaa.gov/*).

Research Findings

The research outcomes concerning the involvement of the public sector in Thai agricultural insurance, aimed at enhancing the efficacy of insurance and risk management, unveil a notable deficiency in information, comprehension, awareness, and knowledge regarding agricultural insurance among Thai farmers across diverse agricultural domains. This revelation is unexpected considering the exposure of these farmers to numerous natural disasters and climate change risks. Additionally, a substantial proportion of farming households grapple with poverty, impeding the voluntary adoption of agricultural insurance by Thai farmers and resulting in a relatively low penetration rate. Moreover, the prevalent adoption of calamity-based pay-out schemes in many crop insurance products has contributed to negative perceptions, attitudes, and low levels of trust among insured farmers towards agricultural insurance. Nevertheless, the study indicates that impoverished Thai farmers, particularly those engaged in crop and livestock farming, express interest and willingness to participate voluntarily in agricultural insurance if they are offered a premium subsidy ranging from 50% to 70%. In contrast, aquaculture producers express a demand for voluntary aquaculture insurance even without premium subsidies. Concerning insurance coverage, farmers exhibit a preference for yield-based insurance products to mitigate yield loss, displaying diminished interest in revenue-based insurance. Moreover, the study's analysis reveals unfavourable outcomes for Thailand's private insurance sector, evidenced by high loss ratios in NPCI rice and maize insurance. This poses a substantial threat to the profitability and viability of insurers. In-depth interviews conducted for the study distinctly convey that private insurers in Thailand actively seek governmental support to transfer agricultural risks from the private sector, particularly in instances of natural disasters, where the loss ratio surpasses 120% or 130%. This assistance would result in cost reductions and improve affordability for insurers. Ultimately, the results underscore the shared perspective among regulators, agricultural and insurance experts, and the private insurance sector concerning dedicated agricultural insurance legislation and the need for robust public-private partnerships in Thai agricultural insurance. There is a widespread consensus that these partnerships should be sustained and expanded to foster the development of resilient agricultural insurance programs. Moreover, it is highlighted that a conducive legal and regulatory framework is imperative for the establishment and implementation of a sustainable agricultural insurance system in the country. Agricultural insurance legislation should empower the Thai government to provide public support and subsidies without reliance on annual cabinet approvals and resolutions.

The research findings concerning area-yield rice crop insurance unveil notable statistical correlations among variables, as delineated in Table 2. Specifically, flood depth and flood duration manifest a negative correlation with the production rate, indicated by correlation coefficients of -0.661 and -0.631, respectively. This implies that an extended duration of submergence or an elevated water level in the rice paddy is associated with a decline in rice production. Additionally, the rice state exhibits a negative correlation with the production rate, with a correlation coefficient of -0.308. This implies that the rice lifecycle, particularly post the booting stage, is more vulnerable to the detrimental effects of floods, resulting in a reduction in the production rate.

Table 2. Correlation among flood depth, flood duration, rice state, and production rate

	Flood Depth	Flood Duration	Rice State	Production Rate
Flood Depth	1.000	0.442***	0.204**	– 0.661***
Flood Duration		1.000	0.171**	– 0.631***
Rice State			1.000	– 0.308***
Production Rate				1.000

Note: *** Significant level at 0.01 ** Significant level at 0.05

The results of the study reveal a robust accuracy level in predicting rice yield loss using the employed models. As depicted in the research findings presented in Table 3, the 2nd and 3rd degree multivariate polynomial regression models exhibit an R-square in the range of 83-84%. Notably, decision trees display the highest accuracy level with an R-square approximately at 97%, accompanied by the lowest mean absolute error (MAE) of 0.018 and the lowest root mean square error (RMSE) of 0.041 in predictions. Intriguingly, random forests also demonstrate a notable accuracy level, showcasing an R-square of approximately 95%, a low MAE of 0.020, and a low RMSE of 0.050 in prediction.

To ensure the robustness and reliability of the study's findings, a K-fold cross-validation methodology was employed to evaluate the performance of the 2nd and 3rd degree multivariate polynomial regression, decision trees, and random forests algorithms. The utilization of cross-validation allowed for the assessment of these algorithms' performance across various train and test dataset configurations, facilitating a comprehensive analysis of their predictive capabilities. The average values of R-Square, MAE, and RMSE were computed for each algorithm through a 10-fold cross-validation process, as outlined in Table 4.

Table 3. Measurement model assessment

Machine learning algorithm	R-Square	MAE	RMSE
2nd degree multivariate polynomial regression	0.827	0.073	0.095
3rd degree multivariate polynomial regression	0.846	0.053	0.089
Decision trees	0.967	0.018	0.041
Random forests	0.952	0.020	0.050

Table 4. 10-Fold validations for model assessment

Machine learning algorithm	Average R-Square	Average MAE	Average RMSE
2nd degree multivariate polynomial regression	0.784	0.097	0.122
3rd degree multivariate polynomial regression	0.797	0.083	0.117
Decision trees	0.723	0.074	0.124
Random forests	0.803	0.068	0.110

Upon analysis, it is observed that the prediction accuracy and performance of the various algorithms are comparatively similar. However, multivariate polynomial regressions display marginally higher mean errors, with an average MAE ranging from 0.083 to 0.097 and an average RMSE ranging from 0.117 to 0.122. In contrast, decision trees manifest diminished accuracy, evident through a reduction in R-Square during the validation process. Furthermore, the performance of decision trees in cross-validation indicates elevated mean errors compared to random forests, with an average MAE of 0.074 and an average RMSE of 0.124. This suggests a higher susceptibility of decision trees to overfitting. Conversely, random forests consistently demonstrate elevated R-square values and low errors in both model fitting and validation stages Significantly, the predicted values generated by random forests consistently align within the range of the training set values for the target variable, conforming to the expected range of the rice production rate (0% to 100%). Consequently, random forests emerge as the optimal machine learning algorithm for the provided dataset. Consequently, based on these findings, random forests are identified as the most fitting algorithm for implementation in the area-yield rice insurance model for Jasmine-105 rice cultivation in Ubon Ratchathani and Sisaket provinces.

The analysis of the impact of climate change on flooding suggests a potential escalation in daily extreme precipitation in the future for Ubon Ratchathani and Sisaket provinces. Table 5 outlines the daily precipitation threshold (u) and furnishes details on the distribution, along with the goodness-of-fit test utilizing the GPD. Results indicate an exponential distribution in the daily precipitation of both provinces. Additionally, the assessment of the 10-100 year return levels of daily maximum precipitation, based on the GPD, indicates the likelihood of daily extreme precipitation surpassing 100 mm in both provinces within the next 10-100 years.

Table 5. Threshold value, distribution, and return periods for precipitation in Ubon Ratchathani and Sisaket provinces

Province	Station	u	Distribution	KS P-Value	Province	Station	u	Distribution	KS P-Value
Ubon	48407	36.032	Exponential	0.5801	Sisaket	48409	24.272	Exponential	0.9374
Ratchathani	48408	33.650	Exponential	0.7085					

Province	Station	Return Period (Years)				Province	Station	Return Period (Years)			
		10	25	50	100			10	25	50	100
Ubon Ratchathani	48407	115.83	138.10	156.84	177.39	Sisaket	48409	89.57	109.33	126.38	145.50
	48408	104.04	120.47	133.56	147.26						

Discussions

The results revealed that a pertinent form of crop insurance is the area-yield index insurance, particularly well-suited for small-scale rice farmers in Thailand. The findings of Chen et al. (2017) and Stutley (2022) suggest that area-yield index insurance stands as a feasible choice for these farmers, offering protection against various perils, including pests and diseases. This aligns with the demand response observed among rice and maize farmers in Thailand, aiming to mitigate the impact of yield loss. Conventional insurance products, such as named-peril insurance as emphasized by Elabed et al. (2013), prove impractical for small-scale agriculture due to elevated transaction costs, moral hazard, and adverse selection. Conversely, both area-yield and index-based insurance methods offer a substantial reduction in the necessity for on-site verification of losses, effectively diminishing administrative costs and enhancing transparency (Shirsath et al., 2019). Moreover, the integration of area-yield crop insurance with machine learning holds promise for mutual advantages for both insurance firms and farmers. Xu et al. (2020) indicate that machine learning algorithms have the capacity to augment risk management and mitigate the likelihood of moral hazard. In the realm of agricultural insurance, the application of machine learning algorithms holds substantial potential for enhancing precision and performance in predicting yield losses. Machine learning methodologies are acknowledged as effective instruments for accurately forecasting intricate models, as underscored by Murdoch et al. (2019). These methodologies exhibit significant utility within the agricultural sector, specifically in the context of area-yield crop insurance. The investigation underscores the capability of machine learning algorithms to enhance accuracy and performance in predicting yield losses. Utilizing diverse machine learning algorithms, the study discerned that random forests exhibited superior performance, attaining a notable R-square of 95.2% during model fitting and 80.3% in the validation process. Furthermore, random forests consistently demonstrated minimal errors in both MAE and RMSE during both fitting and validation of the model. These results align with the findings of Sharma et al. (2023), supporting the assertion that random forests stand out as a high-performing algorithm for crop yield prediction. Additionally, the study posits that decision trees may be susceptible to overfitting, resulting in diminished accuracy and increased errors during the validation phase. This finding aligns with the observations of Ursenbach et al. (2019).

The results of this investigation underscored the influence of climate change on intense precipitation in the provinces of Ubon Ratchathani and Sisaket. These outcomes are congruent with the observations made by Li et al. (2019) and Chen et al. (2023) suggesting that excessive rainfall has the potential to result in considerable loss of yield, thereby presenting notable risks to both agriculture and insurance. Sinnarong et al. (2019) examined climate change effects on Thai rice production, revealing a potential 0.07-1.39% decrease with heightened precipitation. Emphasizes the need for adept risk management to address extreme precipitation impacts.

The results highlight the imperative for the efficient establishment of the agricultural system in Thailand to attain sustainability. The Thai government should expound upon the development plan and execute forthcoming scaling-up initiatives, incorporating robust sovereign insurance schemes. These findings resonate with the National Economic and Development Board (NESDB), which advocates a 20-year national strategic framework. This framework seeks to fortify the agricultural sector, tackling farmers' challenges with the overarching objective of securing national prosperity and sustainability (Royal Thai Government Gazette, 2018). T In pursuit of this objective, the present study advocates six essential mechanisms for the engagement of the public sector in agricultural insurance in Thailand.

1. Agricultural insurance legislation: Enacting suitable legal frameworks and regulations that foster the expansion and efficacy of agricultural insurance within a nation. This alignment is substantiated by the investigation conducted by Lata et al. (2020), underscoring the significance of the adept implementation of agricultural insurance legislation in facilitating the proficient execution of insurance and risk management functions.
2. Government support and subsidies: Ensuring ongoing support and financial aid to farmers through subsidies and incentives, thereby improving their accessibility to and affordability of agricultural insurance. Studies by Du et al. (2017) and Tok et al. (2023) indicate that governmental backing and financial subsidies constitute judicious and efficacious strategies in the mitigation of agricultural risks. These interventions enhance the appeal and financial feasibility of crop insurance for farmers, thereby contributing to an augmentation of its overall efficacy.
3. Agriculture reinsurance and catastrophe risk financing and management: Instituting reinsurance mechanisms, along with robust risk financing and management strategies, is imperative for addressing catastrophic risks and ensuring the stability and sustainability of the agricultural insurance sector. The escalating exposure of the insurance industry to climate-related risks underscores the pivotal role of government support in tackling these challenges An exemplary illustration of managing catastrophe risk financing and management in an emerging market is evident in the study by Başbuğ-Erkan and Yilmaz (2015) focused on the Turkish Catastrophe Insurance Pool. This case study underscores the crucial role played by government support in fortifying the agricultural insurance sector.
4. Agricultural insurance product design and development: Fostering the creation of inventive and customized insurance products designed to meet the distinct requirements and challenges encountered by farmers across various agricultural domains is imperative. The investigation emphasized the significance of area-yield crop insurance as a valuable instrument for mitigating yield loss risks among small-scale rice farmers in Thailand. These conclusions are congruent with the outcomes of prior research undertaken by Sethanand et al. (2023).

5. Data provision and digital technology: Allocating resources to establish resilient data collection systems and harnessing digital technologies to streamline the precise evaluation of risks, estimation of losses, and processing of claims within the agricultural insurance sector. This strategy aligns with the conclusions drawn by Mateos-Ronco and Server Izquierdo (2020) indicating that government backing functions as a catalyst for the incorporation of digital technology, enhancing its efficacy in advancing insurance and risk management processes.
6. Strong and effective public-private partnerships: Cultivating synergies and alliances between the public and private spheres is crucial for bolstering the agricultural sector and safeguarding the livelihoods of farmers. Government support, through the provision of essential resources, expertise, and a regulatory framework, augments the capabilities of public-private partnerships, thereby amplifying their efficacy in insurance and risk management initiatives (Botzen et al., 2010).

Conclusion

The study investigated the impact of government support on enhancing insurance risk management in Thailand's agricultural, fishery sectors and livestock. Through hypothesis formulation and data analysis, the study identified key mechanisms of government involvement, emphasizing the use of machine learning (random forests) in area-yield crop insurance to estimate provincial rice production. The findings underscored the economic viability and sustainability of the Thai rice industry. Additionally, the research highlighted the imperative for effective reinsurance and risk management practices in light of anticipated heavy rainfall due to climate change over the next 10-100 years. Conclusively, the study affirmed the Thai government's dedication to advancing a proficient and enduring agricultural insurance scheme, motivating farmers to secure their agricultural vulnerabilities and steering the nation towards sustainability.

Limitations

The study recognizes specific constraints that necessitate prudent contemplation. Despite the examination of six mechanisms through which government support can enhance insurance and risk management in agriculture, there exists the possibility of additional mechanisms meriting exploration. Moreover, the research model framework, encompassing factors like flood depth, flood duration, and rice state as contributors to predict rice production loss, underscores the necessity for researchers to broaden their focus to incorporate additional dimensional datasets such as soil nutrients, satellite data, and index parameters. This expansion is crucial for achieving more comprehensive and accurate predictions in the realm of agricultural decision-making.

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