Forecast Based Financing for Precision Agriculture in Indonesia

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Abstract. As a developing nation, Indonesia's economy relies heavily on agriculture. Despite being the largest food producer in Southeast Asia, the Indonesian government is primarily concerned with ensuring domestic food security. Consequently, the Indonesian government is actively working to enhance agricultural infrastructure and capabilities. However, this objective faces various emerging challenges, such as the uncertainties and risks associated with extreme weather events and climate fluctuations. To address these challenges, the Government of Indonesia is exploring an innovative approach known as Climate Smart Agriculture (CSA). This CSA concept not only aims to enhance agricultural facilities but also provides support to farmers through prediction-based financing, incorporating index-based insurance and predictive indices, particularly in relation to weather events associated with the El Niño Southern Oscillation (ENSO). This research endeavors to introduce the concept of forecast-based financing, which combines index-based insurance and predictive indices to safeguard Indonesia's agricultural activities. In essence, index-based insurance offers a distinct and valuable alternative to conventional insurance products, especially in Indonesia, where administrative capacity is limited, credit options are scarce, and relief efforts for past disasters have experienced delays. Index-based insurance has the potential to significantly bolster community resilience.
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1 Introduction

The agricultural industry in Indonesia has traditionally been a significant source of income for local households and has also contributed essential export revenues. Historically, [1] this sector has been a cornerstone of Indonesia's economy, but it has not yet reached its full potential, despite considerable advancements in recent years. Despite notable progress, several obstacles still constrain the improvement of crop yields, including limited access to financial resources for farmers, the agricultural sector's vulnerability to the impacts of unpredictable weather and climate patterns, and outdated infrastructure. To address these challenges, the government has increased investment in mechanized agricultural technology, upgraded infrastructure, [2] and expanded the cultivated land area. While these efforts have led to increased agricultural output, the sector still faces challenges in downstream segments, and small-scale farmers, who constitute a significant portion of rural income, continue to struggle with limited access to financing and technology. [3] This directly affects the commercial viability of agriculture. Additionally, historically, agriculture has played a crucial role in the labor market. [4]

Taking into account the dynamic nature of weather and climate conditions, the FAO has developed the concept of Climate Smart Agriculture (CSA) to serve as a guiding framework for agricultural management in the context of climate change. To complement the established CSA framework by the FAO, [5] this study introduces a novel concept: a funding platform for the agricultural sector based on weather and climate predictions. This platform is designed to provide valuable insights into the potential risks of agricultural failure due to fluctuations in weather and climate dynamics. [6] Climate Smart Agriculture represents a comprehensive approach to guide agricultural management amidst the challenges of climate change. Its primary objective is to establish universally applicable principles for sustainable agriculture management, ensuring food security in a changing climate. [7] These principles can serve as a foundation for policy development and recommendations, particularly in the realm of global climate change policy. Given the inherent uncertainties associated with climate change, a cautious and conscientious approach to climate policy is essential. CSA also places a significant emphasis on mobilizing new and potentially substantial sources of climate finance, including carbon markets, to support the transition toward sustainable agriculture. [8] However, it's crucial to acknowledge and address significant barriers, such as the high transaction costs that hinder small-scale agricultural producers from accessing and benefiting from climate finance. To address this challenge, the application of CSA in the context of small-scale agricultural producers can be facilitated through Forecast-based Financing. This study builds upon previous research efforts and combines them into the concept of Climate and Weather Forecast-based Agricultural Financing tailored for Indonesia. In formulating this concept, Perez. [9] aimed to establish a funding system that integrates weather, climate, and hydrological information predictions in a systematic manner, with the accuracy of predictions being essential for the specific area in question. Weather and climate prediction information is processed and presented as early warnings, which are subsequently verified for accuracy and transformed into actionable insights. [10]

This mechanism is expected to minimize loss and damage caused by weather and climate hazards, and reduce the need for humanitarian assistance thereafter. Activities carried out in accordance with national priorities, so as to improve field expertise at the local level and be able to build existing coordination mechanisms. Thus, when systems function properly, they can solve economic problems that prevent rapid response and the development of operating procedures that guarantee a sustainable return on investment.

2 Material and methodology

2.1 forecast based financing in precision agriculture in indonesia

By referring to the FbF concept previously explained, the agricultural sector in Indonesia can adopt the FbF concept in funding mechanisms for traditional farmers who have limited access to capital or protection of agricultural failures from disasters caused by weather and climate dynamics. Based on the CSA concept, precision agriculture can be used as one of the crystallization of agricultural methods that consider accuracy based on data on natural conditions on the agricultural land concerned. [11] One example of the application of precision agriculture is agriculture that applies the concept of FbF to the agricultural sector in Indonesia. However, in the application of FbF, there are differences in the mechanism that has been proposed by Perez et al. so that in this study will be explained the FbF mechanism that integrates weather and climate prediction for the agricultural sector. [12]

2.1.1 Tailor Predictions to Actions

In the first component, depending on the impact, there are a number of measures that can be taken to prevent crop failure; However, only a small percentage of actions are appropriate based on certain predictive information. Of all the possible actions, a matching process is required to select the action that best fits *the time window* and the degree of probability of an *event* occurring based on predictions. Indonesia has a chance (p) of very high rainfall intensity as a result of the La Nina phenomenon and the potential for flooding in several agricultural areas for 1 week in a row. [13] Warnings of extreme rains and potential floods causing crop failure have been disseminated, but not all action can be taken by recipients of information, especially farmers who have difficulty accessing warnings and the small time lag that farmers must take to take action between the time the prediction information is provided and the event occurs. This tends to happen often in Indonesia and makes farmers have to accept losses and let their rice fields flood until the flood recedes. So, although there is a list of actions to be taken based on the probability of an event occurring, actions must be taken. So, If the prediction misses, it causes the farmer to act-, but if the opposite condition occurs, the farmer will fail. [14]

Table 1. Contingency table based on predicted thresholds p

	It's already happening	Don't Happen
Predictions >= p	*Hit* a (p)	*Fake Alarm* b (p)
Prediction does not >= p	*Ninth* $c(p)$	*Correct Rejection* $d(p)$

[15] The scenario matrix is used to measure the accuracy of actions taken against the prediction of *events* that occur. By measuring such accuracy, the system can evaluate appropriate actions. Thus, the accuracy factor of the odds of weather and climate prediction affects the taking of Action.

$$R(p) = \frac{a(p)}{a(p)+b(p)} \quad (1)$$

To trigger contingency plan actions, most action lists will be eliminated if farmers are unable to complete actions from the available time lag to before the anticipated flood event. [16] Therefore, lead-time *climate weather prediction* has a very important role in providing a time lag for farmers to take appropriate actions to reduce losses due to flooding. However, on the other hand, if the prediction made misses, then farmers have actually taken action "-", which has an impact on the distrust of farmers and investors towards the mechanism built. Therefore, in table 2 a scenario matrix is constructed for prediction-based actions against the prediction of events that occur. [17]

Table 2. Contingency table describing scenarios that will occur for prediction-based actions

	Yes Happens	Not Happening
Action Done	*Hits* (*a*)	*False Alarm* (*b*)
Action does not Done	*Miss* (*c*)	*Correct Rejection* (*d*)

The scenario matrix serves as a tool for assessing the accuracy of actions taken in response to predicted events. Through this evaluation of accuracy, the system can determine the appropriateness of these actions. Consequently, the accuracy of weather and climate predictions becomes a crucial factor in decision-making. This implies that each action taken carries significant economic significance, as depicted in Table 3 [1] In Table 3, denoting costs as C and losses as L, [18] the value remains constant irrespective of the prediction's probability. When it comes to the "act in vain" category, there is a modification to the original cost, denoted as ΔC, which may arise due to factors like reputational risk or the need to dismantle preparations and return them to storage. The additional cost, ΔC, can be substantial, and the reputational risk associated with false alarms might outweigh the potential benefits of a viable action. It's essential to recognize that this is a simplified representation of reality and does not encompass, for instance, the likelihood of a successful action preventing the loss of the target. Furthermore, the cost of acting recklessly may differ from that of a feasible action, considering the effort required to rectify erroneous warnings and return inventory to storage.

Table 3. Contingency table for costs and losses resulting from actions taken in action. The value of the level of accuracy is obtained from the following equation 1.

	Yes Happe Ns	Not Happening
Action Done	*Hits* (*a*)	*False Alarm* (*b*)
Action does not Done	*Miss* (*c*)	*Correct Rejection* (*d*)

Indeed, there are two possible outcomes: one where the action is implemented, and the other where it is not. The decision to take action is contingent on specific predefined thresholds being met. Notably, when constructing this mechanism, the inflation rate is not factored in when the actions have a timeframe of less than one year. Consequently, the inflation rate's influence is minimal compared to the prevailing uncertainty in such cases. However, for actions spanning several years, it becomes more advisable to consider the inflation factor, which may diminish the relative weight of the benefits, assuming they

occur less frequently than the costs involved. More intricate versions of this approach may also account for the probability density function of the disaster's impact magnitude, while the fundamental principles outlined here remain applicable. In light of the preceding description, [19] when making decisions based on probability estimates, such as in a Business-as-Usual (BAU) scenario with no action compared to scenarios involving action based on forecasts, the combined costs and losses in the latter scenario should be exceeded by the estimates in the former scenario to justify taking action. (Equation 2).

$$L\frac{a+c}{n}(p) >$$

$$C\frac{a+b}{n}(p) + \Delta C\frac{b}{n} + L\frac{c}{n}(p) \qquad (2)$$

However, not all catastrophic consequences can be expressed in economic terms, therefore this relationship also needs to be qualitatively accepted by implementers. In addition, many of these actions will have long- term benefits, regardless of the catastrophic incident.

2.1.2 Funding Mechanism

The second element is the preparedness fund, which serves as a standard financial mechanism for forecast-based financing and is intended to be activated before a potential disaster occurs. This fund is designed to be deployed when forecasts are issued, ensuring there is adequate funding available to execute the selected course of action, even though there may be instances where resources are expended on actions that ultimately prove unnecessary. To facilitate the swift release of funds when early warnings are issued, financial procedures are put in place. Moreover, stringent accountability measures are implemented to ensure that these funds are exclusively allocated to the initial measures aligned with the early warnings. The most straightforward method for determining the required funding for this mechanism over a specified time frame is to assume that all conceivable actions based on lead-time weather-climate predictions are accounted for, and funds are allocated each time a corresponding estimate is issued. If we denote C as the cost associated with taking action based on a single warning, then the total preparedness fund required for farmers, represented as "T," can be calculated as follows: $a + b$ b

$$T = C\,.\,\frac{a+b}{n}(p) + \Delta C\,.\,\frac{b}{n}(p) \qquad (3)$$

If there are multiple forecast probabilities, or several different forecast types, for which action is suggested, the total funding required will be the amount of funding required for each. However, be aware that forecasts that occur sequentially need not repeatedly fund the same actions, and provisions need to be made to autocorrelate forecasts. For example, rainfall classes in Indonesia have four forecast levels: normal, alert, alert and alert. which relates to the probability of a given rain threshold. Since each forecast must be matched with different actions based on lead-time and threshold probabilities, the preparedness fund must take into account the likelihood of each probability being issued, as well as its correlation in the time dimension. If the probability of a prediction is defined as p, then the total amount of funds required to react to all possible probability forecasts can be represented as

$$T = \int_{2}^{1} C \cdot \frac{a+b}{n}(p)dp \qquad (4)$$

In a scenario as depicted, Equation 3 can be simplified by combining the costs associated with taking action across the four alert categories. When the risk of a disaster

increases significantly, denoted by an increase in R(p), Equation 2 allows more actions to be selected for a given forecast. Therefore, the greater the possibility of a disaster, the greater the disbursement of funds. In practice, additional factors will be included to account for external drivers, such as repeated political consequences of ineffective actions and the impact of interactions between different actions. In many cases, there may be an upper limit on the initial allocation of funds (T) to activate this mechanism within a certain time period. In cases like this, preparedness funds need to be distributed to those that are likely to occur. Each estimated probability (p) corresponds to an amount of disbursement (D) that is proportional to the predicted impact of the flood on farmers based on the given predictions. This disbursement amount must be divided among all possible actions. If the funds distributed (D) are limited, then only the most critical actions will be implemented. Statistically, the D value will be calculated to ensure that T is fully utilized at the end of the allocated time period.

$$T = \int_{0}^{1} C \frac{a+b}{n}(p). D(p)dp \quad - \qquad (5)$$

Using this method, there may be a number of probability forecast categories (p) calculated to receive a very small amount of expenditure, which may not be enough to perform the selected action. It has a tendency to occur frequently. However, compared to the result of disbursement at the cost of action C(p), the condition can eliminate the category of condition p which has implications D(p) < C(p). Next, the above-mentioned equation undergoes a recalculation process in which the probabilities (p) are iteratively reduced until all allocations exceed the costs required to carry out the required action for each remaining probability (p). [20] This approach operates on the assumption that funds should be distributed based on the probability of an event occurring. However, this assumption can be replaced by other priorities, such as allocating funds based on the effectiveness of actions. Alternatively, thresholds can be set taking time variations into account, thereby allowing for more structured spending at the start of the available time period and greater flexibility in spending the remaining budget towards the end of the fiscal period. If the system is calibrated over a long period of time, these thresholds can be adjusted to reflect changing insights or change triggers.[21]

3 Result And Analysis

Using the suggested approach, we can identify specific actions that could be investment opportunities, relying on available predictive data. While it is important to maintain standard funding mechanisms and operational protocols to ensure consistent action according to forecasts, the future allocation of funds for risk-based funding mechanisms remains uncertain. Results may differ depending on the specific program, but various long-term disaster risk reduction initiatives have demonstrated favorable cost-benefit ratios [2]. Based on the initial findings of this pilot concept, we can evaluate the potential benefits of a similar probabilistic cost-benefit (B/C) ratio for this methodology, as in equation (6) (not corrected for inflation rate).

$$\frac{B}{C} = \frac{\int_{0}^{1} L \cdot \frac{c}{n}(p) - C \cdot \frac{a+b}{n}(p)\,dp}{T} \qquad (6)$$

Acomparison of outcomes based on Benefit-Cost (B/C) ratios for mitigating long-term climate change-induced risks reveals incremental advantages associated with allocating

additional funding across all categories. This shift in funding allocation restructures the landscape of financial support aimed at reducing crop failure risks and enhancing preparedness, with a strong emphasis on the most impactful actions within each time frame. Additionally, when incentive funds emerge for applications in crop failure risk prediction, prevention, and preparedness, the effectiveness of these systems largely hinges on advancements in weather and climate predictive capabilities. The inability to accurately predict and forecast weather and climate events can jeopardize investments in this funding system, as these capabilities are pivotal considerations when evaluating investments in predictive capabilities and other elements that contribute to the profitability of Forecast-based Financing (FbF) over time. It's worth noting that Indonesia currently faces challenges related to the availability of functional weather stations, including synoptic stations, which restrict the accuracy of meteorological predictions [3]. To bridge this gap, investments in both hardware and software are imperative to bolster meteorological and hydrological services in Indonesia. In the interim, recent research initiatives that combine existing observation station data with satellite information may offer a more precise understanding of climate patterns using historically accessible data [4]. Any increase in the percentage of potential risk of predicted crop failure (also known as hit rate) a/a+c or an increase in the correct alarm ratio a/a+b due to improved forecast-skill will directly improve farmers' ability to prevent and prepare for potential disasters resulting in crop failure. [22]

The framework of this approach offers a straightforward concept that aligns with the practical insights already familiar to many practitioners regarding the opportune moments for early action. This quantification process can also serve as a foundation for presenting investment proposals to agricultural insurance fund management institutions in Indonesia, aiming to facilitate early action, which is often currently unattainable due to the absence of suitable funding. It's important to note that quantification is not a straightforward process; it necessitates a thorough analysis of the specific context. This analysis encounters certain challenges, particularly when there's a lack of historical disaster data. It becomes essential to evaluate the impact of uncertainty in probability forecasting, encompassing both the potential consequences of forthcoming risks and the reliability of predictions. Additionally, it is crucial to establish thresholds that signify a reasonable level of certainty for anticipated events to yield meaningful outcomes. The incorporation of local agricultural knowledge, socio-economic conditions, farmer behavior, and patterns of recurring extreme events into the fund calculation mechanism is possible, even though it introduces inherent uncertainties.

Further investigation is necessary to enable the widespread implementation of Forecast-based Financing (FbF) systems tailored for precision agriculture in Indonesia. Specifically, an evaluation of the assessment and validation of crop failure risk based on rainfall forecasts should be conducted, incorporating both statistical and dynamic techniques in conjunction with hydrological forecasts. It's crucial to acknowledge that numerous variables within this context, encompassing action choices and forecasting capabilities, exhibit significant variations across different regions. [23] Consequently, FbF systems must be custom-designed to address specific hazards at precise geographical scales, as exemplified by the approaches undertaken by Mortensen and Blok and Kusuma, Noy, and Jackson. Standard operating procedures that have been formulated for one particular area are unlikely to be directly applicable elsewhere, emphasizing the importance of region-specific adaptations. Further research endeavors should delve into the impacts of variances in each of these parameters and the resulting disparities in the potential for FbF across various regions.

The calibration of cost and profit estimates presents a complex challenge. For instance, determining the cost of taking appropriate action versus the cost of taking action that ultimately proves unnecessary may require repeated estimation. This assessment may

depend on whether the actor has recently experienced a scenario of acting in vain and subsequently becomes cautious about taking further risks. Likewise, when predictions prove inaccurate, it can erode confidence in the entire system. [24] To enhance the framework's accuracy, additional factors related to "risk perception" can be incorporated, which adjust in response to erroneous warnings or successful interventions. The calibration of these factors will draw upon insights from practitioners. Furthermore, all cost estimates must undergo a sensitivity analysis to gauge the impact on the funding mechanism's efficacy when changes are made to probability and cost estimates. Essential questions to explore include: How do alterations in probability and cost estimates, as reflected in the equation above, influence the outcomes? At what point does uncertainty in these values significantly affect the decision-making process and the assessment of its benefits? Additionally, it's important to consider the interplay between short-term and long-term investments, with the latter often posing challenges to making short-term decisions.

4 Conclusion

Innovation in this context should prioritize enhancing the customization of information to better align with the specific needs of decision-makers in the agricultural sector, rather than merely altering the visual presentation of existing information. The system described above combines established profit forecasting methods with user-defined data regarding the expenses associated with mitigating crop failure risks and losses attributed to weather and climate variations. By incorporating such information into these systems, significant obstacles and requirements that currently hinder the systematic utilization of forecasts in agriculture can be addressed. This also involves developing Standard Operating Procedures (SOPs) that ensure a sustainable return on investment. The implementation of such a system would make farmers in the region aware that numerous potential losses in Indonesia's agricultural sector could be averted through actions prompted by the information provided. Consequently, stakeholders can concentrate on investing in the agricultural sector by offering financial support and insurance to farmers who face lower risks of crop failure due to the unpredictable dynamics of climate and weather that could abruptly devastate their investments. Further research is imperative to quantify the additional value brought by Forecast-based Financing (FbF) schemes, establishing an evidence-based foundation for forecast-based funding and the widespread adoption of weather and climate-driven protocols.

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