Modelling the Emergence of Financial Well-being on the Adoption Process of Mitigation Measures in Human-Elephant Conflict

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ABSTRACT

Advancement in agricultural sector has caused an exponential increase in converting forestry area into agricultural land leading to elephant habitat fragmentation that triggers Human-Elephant Conflicts (HEC) that happens in areas adjacent to protected areas. Although many attempts have been put in place, they have only been effective in the short term and potentially causing another problem, thus a holistic strategy is needed. However, in the midterm, it is crucial to effectively reduce the actual damage to crops caused by elephants to improve coexistence between humans and elephants in shared landscapes. The purpose of this study is to explore the farmers' decision-making process to overcome such issues and the impact of their decisions in terms of financial conditions in Villages near Bukit Tigapuluh National Park by implementing agent-based modelling (ABM) to study this phenomenon. The results showed that insufficient financial resources can lead to a chain of effects that prevent farmers from adopting mitigation techniques and/or properly maintaining their mitigation tools or crops, ultimately resulting in a decrease in the net income that farmers should receive. Farmers with higher cash reserves can endure and overcome the effects of HEC, while the ones with low cash reserve don't. The government should begin to consider the financial well-being of farmers in conflict areas as a factor in designing policies to resolve elephant-human conflict. Failing to address this issue can result in a prolonged negative perception of farmers towards elephants, potentially endangering both elephant conservation and farmer welfare.

ARTICLE INFO

Received August 19, 2023
Accepted September 20, 2023
Available online September 28, 2023

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Keywords:
crop-raiding; HEC mitigation measures; adoption; agent-based Modelling

1. Introduction

Advancement in agricultural sector has caused an exponential increase in converting forestry area into agricultural land (Su et al., 2020) leading to elephant habitat fragmentation (Kuswanda et al., 2022) that triggers Human-Elephant Conflicts (HEC) that happens in areas adjacent to protected areas (Eustace et al., 2018). HEC have resulted in negative impacts for both Humans and Elephants (Mustafa & Abdullah, 2018; Pratiwi et al., 2020; Wahed et al., 2016). Economic loses was estimated around IDR 10 billion on 2018 in Bukit Tigapuluh National Park, Jambi due to HEC (Ajudin et al., 2020) provoking affected communities to retaliate by repelling elephant (Pratiwi et al., 2020), or worse, killing elephant (Mustafa & Abdullah, 2018). In Aceh Province, HEC has been reportedly causing 10 elephant death in 2017(Mustafa & Abdullah, 2018). This response potentially endangering elephant's existence that can lead to local extinction (Febryano et al., 2020).

Due to habitat fragmentation and decreasing in resource availability, elephants occasionally moving out from the protected areas (Kuswanda et al., 2022; Tiller et al., 2021). It is known that most of the elephant population had moved outside of the protected area approaching farmers' agriculture land. In Aceh, it was reported that this elephant's behavior has accounted 70% of crops destruction (Berliani et al., 2018). This incident has led to an increasing number of elephant crop-raiding cases and widening conflict-areas becoming a major issue in the villages nearby protected areas (Ajudin et al., 2020).

Most of the human-elephant conflict occurs in the form of crop-raiding, where elephants enter community plantation areas due to the reduction of buffer zones caused by agricultural activities (Berliani et al., 2018; Rachmawaty et al., 2022). Conflict points have a higher intensity on farmland located near forests and rivers (Naha et al., 2020). (Supun & Prakash, 2020) argue that human-elephant conflict has increased in both intensity and the expansion of conflict areas. These large cases of elephant entering agricultural areas causes crop damage and create a negative perception towards elephants among the affected communities (Pratiwi et al., 2020) with the majority communities that most-likely hold negative perception were low-income individuals, those who have had unpleasant encounter elephants raid-attack and agricultural workers.

Several attempts have been made by both government and local communities to mitigate the effect of crop-raiding (Yoza, 2016). Government attempting translocation of rouge elephants and deploying elephant response unit to cast out any elephant coming to human settlement or agriculture land (Direktorat Jenderal KSDAE, 2020). Whereas local communities applying several measures around their perimeter such as electric fence, trench, spotlight, cannon (Yoza, 2016), and chili-fence (Gunaryadi et al., 2017) and recommended by government to be adopted individually (Departemen Kehutanan, 2007; Febryano et al., 2020). These previously mentioned mitigation measures had different effectiveness and characteristics. Electric fences known to be the most effectives methods and brings no harm for the elephant (Margaretha & Moßbrucker, 2014), yet it was rarely implemented due to high maintenance and acquisition cost (Yoza, 2016). Whereas the most used mitigation tools in the study area was cannon due to its cheap cost, yet relatively ineffective.

Although many attempts have been put in place, they have only been effective in the short-term (Nuryasin et al., 2014) and potentially causing another problem (Yoza, 2014). Thus, the issue of HEC has not yet been resolved effectively (Enukwa, 2017) and remains a significant challenge to overcome (Shaffer et al., 2019). Mitigation measures of crop-raiding requires a holistic strategy that considers regional planning, community interest, and conservation aspect (Marie-Claire Oelrichs et al., 2016) which could present challenges and difficulties beyond simply implementing technical measures to decrease crop damage caused by crop-raiding incidents (Kiffner et al., 2021).

Holistic strategy needs a long time to implement and requires a lot of resource and commitment by various stakeholders (Marie-Claire Oelrichs et al., 2016). However, in the midterm, it is crucial to effectively reduce the actual damage to crops caused by elephants to improve coexistence between humans and elephants in shared landscapes (Kiffner et al., 2021). If there are no actions for the midterm, the loses caused by HEC will continue to rise and will negatively affect both elephants and humans (Feuerbacher et al., 2021; Marie-Claire Oelrichs et al., 2016; Shaffer et al., 2019). The government needs to address the issue of human-elephant conflict that arises in the mid-term, especially for communities who are most likely will encounter crop-raiding (Yoza, 2016).

It is known that elephant movement had a certain pattern and has tendency to revisit a certain area (Rachmawaty et al., 2022) which also dependent on resource availability (Mohandas et al., 2021) and home-range size (Moßbrucker, Fleming, et al., 2016). Various research had attempted to predict elephants' movement pattern via bioavailability of an areas (Diaz et al., 2021), foraging theory (He et al., 2022), and environment features (Mamboleo et al., 2021). Although, due to significant conversion in protected forest to agricultural land, it is expected that elephants will wander across much extensive territories than previously thought (Moßbrucker, Fleming, et al., 2016) and the probability of elephant raid attacks will vary across different regions (Kwartina & Antoko, 2007).

Given those conditions and the effectivity characteristics of mitigation measures, one need to assess how individual decisions manages conflict in each location (Carter et al., 2020). However, policymakers faced challenges such as difficulty conducting field studies to gather accurate data (Mamboleo et al., 2021; Neil et al., 2020) and understanding the reciprocal interactions between elephants and humans (Kuswanda et al., 2022). These challenges could be addressed using agent-based modeling (ABM) (Neil et al., 2020). ABM has been widely applied in agriculture to recommend policies (Mora-Herrera et al., 2021) and well-suited for modeling adoption processes (Rand & Stummer, 2021), capturing cognitive process (Chion et al., 2011), and socio-ecological behavior (An et al., 2021).

Individuals who have previously experienced human-elephant conflict are more likely to perceive a higher risk of encountering another attack (Kiffner et al., 2021; Pratiwi et al., 2020) with decreasing risk perception as they located further from protected areas (Kiffner et al., 2021). However, because of habitat fragmentation and changes in land use, elephants may move beyond protected areas (Sanare et al., 2022) individual decision-making to utilize certain mitigation measures need to account human risk perception, not only their respective distance from protected areas, in their decision-making process (Carter et al., 2020) considering their likelihood to encounter such elephant attack. Protection Motivation theory (Rogers, 1975) has been widely used to model human decision-making for communities exposed certain level of danger such as floods (Faruk & Maharjan, 2022; Haer et al., 2016; Luu et al., 2019; Pagliacci et al., 2020; Raza et al., 2019; Schrieks et al., 2021), epidemics (Abdulkareem et al., 2018), and climate change (Dang et al., 2014). This research will address the adoption process of mitigation measures to reduce individuals risk perception under the presence of human-elephants conflict using protection motivation theory as the basis of human decision-making process.

2. Theoretical Background

2.1 Human Elephant – Conflict Mitigation

Various attempts to mitigate human-elephant conflict have been developed by communities and local policymakers and evaluated by many researchers (Berliani et al., 2018; Feuerbacher et al., 2021; Mutinda et al., 2014; Van Eden et al., 2016; Yoza, 2016) Many methods for mitigation have been developed by modifying the arrangement of agriculture based on elephant food preferences, driving elephants away, excluding agricultural areas, and changing the physical conditions of elephants.

Berliani et al. (2018) attempted to mitigate conflict based on elephant food preferences. This proposal supported by the elephant's selectiveness in choosing foods. Thus, farmers can determine which commodities to cultivate based on elephant food preferences to reduce human-elephant conflict. However, this effort has not been proven successful since elephants do not only consume the fruit of a plant but also other parts such as branches, leaves, and other parts as well (Berliani et al., 2018).

Meanwhile, Mutinda et al. (2014) reviewed mitigation techniques based on changing the physical conditions of elephants by detusking. This method is done by cutting the tusks of elephants that are considered rebellious and disturbing human areas. However, this attempt must be complemented by other mitigation measures such as fencing to isolate elephants from agricultural areas. In its implementation, this method has significant ethical challenges since modifying the physical condition of elephants is contrary to conservation principles and has negative impacts on elephants such as being shunned by their herd and difficulty finding a mate (Mutinda et al., 2014).

Another method was also evaluated by Yoza (2016) who found that in Indonesia, the mitigation method widely used and perceived as effective by the community is to drive away elephants using flying squads, fire, and noise. These mitigation measures are less effective because elephants can adapt to these mitigation efforts. Mitigation by isolating agricultural areas is done by installing trenches, fences, and electric fences (van de Water & Matteson, 2018; Van Eden et al., 2016). This method has drawbacks in terms of maintenance and supervision because the effectiveness of this method will decrease over time if had not been properly maintained (van de Water & Matteson, 2018; Van Eden et al., 2016). The use of low-cost electric fencing has been proven to be highly effective in reducing human-elephant conflict and suitable for moderate-scale farmers (Feuerbacher et al., 2021).

2.2 Protection Motivation Theory in Decision-making Process

According to Protection Motivation Theory, an individual is likely to adopt a protective measure if they perceive a threat that surpasses their threat threshold and possess the capability to execute such measures (Rogers, 1975). Researchers have primarily operationalized Protection Motivation Theory using regression-based techniques such as Structural Equation Modelling (SEM) (Luu et al., 2019; Wang et al., 2019; Zhu et al., 2022) and Logistic Regression (Liu & Jiao, 2018; Ward et al., 2018).

Several studies have found that other psychological theories related to individual decision-making can be combined with Protection Motivation Theory. Zhu et al. (2022) combined Protection Motivation Theory with the Theory of Reasoned Action (TRA), while Wang et al. (2019) and Luu et al. (2019) combined it with the Theory of Planned Behaviour (TPB). These studies attempt to further explain factors that cannot be explained using Protection

Motivation Theory alone. Each study concluded that the attitudes variable has an influence, either directly or indirectly, on an individual's decision-making intention. However, Wang et al. (2019) and Zhu et al. (2022) added that subjective norms are the most significant variable in determining an individual's decision-making intention, while Luu et al. (2019) did not reach the same conclusion in their study. The differences in conclusions drawn in each study may be due to differences in the type of problem addressed or the respondents of the study, so a comprehensive conclusion that can be applied to every type of problem cannot be found.

Protection Motivation Theory has been coupled with agent-based modelling as the basis for agent decision-making by several researchers (Abdulkareem et al., 2018; Burns et al., 2017; Haer et al., 2016; Pagliacci et al., 2020), focusing on different issues. However, most studies tend to model the threat variable in detail (Haer et al., 2016; Michaelis et al., 2020; Pagliacci et al., 2020; Wens et al., 2020) and tend to overlook the coping appraisals variable by treating it as a static latent variable. Meanwhile, coping appraisals have a more significant influence on an individual's intention towards decision-making than threat appraisals (Babcicky & Seebauer, 2019). Studies that coupled agent-based modelling with Protection Motivation Theory tends to use material aspects to operationalize the threat variable as a form of perceived threat level by an individual, such as loss of resources or financial loss while coping appraisals variable is modelled based on inter-agent interactions.

3. Methodology

3.1 Study Location

This study was located in three districts, namely Muara Sekalo, Semambu, and Suo-suo which was under the Datuk Gedang Ecosystem Esential Area covering an area of ± 18,074 hectares (Peraturan Gubernur Jambi No. 8 Tahun 2022: Pengelolaan Kawasan Ekosistem Esensial Koridor Hidupan Liar Datuk Gedang Di Bentang Alam Bukit Tigapuluh Kabupaten Tebo, 2022). The research subjects observed in this study are the interactions that occur between elephants and humans. This research aims to model the decision-making process of farmers in the area regarding the implementation of mitigation measures to prevent crop-raiding damage using protection motivation theory.

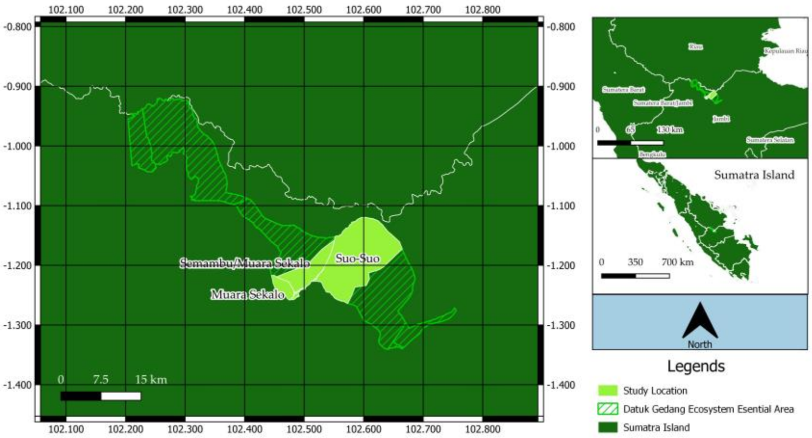


Figure 1. Study location

3.2 Agent-Based Model

Human-elephant conflict is a problem caused by negative interactions between humans and elephants in the same space (Shaffer et al., 2019). In the individual context, the implementation of human-elephant conflict mitigation techniques is aimed as an intervention to eliminate the impact of human-elephant conflict for an individual (Rand & Stummer, 2021). The individual's decision-making process to implement protective measure is a consequence of the exchange of information between one individual and another and the individual's interaction with the environment. The individual's decision to implement protective measure affects the individuals around them (Abdulkareem et al., 2018; Haer et al., 2016). Agent-based modelling is used to model the macro phenomenon of individual decision-making processes in aggregate because of the interaction between the individual and the environment and other individuals.

Similar studies have been conducted using ABM models to describe macro phenomena that occur as a result of individual decision-making caused by interactions between individuals and their social networks (Haer et al., 2016; Han et al., 2022; Schrieks et al., 2021). In addition, this research will be expensive if experimental processes are carried out on real systems, so ABM is used in research as a process of system abstraction in conducting experiments that will be costly if done directly on real systems (Mamboleo et al., 2021).

3.2.1 Model Overview

This Section describes the development process of an agent-based model following ODD Protocol (Grimm et al., 2020). The purpose of the models is to study the adoption pattern of elephant mitigation tools and financial conditions by the agriculture farmers under the presence of elephant crop-raiding using Protection Motivation Theory and the influence of communication channel. This model aims to analyse the decision-making process to elucidate the pattern of adoption of various mitigation measures for protecting crops from crop-raiding attacks and concentrates solely on farmers residing near the elephant home range area while only depicting the environment in relation to the impact of crop raiding on their crop. In this model, the agents being simulated are farmers, who own a subset of cells within a landscape referred to as “land”. Each farmer will cultivate one of two types of this crops on their land, namely palm oil tree (Elaeis guineensis) and rubber tree (Hevea brasiliensis). On each time-step the farmers will measure the subjective threat-levels that they perceive based on the past encountered elephant’s raid attack or the information given from their social network. The farmers will seek further information regarding the mitigation measures to protect their farmers based on their social network and third parties. The farmer’s decision-making process to adopt specific mitigation measures were designed based on protection motivation theory which in this simulation will be influenced by information passed by their social network and their threat levels. From this simulation, the output that was recorded in this simulation are: the threat levels perceived by the farmers, the mitigation measures that was adopted by farmers, and the farmers income and losses due to the elephant’s raid incident.

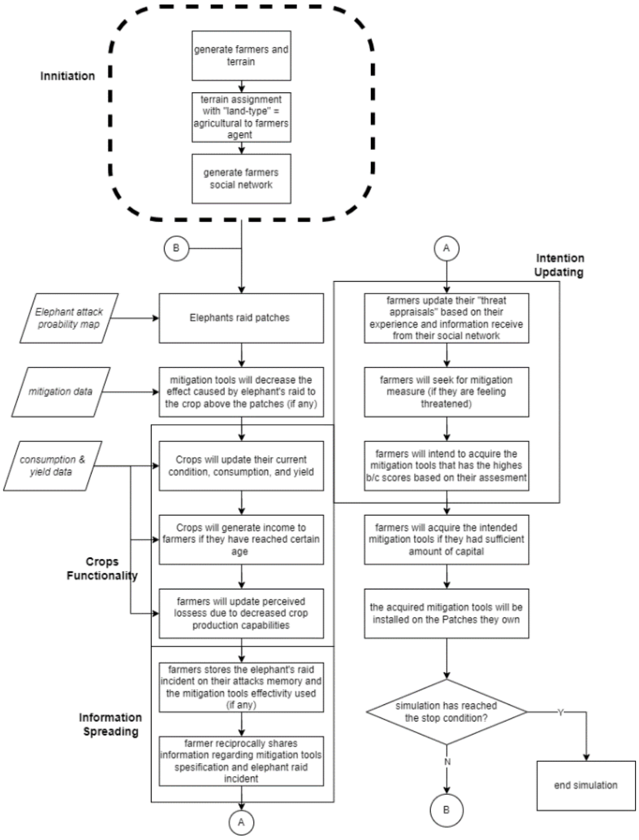


Figure 2. Process overview of the model

The simulation in this research will be conducted for 20 years with each timestep representing 3 months and located on the Desa Muara Sekalo and Suo Suo in the Datuk Gedang Essential Ecosystem Area. This area solely serves as a representative example from which we can obtain specific results from the region and potentially observe similar phenomena in other elephant-conflict areas. However, Different Characteristics of elephant's behaviour and home range might produce different results. Therefore, the detail technical implementation, for the sake of reproducibility, ODD is provided on the (Grimm et al., 2020).

3.2.2 Farmers Agent

Agent farmer represents a group of people who works together to take care of the same agricultural land. Each farmer has a spatial location in the simulation world and linked to their social network consisting of other farmers. The following sections describes the submodule used to operate farmers agents.

3.2.2.1 Human Decision Making

According to the Protection Motivation Theory, an individual will seek protective measures when they perceive a threat. The decision to adopt a specific protective measure is influenced by the perceived efficacy of the measure and the individual's self-efficacy in using it to mitigate the threat. This model simulates how farmers may implement protective measures based on their threat and coping appraisals. The perceived threat arises from economic losses due to crop raiding by elephants and the presence of crop raiding in their surroundings. If the threat appraisal exceeds a certain threshold, the farmer may seek alternative measures in the market to reduce their perceived threat. If the farmer feels threatened but is unable to reduce their threat appraisal, they may engage in non-protective behaviour. Once the farmers threat-appraisals exceed their individual threat threshold, the farmer will search for protective measures or mitigation products in the market. The farmer will select specific mitigation products based on their intention towards the products that they do not already possess. The Intention calculation towards a mitigation measures j is shown in Equation (1):

$$Int_j = \sum_{0}^{i} \alpha_i threat_i + \beta_{i,j} Coping_{i,j} \tag{1}$$

If the farmers agent has not adopted any mitigation measures before and reach their intention threshold levels for one or more products and given that the farmers are looking for mitigation products (shown by threat appraisals exceed their threat threshold), then the farmers will assess the best mitigation tools that already exceed their intention threshold using benefit-cost analysis (Eq. 2). Basically, the farmers will compare, from the information that the farmers had acquired, each of mitigation tools' effectiveness given the price. The farmers will select the mitigation products that have the highest benefit-to-cost ratio. But if the farmers already possessed mitigation measures, the farmers would compare the effectiveness of the mitigation measure with the highest benefit-to-cost ratio and their already possessed mitigation measures. If the farmers feels that the candidate is less effective than the already possessed one, the farmers then will seek the second highest benefit-to-cost ratio and so on. The farmers will not be having any intention to acquire any mitigation tools if none of the candidates is perceived to be more effective than the already possessed one.

$$P_b = \max_i \frac{b_i}{c_i} \tag{2}$$

The farmers agent will acquire the selected mitigation product if their financial capability exceeds the cost to acquire the mitigation product. If the farmers agent doesn't have the capability to acquire the mitigation product, then the farmers will withhold the decision to acquire the selected mitigation product until the farmers agent has the financial capacity to acquire it for a certain amount of time (which can be defined by the simulator).

3.2.2.2 Threat Model

To assess the threat appraisals of each farmer agent, the agents need three pieces of information, namely Epidemical Evidence, perceived economical losses, and crops-susceptibility. (1) Epidemical evidence operates using

Bayesian inference by calculating the effect of elephant's raid attack given on another farmers agent's crops when using certain mitigation tools or without. (2) Perceived economical losses accounts economical losses on crops when elephant's raid took place, calculated by summing the amount of expense by the farmers to rear the damaged crops due to elephant's raid and the losses of potential income from those damaged crops from the time it was damaged until end of crops' life. (3) Crops susceptibility is a measure of farmers agent's subjectivity of their crops' resilience towards elephant's attack that is dependent upon the crops' age.

3.2.2.3 *Information Spreading*

The farmers will receive information regarding a specific product from two sources once they reach a certain threat-appraisals level with each farmer having a different threshold level, namely their neighbour and external sources. The information received by the agent through the media follows the top-down communication concept proposed by (Haer et al., 2016) where the information will be spread massively, whilst having a small chance that an individual farmers will receive or believe the information. In this simulation it is modelled by high probability to reach ~N(.8, .05); showing the information will spread on huge amount of farmers agent; and low probability of success ~N(.2, .05); showing that a farmer doesn't necessary accept the information.

The information spreads by the neighbours depends on the social network structure inspired by the works of (Carter et al., 2020), distance-weighted preferential attachment model, where each agent will choose another agent relatively close to them until a certain number is reached (defined by the global variable: average-node-degree). Each farmers agents' neighbour will only give information based on their experience (e.g., the information gathered by experiencing using a certain mitigation measurements) and will not give information that has been gathered from media (external sources). The information gathered from their neighbours has 100% accuracy that the information will be reached and received.

3.2.3 Patches

Patch represents a land-area that stores various geographical information and/or can become some types of landscape determined by the state variable "Land-Type". If the "land-type" state variable is coded "agriculture-land", it means that that patch is owned by someone, declared by "ownership" state variable. Each timestep, the 'agriculture' patch will. At each timestep, patches with agricultural type have a chance of being attacked by elephants, updating the crop condition if a successful elephant attack occurs on those patches, and sending income to their owners based on the crop condition. The following sections will describe the patches submodule.

3.2.3.1 *Elephant Attack Model*

Each of the farmers agriculture inherit a probability of getting visited by the elephant that was given by attack probability raster map stored in *visited-probability-from-raster-data* state variable. For each timestep, each agriculture land will acquire a random number that was stored in *rng-visited-chance*. Each agriculture land will compare this generated random number and compare it to *visited-probability-from-raster-data*. If the *rng-visited-chance* is smaller than the *visited-probability-from-raster-data*. The simulator will choose 10 agriculture land that has greatest difference between the random number generated and the *visited-probability-from-raster-data* state variable. If we consider A to be the list of all agriculture land that has higher *visited-probability-from-raster-data* values than *their rng-visited-chance*, then subset B is the patches that will be raided at timestep-t which was shown in Equation 3.

$$B = arg \max_{A' \subset A, |A|=10} \sum_{a \in A'} a \tag{3}$$

3.2.3.2 *Crops Growth Model*

The farmers' agent's that possessed a crop will expense a certain number of financial resources to cultivate their crops which is dependent to the crops age, the crops condition, and the type of crops itself. Generally, the crops will not generate income until the crop reaches a certain age, though each crop will be able to generate revenue differently depending on the crop's age.

When the crops were encountered an elephant attack and under the condition that the mitigation tools installed on the patch failed to deter elephant's coming to that patch (see more on mitigation effect on crops), it will receive a certain amount of damage causing a permanent decrease in the crop condition. The damage that the crop will receive will be dependent on the crop's age and will diminish as the crop gets older. This will also cause the decreasing capability of the crop to produce yields and indirectly reduce the potential income of the farmer. Concurrently, the farmers agent which possessed the crops will be perceived a certain number of economic losses due to decreasing conditions of their crop.

4. Results

According to the literature, the modelled plant is known to not directly produce commodities for several years after being planted (Pakalla Marampa' & Af, 2014). Subsequently, plants under the age of 5 are more vulnerable to elephant attacks because they will be destroyed (Ajudin et al., 2020), unlike plants that can produce commodities and will not be destroyed when attacked by elephants. Therefore, it is crucial to take care of these plants while also protecting them from elephant attacks so that farmers can generate optimal income.

In exploring the model, this study will be divided into two experiments with different objectives. In the first experiment, further exploration of the adoption process of protective measures used in this model will be conducted. This first part also serves as a baseline scenario for studying the adoption process of protective measures. In the second experiment, model exploration is focused on exploring the impact of financial well-being on the adoption process and the financial impact received by farmers as the consequence this adoption process. To achieve this, several scenarios were conducted by varying the average farmer's initial wealth to assess the adoption rate of certain mitigation measures and how they will impact their net income based on average population wealth.

4.1 Experiment I: Exploration on Adoption Process

The simulation conducted in this section is conducted using a single scenario to explore the adoption process in this model, which is built using protection motivation theory combined with benefit-cost-assessment as the final decision-making process in acquiring protective measures. The simulation will be carried out for 80 timesteps using parameters described in Table 1. (See ODD for an explanation of each parameter).

Table 1. Parameter Values used in Experiment I

Parameter	Values
farmers-population	50
avg-wealth	10000000
average-node-degree	6
std-wealth	1000000
attacks-memory-len	40
std-attack	10
mean-attack	20

4.1.1 Threat Appraisals Effect towards Adoption

Threat appraisals are a latent variable that indicates an individual's sense of threat due to elephant's raid attacks. In this study, it is assumed that threat appraisals are influenced by epidemic evidence, which is an individual's perception that there is potential for damage if elephants visit their land, perceived losses, which are the losses that farmers have received due to elephant's raid attacks, and crop susceptibility, which is the vulnerability of crops when attacked by elephants modelled as a function of plant age. PMT theory assumes that an individual will seek a protective measure if they feel threatened with the aim of eliminating that threat. In this section, the causal relationship between threat levels and the adoption of a protective measure using the Granger causality test. In this scenario, there is significant Granger causality when the lags used are 10 (Table 2.). In other words, there is Granger causality between threat appraisals and the adoption of protective measures.

Table 2. Granger Causality Threat Appraisals towards Adoption for Various Number of Lags

Granger Causality direction	Number of Lags	F test	P value
Threat Appraisals → Adoption	7	1.0338	.4181
	8	1.1056	.3742
	9	1.9331	.0678
	10	8.0190	.0000*
	11	24.5649	.0000*

**Significant at p < .05*

4.1.2 Adoption Process

Figure 3 shows that the adoption of mitigation techniques reached its peak at timestep 24 and tended to be constant until timestep 80 (20 years). With a total of 9% new adopters reaching peak adoption at timestep 24. If we look further into the adoption of each mitigation technique, most farmers choose to adopt electric fences where 37% adopt electric fences and take up to 40 timesteps and tend to be constant thereafter until the end of the simulation. In this scenario, 25% of the population are new adopters of electric fences throughout the simulation. Bonfire reached peak adoption with 40% adoption at timestep 27 and then experienced a drastic decline at timestep 28 and tended to be constant thereafter until the end of the simulation. There was a decrease in the number of adoptions of spotlight mitigation techniques by 3% during this simulation. Over time, the use of carbide cannons tends to decrease, with only 13% of farmers adopting them by timestep 30, and this number remains constant until the end of the simulation. In this experiment, there was a decrease in the number of adoptions of carbide cannon mitigation techniques by 17%.

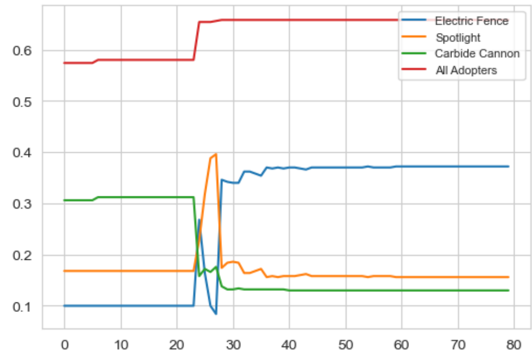
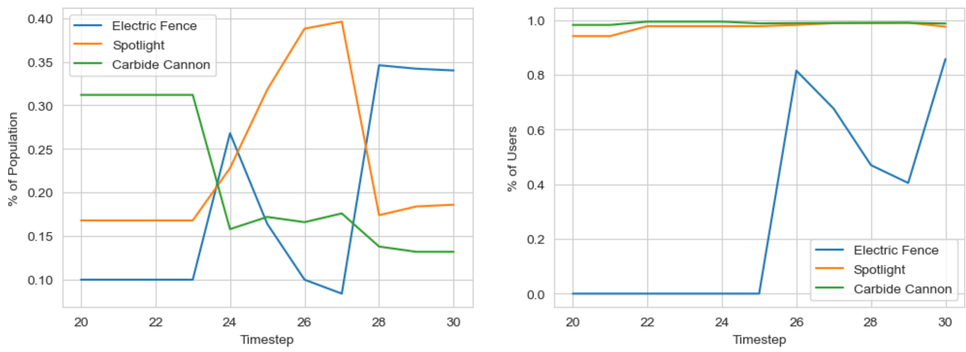


Figure 3. Temporal pattern of farmers that implementing mitigation measures on experiment (i)

Electric fences have the highest effectiveness even with a relatively high cost of acquisition and operational cost compared to the other two mitigation techniques. The effectiveness of mitigation is influenced by the ability of farmers to meet the operational costs of a mitigation technique. The effectiveness of this mitigation technique will be zero if farmers are unable to meet the operational costs of this mitigation technique. Each farmer will adopt the most effective mitigation technique based on information received from external media entities or from their social network so that the information obtained by these farmers can differ from one another.

Most farmers adopt electric fences because every farmer who uses electric fences feels their effectiveness and spreads this information on their social network. At the same time, external media entities also provide exposure to each farmer with a certain procedure related to its effectiveness. Thus, the perceived effectiveness value by farmers will reach a convergence approaching its true effectiveness value after farmers have financial ability to meet operational costs from a mitigation technique so that farmers will tend to choose electric fences over other methods. However, there is variation in adoption that occurs between timesteps 20-30 but there is no addition of new adopters from a mitigation technique. This indicates that there are no new farmers who significantly adopt a mitigation technique, but this variation is dominated by farmers switching between one mitigation technique and another.

Variation occurred when farmers begin to receive income from their crops, therefore farmers had the financial capability to adopt a mitigation technique or switch to a mitigation technique that is perceived to be more effective than the one they are currently using. At timestep 23, 12% of carbine cannon users switched over to electric fence or spotlight. This can be explained because carbide cannon is a mitigation technique that has the lowest true effectiveness value among the two mitigation techniques. However, at timestep 24, 17% of electric fence users switched over to spotlight. This can be explained because electric fence users were unable to meet the operational costs of electric fences, so the effectiveness of the adopted electric fences decreased drastically.



(a) (b)

Figure 4. (a) Temporal pattern of farmers that implementing mitigation measures during timestep 20 – 30; (b) Temporal pattern of functioning mitigation measures during timestep 20 – 30.

Figure 4(a). shows that during timestep 20-24, the number of farmers adopting electric fences increased by 17%, but no farmers were able to maintain the functionality of electric fences by meeting the operational costs of electric fences. This can be proven by significant Granger causality between the number of electric fence users who are able to meet the operational costs of electric fences with fluctuations in electric fence users switching to other mitigation methods with a lag amount of 2 (Table 3). At the same time, farmers who previously adopted electric fences and some farmers who used carbide cannons switched to spotlight, resulting in an increase in spotlight users by 20%. However, at timestep 25, the functionality of electric fences increased along with the income obtained from harvesting commodities cultivated by farmers (note: harvesting is done every 4 timesteps). Thus, farmers who use electric fences at that time will have high effectiveness in protecting their crops from elephant attacks. These electric fence users will then spread information about the effectiveness value of electric fences to their social network, causing an increase in electric fence adopters by 25% which occurred at timestep 28. Figure 4(b) combined with an increase in farmer wealth at that time due to income obtained from planted commodities.

Table 3. Granger causality electric fence functionality towards electric fence adoption for various number of lags

Granger Causality direction	Number of Lags	F test	P value
Mitigation Functionality → Adoption	1	2.8303	.1119
	2	11.0872	.0015*
	3	12.3335	.0011*
	4	12.9656	.0024*
	5	34.6172	.0022*

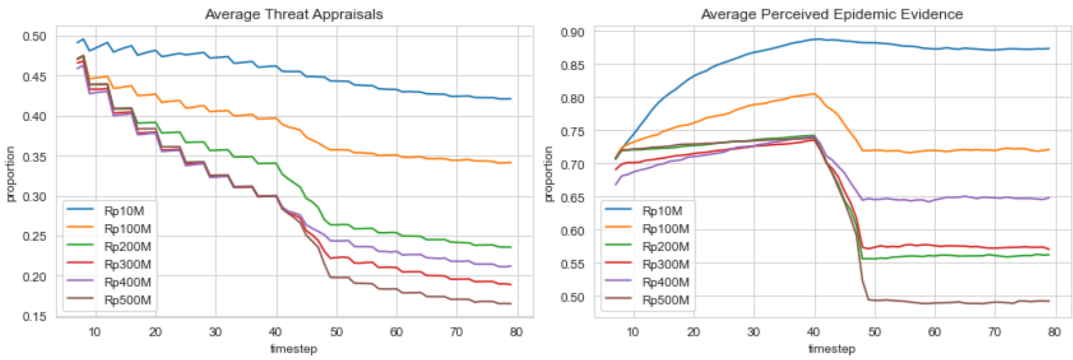
**Significant at p < .05*

The variation in the adoption process is due to the decision-making process of farmers to acquire a mitigation measure used in this model, which only considers perceived effectiveness and the cost of acquiring a mitigation technique after the farmer feels the need for protective measures. Fluctuations in adoption are largely due to farmers having the financial resources to acquire mitigation techniques but lacking the ability to meet their operational costs, resulting in zero effectiveness. This is because farmers' income, which comes from the commodities produced by their crops, varies over time. As a result, the cash reserve held by farmers becomes an important factor to consider due to the uncertainty of their income.

4.2 *Experiment II: exploring the impact of financial well-being on the adoption process*

Based on the second experiments, it was observed that there was a variation on the adoption process. In this second experiment, the impact of the cash reserve held by farmers at the start of the simulation on the adoption process and the financial consequences for farmers of this adoption will be further elaborated. Six scenarios were developed by initializing the average farmer's wealth at the beginning of the simulation, namely: IDR 10 million, 100 million, 200 million, 300 million, 400 million, and 500 million. Based on this scenario, several outputs are presented in this section in terms of the variable of interest: (1) Threat Levels, (2) Epidemic Evidence, (3) Income and Perceived Losses, and (4) Epidemic Evidence.

4.2.1 Threat Appraisals



(a) (b)

Figure 5. (a) The temporal pattern of average threat appraisals in various scenarios; (b) Average Condition of Crops overtime in various scenarios

Epidemic Evidence refers to an individual's perception that there is potential for damage if elephants visit their land. This perception is based on historical events of crop damage when elephant attacks occurred on nearby land (see the Threat Appraisals sub-model in the ODD). In this model, it is designed that each farmer could recall the first 40 events that occurred in their social network.

In Epidemic Evidence, there is an increasing trend in the first 40 timesteps. However, there is a decrease after 40 timesteps, where the higher the initial cash reserve, the faster the decrease in the epidemic trend. This occurs because of the use of mitigation measures applied by the farmers, leading to a decrease in their perception of the potential impact if elephants raid occurs on their land. More than 90% of farmers adopt a mitigation technique in scenarios III, IV, V, VI, while only 65% and 85% do so in scenarios I and II, respectively. This phenomenon caused the farmers to start perceiving the benefits of mitigation measures installed on their agriculture land based on their past experiences of the mitigation measure's capability to prevent those attacks. However, there is no linear relationship between the use of mitigation techniques and perception. For example, Scenario V has a higher proportion of adopters compared to Scenario IV but has a higher Epidemic Evidence value. This phenomenon is influenced by how effective the mitigation technique is in performing its function, which will be discussed in the following subsection.

Threat appraisals refer to an individual's perception of their level of threat because of elephants' raid events. In this study, threat appraisals are influenced by the current age of the crops they own, the losses farmers have incurred due to elephant attacks, and Epidemic Evidence. The temporal pattern of the average threat level perceived by the farmers is shown in Figure 5(a). It is shown that, in most scenarios, threat levels tend to decrease after 40 timesteps (10 years) after the simulation started, in line with the decrease in Epidemic Evidence. However, in Scenarios I and II, there is no significant decrease, implying that their threat level remains high during production time due to low mitigation measure's adoption and lack of financial capabilities to remove such threat. Figure 6 shows the temporal pattern of total adoption rate from different scenarios.

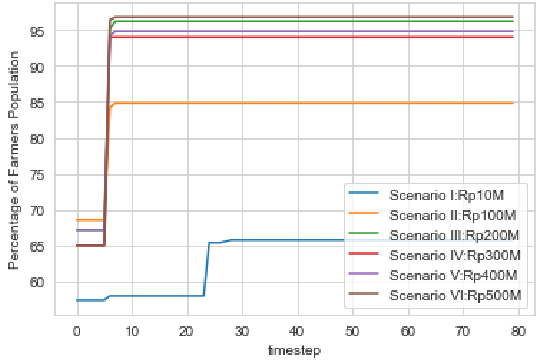


Figure 6. Temporal pattern of farmers that implementing mitigation measures

4.2.2 Adopted mitigation measures by the farmers

There is a tendency to increase the adoption of mitigation tools as the initial wealth of the population is increasing. Figure 7(a) and Figure 7(b) shows that on Scenario I and Scenario II, peak adoption happened at the 65% and 85% of the population, consecutively, while the other scenario had their peak adoption at above 90% of the population. Subsequently, amongst the scenario, most of them happened at the first year (timestep 4) since the planting happened, except on the 1st scenario which happened at the fifth year (timestep 24) since the planting happened. There was a consistent pattern that as the average initial wealth increased, the tendency of switching from one mitigation measure to other starts decreasing, as presented in Figure 7. As elaborated in Experiment I, the phenomenon occurred due to insufficient cash reserve held by the farmers to fulfil the mitigation's operation cost. However, the tendency of switching from one mitigation measure to another increasing on the second scenario (IDR 100 million) and starts decreasing at the third scenario (IDR 200 million). It should be emphasized that, in this model, farmers will only transition to other mitigation measures if they perceive the current measure to be ineffective and the mitigation measures becoming ineffective if only the farmers cannot fulfil the operation cost that occurred overtime if the farmer possess such mitigation measures.

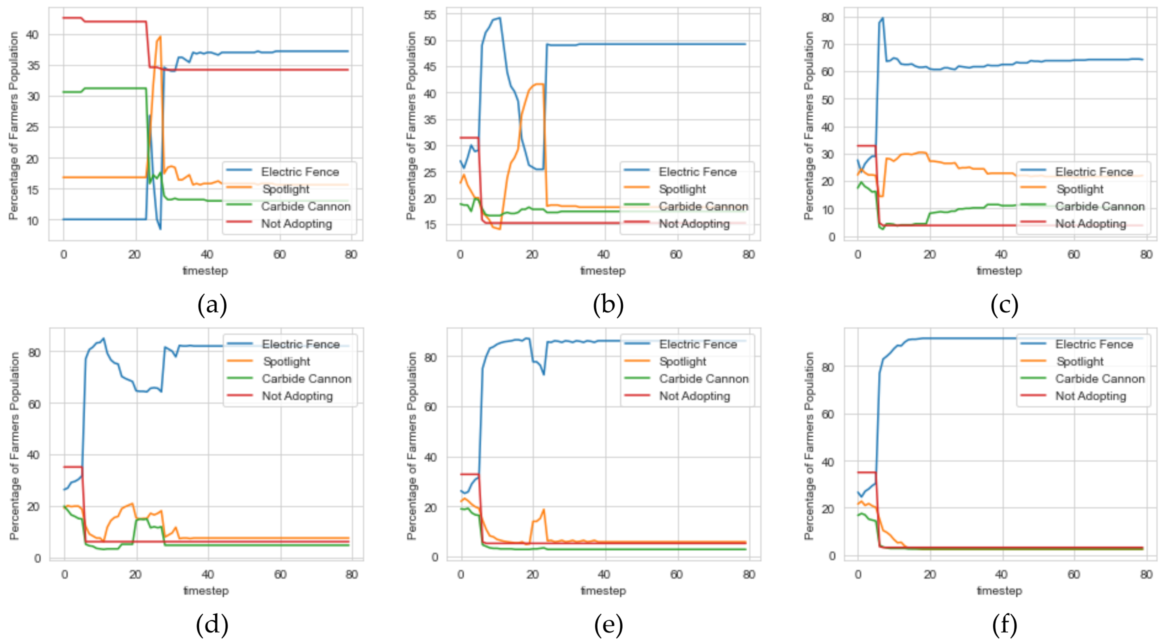
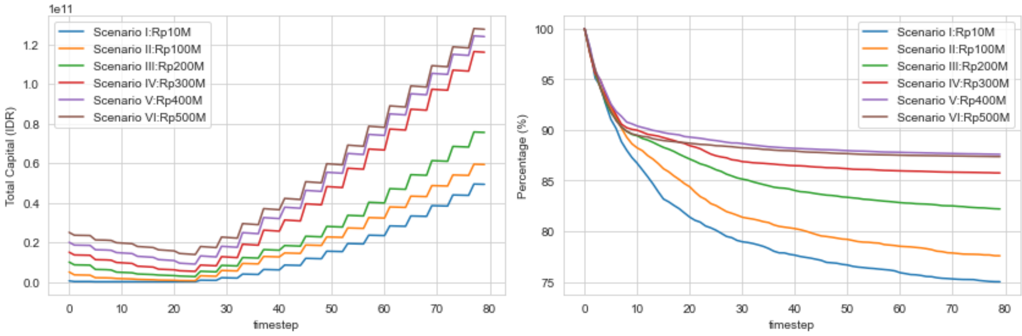


Figure 7. Temporal pattern of adoption in various scenarios. (a) Scenario I; (b) Scenario II; (c) Scenario III; (d) Scenario IV; (e) Scenario V; (f) Scenario VI

Most of the adoption starts at stable phase, where there are no more switching happens, starts at timestep 40 (10 years) on scenario I, II, and III and at timestep 24 (6 years) which most of them starts converging to adopting electric fences. These temporal patterns and switching behaviour from one mitigation to another amongst these scenarios will bring impact to their crop's conditions and their net income at the end of the simulation.



(a) (b)

Figure 8. (a) The temporal pattern of total capital at timestep-t in various scenarios; (b) Average condition of crops overtime in various scenarios

4.2.3 Consequences of Adopting Mitigation Tools

As presented in Figure 8(b), 10% of the reduction in conditions happened at the first 5 timestep (16 months) after the crops planting begun. This can be attributed to the fact that, at that time, many farmers had not yet adopted certain mitigation techniques. However, after 5 timestep (16 months), the last three scenarios show no significant reduction in terms of average crops conditions while the first three scenarios still encounter reduction. This was suspected due to the percentage of farmers that implemented mitigation measures and the behaviour of switching from one mitigation measure to another because the farmers cannot fulfil the operation cost that occurs overtime. This results in a significant difference in terms of net income received by the farmers overtime from the three former scenarios to the three latter as shown in Figure 8(a).

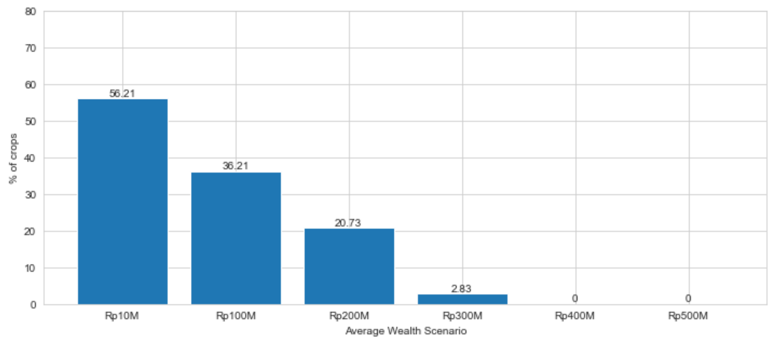


Figure 9. Average undermaintained crops overtime

In addition to the aforementioned causes, if we highlight the II and III scenarios, there are two other intermediary factors responsible for the income disparity resulting from the adoption of a mitigation technique. Despite high adoption rates of mitigation techniques in scenarios II and III, the percentage of under-maintained crops is also high (Figure 9). This indicates that, although most farmers in these scenarios have the financial means to adopt a mitigation technique, they are unable to properly maintain their crops to achieve optimal income. Furthermore, when examining the percentage of functional mitigation tools in each scenario, it is noteworthy that the highest percentage of non-functional tools is found in scenarios II and III. Of all the adopters of mitigation techniques, more than 14% of the tools were non-functional, with over 10% being electric fences, which were deemed to have the highest effectiveness ([Davies et al., 2011](#)). In Contrast, only 7% of the mitigation measures adopter couldn't fulfil the mitigation operation cost and less than 2% in the 4th and 5th scenario (Figure 10). This was due to farmers in these scenarios being unable to meet the operational costs of the mitigation tools. This explains the high variation in the temporal pattern of adoption, where farmers switch from electric fences and then revert to adopting them.

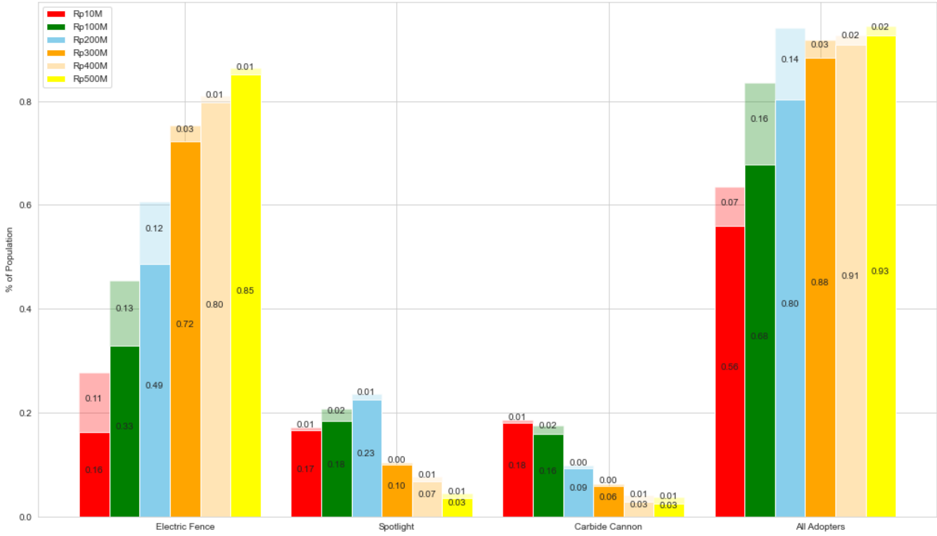


Figure 10. Functioning mitigation measures by different average wealth scenario

It can therefore be concluded that, although farmers may have sufficient funds to adopt a mitigation technique, this does not guarantee that they will achieve optimal income from their crops. It should be noted that when a farmer adopts a mitigation technique, they also have the responsibility of financing the possessed mitigation measures to protect against crop damage from elephant raid attacks while also simultaneously considering sparing some of their capital to maintaining their crops to achieve maximum yield.

4.2.4 The total net Income and Perceived Losses by the farmers Amongst different Scenarios

Figure 11 shows the Net income received and the losses perceived by the farmers. When examining the first three scenarios, there is an increase in both income and perceived losses experienced by farmers, but not significantly. While on the latter three scenarios, there is no trend of increasing income, but there is a trend of decreasing perceived losses with the addition of average initial wealth. However, there is a significant difference in net income between the first three scenarios and the last three scenarios. In the first three scenarios, there is an increase in perceived losses due to resource expenditure by farmers in scenarios II and III for crop maintenance. These farmers experience greater losses when there are elephant attacks because, in scenarios II and III, farmers spend more of their resources on crop maintenance.

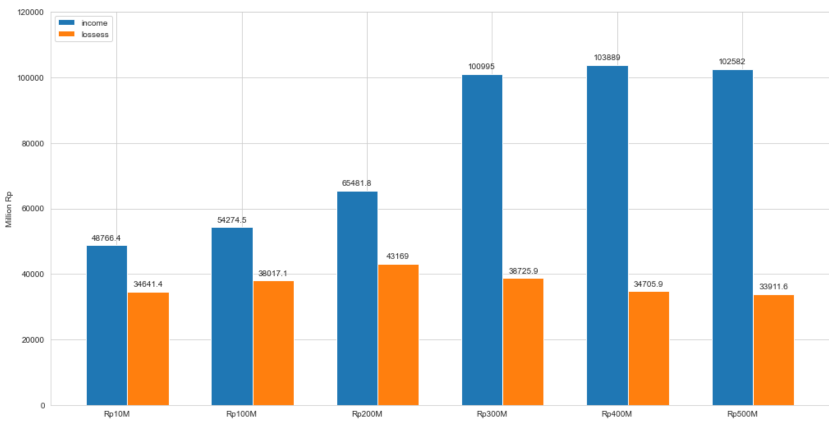


Figure 11. Total perceived losses and income by different average wealth scenario

In scenario I, farmers do not have sufficient resources for crop maintenance, so they do not perceive any losses from elephant attacks as no costs were incurred for crop maintenance. This can be seen in Figure 9 regarding under-maintained crops. Additionally, farmers in scenarios II and III adopt more mitigation techniques compared to farmers in scenario I. As a result, farmers in scenarios II and III achieve higher net income compared to farmers in scenario I.

However, when comparing scenarios II and III with scenario IV, the difference in net income is significant, even though the number of farmers adopting mitigation techniques is not much different from farmers in scenario IV (see Figure 6 regarding adoption). This can be explained by the insufficient financial resources of farmers in scenarios II and III to finance crop maintenance and mitigation tool maintenance. This is evidenced by the significant difference between scenarios II and III and scenario IV in terms of under-maintained crops (Figure 9) and functional mitigation tools (Figure 10). The high percentage of non-functional mitigation tools in scenarios II and III (16% and 14%, respectively) results in a significant difference in crop conditions between scenarios II and III and scenario IV (see Figure 8(b) regarding crop conditions).

In the last three scenarios (IV, V, and VI), there is no significant difference in net income among the three scenarios. This is because, in these scenarios, the majority of farmers have sufficient financial resources to adopt electric fences as the most effective mitigation tool, maintain their functionality, and maintain their crops. In these three scenarios, most farmers (90%) adopt a mitigation technique, with most of them adopting electric fences (> 80%). It can therefore be concluded that the addition of initial wealth after scenario IV does not have a significant impact on the net income received at the end of the crop's productive life. The author argues that, if the cash reserves of a population has reached or exceeded the initial wealth in scenario IV (IDR 300 million), then another factor that can be done to increase net income at the end of crop production is to acquire a mitigation tool as soon as possible with planting time. This opinion is justified by the fact that farmers will experience the greatest losses when their crops are attacked by elephants when the crop is less than 5 years old (Ajudin et al., 2020).

5. Discussion

Protection Motivation Theory (PMT) has been widely used to explain the phenomenon of decision-making processes under the presence of threat for adopting protective measures with the aim of eliminating threats (Abdulkareem et al., 2018; Haer et al., 2016; Schrieks et al., 2021; Wens et al., 2020) and can be applied in the context of Elephants' crop raiding. In this study, threat appraisals are modelled as a combination of social contagion processes (Abdulkareem et al., 2018; Haer et al., 2016), modelled by an agent obtaining information from their surroundings, and internal processes (Abdulkareem et al., 2018), namely the impact of elephants' crop raiding causing damage to their crops. Threat appraisals can be a trigger for protective measures (Bamberg et al., 2017) to eliminate the threat of elephant raid attacks, as evidenced by using the Granger causality test that threat levels temporally have Granger causality towards the adoption process. This findings in line with several research that use PMT as decision-making foundation of agents (Haer et al., 2016; Schrieks et al., 2021; Wens et al., 2020).

This model combines the psychological model of PMT to model the upstream decision-making process (information gathering) and an economic model using benefit-cost analysis for the downstream decision-making process. However, this model only considers cost-of-acquisition in its acquisition process and does not consider the characteristic Source of Income from farmers. Income obtained from farmers comes from commodities produced by their crops, so farmers' income is not always the same over time. This causes fluctuations in adoption due to farmers in this model being able to meet acquisition costs but not having sufficient financial resources to meet operational costs due to income obtained during certain periods that are still small. Therefore, in this study, a scenario was developed to explore the cash reserve held by farmers at the start of the simulation to further explore their financial resilience to protect their crops from elephant's raid attack and concurrently maintaining their crops to produce optimal yield.

From all the scenarios tested on Experiment II, the adoption of electric fences was found to have the highest proportion compared to other mitigation methods. Despite a significant number of farmers initially switching from electric fences to other mitigation techniques and then back to electric fences during the simulation, further analysis revealed that this shift was primarily due to farmers being unable to allocate their financial resources to cover the operational costs of the electric fences, resulting in decreased effectiveness. However, when farmers' crops began to produce enough yields to afford electric fences, they switched back to using them. This indicates that while electric fences are an effective mitigation tool (Davies et al., 2011), they require substantial operational costs to maintain their effectiveness (van de Water & Matteson, 2018) hence large amounts of capital are required (Shaffer et al., 2019). A similar phenomenon occurred in Bukit Tigapuluh National Park Jambi, where some groups of farmers who had been granted electric fences tended to have difficulty in maintaining the fences due to insufficient funds (Ajudin et al., 2020).

It was observed that farmers with low amount of cash reserves (IDR 10 million) were unable to acquire electric fences due to its high acquisition cost (Shaffer et al., 2019), while farmers with moderate cash reserves (IDR 100-200 million) were able to acquire electric fences but struggled to finance their operation and allocate financial resources for crop maintenance (Kamdar et al., 2022). At least 20% of the total production cost (IDR 400 million) of cash reserves is required to generate maximum net income from the crops produced. It is safe to assume that farmers in elephant-human conflict zones need to have a higher amount of cash-in-hand compared to farmers not in conflict zones.

There is a trend of decreasing damage rates to oil palm and rubber crops as the plant age increases, where most of the damage occurs in the first five years due to the greater impact of successful crop-raiding incidents on young plants (Tamtama, 2018). Farmers with high cash reserves experienced a 10% decline in condition in the first year and no significant damage afterwards because most farmers had adopted electric fences in the following year. Farmers with low cash reserves continued to experience declining condition due to their inability to adopt electric fences. Electric fences need to be implemented as early as possible on plantation land relative to planting time to prevent large damage when the plants are still unproductive. In a different case where the crops cultivated by farmers are legumes and corn, it is recommended to use protective measures only when the plants are mature and ready for harvest (Kiffner et al., 2021). Characteristics of the crops being cultivated becomes important consideration in determining the strategy for implementing mitigation measures.

As discussed in previous sections, insufficient financial resources can lead to a chain of effects that prevent farmers from adopting mitigation techniques and/or properly maintaining their mitigation tools or crops, ultimately resulting in a decrease in the net income that farmers should receive. Aligned with Adimassu & Kessler (2016), farmers with low cash reserves don’t have financial capacity compared to farmers with high cash reserves, thus preventing them to eliminate the threats they perceived. This phenomenon can trap low-income farmers in a cycle that causes them to perceive a high level of threat. In line with the opinion of Nyirenda et al. (2018), financial well-being is an important factor in resolving elephant-human conflict. According to this study, low-income and moderate-income farmers receive significantly lower income compared to high-income farmers. Additionally, the perceived threat level of low-income farmers remains high over time, unlike high-income farmers who experience a significant decrease in their perceived threat level.

Continuously high threat levels have resulted in many negative impacts on elephant conservation, such as elephant killings (Nuryasin et al., 2014; Nyirenda et al., 2018) and a decline in elephant populations (Rachmawaty et al., 2022). In a study presented by Mustafa & Abdullah (2018), the community has perceived elephants as pests to their crops. This is indirectly caused by the high level of threat perceived by farmers. If this is not addressed promptly, the negative stigma will persist and potentially normalize elephant killings as a means of resolving the impacts of elephant-human conflict.

The government should begin to consider the financial well-being of farmers in conflict areas as a factor in designing policies to resolve elephant-human conflict. Financial well-being considered to be one of the factors that contribute to negative perceptions of elephants and indirectly exacerbate the impacts of elephant-human conflict. In line with (Nyirenda et al., 2018) research, this study argues that there is a reciprocal effect between farmers’ ability to mitigate the impacts of elephant raid attacks and the income received by farmers. Meanwhile, the low ability of farmers to mitigate the impacts of elephant raids affects the level of threat perceived by farmers.

5.1 Managerial Insights

This study emphasizes the importance of considering the financial resilience of farmers in enhancing their ability to implement mitigation techniques to prevent crop-raiding incidents. The amount of cash reserves affects the farmers' ability to protect their plantation land, ultimately influencing their final income. Electric fences are the most widely adopted protective measures by farmers as a mitigation technique with the highest effectiveness among others. However, the farmers' ability to adopt and maintain electric fences depends on the amount of initial capital they have. This is because electric fences require expensive installation and maintenance costs (Kamdar et al., 2022).

The findings in this study found that only farmers who had initial capital above 20% (IDR <400 million) of the total palm oil production costs were able to use electric fences from the beginning. Farmers with low cash reserves (< IDR 100 million) were unable to buy electric fences, while farmers with cash reserves (IDR 200 – 300 million) were unable to finance the operation of electric fences. In addition, the number of farmers who adopted electric fences affected the amount of land damage that occurred and ultimately the final income of the farmer population. This resulted in farmers with low cash reserves generating 50% income, while farmers with medium cash reserves generating 37% lower income than farmers with high cash reserves who were able to protect their plantations well. For palm oil and rubber crops, financial assistance needs to be prioritized for farmers who have palm oil planting age 0 - 8 years compared to plants that are over 15 years old. This is because damage is most likely to occur at that time if they experience crop-raiding incidents, especially farmers will lose all potential income that will be obtained by the plant so that farmers need to maintain their plantations more intensively in the early planting period. Although farmers have been able to adopt electric fences, the use of mitigation techniques cannot eliminate threats completely because electric fences themselves do not guarantee 100 percent security from crop-raiding incidents. It is known that in the long run it can trigger a shift in conflict points to other areas (Osipova et al., 2018). Therefore, a holistic conflict resolution strategy still needs to be implemented.

5.2 Future Research

There are several limitations that should be addressed for future research. In the context of modeling, the model used in this study does not consider the heterogeneity of agents in terms of decision-making strategies (van Duinen et al., 2016). Additionally, this model also only models' elephants as abstract entities and does not account for the changing trend of elephant's raid attack, where in the field conditions there is a shift and increase of elephants' raid attack due to increasing agricultural activities (Moßbrucker, et al., 2016). Therefore, future model development can be done by considering the decision-making strategy of farmers and modelling elephants as separate entities that move and visit farmers' fields with certain heuristics(Mamboleo et al., 2021). This research only explores the effects of initial cash reserves to the adoption process which leads to their net income at the end of the simulations. However, this model presented in this research can explore the effects of social networks to explain the adoption process and their net income. Moreover, it is widely known that the phenomenon of HEC in the shared landscape are site specific and species-specific, therefore the results might differ from one location to another. The author encourages future research to explore the effects of social networks towards the adoption of mitigation tools and using this model to explore the phenomenon of adopting mitigation tools and the effects their decisions on the specific site

6. Conclusion

This study sequentially presents the serial effects that occur, starting from farmers' decisions to adopt a mitigation technique to the net income received by farmers based on the average initial wealth scenario of each farmer. Farmers with low initial wealth tend to adopt a mitigation technique and properly maintain their crops. Meanwhile, farmers with moderate economic conditions can adopt mitigation techniques but experience financial difficulties in maintaining them. On the other hand, farmers with high economic conditions can adopt and maintain their crops. This results in a significant difference in final income between middle- and lower-class farmers and high-class farmers. Farmers need cash reserves of at least 8% of the total production cost required for maintenance from the planting phase to the end of the crop's life before starting oil palm cultivation to optimally maintain their crops and their mitigation tools to prevent losses caused by elephant attack.

The perceived threat level of farmers decreases at a higher rate as their initial economic conditions improve during the simulation. However, in low economic conditions, there is no significant decrease in the threat level trend, indicating that the threat is always present throughout the life cycle of their crops. If left unchecked, high, and prolonged threat levels can result in negative perceptions from the community that threaten elephant conservation. Furthermore, there is potential for normalizing elephant killings as an effort to reduce the impact experienced by farmers due to elephant-human conflict.

Although if a farmers could acquire and maintain a mitigation tool, private adopted mitigation tools cannot eliminate the threat occurred due to elephant's raid event. To address this issue, the government needs to intervene to eliminate the residual threat perceived by farmers. Therefore, the government should use the economic conditions of the target community as a reference in formulating strategies for resolving elephant-human conflict and take part in the resolution process between elephant-human conflict.

Appendix: ODD Protocol

PURPOSE

The purpose of this model is to study the adoption pattern of elephant mitigation tools by the agriculture farmers under the presence of elephant crop-raiding using Protection Motivation Theory and the influence of communication channel.

ENTITIES, STATE VARIABLES, SCALES

Entities

- **Patches**
  Patch represents a land-area that stores various geographical information and/or can become some types of landscape determined by the state variable “Land-Type”. If the “land-type” state variable is coded “agriculture-land”, it means that that patch is owned by someone, declared by “ownership” state variable.
- **Farmers**
  Agent farmer represents a group of people who works together to take care of the same agricultural land. Each farmer has a spatial location in the simulation world and linked to their social network consisting of other farmers.
- **External Media**
  External media is an abstract representation of third-party entities that are involved in the process of elephant’s mitigation tools by the agriculture farmers by providing (advertising) product’s information to the farmers through top-down communication process.

Parameters

Parameters were the global variable that was static overt the simulation time and can be configured by the simulators.

Parameter	Variable Type and Units	Meaning
farmers-population	integer	The number of farmers agent that will be simulated
avg-wealth	float (IDR)	The average amount of cash that will be held by the farmers agent at the beginning of the simulation
average-node-degree	float	The average number of other farmers that will be assigned as the farmers social network
std-wealth	float (IDR)	The deviation amount of cash that will be held by the farmers at beginning of the simulation
attacks-memory-len	Integer	A number that regulates the maximum memory span of a farmers’ agent to store information about elephant attacks and their impact on his social network that the farmers can remember.

std-attack		The deviation value of elephant's raid event that will occur to farmers agricultural land during timestep-t
mean-attack		The average value of elephant's raid event that will occur to farmers agricultural land during timestep-t

State Variables

- *Patches state variable*

Table 2. Patches State Variables

Variable Name	Variable Type and Units	Meaning
cell location	Static	the location of a particular patch
Land_Type	Static	type of a land use of that patch
Ownership	Static	The belonging of a particular patch
Crop_type	Static	Type of crops cultivated on the patch
Age	Dynamic; integer	The age of a crop on that patch
Crop-lifetime	Dynamic; integer	The crop lifetime on that patch
Crop-condition	Dynamic; float	The condition of a crop on that patch
Time-to-harvest?	{0,1}	1: the yield produced by the crops are ready to be transferred to the owner 0: there are no yield
Crops-ability-to-produce	0: could produce, 1: end of life 2: farmers incapable to meet the cost required	The crops capability of producing yield that should be received by the owner at timestep-t
Historical-data	Table-formatted variable consisting of: (1) year, (2) condition, (3) cost, (4) yield, (5) opportunity losses	(1) Year: the age of the current crops on that patch at timestep-t (2) Condition: the current condition of the crops on that patch at timestep-t (3) Opportunity losses: the losses that farmers will perceive due to decreasing in crops condition caused by elephant raid attack
Attacked?	[0,1]	1: showing that the crops are raided at timestep-t 0: showing that the crops are not raided at timestep-t
Pot-damage-before-mit	Dynamic; Float	The potential damage that the crop on the patch should be receiving due to elephant raid attack
Mitigation-used	Dynamic; List	Mitigation tools that are installed on the patch

Mit_1-effect	Dynamic; List	The historical data of effectivity of a particular mitigation tool that is installed on the patch

- *Farmers State Variable*

Table 3. Farmers State Variables

Variable Name	Variable Type and Units	Meaning
Rcost-intallment-cost_used	List; IDR	Farmer knowledge about the price needed to acquire mitigation tools that has installed on their land
Rcost-operation-cost_used	List; IDR	Farmers knowledge about the price needed to maintain the mitigation tools that has installed on their land
s-product-support_used	List; Int	Farmers knowledge about the tehcnical support by the third parties of the mitigation tools that has installed on their land
Effectivity-mit_1	Dynamic; float	the effectivity of a mitigation tools that is being used on their owned land
Threat-appraisals	Float	A number that showing their threat appraisals level
t-epidemical-evidence	float	Defined as one's observation of the severity of elephant's raid in their neighborhood (estimated by Bayesian inference as a probability damage given an attack)
t-perceived-economical-losses	Float	Defined by potential losses in the next round (t + 1) given the agricultural losses happens as time t
t-crops-susceptibility	Float	Defined by the inverse-median from all crops on his possession at round- t
t-threshold	Float	The number of threat-appraisals variable required for the farmer feeling threatened
S-eff_i	Float	Composite variable, the aveage value of s-product_awareness_i and s-product_knowledge_i
s-product_awareness_i	Int	Product awareness measures how a person has been familiar to a specific product (estimated by how much their neighbors have been adopted a specific measures/ product)
s-product_knowledge_i	Int	Product knowledge is a measure of individual knowledge to operate a specific measurement/product

M-eff_i		
m-effectivity-info	Int	Effectivity is defined as how capable a spesific measurement or product to reduce or eliminate a potential damage caused by the elephant's raid (estimated using Bayesian inference as a probability damage level given attack)
R-cost_i		Composite variable, the aveage value of r-installment_cost_info and r-operation_cost_info
r-installment_cost_info	Int	Defined as a cost occurring in one-time in-advance before adopting a specific product or measurement
r-operation_cost_info	Int	Defined as a cost that will be occurred per three-month as an action to keep the products fully function
Intention_i	Float	Defined by individual intention degree and will be compared to their threshold to make an action (adopt a specific product)
Looking-for-alternatives-tools	{True, False}	The status of the farmers that he/she is seeking for mitigation tools to be installed on their owned land
Adoption_readiness_i	{1,0}	Defined by an individual readiness to adopt a specific measure (estimated by comparing to each individual intention-threshold)
Hold-decision?	True False	The status of keeping the intended mitigation tools after acquiring the mitigation tools that he/she is intended to buy but he/she didn't have the capital resource required
Decision-hold-since-t	int	Time since farmers holding their decision to keep pursuing the intended mitigation tools until he/she has sufficient capital required
Mit_used_list	List	The mitigation tools that had acquired and installed on their owned land
Last-time-adopted	Int	Timestep when the farmer last time acquires a mitigation tool
Intention-threshold	Float	The value needed for the farmers in order "intending" to buy a mitigation tool
My_firstd_neigh	Agent-set of farmers	List of farmers on his/her inner circle social network

My_secondd_neigh	Agent-set of farmers	List of farmers on his/her outer circle social network
Attacks-memory	List	The past attack incident that occurred on their owned land
Attacked-at_t?	{1,0}	A status that showing owned land is being raided
Damaged-at_t?	{1,0}	A status that showing there are impact on an elephant raid incident at time-t
ee-from-neighbor	List	The past attack incident of all farmers on his/her social network
Capital_assets	Float	The amount of money that farmer currently possessed
Land-owned	Agent-set of patches	The list of owned patches

Scale

- one timestep represents three months.
- one farmers agent representing the owning land of agricultural land.
- one patch represents 1 hectare.

PROCESS OVERVIEW AND SCHEDULING

Process

The simulation model is developed to study the adoption process of several mitigation measures by the farmers, namely (1) Electric Fence, (2) spotlight, (3), Carbide/spirit cannon. The decision-making process beneath it are operated using protection motivation theory, whereas a farmer will adopt one of these mitigation tools if feels threatened by elephant's raid attack that happened within their crop land or their surroundings and if the farmer has the capability to acquire and possessed such mitigation tools. This simulation consist of seven processes, (1) the elephants will choose several crop land to be raided, (2) if any mitigation tools that are installed on the crop land, it will be reducing the damage that the crop above it supposed to receive it, (3) the crop on the attacked land then will receive an amount of damage based on the reduced damage and will update its state variable regarding the current condition of the crops, the current costs needed to cultivate the crops, and the yield that the plan will produce on that timestep based on their age and condition, (4) the farmer that owns that crops then will perceive that attack as threat; increasing their threat level; and will record that incident in their memory that later will be diffused across their social network(5) the information spreading process, then, occurs within the farmers social network and from External Media to spread knowledge about a mitigation tools specifications, (6) Based on the farmer threat levels and the information acquired from their social networks and their threat appraisals, the farmers then will update their intention towards the previously mentioned mitigation tools and will decide whether they will intent to acquire a certain mitigation tools or not, (7) lastly, the farmers then will buy the mitigation tools that is intended to acquire if their capital assets exceed the cost of acquisition of such mitigation tools.

Schedule

The processes that are mentioned in the previous sub section are happened on each time step and preceded by the elephant's raid attack event on the selected patch with state variable *Land_Type* "agriculture" followed by each agent on this simulation will update their state variable on this consecutive order:

Patches

(1) the patch will update their *crop-condition* there are any crop on the respective patch was attacked based on the damage reduced by the mitigation tools installed on the crops explained by state variable *mit_used.*
(2) the patch will update their state variable *age*.
(3) Based on the patches state variable *age* and state variable *crop-type,* the patches will acquire the capital amount needed to cultivate the crop and the yield that it will produce explained by state variable "*historical data".*
(4) the patches will update the *crops-ability-to-produce* state variable by seeking the owner's *capital_assets* state variable that is explained by the state variable *ownership* to ensure that the *ownership* farmer agent having enough capital needed in their *capital_assets* state variable to fulfill the cost needed to cultivate the crop based on *historical data* state variable. The patches will update the *crops-ability-to-produce* to "1" if it reaches its end of life, "2" if the farmers unable to fulfill the cost needed to cultivate the crops, "0" if it hasn't reached end of life and the farmers can fulfill the cost needed.
(5) The patches then will deduct the owner's state variable *capital assets* for an and will transfer some amount to *capital assets* if the crop producing yield for an amount that is explained by the *historical data.*
(6) Finally, under the condition of state variable *crops-ability-to-produce,* if that state variable is showing "2", Then, the patches will deduct owner's state variable *capital assets* by the amount explained in *replacement cost* state variable.

Farmers

(1) The farmers will receive information from the External Media through *top-down-communication-process* procedure regarding a specific mitigation measure.
(2) The farmers then calculate their threat-appraisals levels based on the elephant raid event that happens on their social network by accessing the farmer's *attacks-memory* within their social network listed in *my_secondD_neigh* state variable, the perceived economical losses by accessing their possessed crops; which is mentioned by state variable *land-owned; historical-data,* and their crops susceptibility by accessing their crops' state variable *age.*
(3) If the farmer's threat appraisals are exceeding their threat threshold, then the farmer will execute *gather-info-for-operationalizing-construct* procedure. This procedure basically will gather further information needed from their social network listed in *my_secondD_neigh* to calculate their *intention_i* state variable.
(4) Based on their *intention_i,* the farmers will assess their readiness to adopt a certain mitigation tool and will be stored in *adoption_readiness_i* state variable and further will be analysed using *bc-assessment* procedure to obtain the mitigation tools that should be adopted.
(5) The farmers will acquire a mitigation tool if the farmer has a capital asset needed to acquire the intended mitigation tools or will be holding their decision for a length of timestep configured by the simulator by accessing the *between-adoption-time-delay* state variable.
(6) If the acquisition process is successful, then the mitigation tools acquired will be installed on their own patches that will be listed in *mitigation_used* state variable.

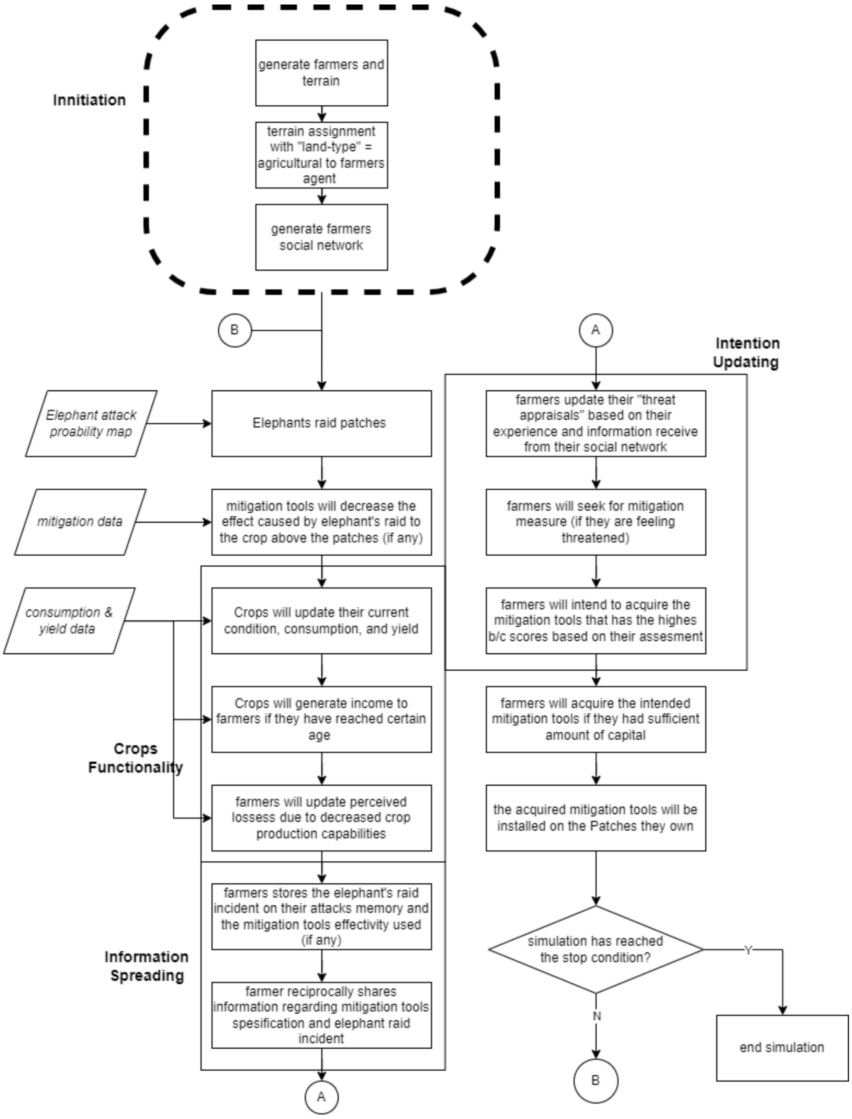


Diagram 1. Process Overview

DESIGN CONCEPT

- **Basic principles**
  This model is based on the elements of protection motivation theory (Rogers, 1975). Protection motivation theory itself has been used in various research on adoption of mitigation products under the presence of long terms disastrous events, namely flood (Babcicky & Seebauer, 2019; Bamberg et al., 2017; Haer et al., 2016). In the context of making this model using protection motivation theory, authors presumes that human-elephant conflict has share the same characteristics with flood disaster as it happens on the long-term effects with reasonable uncertainties regarding when it will happen. This model attempts to simulate how the farmers will implement certain protective measures under the effects of the influence of threat appraisals and coping appraisals. The threat appraisal that farmers perceive came from the perceived economical losses due to raided crops by the elephant and the crop raided on their surroundings. If their threat appraisals are exceeding their threshold, then the farmer will seek onto the market for alternative measurement to reduce their threat appraisals. If the farmers are feeling threatened and doesn't have the ability to reduce their threat appraisals level, then non protective behavior are initiated.

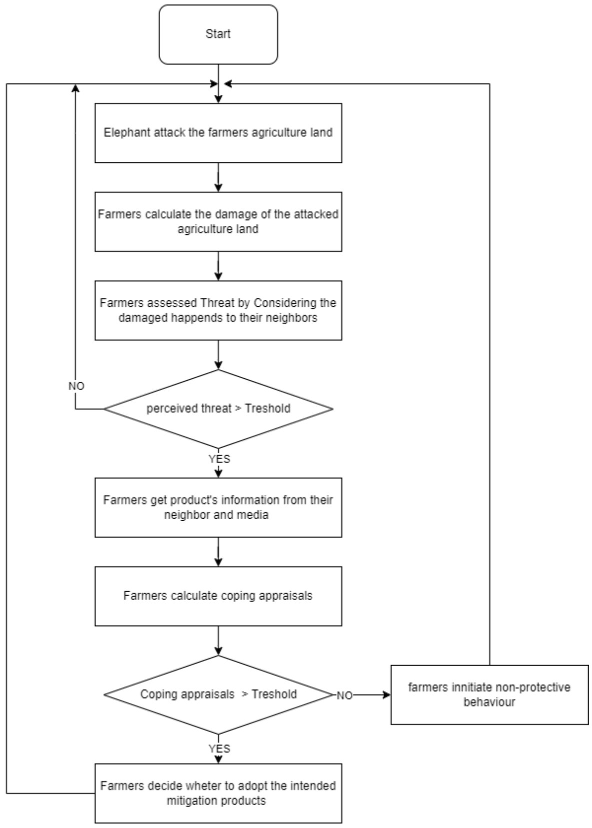


Diagram 2. Protection Motivation Theory Operationalization

- **Emergence**

  The emergence phenomenon that will be analyzed in this simulation are:

  1) The adoption pattern for each mitigation product that was affected by the effectiveness of each mitigation product and the information spread via social network and external media entities. This pattern also will be further analyzed based on current location and the crop-type that the respective farmers cultivate.
  2) The average wealth of a farmer as the consequences of adopting a certain mitigation tools.

- **Interaction**

  The interactions that occur in this simulation are about information exchange which afterward will modify the farmer's state variable and will be divided into two categories; the interaction that happens between each farmer and the interaction between external media entities and the farmers. The interaction that occurs between farmers happens reciprocally within their respective social network. Each farmer is capable of transferring information regarding mitigation measurements and elephant attacks that occur on their land through Information Spreading Model submodule and Threat model Submodule, consecutively. Whereas the interaction that happens between external media entities happens in one-way communication, that is from the external media entities to farmers. The information that will be communicated are only the advertised product's specifications regarding a certain mitigation tool.

- **Stochasticity**

  Stochasticity is used in initiation and simulation phase. On the initiation phase, the farmers agent will be placed across the simulation world extent, selecting the other farmers agent on their surrounding randomly as their social network, and assigned their mitigation used declared by the state variable *alternatives_i* randomly. The farmers, then, will make their neighboring patches as their land and randomly set the crops that will be cultivated by the farmers declared by the *crop_type* variable.

On the simulation phase, stochasticity occurs on the information spreading process by the external media and the procedure of a patches encounter elephant raid attack. Stochasticity process on the information spreading process by the external media has two parameters, the reaching process, and the acceptance process. These two processes follow a normal probability distribution in terms of the farmers agent that will receive the information given by the external media and the probability that the farmers agent will accept the information given that the information is reached by the farmers agent.

On the procedure of a patches encountering elephant raid attack, stochasticity occurs on the number of patches that will be raided during timestep-t based on two parameters, *mean-attack* and *std-attack*. Each patches have a random value *rng-visited-chance* and have a static value of *visited-probability-from-raster-data*. The patches then will be sorted in a descending order based on the difference on *visited-probability-from-rasted-data* and *rng-visited-chance.* The simulation then will choosing a random number of patches based on the sorted patches.

- **Observation**
  There is no observation process in this model.
- **Collectives**
  There is no collectives process in this model.
- **Adaptation**
  The Farmers agent have one adaptive behavior: deciding whether the agent will adopt mitigation tools to protect their crops. The decision-making process beneath it is operated using protection motivation theory: farmers will start to seek any mitigation tools that could be adopted if and only if they are feeling threatened. After the farmer feels threatened, they will measure his/her ability to possess such mitigation tools and their effectiveness.
- **Objectives**
  The farmers then will assess each of the mitigation methods that exceeds their intention threshold using benefit-cost assessment. The benefit of mitigation method is approached using effectiveness information that has been gathered by the farmer, while the cost approached using their installment cost; the cost of acquiring the mitigation tools; using the formula $\frac{benefit}{cost}$ for each mitigation method that exceeds their intention threshold. The farmers then will try to acquire the mitigation method that has the highest benefit-cost ratio. The justification beneath it are if the farmer feeling threatened and already has the capability to possess such mitigation tools, then the farmers will choose the mitigation tool that has bigger benefits with the lowest cost possible.
- **Learning**
  There is no learning process in this simulation model.
- **Prediction**
  There is no prediction in this simulation model.
- **Sensing**
  The farmers are assumed will acquiring information from other farmers or given by the external media entities. The information acquiring processes from other farmers will be proceeded under the *gather-info-for-operationalizing-construct* process, while the information given by the external media entities are proceeded under the *top-down-communication-process*. Each of these pieces of information are stored under various state variables depending on the type of information the farmer possesses: *s-technical-dependency, s-access-to-credit, m-effectivity-info, r-installment-cost-info, and r-operation-cost-info* (see farmer's state variable for further information). The difference between these information gathering process is the information acquired from other farmers only limited on the farmer social network, while the information given by the external media entities are spread via random process (for more information see Information Spreading Model under the Submodels section).

INITIATION

1. The process started with importing raster data of land use type and the probability distribution of elephant attack.
2. Then the process continued with importing non-spatial data: Plant-database data and product-specification data. the first file containing the cost needed to maintain a particular type of crop and the yield it will producing on a yearly basis, while the second file containing the product that will be simulated that both procedures called by “import-plant-commodity-db and “import-simulated-product-info” procedure.
3. Create a farmers defined by “farmers-population” and placed it randomly across the simulation world extent.
4. Each of the farmer state variable will be updated using their respective distribution function.
5. Some of the farmer will be designed that has already adopting certain mitigation tools based on the collected data of population fraction that has adopted such mitigation stored in *alternatives_i* state variable.
6. The patch then will be assigned to the farmer by assigning the patch into *land-owned* state variable, while the land will be assigned their owner via *ownership* state variable.
7. Based on *alternatives_i* state variable of their ownerhsip, the patch that owned by such farmer, the patch’s state variable *mitigation_used* will be inputed by *alternatives_i* state variable of their owner that was declared by patch’s *ownership* state variable.
8. The farmers than called procedure “generate-crops” to set the crops that will be cultivated above their owned land.
9. the farmer then will build their social network that was generated by “spatial-clustered-network-configuration-setup” and the agent-set of their respective social network was saved in *my_firstd_Neigh* and *my_Secondd_Neigh* state variable for their inner social circle and outer social circle respectively.

INPUT DATA

This model uses three input data. the first one regarding the plant growth-degrowth sub model. This dataset is being used to model crops yield and expense at timestep-t based on their *crop-type* and patches *age* variable, hence not all patches will be operated using this data and only patches with state variable *land_type* “agriculture”. The dataset contains crop-type and their respective yield and expense based on the crop age. This simulation will recalculate the crops yield and expense based on state variable *crop-condition* (See Crops Growth-degrowth model under Submodule section for more detail). At each timestep, the value will be stored under patch state-variable *historical-data*.

The second input data regarding the mitigation measures effectiveness to deter elephant’s raid to cast damage when visiting a particular patch. This input was gathered from Davies et al. (2011) regarding effectiveness of intervention method against crop raiding animal. Each mitigation method will successfully deter an elephant attack if the random number generated from each patch that has certain mitigation method yields smaller value than the effectiveness value of such mitigation method.

The third input data regarding the elephant attack model which contain the probability distribution of elephant attack, the data was formatted on a raster data which will be applied to each patch on this simulation model, processed by Pasasi (2023) during his fieldwork in Bukit Tigapuluh National Park. The probability distribution of elephant attack data raster was loaded on the initiation phase of the model and this data will be the basis of how likely a patch will be incurring an elephant raid.

SUBMODELS

THREAT MODEL

To assess the threat appraisals of each farmer agent, the agents need three pieces of information, namely Epidemical Evidence, perceived economical losses, and crops-susceptibility. (1) Epidemical evidence operates using Bayesian inference by calculating the effect of elephant's raid attack given on another farmers agent's crops when using certain mitigation tools or without. (2) Perceived economical losses accounts economical losses on crops when elephant's raid took place, calculated by summing the amount of expense by the farmers to rear the damaged crops due to elephant's raid and the losses of potential income from those damaged crops from the time it was damaged until end of crops' life. (3) Crops susceptibility is a measure of farmers agent's subjectivity of their crops' resilience towards elephant's attack that is dependent upon the crops' age. Each piece of information has their own weight respectively that will be summated using weighted summation techniques.

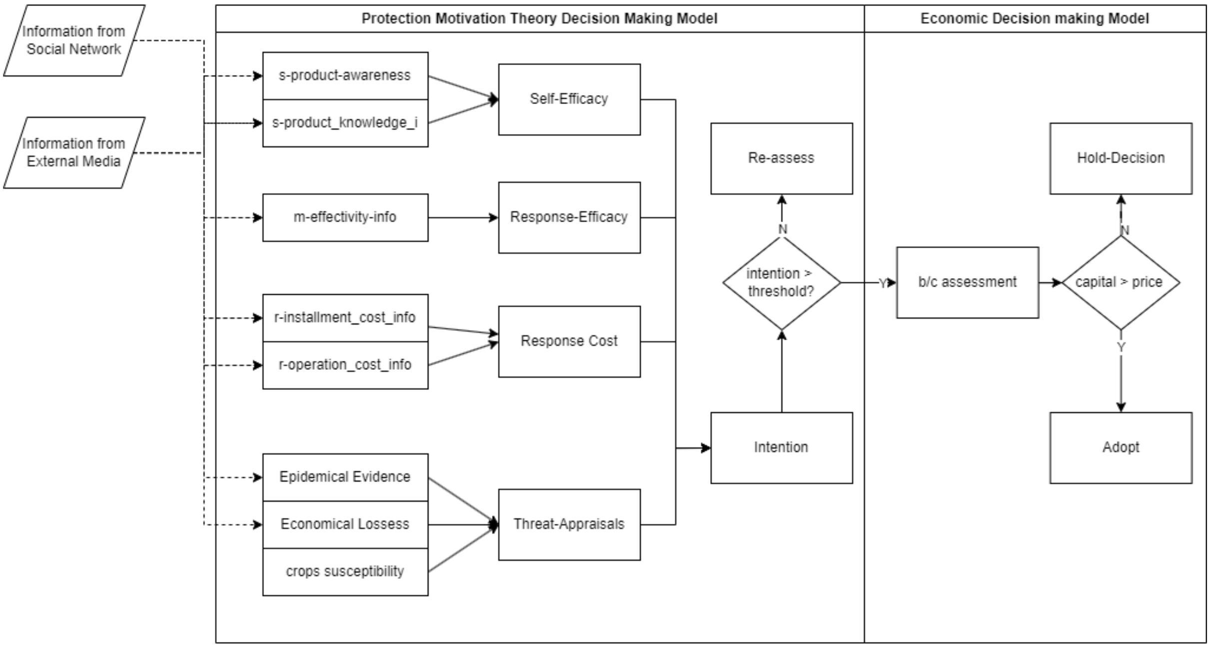


Diagram 3. Human Decision-Making Operationalization

INFORMATION SPREADING MODEL.

The farmers agent will receive information regarding a specific-products from two sources once they reach a certain threat-appraisals level with each farmers' agent having different threshold level, namely their neighbor and external sources. In this documentation, neighbor is defined not by the spatial proximity of farmers' agent, but the availability of information sharing. The information that will be gathered by the farmers agent are (1) s-product_awareness_i, (2)s-product_knowledge_i, (3) r-installment_cost_info, (4) r-operation_cost_info, (5) m-effectivity_info and each piece of information related to mitigation products.

The information received by the agent through the media follows the top-down communication concept proposed by (Haer et al., 2016) where the information will be spread massively, whilst having a small chance that an individual farmers agent will receive or believe the information. In this simulation it is modelled by high probability to reach ~N (.8, .05); showing the information will spread on huge amount of farmers agent; and low probability of success ~N (.2, .05); showing that a farmer agent doesn't necessary accept the information.

The information spreads by the neighbors depends on the social network structure inspired by the works of (Carter et al., 2020), distance-weighted preferential attachment model, where each agent will choose another agent relatively close to them until a certain number is reached (defined by the global variable: average-node-degree). Each farmers agents' neighbor will only give information based on their experience (e.g., the information gathered by experiencing using a certain mitigation measurements) and will not give information that has been gathered from media (external sources). The information gathered from their neighbors has 100% accuracy that the information will be reached and received.

After the information is gathered from media and from neighbors, in this simulation, the farmers agent will process each piece of information differently. For information that assumed to be no difference between the media and neighbor experience, such as (1) s-product_awareness_i, (2)s-product_knowledge_i, (3) r-installment_cost_info, (4) r-operation_cost_info, (5) m-effectivity_info, the farmers agent will choose either of gathered information regardless the sources. These processes were justified under the assumption that the information that will be spread from the media and what has been experienced by the neighbors were the same. Meanwhile the information regarding (5) m-effectivity_info that tells the effectiveness of certain mitigation products might be different between what has been advertised by the media and what has been experienced by the neighbor. Thus, the farmers will process the gathered information by averaging these two pieces of information gathered from media and neighbor.

INTENTION OPERATIONALIZATION MODEL

Once farmers agent's threat-appraisals exceed their individual threat threshold, the farmers agent will be looking for a protective measure (or mitigation products) on the market and will choose specific mitigation products based on their individual intention towards the products, aside that the farmers agent already adopted certain mitigation tools before. This simulation will be using protection motivation theory (Rogers, 1975) to measure farmers agents' intention towards each product which will be discussed under this sub module.

The protection motivation theory assumes that an individual will seek protective measures when the individual feels threatened by such circumstances. To seek a specific protective measure this theory assumes that an individual will be considering the efficacy of the products (namely measurement efficacy) and the individual capability of using the products (namely self-efficacy) with purpose to alleviate such threat. This simulation will be using mitigation effectivity to measure farmers agents' measurement efficacy perception towards a specific product and (1) technical dependency, (2) access to credit, (3) product awareness, (4) educational level, (5) income category, and (6) product knowledge to measure farmers agents' self-efficacy perceptions towards a specific product (see diagram 3 for visualization.

The calculation process from the measurable variables into farmers agents' intention are operationalized using multiple regression model. After inquiring the farmer agents' intention towards each mitigation product, the intention then will be compared to farmer agents' intention threshold. This intention threshold measures the farmers agents' acceptance towards products. Once it has been reached the threshold, then the farmers agent will choose to buy (if the farmers agent has the financial capability) or to hold their decision (if the farmers agent doesn't have the financial capability) which will be discussed under the sequential adoption sub model.

ADOPTION MODEL

After the farmers agent reach their intention threshold levels for one or more products and given that the farmers are looking for mitigation products (shown by threat appraisals exceed their threat threshold), then the farmers will assess the best mitigation tools that already exceed their intention threshold using benefit-cost analysis (shown in Eq. 1). Basically, the farmers will compare, from the information that the farmers' agent has acquired, each of mitigation tools' effectiveness given the price. The farmers will select the mitigation products that have the highest benefit-to-cost ratio and haven't possessed that mitigation product before.

$$P_b = \max_i \frac{b_i}{c_i}$$

Equation 1. Benefit-Cost Assessment

The farmers agent will acquire the selected mitigation product if their financial capability exceeds the cost to acquire the mitigation product. If the farmers agent doesn't have the capability to acquire the mitigation product, then the farmers will withhold the decision to acquire the selected mitigation product until the farmers agent has the financial capacity to acquire it for a certain amount of time (which can be defined by the simulator). The mitigation products that the farmers can acquired, in this simulation, is limited to three and the farmers agents will not acquire another mitigation product even their threat appraisals exceed their threat threshold, but the farmers can substitute their possessed mitigation tools with other tools using the same mechanisms.

CROPS GROWTH-DEGROWTH MODEL

The farmers' agent's that possessed a crop will expense a certain number of financial resources to cultivate their crops which is dependent to the crops age, the crops condition, and the type of crops itself. Generally, the crops will not generate income until the crop reaches a certain age, though each crop will be able to generate revenue differently depending on the crop's age.

When the crops encounter an elephant's raid attack and under the condition that the mitigation tools installed on the patch failed to deter elephant's coming to that patch (see more on mitigation effect on crops), it will receive a certain amount of damage causing a permanent decrease in the crop condition. The damage that the crop will receive will be dependent on the crop's age and will diminish as the crop gets older. This will also cause the decreasing capability of the crop to produce yields and indirectly reduce the potential income of the farmer. Concurrently, the farmers agent which possessed the crops will be perceived a certain number of economic losses due to decreasing conditions of their crop. The economic losses perceived by the farmers agents; formulated as sunk costs of expense before the attack and the marginal opportunity losses due decreasing producing capabilities of the crop from the time of attack until the end of life; inspired by (Ajudin et al., 2020). These perceived economic losses will be aggregated by the farmers every time their possessed crops are encounter an elephant's raid attack.

$$Lossess_t = (c - d)\left(\sum_0^t C_t + \sum_t^{EOL} Revenue_t\right)$$

Elephant Attack Model

Each of the patches inherit a probability of getting visited by the elephant that was given by attack probability raster map stored in *visited-probability-from-raster-data* state variable. For each timestep, each patch will acquire a random number that was stored in *rng-visited-chance.* Each patch will compare this generated random number and compare it to *visited-probability-from-raster-data*. If the *rng-visited-change* is smaller than the *visited-probability-from-raster-data*. The simulator will choose 10 patches that has greatest difference between the random number generated and the *visited-probability-from-raster-data* state variable. If we consider A to be the list of all patches that has higher *visited-probability-from-raster-data* values than their *rng-visited-chance*, then subset B is the patches that will be raided at timestep t.

$$B = \arg \max_{A' \subset A, |A|=10} \sum_{a \in A'} a$$

If the patches from subset B is a agricultural land (declared by state variable *land-type* = "agriculture"), then the crop above the patches will encounter elephant raid attack and will receive a permanent decrease in the crop condition. This behavior is modelled under the Crops Growth-degrowth sub model.

Mitigation Effect on Crops

As mentioned in Elephant Attack Model, if the patch that was chosen to be visited by elephant has state variable *land-type* = "agriculture", before the damage is received by the crop, the damage itself will be removed if the patch has mitigation measure installed on the patch which was declared by state variable *Mitigation-used* with a particular successful rate. The success rate was different across multiple mitigation measure that was modelled which was determined from Davies et al. (2011) paper. The process to deter an elephant started by generating a random number by the patch that was installed above the patch each time that patch was being visited by the elephant. If the generated number was smaller than the random number, the elephant raid was considered deterred, and no damage will occur to the crop above that patch. But if the opposite conditions happen, then the crop will suffer some damage and decrease their conditions based on the state variable *age* of the plants.

Declaration of Conflicting Interests. The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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To Cite This Article: Fath, H. & Imron, M. A. (2023). Modelling the Emergence of Financial Well-being on the Adoption Process of Mitigation Measures in Human-Elephant Conflict. *Journal of Industrial Engineering and Education,* 1(2), 136-170.