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EXECUTIVE SUMMARY

Human-elephant conflict (HEC) is a major conservation concern in Sri Lanka, affecting the livelihoods of rural farmers and conservation of the endangered Asian elephant. Near-term predicted changes in climate and agricultural practices are expected to impact patterns of HEC. I examine how HEC occurrence might temporally increase or decrease in the context of socio-environmental change using a dynamic Bayesian network (DBN) to model how physical drivers and mitigation actions of HEC interact to influence HEC occurrence. The DBN was intended to be a proof of concept model encoded to reflect qualitative knowledge and assumptions of the HEC system.

The influence diagram of the DBN was created through a combination of literature synthesis and expert elicitation from an elephant conservationist with knowledge of HEC in Sri Lanka. The DBN's nodes include two physical drivers of HEC (farm-to-forest ratio and length of time under cultivation) and four mitigation action nodes (use of electric fences, use of firecrackers, shooting, and other forms of lethal action). The influence diagram depicts how these nodes can affect (i.e., increase or decrease) elephant population and the likelihood of HEC occurring, and thereby total HEC that occurs. The probabilities inputted into the DBN are not numerically accurate but reflect qualitative expert knowledge and opinion. However, the probabilities for the 'Precipitation' and 'Farm-to-forest ratio' nodes are based on real-world data to show how the DBN might integrate quantitative evidence. Lastly, the DBN of the conceptual model of HEC was slightly modified to incorporate a feedback loop that models how humans can directly impact elephant population through lethal action.

Both models, the conceptual model of HEC and the model incorporating a feedback loop, were run under scenarios reflecting positive and negative elephant conservation conditions. The results demonstrate the applicability of a Bayesian approach in integrating both quantitative and qualitative data that are uncertain and incomplete. The model framework can also be applied to other regions where HEC is prevalent.

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LIST OF ABBREVIATIONS

HEC – Human-elephant conflict

BN – Bayesian network

DBN – Dynamic Bayesian network

PA – Protected area

CPT – Conditional probability table

1 INTRODUCTION

Conflict between humans and elephants is a major conservation concern in Sri Lanka, affecting rural poverty of farmers and the population and distribution of the endangered Asian elephant (Santiapillai et al., 2010; Fernando et al., 2011; Janssen et al., 2013; etc.). Elephants frequently encounter human settlements and farm areas, often eating and destroying crops and damaging property, leading humans to retaliate by attempting to chase off, injure, or kill the elephants (Santiapillai et al., 2010). Driven by the proximity between humans and elephants, human-elephant conflict (HEC) leads to crop-raiding incidences, property damage, human death and injury, and elephant death and injury (Santiapillai et al., 2006; Janssen et al., 2013; Fernando et al., 2011; Fernando et al., 2018; etc.).

A study using survey data suggests that elephants occupy 60% of Sri Lanka's terrestrial area, with 70% of humans residing in elephant ranges (Fernando et al., 2018). This nearness of coexistence leads to approximately 70 human and 250 elephant fatalities in Sri Lanka annually, with experts pointing to an increasing intensity in recent conflict since at least the 1990s, as well as an increase in elephant deaths per year (Figure 1) (Fernando et al., 2011; Perera, 2009).

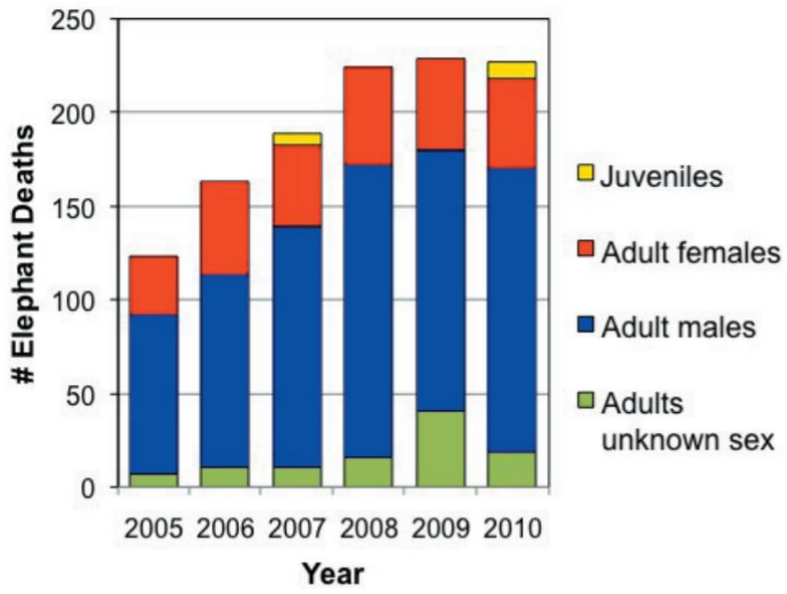

Figure 1: Elephant deaths per year in Sri Lanka. Figure from Fernando et al. (2011) with data from the Sri Lanka Department of Wildlife Conservation.

Moreover, crop-raiding incidences happen so frequently that they are not even reported; in high-conflict areas, an elephant can wander into a farm area every night during peak times when crops are maturing, about 3-4 months per year (de Silva and Gilkmam, 2019). Crop-raiding incidences lead to high economic losses for farming families: in a survey

of five conflict-prone provinces in Sri Lanka, Santiapillai et al. (2010) found that 43% of farming families, which average an annual income of less than USD $1,200, lose USD $200 to HEC (>17% of income). Patterns of HEC and their negative effects on farmers and elephants also occur in other range countries of the Asian elephant and the IUCN-vulnerable African elephant inhabit, including sub-Saharan Africa (e.g. Namibia, Mozambique, Tanzania) and other parts of South and Southeast Asia (e.g. India, Myanmar, Malaysia) (Shaffer et al., 2019). Thus, HEC is a serious, systemic problem for both human livelihoods and wildlife conservation in multiple regions. Using Sri Lanka as a case study, this dissertation aims to develop a formal conceptual model to describe the HEC system.

The ultimate drivers of HEC identified in literature are elephant habitat loss and fragmentation from human encroachment, as a decline in sufficient habitat pushes elephants to compete with humans for ecological resources (Gubbi, 2012; Janssen et al., 2013; Santiapillai et al., 2006; etc.). Other proximate and correlative factors may increase the risk for conflict occurrence, including the types of crops farmers plant, the timing of when crops ripen, the onset of monsoon season and rainfall, the distance between settlements and protected areas (PAs) for elephants, and human perceptions and tolerance of HEC (Santiapillai and Read, 2010; Gubbi, 2012; Santiapillai et al., 2012; Janssen et al., 2011). For example, elephants are attracted to crops due to keen olfactory senses when they ripen just before harvest, which depends on monsoon seasonality and how spatially close elephant habitats are to farms, leading these factors to increase the likelihood of conflict between farmers and elephants (Santiapillai and Read, 2010).

Several mitigation strategies are used to ameliorate HEC, including construction of physical barriers to deter elephants from entering agricultural areas, firecrackers to scare off elephants, and compensation by the government to farmers for damage done to crops (Janssen et al., 2013). However, these mitigation strategies are oftentimes not enough to eliminate conflict, as they are both slow and costly to implement and elephants may adapt to the presence of fences or sounds of firecrackers and destroy crops regardless (Janssen et al., 2013; Santiapillai et al., 2010). Furthermore, the mitigation strategies employed by wildlife managers address symptoms of conflict, rather than focusing on underlying conflict drivers: natural resource management, loss of habitat and landscape connectivity, and human cultural values associated with elephant conservation (Shaffer et al., 2019).

Driven by the overlap between elephant habitat and human settlements, and only somewhat offset by mitigation effectiveness, HEC is a pressing issue in Sri Lanka for farmers and elephant conservationists (Fernando et al., 2011; Santiapillai et al., 2010). Shaffer et al. (2019) highlights the need for a coupled natural-human systems approach in “understanding the interactions between human and elephant behaviour and resource use at the landscape level.” As such, the motivation of this dissertation is to understand the mechanisms of HEC

cause-prevention-effect and provide a formal framework of the HEC system, with Sri Lanka as a case study for this framework.

Socio-environmental changes, such as infrastructural developments and climate change, are expected to alter patterns of HEC in Sri Lanka. For instance, near-term plans to construct new irrigation canals, damming of rivers, and development of small rain-red reservoirs will result in elephant habitat loss and fragmentation, exacerbating HEC (Fernando et al., 2011). These actions may increase farmers' access to water and change cultivation practices, such as the size of cultivated area, crop type, and frequency of cultivation (de Silva, 2019, pers. comm.). This may lead to increased incidences of HEC if agricultural expansion encroaches on elephant habitat, farmers increase frequency of crop cultivation in a year, or shift to more profitable crops also become more attractive to elephants and increase crop-raiding. Predicting how HEC responds to future environmental change is a pressing issue for elephant conservation managers and policy makers.

Although there is extensive literature and research on HEC, few studies have attempted to develop a formal model to conceptualise the HEC system, including its causes and effects, in the context of socio-environmental change. For instance, Shaffer et al. (2019) in their conceptual model of HEC (Figure 2) acknowledged that climate change and other socio-ecological factors will alter patterns of conflict, but they did not formally model the relationship between these variables. Perera (2009) points out that "gaps in knowledge do exist and require studies to document the quantitative effects of HEC and to determine the most appropriate combination of methods that can mitigate HEC under the specific conditions of each location." Thus, a need exists to explore the collective effects of multiple physical drivers and mitigation strategies on HEC, how these variables might themselves change, and how these changes will affect HEC.

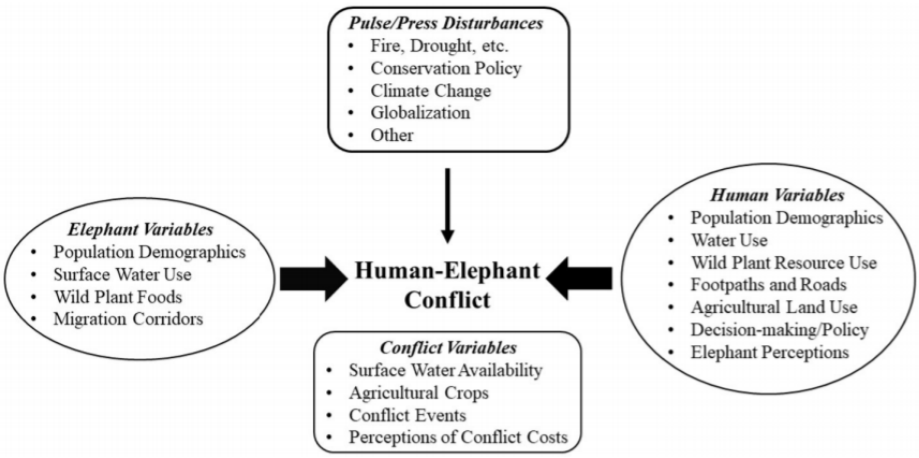

Figure 2: Correlates of general human-elephant conflict. Figure from Shaffer et al. (2019).

This dissertation aims to address this gap by developing a formal conceptual model of HEC using a Bayesian network approach. Combining literature synthesis with survey data from elephant conservation experts, the model will be a proof of principle that explicitly defines the components of the HEC system and the causal relationships therein. The model will then be used to test different potential future scenarios where different physical drivers and mitigation strategies interact, showing how the likelihood of conflict can increase or decrease depending on the combination of conflict-positive and/or conflict-negative variables in effect.

1.1 RESEARCH OBJECTIVES

In this vein, computational, explicit models can be used to formally articulate the HEC system in the context of socio-environmental variability and its potential impacts on conflict occurrence. The underlying motivation of this dissertation is to create a quantitative model that reflects the causal structure of the HEC system and addresses how conflict might increase (or decrease) with different agricultural and environmental changes. The model could then be presented to and used as a tool for on-the-ground conservationists and policy makers in Sri Lanka.

This dissertation was done in collaboration with Dr Shermin de Silva, an expert elephant conservationist and scientist based at Trunks & Leaves Inc, an Asian elephant conservation non-profit, with over ten years of experience studying behavioural ecology and demography of Asian elephants. As a socio-ecological system, human-elephant conflict is highly complex and stochastic by nature, making it difficult to obtain complete quantitative data on all its facets. Knowledge and opinion from experts familiar with the HEC system can be used to supplement gaps in data. Thus, to leverage Dr de Silva's expert knowledge and account for inherent uncertainty, a dynamic Bayesian network (DBN) was chosen as the modelling approach for this dissertation.

A DBN is a type of statistical model that can integrate both quantitative and qualitative data (Pollino and Henderson, 2010; Chen and Pollino, 2012). DBNs operate by using probabilities to express causal relationships between variables and defining the strength of these relationships (i.e., weak vs strong; negative vs positive) (Chen and Pollino, 2012). They combine prior information and beliefs (e.g. initial intuitions about how a system operates) with new data to obtain posterior information and beliefs (Uusitalo, 2007).

Rather than attempting to mechanistically and numerically capture every facet of HEC, the DBN is intended to be a proof of concept model that represents a holistic, general overview of significant HEC drivers in Sri Lanka. While data on HEC may be difficult to comprehensively collect, the DBN model is able to numerically formalise institutional

knowledge and qualitative information generally understood about the HEC system. As an early-stage model, the DBN examines how significant drivers and correlates of HEC interact to influence the likelihood of a conflict occurring. The model was developed from a combination of existing data and information in literature, as well as from input provided by the collaborator at Trunks & Leaves, Inc. and other experts with knowledge of Asian elephants in Sri Lanka.

The model aims to address the following questions:

1) What are the most significant physical drivers of human-elephant conflict?
2) How do concurrent HEC drivers and mitigation strategies influence the likelihood of conflict?
3) How will HEC likelihood respond under various potential future change scenarios, such as changes in climate and agricultural practices?

These questions were first addressed using a combination of literature synthesis and discussions with our expert collaborator to determine the most important variables that should be included into the model. To determine how these variables influence HEC (e.g., strongly, weakly), a questionnaire was sent out to other experts with knowledge of HEC. A conceptual DBN was created to encode these survey responses and beliefs about the HEC system. After creating the conceptual model that reflects the contemporary HEC system, the model inputs will later be modified to create potential future scenarios of HEC in the context of environmental variability, such as changes in climate and agricultural practices. Results from modelling these scenarios can predict the likelihood of a conflict occurring alongside expected environmental changes in Sri Lanka, such as annual increases in rainfall and/or habitat encroachment. Although this DBN model was applied to Sri Lanka, it could conceivably be applied to other regions where HEC is prevalent, provided that the model's variables are adjusted to account for region-specific correlates that do not drive conflict in Sri Lanka, such as elephant poaching.

I will first present a background of HEC in Sri Lanka, as the DBN was constructed for a Sri-Lanka specific case.

2 BACKGROUND AND LITERATURE REVIEW

2.1 HUMAN-ELEPHANT CONFLICT IN SRI LANKA

In Sri Lanka, the population decline of the Asian elephant has been driven by elephant habitat loss and fragmentation due to human population growth and encroachment, civil war, and economic development leading to deforestation and agricultural expansion (Santiapillai et al., 2006; Janssen et al., 2013; Fernando et al. 2011). Current population estimates, based typically on 'educated guesses', vary significantly in the literature but are usually listed at around 4,500-6,000 elephants (with a lower range near 2,000 elephants), with pre-human population estimates ranging from 6,000 to 12,000 elephants. The literature also indicates an estimated 50 to 70% habitat loss over the past 100 years (Fernando et al., 2011; De Silva, 1998; Wickramasinghe and Santiapillai, 2000). The Asian elephant is a keystone and culturally flagship species, currently on the IUCN Red List, and listed in the Convention on International Trade in Endangered Species (CITES) (Janssen et al., 2013; Desai, 1998). Sri Lanka contains 10% of all Asian elephants (Santiapillai et al., 2010). Given the severe population decline, it is critical to understand the drivers of HEC and certain mitigation interventions may or may not work, as well as project how conflict will increase (or decrease) given future environmental change.

Conflict with humans is the most significant threat to elephants in Sri Lanka (Fernando and Pastorini, 2011). Human-elephant conflict, according to the IUCN Species Survival Commission, is 'any human intervention, which results in a negative effect on human social economic or cultural life, on elephant conservation, or on the environment' (IUCN, as cited in Janssen et al., 2013). Conflict is driven by the high loss and disturbance of elephants' natural habitat, which forces elephants to more frequently encounter agricultural and human-disturbed areas and raid properties for food (Santiapillai et al., 2010). HEC manifests primarily as crop-raiding incidences, whereby farmers retaliate by attempting to chase away, wound, or kill elephants, often with guns or other home-made weapons (Fernando et al., 2011; Janssen et al., 2013).

In conservation management, protected areas (PAs) are used to create natural habitat for wildlife, separating them from humans (Hansen and DeFries, 2007). Sri Lanka's current network of PAs – about 13% of the island's total land area – is not sufficient to support elephant conservation, as 50 to 70% of Sri Lankan elephants live outside of PAs (Santiapillai et al., 2006; DWC survey in 2004 as cited in Fernando et al. 2011). Asian elephants persist mainly in forest or secondary habitat and disturbed mosaic areas that are a mix of farmland and natural vegetation, where they can opportunistically access readily available crops and forest cover (Calabrese et al., 2017). HEC in Sri Lanka occurs almost

entirely outside of PAs, most often in croplands and these human-disturbed mosaics (Fernando et al., 2018; Calabrese et al., 2017).

Figures 3 and 4 show a spatial comparison of HEC occurrence and land cover type in Sri Lanka, respectively. The map of HEC occurrence (adapted from Fernando et al., 2018) is the first analysis of conflict intensity at a country-wide scale, based on survey data collected from over 2,700 grid cells of 5 km resolution from 2011-2015 (non-grid areas on the map are where elephants have been extirpated). The map of land cover type (adapted from NASA LP DAAC at the USGS data and created in Google Earth Engine) is based on 500 m MODIS satellite imagery from 2016.

A visual comparison of the figures reveals that many areas of major HEC intensity correspond to areas in Sri Lanka where the land cover type is classified as 'croplands' (area at least 60% cultivated croplands) or 'cropland-natural vegetation mosaics' (areas of small-scale cultivation, or 40-60% cultivated, with natural tree shrub or herbaceous vegetation) (NASA LP DAAC, 2016). In the central-west, central-south, and west areas of the country, areas with major conflict (red grid cells in Figure 3) coincide with croplands and mosaics (orange and red land cover types in Figure 4). The relationship between areas of high conflict intensity and areas of croplands and mosaics will be explored further in this dissertation's model.

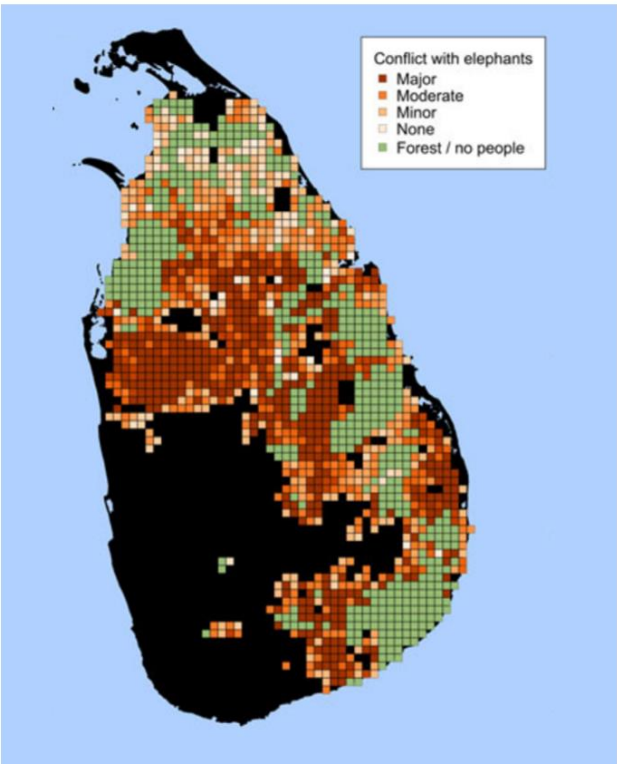

Figure 3: Country-wide map of HEC intensity. Image from Fernando et al. (2018). Grid ells are 5 x 5 km, with data gathered from 2011-2015.

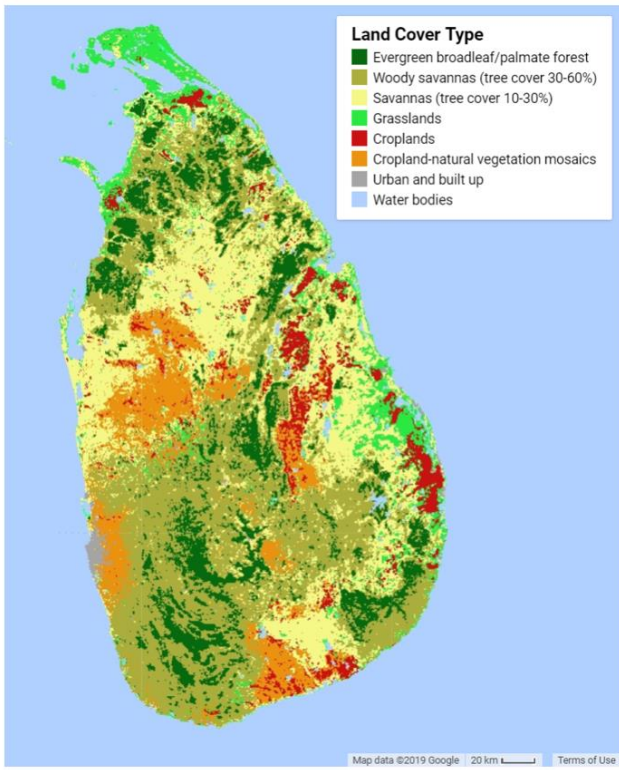

Figure 4: Country-wide map of land cover type. Image created in Google Earth Engine, with data provided from MODIS Land Cover Type (MCD12Q1) (NASA LP DAAC). Resolution is 500 m, with data from 2016.

2.1.1 MITIGATION

Various efforts are taken to prevent and mitigate conflict, including conservation management actions by authorities and actions undertaken directly by farmers. Janssen et al. (2013) identified the 'best' HEC mitigation strategies (assuming they operate adequately) as based on weighing socioeconomic and ecological trade-offs: construction and maintenance of electric fences, economic compensation, habitat enrichment (i.e., increasing food supply for elephants), creating areas of fenced chena (slash-and-burn areas) inside protected areas, and using live fences (made of hedgerows or thorny plants). Other common HEC mitigation strategies that were emphasised or mentioned frequently in scholarly literature include firecrackers and farmers patrolling and guarding crops at night-time (Santiapillai et al., 2006; Janssen et al., 2013; Fernando et al., 2011). Less under-utilised and popular mitigation strategies include creating and maintaining elephant corridors, elephant drives, translocation of conflict-prone elephants, thunder flashes, noise deterrents, development of community-based eco-products (e.g. paper and fertilisers made from elephant dung), ex situ conservation, culling of elephants, and chemically masking the smell of crops during ripening periods (Janssen et al., 2013; Santiapillai et al., 2006; Santiapillai and Read, 2010).

However, these mitigation strategies are financially, socially, and ecologically costly to implement and not always sufficient to prevent or lessen conflict. For instance, monetary compensation by the government, for farmers whose crops have been raided by elephants, is often inadequate due to administrative inefficiency, corruption (false and inflated claims, deliberate farming in conflict-prone zones), and insufficient funds of the Sri Lankan government (Gubbi et al., 2012; Janssen et al., 2013; Fernando et al., 2011). Other mitigation strategies like translocation and elephant drives prove to be costly, do not eliminate elephants from a single area totally, and make elephants more aggressive (Fernando et al., 2011). Mitigation strategies used directly by farmers to deter HEC can lead to negative impacts on welfare; for example, a household survey in conflict-prone areas revealed that 75% of respondents do not sleep when guarding crops at night-time in the growing seasons (Janssen et al., 2013). Use of fences and physical barriers are effective only with proper construction and maintenance, which can readily deteriorate over time (Fernando et al., 2011; Hill and Wallace, 2012).

Moreover, expert knowledge from elephant conservationists suggests that physical mitigation strategies do not actually decrease conflict overall, as they simply 'push' elephants from one farm to another (de Silva, 2019, pers. comm.). In other words, if one farm manages to drive an elephant off their land, the elephant will simply try to raid another

farm. Ultimately, fencing displaces elephants onto other neighbouring farms and does not likely decreasing conflict overall.

Mitigation strategies are also short-term solutions, as their effectiveness decrease with time and with wider usage (de Silva, 2019, pers. comm.). For instance, if farmers employ firecrackers to prevent conflict, elephants may be accustomed to the noise with time and attempt to raid crops after an adjustment period. One of the HEC experts consulted in this dissertation (see Section 3.2.4) suggested that the overuse of firecrackers and guns actually increases conflict by making elephants more aggressive.

This issue may be compounded further and faster if an increasing proportion of farmers in an area begin using firecrackers, resulting in a feedback loop: over time, more farmers will partake in using mitigation strategies, following a sort of game theory behaviour (de Silva, 2019, pers. comm.). In other words, even though overuse of a mitigation strategy will deteriorate the strategy's effectiveness overall, an individual farm will *not* want to be the only farm that doesn't employ the mitigation strategy and will partake in the action, provided the mitigation strategy is relatively accessible. This dissertation's model will explore these dynamic patterns.

2.1.2 BROADER IMPACTS

Agriculture accounts for more than 25% of the labour force in Sri Lanka (Export.gov, 2019). Rural farmers bear the cost of human-elephant conflict and are the main stakeholders in addressing conflict, as crop-raiding most frequently occurs on rural farms (Janssen et al., 2013). Due to crop loss and damage to property, HEC directly exacerbates rural poverty, as more than a quarter of people in rural areas live below the poverty line (Janssen et al., 2013). Janssen et al. (2013) posits that elephant conservation and mitigation of HEC cannot be successful without addressing the financial and physical needs of the rural population. For farmers, HEC results in crop and income loss, fewer productive working days, damage to property, stress and disruption to families, and sleepless nights spent guarding crops (Janssen et al., 2013). HEC can also directly limit employment and livelihood opportunities, such as deterring potential farmers to grow crops if they expect conflict to occur (Sampson et al., 2019).

Socio-environmental changes in Sri Lanka, particularly climate change and water resource developments, are further expected to affect agricultural practices, frequency and likelihood of HEC, and farmer livelihoods (de Silva, 2019, pers. comm.). 66% of the country's croplands are rainfed, and farmers plant crops in two growing seasons in accordance with the island's two distinct monsoon seasons, Maha and Yala, which occur from October to December and April to June, respectively (Biradar et al., 2009). However, climate change is

altering contemporary rainfall patterns, causing an overall increase in rainfall throughout time, erratic and unpredictable intra-seasonal storm events, delays in monsoon onset, and extremes in droughts and flooding (Panabokke and Punyawardena, 2010). Farmers are forced to adapt to climate change by changing their agricultural practices, such as planting at later dates than usual, shortening their growing seasons, using irrigation, and switching to drought-resistant crops (Menike and Arachchi, 2016). Almost 75% of Sri Lanka's agricultural land holdings are relatively small (less than one hectare), making small-scale farmers particularly vulnerable to climate change impacts.

Plans to increase Sri Lanka's water resources may offset the impacts of interannual precipitation variability (Weligamage et al., 2009). However, irrigation developments for canals and reservoirs may also contribute to HEC frequency and intensity. For example, farmers with increased access to water may expand their farmland or attempt to cultivate their crops more frequently each year in order to maximise profits (de Silva, 2019, pers. comm.). Expanded agricultural land and the amount of time in which crops are cultivated per year can increase the likelihood of conflict, as elephants will have a higher spatial and temporal chance of encountering farms and raiding crops.

It is not clearly understood if these interrelated biophysical and environmental changes (precipitation, irrigation infrastructure, frequency of crop cultivation, agricultural expansion) are synergistic or antagonistic in increasing HEC occurrence. Thus, this dissertation aims to examine how these drivers influence the likelihood of HEC, as well as investigate mitigation actions and their variable effectiveness over time, by using a dynamic Bayesian network to model the causal relationship between drivers.

2.2 MODELLING APPROACH

The next two sections introduce Bayesian networks (BNs) and dynamic Bayesian networks (DBNs), a subset of BNs and the model type chosen.

2.2.1 BAYESIAN NETWORKS

Bayesian networks, or Bayesian belief networks, are a form of probabilistic graphical models (a subset of statistical models) (Pearl, 2000). BNs are directed acyclic graphs that depict causal relationships between a set of variables through an influence diagram (Koller and Friedman, 2009)[1]. The model uses probabilities to capture the strength of relationships

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[1] *This section was adapted widely from Koller and Friedman (2009); see for a more detailed explanation of probabilities, probabilistic graphical models, and Bayesian networks.*

between the variables (Koller and Friedman, 2009). An example of a simple Bayesian network is shown in Figure 5 below.

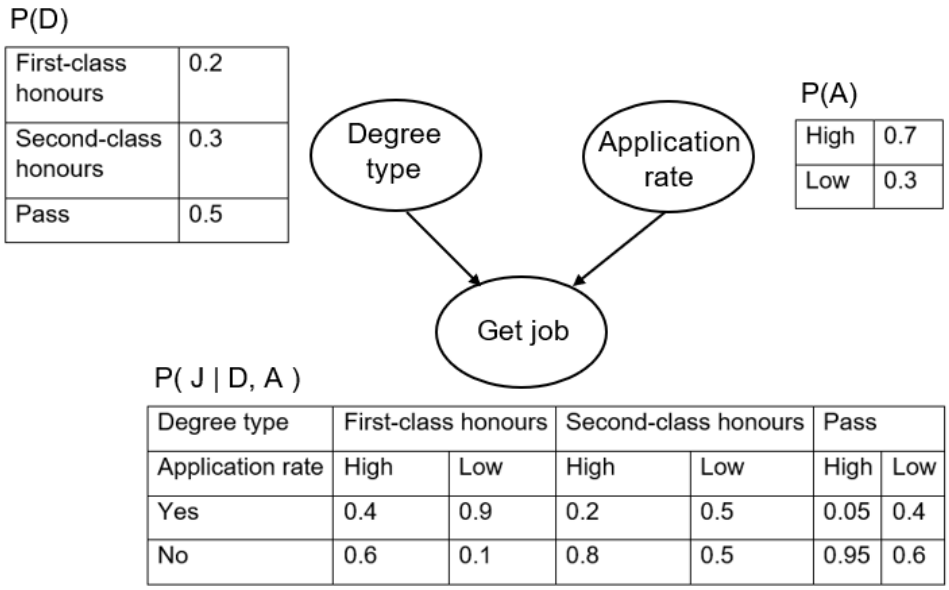

Figure 5: Example of a simple Bayesian network.

In this simple Bayesian network, a cause-and-effect relationship is expressed by nodes (i.e., the variables) connected through arcs (i.e., the arrows), with the nodes specified by states (i.e., ‘Degree type’ (D) is specified by the states ‘First-class honours’, ‘Second-class honours’ and ‘Pass’). The nodes ‘Degree type’ and ‘Application rate’ are parent nodes (that is, no other arcs lead into them) and the node ‘Get job’ is a child node. Each node has a probability table associated with it that expresses the probability of each state occurring. The probabilities for parent nodes express the likelihood of each state occurring. The probabilities for child nodes are expressed through conditional probability tables (CPTs) and are dependent on the states of the parent nodes. CPTs define the strength of causal relationships, from parent nodes to their child nodes (Chen and Pollino, 2012).

The core features of BNs are their capability to represent causal relationships explicitly; capability to incorporate information from both quantitative and qualitative sources, including intuitions or beliefs about a system in the form of expert elicitation; capability to rapidly propagate new information or data throughout the model; and capability to consider uncertainty (Chen and Pollino, 2012). Because uncertainty is inherent in socio-environmental systems (e.g. stochasticity, complexity), Bayesian networks can be advantageous over deterministic models (Pollino and Henderson, 2010).

The main benefit of using a BN for this dissertation was the capability to leverage knowledge of human-elephant conflict experts and include such expertise directly in the

model. Moreover, the intuitive nature of BN diagrams is desirable for presenting this model to conservation managers and policymakers on the ground. A further advantage of using a Bayesian approach is flexibility: the Bayesian network diagram created in this dissertation can be expanded upon in the future to capture greater nuances of the HEC system in Sri Lanka, as well as applied with modification to other countries where HEC is prevalent, such as India and Namibia.

In biodiversity conservation, Bayesian networks have been applied in population viability studies in fish, prediction of cheetah populations in Namibia, and in demonstrating how smallholder farms act as elephant corridors in northern Tanzania (Marcot et al., 2001; Johnson et al., 2013; Pittiglio et al., 2014).

2.2.2 DYNAMIC BAYESIAN NETWORKS (DBNS)

Because it was necessary to account for temporal variability in modelling human-elephant conflict (e.g. how the effectiveness of mitigation strategies deteriorate over time, habitat encroachment over time, temporal changes in irrigation use), a dynamic Bayesian network (DBN) was used for this study. Although traditional Bayesian networks are limited in representing temporal dynamics, DBNs can express changes in a system throughout time by replicating the influence diagram and updating probabilities in multiple iterations that represent time. An example of a DBN, adapted from de Kock (2008), is shown in Figures 6 and 7.

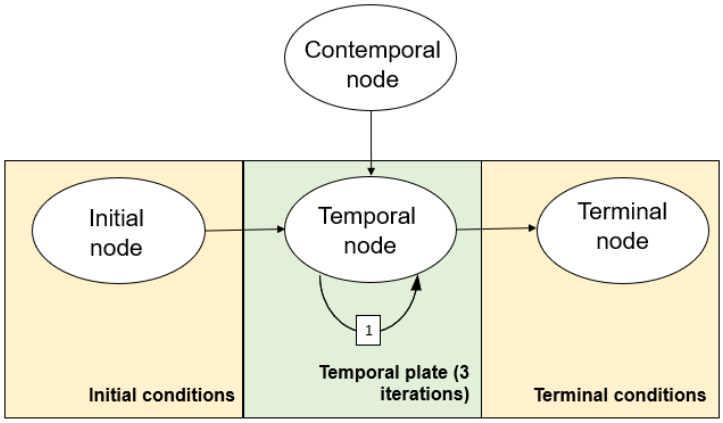

Figure 6: Example of a rolled DBN. Figure adapted from de Kock (2008).

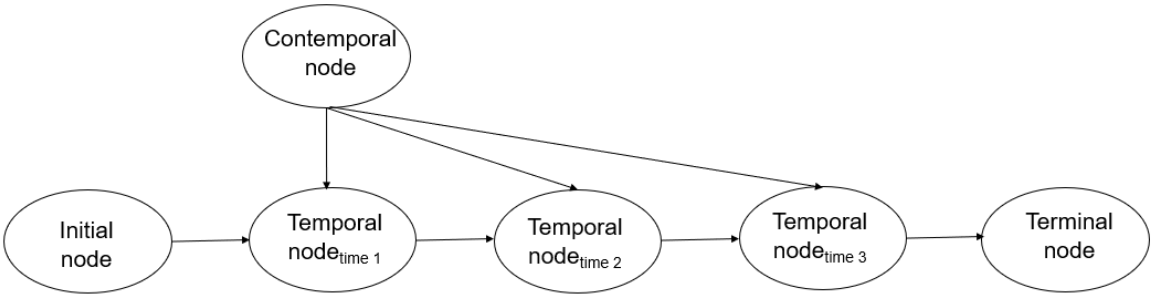

Figure 7: Example of an unrolled DBN. Figure adapted from de Kock (2008).

In this representation in these figures, a 'rolled' DBN consists of temporal, contemporal, initial, and terminal nodes. Nodes on a temporal plate are replicated and continuously updated as the DBN models runs for a fixed number of iterations, representing how a node's states can change over time. The temporal node contains an arc directed into itself with a boxed number '1,' which signifies that the temporal node at time *t* depends on its states' probabilities at time *t-1*. Temporal nodes can be attached to contemporal nodes, which remain the same for each iteration. A DBN is essentially an extended version of a typical Bayesian network; when the DBN is 'unrolled,' it looks very similar to a normal BN. Thus, a DBN can model dynamic phenomena using the same 'stationary' principles as a normal BN, including the use of prior beliefs and conditional probabilities to obtain posterior beliefs (Murphy, 2002). In this dissertation, the priors and conditional probabilities used to develop the DBN came from survey answers of HEC experts.

There are some limitations[2] and risks that should be noted when using Bayesian networks. For example, although BNs can incorporate expert elicitation, such information may not always be robust if there is incomplete knowledge, bias, or other forms of epistemic uncertainty (Pollino and Henderson, 2010). Another limitation of BNs is that they are not spatially explicit, although some hybrid models integrate GIS with BNs, and descriptor nodes can act as a proxy for spatial representation (Chen and Pollinno, 2012; Koller and Friedman, 2009). It should be noted that other models or methodologies could have been selected for this dissertation to predict future conflict in the context of environmental variability. For instance, Packer et al. (2018) predicted future risk of wildlife attacks on humans by statistically analysing spatiotemporal patterns of previous attacks, and Sitati et al. (2003) used GIS analysis and statistics to determine spatial correlates of HEC in Kenya. However, a Bayesian network approach was ultimately selected because of its capability to incorporate expert knowledge and intuitions about the changing patterns of HEC in a highly variable and uncertain landscape. The capability to integrate expert intuitions is an

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[2] *The DBN in this dissertation operates under the Markov assumption and time invariance, which are reasonable assumptions in environmental modelling (Pollino and Henderson, 2010 – see for explanation of these assumptions).*

advantageous feature of BNs particularly in the context of climate change, which is expected to change Sri Lanka's agricultural patterns and HEC (de Silva, 2019, pers. comm.). Moreover, the use of a Bayesian approach is novel: to date, virtually no studies have applied BNs or DBNs to conceptually model the human-elephant conflict system as a whole, let alone in Sri Lanka.

3 METHODS

The DBN model in this dissertation was created with the initial intention of conceptually formalising knowledge of HEC found in literature and from expert elicitation. The methodology was carried out in three major steps:

1) Develop a conceptual model of the physical drivers and mitigation strategies and correlates of the human-elephant conflict system in Sri Lanka.
2) Calibrate and validate the model according to expert elicitation and a comparison of spatial land cover type and HEC intensity.
3) Apply the model to create future potential scenarios of socio-environmental change that may impact the likelihood of HEC occurring.

The influence diagram of the conceptual model was developed from literature reviews and discussions with our collaborator. Following creation of the influence diagram, a survey was sent out to experts with knowledge of HEC in Sri Lanka, in accordance with the University of Oxford's research ethics guidelines. The experts were identified by contacts from our collaborator, and their survey responses were used to calibrate the DBN by encoding into the model a set of assumptions that reflect the experts' knowledge. Finally, the calibrated model was used to create various scenarios of socio-environmental change, along with the addition of a population feedback loop.

The DBN was created in the free software modeler GeNIe 2.3 Academic (BayesFusion). Following discussions with our collaborator, we decided to model HEC on a year-to-year basis; that is, each iteration of the DBN represents approximately one year in time. The DBN's temporal plate has 10 iterations[3], corresponding to approximately 10 years.

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[3] *Due to incorporation of a feedback loop in the DBN (Section 4.2), the temporal plate became too complex to run over 10 iterations in the GeNIe software.*

3.1 MODEL DEVELOPMENT

3.1.1 SIMPLIFCATIONS OF THE DBN

As human-environmental systems in the real world are complex and nuanced, this model will be a necessarily simplistic representation of HEC, defined for a 'conceptual landscape' spatial extent where conflict is most likely to occur. Essentially, this spatial extent might represent a landscape area within Sri Lanka that consists of a number of small-scale farms near protected areas or forest. For this dissertation's DBN, the 'conceptual landscape' scale was set to be approximately 1 x 1 km. Conceptually, this could also resemble one of the grid cells designated with major conflict from the Fernando et al. (2018) map of HEC intensity in Figure 3. The DBN also does not account for dynamics outside of this conceptual landscape scale.

However, these simplifications were needed for the scope of this dissertation, as increasing the scale of the model would require more variables to account for size. The further addition of variables naturally dilutes the conceptual scenarios that can be run to test the system in principle, as it becomes very difficult to determine cause-and-effect if the model is too complex.

In addition, non-physical factors that affect the occurrence of HEC were not included in this model. Although such factors (e.g. education, communication and awareness programs, market price of crops, compensation schemes to farmers) are potentially significant, they were not included in the Bayesian network due to the difficulty in expressing these variables succinctly and concerns with making the Bayesian network too large and complex. However, the flexible nature of a Bayesian approach can allow for the model to be expanded upon in the future to include other non-physical factors central to the socio-ecological system.

3.1.2 VARIABLE SELECTION

The first step of creating the DBN was to develop an influence diagram of variables and their causal relationships central to the HEC system. Creating the influence diagram required an assessment of which variables should be included, i.e., what are the most important physical correlates of HEC in Sri Lanka that can be included in the scope of this model.

Table 1 shows a broad list of common correlates of HEC that appeared in the literature, an assessment of whether the correlate was classified as a driver of HEC, a mitigation strategy, or a covariable, and whether the correlate was ultimately included in the

DBN. Because quantitative models require a trade-off between simplicity (uninteresting) and complexity (too difficult), the initial aim was to include only the most relevant variables in the DBN and minimise the number of variables as much as possible. The variables selected to be included in the DBN were very commonly mentioned in literature, and variable selection was further refined by discussions with our elephant conservationist collaborator.

Non-physical correlates of HEC in Table 1 were not included in the DBN due to complexities in capturing these correlates in a proof of concept DBN (Section 3.1.1). Some variables in Table 1 not included in the DBN reflect intra-annual variation (e.g. crop seasonality, timing of the day), as the DBN models conflict on an inter-annual basis. Other correlates in Table 1 were not included in the DBN because they were spatially explicit phenomena that would be difficult to capture in the DBN (e.g. wildlife corridors), unpractical to include from a near-term, management-oriented (e.g. habitat fragmentation, economic development), or unpopular mitigation strategies (e.g. translocation, culling).

*Table 1: List of prominent relevant correlates of HEC in Sri Lanka. * indicates that the source studied HEC not in Sri Lanka.*

Correlate of HEC	**Driver, mitigation strategy, or covariable**	**Included in DBN?**	**Source***
Land use change (habitat encroachment, agricultural expansion)	Driver	Yes (indirectly via farm-to-forest ratio)	Shaffer et al. (2019)* Janssen et al. (2013) Gubbi et al. (2012)* Fernando et al. (2011) Santiapillai et al. (2006) Sitati et al. (2003)*
Changing cropping patterns	Driver	Yes (frequency of cultivation, crop type)	Janssen et al. (2013) de Silva (2019), pers. comm.
Water use	Driver	Yes (irrigation)	Shaffer et al. (2019)* de Silva (2019), pers. comm.
Precipitation	Covariable	Yes	Shaffer et al. (2019)* Sitati et al. (2003)*
Use of physical barrier / electric fence	Mitigation strategy	Yes (electric fence)	Shaffer et al. (2019)* Janssen et al. (2013) Gubbi et al. (2012)* Fernando et al. (2011)
Use of firecrackers	Mitigation strategy (possible driver)	Yes	Shaffer et al. (2019)* Janssen et al. (2013) Perera (2009)
Use of shooting	Mitigation strategy (possible driver)	Yes	Fernando et al. (2011) Perera (2009) Santiapillai et al. (2006)
Use of other forms of lethal action (e.g. explosives, poison)	Mitigation strategy (possible driver)	Yes	Fernando et al. (2011) Perera (2009) Santiapillai et al. (2006)
Vicinity of farm/settlement to forest or PA	Covariable	Yes (indirectly via farm-to-forest ratio)	Janssen et al. (2013) Gubbi et al. (2012)* Santiapillai et al. (2010)
Elephant population / density	Driver	Yes	Shaffer et al. (2019)*
Nighttime crop guarding	Mitigation strategy	Yes (assumed with use of firecrackers)	Janssen et al. (2013) Fernando et al. (2011)
Elephant migratory patterns	Covariable	No	Shaffer et al. (2019)* Janssen et al. (2013) Gubbi et al. (2012)*
Monetary compensation	Mitigation strategy	No	Shaffer et al. (2019)* Janssen et al. (2013) Fernando et al. (2011)

Correlate of HEC	Driver, mitigation strategy, or covariable	Included in DBN?	Source*
			Perera (2009)
Habitat fragmentation	Driver	No	Gubbi et al. (2012)* Santiapillai et al. (2006) Fernando et al. (2011)
Human population density / growth	Driver	No	Santiapillai et al. (2006) Sitati et al. (2003)* Fernando et al. (2011)
Scarcity of food and water for elephants	Driver	No	Shaffer et al. (2019) Janssen et al. (2013)
Elephant corridor	Mitigation strategy	No	Shaffer et al. (2019)* Janssen et al. (2013)
Light-based deterrents	Mitigation strategy	No	Shaffer et al. (2019) Santiapillai et al. (2006)
Acoustic noise deterrents	Mitigation strategy	No	Shaffer et al. (2019)* Santiapillai et al. (2006)
Crop seasonality (phenophase period)	Covariable	No	Sitati et al. (2003)* Santiapillai et al. (2010) Santiapillai and Read (2010)
Timing of day (dusk to dawn)	Covariable	No	Sitati et al. (2003)*
Economic development	Driver	No	Janssen et al. (2013)
Civil war	Driver	No	Janssen et al. (2013)
Poverty	Covariable	No	Janssen et al. (2013)
Resettlement of high-risk villages	Mitigation strategy	No	Janssen et al. (2013) Perera (2009)
Translocation of conflict-prone elephants	Mitigation strategy	No	Shaffer et al. (2019) Janssen et al. (2013) Fernando et al. (2011) Perera (2009)
Elephant drives	Mitigation strategy	No	Janssen et al. (2013) Fernando et al. (2011)
Crop type	Covariable	No	Gubbi (2012)* Santiapillai et al. (2012)
Habitat enrichment	Mitigation strategy	No	Janssen et al. (2013) Santiapillai et al. (2006)
Fenced chena (slash-and-burn land) inside park	Mitigation strategy	No	Janssen et al. (2013)
Community-based eco-products	Mitigation strategy	No	Santiapillai et al. (2006) Santiapillai et al. (2010)
Landscape integration, management of PA buffer zones	Mitigation strategy	No	Santiapillai et al. (2006) Santiapillai et al. (2010) Fernando et al. (2011)
Ex situ conservation, capture and domestication	Mitigation strategy	No	Santiapillai et al. (2006) Fernando et al. (2011)
Elephant perceptions (education and awareness programs)	Mitigation strategy	No	Shaffer et al. (2019)* Fernando et al. (2011) Santiapillai et al. (2010) Bandara and Tisdell (2002)
Proximity to roads	Covariable	No	Shaffer et al. (2019)* Sitati et al. (2003)*
Proximity to major settlements	Covariable	No	Sitati et al. (2003)*
Forest fire occurrence	Covariable	No	Shaffer et al. (2019)*
Culling	Mitigation strategy	No	Shaffer et al. (2019)* Fernando et al. (2011)

The following section presents an overview of the variables selected for the DBN.

3.1.3 CONCEPTUAL OVERVIEW OF THE INFLUENCE DIAGRAM

The most prominent physical driver of conflict in Sri Lanka that appeared in the literature was habitat encroachment – that there is insufficient natural habitat remaining for elephants, and elephants reside by necessity in or very near human-dominated lands (Shaffer et al., 2019; Janssen et al., 2013; Fernando et al., 2011; etc.). After speaking with

our collaborator, we aimed to model this correlate alongside other pressures, namely changing agricultural practices: farmland expansion and the number of growing seasons a farmer aims to cultivate crops. As mentioned in section 1, these are major concerns in the context of near-term irrigational developments and climate change that can alter rainfall patterns.

Thus, this dissertation aimed to model how elephants are increasingly attracted to crops and more likely to raid them when they have more opportunities to encounter farms (de Silva, 2019, pers. comm.). In other words, agricultural expansion (leading to habitat encroachment) and an overall increase in crop cultivation in time lead to more opportunities for HEC. These opportunities arise spatially and temporally: with agricultural expansion, more of elephants' natural habitat is lost and they will increasingly encounter farms, and elephants will be further attracted to farms if crops are grown for longer periods throughout a year.

These physical drivers of conflict are offset, in theory, by mitigation effectiveness. While a wide variety of mitigation strategies (e.g. translocation of problem elephants, elephant drives, etc.) can be used to deter conflict, the most significant physical strategies that appeared in literature and were verified by expert opinion from the collaborator were the use of electric fences and the use of firecrackers when farmers guard their crops at night-time during the growing season (Jassen et al., 2013; Fernando et al., 2011; Perera, 2009; etc.). Shooting at elephants and the use of other forms of lethal action, specifically explosives (also known in Sri Lanka as hakka-patas) and poison, are also prevalent mitigation strategies that have negative consequences on elephant conservation, as they can result in elephant death (Rodrigo, 2019). As elephant population decline is already a significant concern in Sri Lanka (section 2.1), actions by humans that result in elephant death are serious concerns. Therefore, the DBN also aimed to explore some elephant population dynamics.

3.1.4 NODES OF THE INFLUENCE DIAGRAM

The influence diagram of the DBN, presented in Figure 8, is a representation of how these physical drivers (agricultural expansion / encroachment and the length of time a farmer cultivates crops) and mitigation strategies (use of electric fence and use of firecrackers) interact to affect the likelihood of HEC occurring. The elephant population density, which is affected by human-caused elephant deaths (shooting and the use of other lethal actions), combines with the likelihood of HEC to represent the total HEC that occurs within the DBN's conceptual landscape scale.

The physical drivers of HEC are reflected in the nodes ‘Length of time under cultivation’ and ‘Farm-to-forest ratio,’ the latter of which corresponds to agricultural expansion (and habitat encroachment). Elephants are found frequently in mosaicked landscapes that consist of both agricultural land and natural habitat, allowing easy access to both cropland and forest cover (Calabrese et al., 2017). Conflict is therefore likely to increase in landscapes where the farm-to-forest ratio is closer to 1, in areas that have a roughly equal split between farmland and forests. Conflict will likely also be high if elephants are pocketed in landscapes of complete or almost complete farmland, forcing elephants to have no choice but to raid crops if forest habitat is far away. In landscapes with fewer farms and more forest cover, elephant population density is lower, therefore decreasing the likelihood of conflict (Fernando et al., 2018; survey in this study). The temporal node ‘Farm-to-forest ratio’ represents this correlate of HEC, expressing by how much a ‘natural’ landscape has already been appropriated for agriculture.

The node ‘Length of time under cultivation’ represents the amount of time (or percentage of time in a year) a farm grows crops, i.e., it is *not* fallow, and is influenced by the amount of water available to a farmer (the node ‘Water availability’) which in turn is determined by the nodes ‘Irrigation’ and ‘Precipitation.’ With access to irrigation and/or sufficient rainfall, it may be possible for farmers to add another growing season within a year. For instance, though farmers typically plant twice a year according to the monsoon seasons, Maha and Yala, they may add a third cultivation during the inter-monsoon period if granted additional access to water (de Silva, 2019, pers. comm.; survey data, this study).

The mitigation strategies correspond to the nodes ‘Use of electric fence’ and ‘Use of firecrackers,’ which combine into a node that expresses total ‘Mitigation effectiveness.’ ‘Farm-to-forest ratio,’ ‘Length of time under cultivation,’ and ‘Mitigation effectiveness’ then combine to influence the ‘Likelihood of HEC.’ The nodes ‘Shooting’ and ‘Other forms of lethal action’ represent the mitigation strategies and drivers of human-caused elephant deaths, which in turn affect elephant demographics. Thus, these two nodes direct into the node ‘Elephant population density’. Finally, ‘Elephant population density’ multiplied by the ‘Likelihood of HEC’ determines ‘Total HEC’ in a conceptual landscape, as the model aims to include some coarse population dynamics to reflect what would happen in the event that conflict severely affects elephant population within the DBN’s conceptual landscape scale.

Because the model aims to illustrate the dynamics of HEC correlates, all of these nodes are on the DBN’s temporal plate, which consist of 10 iterations of the model that roughly relate to 10 years of time. The temporal plate will allow the states of the variables to change (e.g. increase, decrease, stay the same) over the model’s iterations.

In Figure 8, the nodes that are not on the DBN’s temporal plate are contemporal nodes. The contemporal nodes were created for ease of running the model itself and

represent future potential scenarios where the first-order nodes, i.e., 'Irrigation,' 'Precipitation,' 'Use of electric fence,' 'Use of firecrackers,' 'Shooting,' 'Other forms of lethal action,' and 'Farm-to-forest ratio,' could change in time (e.g., increase, decrease, or stay the same). Note that some nodes have a boxed number '1'.

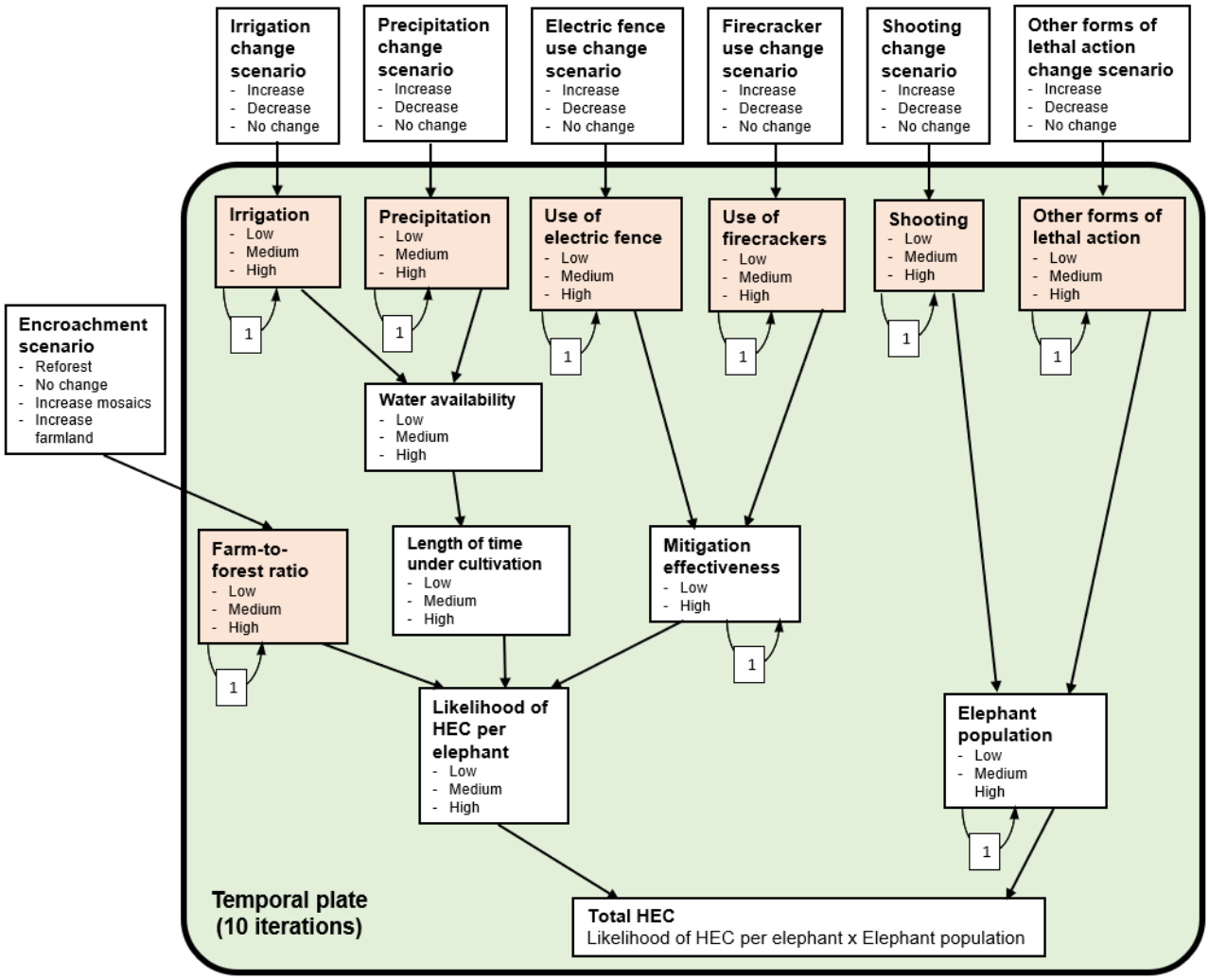

Figure 8: Influence diagram of the HEC dynamic Bayesian network. First-order nodes are shaded in orange. The states of each node are also given. Note that curved arrows are temporal arcs, with boxed numbers expressing by how many iterations the node is delayed by. Each first-order node has an arc directed into itself so that its states can change temporally depending on the scenario of its contemporal parent node.

Section 3.2 further describes the DBN's nodes, their states, and their probability tables in more detail.

3.2 MODEL PARAMETERS: NODE STATES AND PROBABILITIES

Each node in a Bayesian network has a set of states. Table 2 presents a list of the nodes and their state assignments for the model. Because the intention of the DBN is to show a proof of principle, the state assignments for all nodes are qualitatively categorical

(i.e., low, medium, high). In order to ground the model, I also define conceivable quantitative intervals for the 'low,' 'medium,' and 'high' states for several of the DBN's nodes in Table 2. The quantitative intervals correspond reasonably to contemporary conditions of the Sri Lankan HEC system and are elaborated upon in the forthcoming sections.

*Table 2: List of the DBN's nodes and their states. States for all nodes are qualitative; however, several states have quantitative intervals defined which the qualitative states could conceivably correspond to. * refers to a node that is a direct HEC mitigation action. ** refers to a node that is a direct HEC physical driver. *** The 'Total HEC' node is a product of 'Likelihood of HEC' and 'Elephant population density,' both of which have 3 states assigned. As such, 'Total HEC' has 9 possible states.*

Node type	Node	States
Contemporal node	Electric fence – change scenario	Decrease use No change in use Increase use
	Firecracker use – change scenario	Decrease use No change in use Increase use
	Precipitation – change scenario	Decrease precipitation (World Bank Group projected change – 10% confidence interval) No change in precipitation (World Bank Group projected median change) Increase precipitation (World Bank Group projected change – 90% confidence interval)
	Irrigation – change scenario	Decrease use No change in use Increase use
	Encroachment – change scenario	Reforest No change in encroachment Increase mosaics Increase croplands
	Shooting – change scenario	Decrease use No change in use Increase use
	Other forms of lethal action – change scenario	Decrease use No change in use Increase use
Temporal node	Electric fence use*	Low use (0-29% of farmers in landscape) Medium use (30-59% of farmers in landscape) High use (60-100% of farmers in landscape)
	Firecracker use*	Low use (0-29% of farmers in landscape) Medium use (30-59% of farmers in landscape) High use (60-100% of farmers in landscape)
	Mitigation effectiveness	Low High
	Precipitation**	Low (1 std. dev. below historic average) Medium (historic average) High (1 std. dev. above historic average)
	Irrigation use**	Low use (0-29% of farmers in landscape) Medium use (30-59% of farmers in landscape) High use (60-100% of farmers in landscape)
	Water availability	Low Medium High
	Length of time under cultivation	Low (0-4 months per year) Medium (6-8 months per year) High (9-12 months per year)

	Farm-to-forest ratio**	Low (<1 i.e. a majority forest) Medium (~40:60 farm: forest – 60:40 farm: forest, i.e. a cropland-natural vegetation mosaic) High (>1, i.e. a majority cropland)
	Likelihood of HEC	Low (10 raids per km^2 per year per elephant) Medium (20 raids per km^2 per year per elephant) High (30 raids per km^2 per year per elephant)
	Shooting*	Low use (0-29% of farmers in landscape) Medium use (30-59% of farmers in landscape) High use (60-100% of farmers in landscape)
	Other forms of lethal action*	Low use (0-29% of farmers in landscape) Medium use (30-59% of farmers in landscape) High use (60-100% of farmers in landscape)
	Elephant population density	Low (0.2 elephants per km^2) Medium (2 elephants per km^2) High (4 elephants per km^2)
	Total HEC	*** Likelihood of conflict times elephant population (Number of crop raids per km^2 per elephant per year multiplied by number of elephants per km^2)

Each node in the DBN is associated with a probability table to describe the likelihood of the node's states occurring, given the states of its parent nodes (Chen and Pollino, 2012). For nodes that do not have parents (e.g. all of the contemporal nodes in Figure 8), probability tables are unconditional, simply representing the likelihood of that state.

Child nodes, on the other hand, are characterised by conditional probability tables that reflect the strength of relationships from their parent nodes, expressing how likely a child node will be in a particular state given their parent nodes' states (Chen and Pollino, 2012). The size of a CPT depends on its number of states and the number of states of its parents, causing these tables to be quite large. For instance, the temporal node 'Mitigation effectiveness' has three states, two contemporal parent nodes each with three states, and one temporal node with three states (itself at the prior iteration), causing its CPT to have 3x3x3x3=81 possible combinations, hence the motivation to make the DBN as simple as is feasible.

In this proof of concept model, the CPTs encode a set of assumptions that qualitatively reflect how the HEC system operates; in other words, the probabilities are not exact but still ensure for the appropriate nodes that their states' probabilities change correctly (e.g. increase or decrease relatively proportionally) over time, given the conditions of their parents. These probabilities were set following discussions with Dr de Silva, our elephant conservationist collaborator, and then calibrated based on expert elicitation from a survey sent out to wildlife conservationists and managers with knowledge of HEC in Sri

Lanka (see Appendix A for the full survey and responses). The survey responses were used to determine how to set the conditional probabilities in the DBN.

The states and probability tables for each node in the DBN are detailed below.

3.2.1 OVERVIEW OF CONTEMPORAL NODES

In the DBN in Figure 8, contemporal nodes were created for ease of allowing the model to express scenarios in which the model's dynamic variables could change in time, i.e., increase, decrease, or remain the same. Thus, these contemporal nodes are used such that their child temporal nodes ('Electric fence use,' 'Firecracker use,' 'Precipitation,' 'Irrigation use,' 'Farm-to-forest ratio,' 'Shooting,' and 'Other forms of lethal action') can change with time in different scenarios that reflect potential future environmental variability in Sri Lanka. Note that each child temporal node has an arc directed into itself, a feature to allow for the scenarios to occur and for the model to run properly.

The states for the nodes 'Electric fence use,' 'Firecracker use,' 'Precipitation,' 'Irrigation use,' 'Shooting,' and 'Other forms of lethal action' are '*Decrease*,' '*No change*,' and '*Increase*.'[4] For the node 'Encroachment scenario,' the states are '*Reforest*,' '*No change*,' '*Increase mosaics*,' and '*Increase croplands*.' The latter two states differ in that an increase in mosaics refers particularly to small-scale farms near natural vegetation while an increase in farmland refers to landscapes dominated by a majority of farmland (see the cropland vs the cropland-natural vegetation mosaic land cover types in Figure 4).

All the contemporal nodes are non-child nodes (i.e., they do not have parent nodes), rendering their probability table an unconditional expression of the likelihood of each state occurring. As a simplification, the states of these nodes were observed at 0% or 100% in each simulation of the DBN. For instance, in Figure 9, for the node 'Precipitation – change scenario' its state '*Decrease precipitation*' might be set at 100%, while the states '*No change*' and '*Increase precipitation*' would be set at 0%. In another scenario, the state '*Increase precipitation*' would be set at 100%, while the other two states would be set at 0%.

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[4] *Names of states are italicized to distinguish them from names of nodes.*

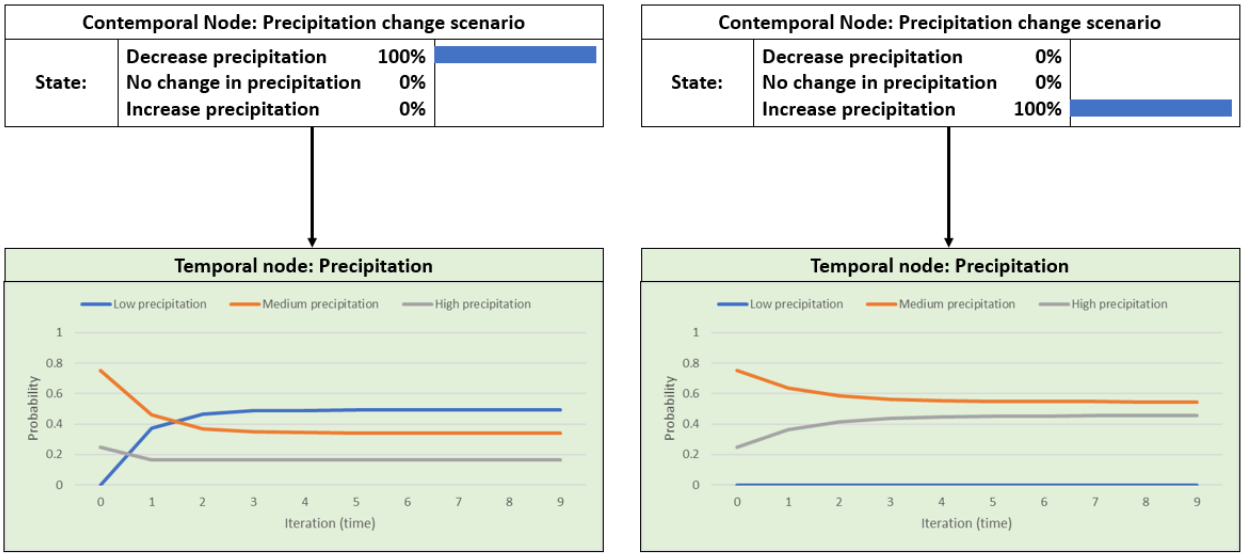

Figure 9: Example of how the states of contemporal nodes are set at 100%.

3.2.2 PRECIPITATION NODE

The node 'Precipitation' at time *t* is dependent on its contemporal parent node 'Precipitation change scenario' and on itself at *t-1*. As mentioned previously, these features allow for the node's states to change according to the scenarios '*Increase*,' '*No change*,' or '*Decrease*' (see Figure 9). Although the node's states are qualitative ('*Low*,' '*Medium*,' '*High*'), I sought to substantiate the states to ground the BDN in realistic settings by defining quantitative intervals. For instance, '*Low*,' '*Medium*,' '*High*' can correspond to precipitation that is 1 standard deviation below the historic monthly average, the historic monthly average, and precipitation 1 standard deviation above the monthly average.

Data on the average monthly rainfall in Sri Lanka from 1901-2016 is provided by the World Bank Group (2019). The historic monthly average from this period is 141 mm/month, with a standard deviation of 78 mm/month. The historic average monthly precipitation for 9 months (January to September) during 1901-2016 fall within 1 standard deviation of 141 mm, while the historic average monthly precipitation for 3 months (October to December) fall above 1 standard deviation of 141 mm (i.e., greater than 141 mm/month + 78 mm/month). Therefore, historically, 75% of months in a year have a '*Medium*' precipitation while 25% of months in a year have a '*High*' precipitation. Based on these data, the prior probabilities (i.e., the initial probabilities at time *t=0*) for the states of the 'Precipitation' node were set. Table 3 summarises the prior probabilities of this node (see Appendix B for the data used in these calculations).

The World Bank Group (2019) also provides data for future predicted rainfall change from 2080-2099 for Sri Lanka, with a median prediction and 10-90% confidence interval (Appendix B). The median prediction, the 10% confidence end of the prediction, and the

90% confidence end of the prediction were used to substantiate the states for the 'Precipitation change scenario' contemporal node. With the median prediction scenario, 9 months out of the year will remain '*Medium*' precipitation, while 3 months out of the year will remain '*High*' precipitation. With projected monthly average precipitation from the 10% end of the confidence interval, 6 months out of the year are expected to be '*Low*' precipitation, 4 months out of the year are expected to remain '*Medium*', and 2 months out the year are expected to be '*High*.' With projected monthly average precipitation from the 90% end of the confidence interval, 7 months out of the year (7/12 = 58.3% of the year) are expected to remain '*Medium,*' while 5 months out the year are expected to be '*High*' (5/12 = 41.7% of the year).

Based on these projected data, the states of the contemporal 'Precipitation change scenarios' node '*Decrease precipitation*,' '*No change*,' and '*Increase precipitation'* could be quantitatively substantiated; that is, we could define explicitly to what degree precipitation will decrease under the '*Decrease precipitation*' scenario or to what degree precipitation will increase under the '*Increase precipitation*' scenario. Therefore, the posterior probabilities (i.e., the final probabilities once the model runs through 10 iterations) for the 'Precipitation' node running under the scenarios '*Decrease precipitation*,' '*No change*,' and '*Increase precipitation'* were set so that the node's CPT encode the following assumptions:

- Under a '*Decrease precipitation*' scenario, the posterior probabilities of the 'Precipitation node will be 50% '*Low*', 33% '*Medium*', and 67% '*High*'
- Under a '*No change*' scenario, the posterior probabilities of the 'Precipitation node will not change, remaining at 0% '*Low*,' 75% '*Medium*,' and 25% 'High'
- Under an '*Increase precipitation*' scenario, the posterior probabilities of the 'Precipitation' node will be 0% '*Low*,' 58.3% '*Medium*' and 41.7% '*High*'

The posterior probabilities are given in Table 3.

Hence, by knowing what the 'Precipitation' node's prior and posterior probabilities could be reasonably set as, it was possible to populate the node's conditional probability table to express the change from the priors to posteriors over the DBN's iterations, for the different scenarios '*Decrease precipitation*,' '*No change*,' and '*Increase precipitation*.' The values populated in the CPT are not exact, yet still ensure that the model operates accordingly. Values for the 'Precipitation' node's CPT under these three scenarios are given in the Appendix C.

This approach in using an average monthly precipitation and standard deviations to quantitatively describe the node's qualitative states ('Low,' 'Medium,' 'High') was chosen following discussions with our collaborator. We sought to clarify these qualitative states with

additional descriptors so that HEC experts could better understand the DBN's variables, grounding the model in realistic applications. Although there are certainly limitations with this approach (the use of months per year to set prior and posterior probabilities may not reflect drought and flooding extreme events), these efforts show that the DBN's structure can allow for the integration of actual quantitative data.

Table 3: Prior and posterior probabilities under different scenarios for the states for the 'Precipitation' node.

State	**Quantitative definition**	**Prior probability of state**	**Posterior probability of state under '*Decrease precipitation*' scenario**	**Posterior probability of state under '*No change*' scenario**	**Posterior probability of state under '*Increase precipitation*' scenario**
Low	1 standard deviation below historic (1901-2016) monthly average: < 63 mm/month	0	0.5	0	0
Medium	1 standard deviation within historic (1901-2016) monthly average: 63 mm/month – 219 mm/month	0.75	0.333	0.75	0.583
High	1 standard deviation above historic (1901-2016) monthly average: > 219 mm/month	0.25	0.667	0.25	0.417

3.2.3 IRRIGATION NODE

The node 'Irrigation' depends on its contemporal parent node 'Irrigation change scenario' and on itself at *t*-1. The states of 'Irrigation' are '*Low use*,' '*Medium use*,' and '*High use*,' which could correspond approximately to 0-29%, 30-59%, and 60% or more of Sri Lankan farmers in a conceptual landscape having access to sufficient irrigation for their crop water requirements.

Survey responses from experts with knowledge of HEC in Sri Lanka were used to set the prior probabilities for the states of the 'Irrigation' node. Out of 4 survey participants, two answered that a medium percentage (30-59%) of farmers affected by HEC use irrigation, one answered that a high percentage (60% or higher) of farmers affected by HEC use irrigation, and one participant did not respond. Based on these responses, the prior probabilities for the states of the 'Irrigation' node were set as 0% '*Low*,' 67% '*Medium*,' and 33% '*High*.' The priors are summarised in Table 4.

Posterior probabilities were also determined for the 'Irrigation' node under the '*Decrease*,' '*No change*,' and '*Increase*,' scenarios. Like with the 'Precipitation' node in Section 3.2.2, the determination of the 'Irrigation' node's prior and posterior probabilities allowed for the node's CPT values to be populated accordingly. For this node, the following qualitative assumptions were encoded:

- Under a '*Decrease irrigation'* scenario, the posterior probabilities of the 'Use of electric fence node will be 100% '*Low*', 0% '*Medium*', and 0% '*High*'
- Under a '*No change*' scenario, the posterior probabilities of the 'Irrigation' node will not change, remaining at 0% '*Low*,' 67% '*Medium*,' and 33% 'High'
- Under an '*Increase irrigation'* scenario, the posterior probabilities of the 'Irrigation' node will be 0% '*Low*,' 0% '*Medium*' and 100% '*High*'

Thus, these assumptions reflect extreme scenarios whereby irrigation use greatly decreases or increases to the most extreme values, as it is difficult to estimate by what degree irrigation use could potentially change by (as was done for the 'Precipitation' node). The posterior probabilities for the 'Irrigation' node are also presented in Table 4. Values for the CPT of the 'Irrigation' node under its various scenarios are given in the Appendix C.

Table 4: Prior and posterior probabilities under different states for the 'Irrigation' node.

State	**Quantitative definition**	**Prior probability of state**	**Posterior probability of state under '*Decrease irrigation'* scenario**	**Posterior probability of state under '*No change*' scenario**	**Posterior probability of state under '*Increase irrigation'* scenario**
Low	0-29% of farmers use irrigation	0	1	0	0
Medium	30-59% of farmers use irrigation	0.67	0	0.67	0
High	60% or more of farmers use irrigation	0.33	0	0.33	1

3.2.4 MITIGATION ACTION NODES

The structure and states of the 4 mitigation action nodes 'Use of electric fence,' 'Use of firecrackers,' 'Shooting,' and 'Other forms of lethal action' are identical to those of the node 'Irrigation.' Each of these nodes depends on its contemporal parent node and on itself at *t-1*. The states 'Low use,' 'Medium use,' and 'High use,' also correspond approximately to 0-29%, 30-59%, and 60% or more of Sri Lankan farmers who employ these mitigation actions.

Like for the 'Irrigation' node, survey responses were used to set the prior probabilities for the states of these four mitigation action nodes. Based on the survey responses, the prior probabilities for the states of these nodes were set. Posterior probabilities (also given in each node's respective table) were also determined for these nodes under the '*Decrease*,' '*No change*,' and '*Increase*,' scenarios. As mentioned for the 'Precipitation' and 'Irrigation' nodes, the determination of prior and posterior probabilities allow for a node's CPT values to be populated accordingly. For these four nodes, the same following assumptions were encoded:

- Under a '*Decrease*' scenario, the posterior probabilities of the mitigation action node will be 100% '*Low*', 0% '*Medium*', and 0% '*High*'
- Under a '*No change*' scenario, the posterior probabilities of the mitigation action node will not change, remaining at the prior probabilities
- Under an '*Increase'* scenario, the posterior probabilities of the mitigation action node will be 0% '*Low*,' 0% '*Medium*' and 100% '*High*'

Thus, these four nodes have the same assumptions for their posterior probabilities to reflect extreme scenarios whereby usage of these mitigation actions greatly decreases or increases to the most extreme values by the end of the model's 10 iterations. For these four nodes, only their prior probabilities differ based on survey responses. Values for the CPTs of each node under their various scenarios are given in the Appendix C.

The prior and posterior probabilities are summarised in Tables, 5, 6, 7, and 8 for the nodes 'Use of electric fence,' 'Use of firecrackers,' 'Shooting,' and 'Other forms of lethal action,' respectively.

Table 5: Prior and posterior probabilities under different scenarios for the states for the 'Use of electric fence' node.

State	**Quantitative definition**	**Prior probability of state**	**Posterior probability of state under '*Decrease electric fencing'* scenario**	**Posterior probability of state under '*No change*' scenario**	**Posterior probability of state under '*Increase electric fencing'* scenario**
Low	0-29% of farms employ electric fences	0.33	1	0.33	0
Medium	30-59% of farms employ electric fences	0.67	0	0.67	0
High	60% or more of farms employ electric fences	0	0	0	1

Table 6: Prior and posterior probabilities under different scenarios for the states for the 'Use of firecrackers' node.

State	**Quantitative definition**	**Prior probability of state**	**Posterior probability of state under '*Decrease firecrackers*' scenario**	**Posterior probability of state under '*No change*' scenario**	**Posterior probability of state under '*Increase firecrackers*' scenario**
Low	0-29% of farms employ firecrackers	0	1	0	0
Medium	30-59% of farms employ firecrackers	0.25	0	0.25	0
High	60% or more of farms employ firecrackers	0.75	0	0.75	1

Table 7: Prior and posterior probabilities under different scenarios for the states for the 'Shooting' node.

State	**Quantitative definition**	**Prior probability of state**	**Posterior probability of state under '*Decrease shooting*' scenario**	**Posterior probability of state under '*No change*' scenario**	**Posterior probability of state under '*Increase shooting*' scenario**
Low	0-29% of farmers shoot at an elephant when it approaches property	0	1	0	0
Medium	30-59% of farmers shoot at an elephant when it approaches property	0.5	0	0.5	0
High	60% or more of farmers shoot at an elephant when it approaches property	0.5	0	0.5	1

Table 8: Prior and posterior probabilities under different scenarios for the states for the 'Other forms of lethal action' node.

State	**Quantitative definition**	**Prior probability of state**	**Posterior probability of state under '*Decrease other forms*' scenario**	**Posterior probability of state under '*No change*' scenario**	**Posterior probability of state under '*Increase other forms*' scenario**
Low	0-29% of farms employ other forms of lethal action against elephants	0.5	1	0.5	0
Medium	30-59% of farms employ other forms of lethal action against elephants	0.5	0	0.5	0
High	60% or more of farms employ other forms of lethal action against elephants	0	0	0	1

3.2.5 FARM-TO-FOREST RATIO NODE

The 'Farm-to-forest ratio' node is similar to the other first-order temporal nodes in that it depends on its contemporal parent node 'Encroachment scenario' and on itself at *t-1*. With encroachment, the proportion of farming area to forested (natural habitat) area increases

with time, and the ratio becomes larger than 1 if more than 50% of a landscape is farming area. Therefore, the states of 'Farm-to-forest ratio' are qualitatively 'Low,' 'Medium,' and 'High' and correspond to a farm-to-forest ratio less than 1, approximately 1 (e.g. between 40%-60% farm-forest and 60%-40% farm forest) and over 1, respectively.

Instead of using survey data, the prior probabilities for the states of the 'Farm-to-forest ratio' node, were set by intuition following literature reviews and discussions with our collaborator. As mentioned previously, Asian elephants persist in forest landscapes that also have a mix of agricultural activities, i.e., in areas where the farm-to-forest ratio is about equal parts farm and forest, causing these landscapes to be areas where HEC is a greater concern (Calabrese et al., 2019). In Figure 10, a visual comparison (the white circles in the figure) of HEC intensity and land cover type shows there is a major conflict in these farm-natural vegetation mosaic areas (the orange land cover type in the figure), which are also surrounded heavily by savanna land cover (classified as having 10-30% tree cover). The purple circles in the figure also indicate that conflict is major in areas of cropland (red land cover type in the figure) surrounded by savannas and grasslands (yellow and green land cover types in the figure, respectively).

Thus, the prior probabilities for the states of these nodes were set as 25% '*Low*', 75% '*Medium'*, and 0% '*High*'. These priors allow for the 'Farm-to-forest ratio' node's states to vary as the DBN as run throughout its time iterations: 1) for forest areas (savannas with 10-30% tree cover in Figure 10) to be eroded and converted into cropland-vegetation mosaics, and 2) for mosaics to be converted into croplands. The priors are summarised in Table 9.

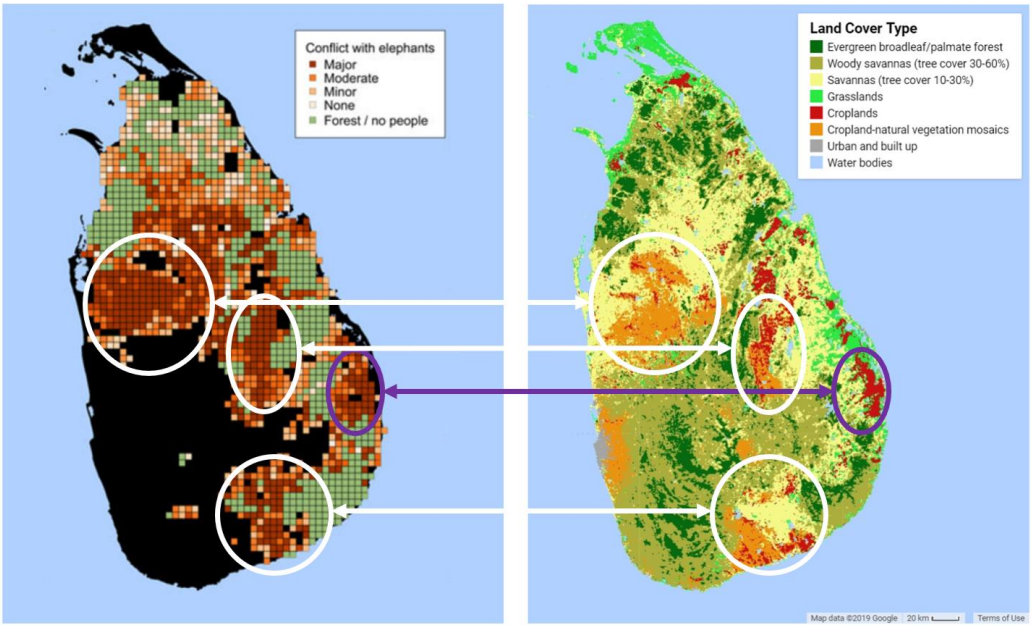

Figure 10: A comparison of HEC intensity in Sri Lanka (adapted from Fernando et al., 2018) and land cover type (adapted from MODIS imagery processed by NASA LP DAAC, 2019). The white circles highlight major HEC intensity related to areas of cropland-natural vegetation mosaics (the orange land cover type). The purple circles highlight major HEC related to areas of cropland (the red land cover type).

Posterior probabilities (also in Table 9) were also determined for the node under the '*Reforest*,' '*No change*,' '*Increase mosaics*,' and '*Increase croplands*' scenarios. The *a priori* determination of prior and posterior probabilities allow for the 'Farm-to-forest ratio' node's CPT values to be populated accordingly. For this node, the following assumptions were encoded:

- Under a '*Reforest* scenario, the posterior probabilities of the 'Farm-to-forest ratio' node will be 50% '*Low*', 50% '*Medium*', and 0% '*High*'
- Under a '*No change*' scenario, the posterior probabilities of the 'Farm-to-forest ratio' node will not change, remaining at the prior probabilities 25% '*Low*', 75% '*Medium*', and 0% '*High*'
- Under an '*Increase mosaics*' scenario, the posterior probabilities of the 'Farm-to-forest ratio' node will be 0% '*Low*', 100% '*Medium*', and 0% '*High*'
- Under an '*Increase croplands*' scenario, the posterior probabilities of the 'Farm-to-forest ratio' node will be 10% '*Low*', 10% '*Medium*', and 80% '*High*'

Thus, these assumptions reflect scenarios where encroachment increases or decreases to somewhat extreme values by the end of the model's 10 iterations. For the '*Reforest*' scenario, the farm-to-forest ratio was set to change from 75% mosaic and 25% forest to 50% mosaic and 50% forest following hypothetical reforestation actions and policies in Sri Lanka. These proportions do not necessarily reflect realistic events in Sri Lanka (as the deforestation rate for the country is still positive, and reforestation efforts often focus on the country's southwestern rainforests, where elephants do not have ranges) (Sudakhar et al., 2017; Jha and Bawa, 2006; Ashton et al., 2001). However, the '*Reforest*' scenario was meant to conceptually show how such a future action might affect the likelihood of human-elephant conflict occurring in this proof of principle DBN.

For the '*Increase mosaics*' scenario, the farm-to-forest ratio was set to change from 75% mosaic and 25% forest to 100% mosaics to reflect a landscape continuously dominated by cropland-natural vegetation mosaics, a reasonable result based on how common such mosaics are in Sri Lanka (see Figure 10). For the '*Increase croplands*' scenario, small probabilities (10%) for the '*Low*' and '*Medium*' states were set in the posteriors to represent that cropland-dominated landscapes will ultimately still be surrounded by forest and farm-forest mosaics by necessity, allowing elephants to have access to the croplands. Values for the CPT of the 'Farm-to-forest ratio' node under these scenarios are given in the Appendix C.

Table 9: Prior and posterior probabilities under different scenarios for the states for the 'Farm-to-forest ratio' node.

State	**Quantitative definition**	**Prior probability of state**	**Posterior probability of state under '*Reforest*' scenario**	**Posterior probability of state under '*No change*' scenario**	**Posterior probability of state under '*Increase mosaics*' scenario**	**Posterior probability of state under '*Increase croplands*' scenario**
Low	Farm-to-forest ratio is less than 1	0.25	0.5	0.25	0	0.1
Medium	Farm-to-forest ratio is approximately 1 (between 40: 60 farm-forest, or 60-40 farm-forest)	0.75	0.5	0.75	1	0.1
High	Farm-to-forest ratio is greater than 1	0	0	0	0	0.8

3.2.6 WATER AVAILABILITY NODE

Water availability is affected by precipitation and irrigation. With climate change affecting the variability and timing of Sri Lanka's twice-yearly monsoon seasons, and therefore the duration of crop growing seasons, there may be a shift to reliance on irrigation (Weligamage et al., 2009). Conversely, an overall increase in precipitation could be sufficient to maintain rain-fed agriculture, provided that major flooding events do not occur. Thus, the influence diagram reflects how these potential future changes might interact by directing the nodes 'Irrigation' and 'Precipitation' to the node 'Water availability'. The states for 'Water availability' are qualitative: '*Low*,' '*Medium*,' and '*High*.'

Unlike the first-order temporal nodes discussed in the previous sections, the CPT for the 'Water availability' node was not populated by determining *a priori* prior and posterior probabilities, as this node's prior probabilities (at time *t=0*) and prior probabilities (at time *t=9* after the DBN's 10 iterations) 'fall' from its parent nodes 'Irrigation' and 'Precipitation'. Instead, the following assumptions were encoded into the node's CPT via intuition following discussions with our collaborator:

- Water availability is higher with high precipitation and higher use of irrigation.
- With high precipitation but a lack of irrigation infrastructure in place, flooding events are likely to occur, causing water availability to be low (i.e., crops cannot be grown).

Thus, the 'Water availability' node's probabilities at each iteration time *t* of the DBN are determined by the probabilities of its parent nodes 'Irrigation' and 'Precipitation' at time

t (which in turn depend on the scenarios '*Increase*,' '*No change*,' and '*Decrease*') and from this node's CPT that reflect the above assumptions. Values for the CPTs are given in the Appendix C.

3.2.7 LENGTH OF TIME UNDER CULTIVATION NODE

In the influence diagram of the DBN, the 'Water availability' node is connected to the 'Length of time under cultivation' node, as with more water, farmers may try to cultivate crops more frequently in the year. The qualitative states for 'Length of time under cultivation' are '*Low*,' '*Medium*,' and '*High*' but could reasonably correspond to 0-4 months per year (0 or 1 growing season in Sri Lanka), 6-8 months per year (2 growing seasons) or 9-12 months (3 growing seasons, or year-round cultivation to increase crop yield).

The 'Length of time under cultivation' node depends on the states of its parent node 'Water availability.' The four survey respondents generally agreed that a substantial increase in precipitation (e.g., 1 standard deviation above the historic monthly average) and an increase in sufficient irrigation can cause farmers to increase the duration of cultivation throughout the year, potentially by 3 to 6 months. Following survey responses from experts with knowledge of HEC in Sri Lanka, the following assumption was intuitively encoded within this node's CPT:

- The length of time under cultivation increases with increased water availability.

The node's CPT is given in Appendix C.

3.2.8 MITIGATION EFFECTIVENESS NODE

In the influence diagram in Figure 8, the nodes 'Use of electric fence' and 'Use of firecrackers' are both directed into the node 'Mitigation effectiveness,' which has only two qualitative estates '*Low*' and '*High*.' The 'Mitigation effectiveness' node also has an arc directed into itself at time order 1, which indicates that the states of the node at time *t* also depend on its states at time *t-1*.

Although the use of electric fences and firecrackers are the two most prevalent mitigation strategies of conflict, according to literature and to our collaborator, they are not equally effective, and their effectiveness often deteriorates with time (see Section 2.1.1). Thus, the following assumptions were intuitively encoded within the 'Mitigation effectiveness' node's CPT:

- Electric fencing is more effective at mitigating conflict than firecrackers.
- A '*Medium*' usage of firecrackers is slightly more effective than a '*High*' usage, as increased firecracker use can make elephants more aggressive and potentially increase HEC.
- Mitigation effectiveness deteriorates over time for all scenarios (decrease, no change, or increase usage of firecrackers or electric fence).

The arc from this node into itself allows for a built-in deterioration of mitigation effectiveness over time. For instance, the prior probabilities at time *t=0* of the 'Mitigation effectiveness' node are 80% '*High*' and 20% '*Low*.' For any scenario, mitigation effectiveness will decrease as the DBN is run through its 10 iterations. Therefore, the probability of 'Mitigation effectiveness' being '*High*' will always be less than 80% at time *t=9*. The CPT for the 'Mitigation effectiveness' node, as it expresses the above assumptions, is given in Appendix C.

3.2.9 ELEPHANT POPULATION DENSITY NODE

The states for the node 'Elephant population density' is defined qualitatively as '*Low*,' '*Medium'*, and '*High*.' According to Sukumar and Gadgli (1989), the 'High' end of elephant population density could reasonably correspond to 4 elephants per km^2 (grassland-savanna habitat) while the '*Low*' end of density could be 0.2 elephants per km^2 (rainforests); thus, '*Medium*' population density could correspond to 2 elephants per km^2.

At time *t*, the node 'Elephant population density' depends on the nodes 'Shooting' at time *t*, 'Other forms of lethal action' at time *t*, and itself at time *t-1*. The latter feature is used as a feedback mechanism to allow a coarse proxy for elephant population to increase over time as the DBN is run through its iterations. As comprehensive data on Sri Lankan elephant population numbers, demographics, and dynamics is lacking, it was assumed for the DBN that the contemporary elephant population growth rate is positive overall, i.e., under *current* conditions in Sri Lanka, elephants are still able to reproduce despite elephant deaths per year due to conflict (de Silva et al., 2013). Moreover, the DBN aims to show that conflict affects (decreases) elephant population; therefore, elephant population (under contemporary conditions) needs to increase within the model by necessity, in order to conceptually show that an increase in shooting and other forms of lethal action will decrease the population.

According to our collaborator in this study, farmers usually aim to injure and not kill elephants when shooting at them, such as by targeting the legs, though 53 elephant deaths

in 2018 were still attributed to gunshot injuries (de Silva, 2019, pers. comm.; Rodrigo, 2019). However, other forms of lethal action, namely the use of explosive devices, result in a relatively high number of elephant deaths per year (64 deaths in 2018) (Rodrigo, 2019). Continued widespread use of these mitigation actions may strongly affect elephant population density.

Thus, the following assumptions were encoded within the 'Elephant population density' node's CPT:

- 'Elephant population density' generally increases with time under contemporary conditions (growth rate is positive).
- 'Elephant population density' is weakly negatively affected by 'Shooting.'
- 'Elephant population density' is strongly negatively affected by 'Other forms of lethal action.'

For example, if the use of 'Other forms of lethal action' is '*High*,' it will have a more significant negative impact on 'Elephant population density' than if 'Shooting' was '*High.*' The CPT for the 'Elephant population density' node, as it expresses the above assumptions, is given in Appendix C.

3.2.10 LIKELIHOOD OF HEC NODE

The node 'Likelihood of HEC' depends on the nodes 'Mitigation effectiveness,' 'Length of time under cultivation,' and 'Farm-to-forest ratio.'

The states of the node are qualitatively defined as '*Low*,' '*Medium*,' and '*High*.' However, an attempt was made to quantify these states. Our collaborator indicated that in major HEC-prone areas in Sri Lanka, for approximately each km^2 area, crop raids can occur nightly for 3-4 months per year, during peak incident periods (de Silva and Gilkmam, 2019), i.e., approximately 90 to 120 times per km^2 per year. Assuming that elephant population density is at its highest (4 elephants per km^2; Fernando et al., 2018) in these major conflict-prone areas, this would yield 23 to 30 crop raids per elephant per km^2 annually ($90 \div 4 = 23; 120 \div 4 = 30$). Taking the maximum of this prediction, this value (30 crop raids per elephant per km^2 per year) was linearly scaled across 3 states: that is, the states '*High*,' '*Medium*,' and '*Low*' for the node 'Likelihood of HEC' correspond to 30, 20, and 10 crop raids per elephant per km^2 in a year.

The CPT for this node was populated based on intuitions encoded about how the parent nodes 'Mitigation effectiveness,' 'Length of time under cultivation,' and 'Farm-to-forest ratio' relate to 'Likelihood of HEC.' As explained in section 3.1.3, the likelihood of

conflict increases with spatial and temporal aspects of agriculture, i.e., the area of cultivated land and whether cropland is grown in land mosaics, and the amount of time crops are growing, respectively.

Survey responses were used to address how ‘Mitigation effectiveness’ influences the ‘Likelihood of conflict.’ Out of the 4 respondents, 2 answered that the use of firecrackers only somewhat decreases the likelihood of a crop-raiding incident and 2 answered that firecrackers have no influence at all. 2 respondents also stated that use of an electric fence can strongly decrease the likelihood of crop-raiding, and 2 answered that an electric fence can somewhat decrease the likelihood of crop-raiding. The respondents also commented that electric fences are only effective if located at the right place (on ecological rather than administrative boundaries), built and maintained properly, factors that are often difficult to entirely address. These beliefs were corroborated by our collaborator, who confirmed that use of electric fences and firecrackers have little effect on actually mitigating HEC long-term. Therefore, even if mitigation effectiveness is high, it does relatively little to decrease the likelihood of conflict occurring.

Thus, the following assumptions were encoded into the node’s CPT:

- ‘Mitigation effectiveness’ only weakly decreases the Likelihood of HEC.
- The Likelihood of HEC increases when ‘Length of time under cultivation’ is higher.
- The Likelihood of HEC is greater when the ‘Farm-to-forest ratio’ is medium (approximately 1), followed by when the ratio is high (greater than 1) and when it is low (less than 1).

The CPT for the ‘Likelihood of HEC’ node, as it expresses the above assumptions, is given in Appendix C.

3.2.11 TOTAL HEC NODE

The node ‘Total HEC’ is a simple product of the states of ‘Likelihood of HEC per elephant’ and the states of ‘Elephant population.’ As there are 3 states for each of these parent nodes (‘*Low*,’ ‘*Medium*,’ and ‘*High*’ likelihood and ‘*Low*,’ ‘*Medium*,’ and ‘*High*’ population), there are 9 combinations of products, shown in Table 10:

Table 10: Combination states of the 'Total HEC' node.

'Total HEC' states	**Elephant population density per km²**	**Likelihood of HEC per km²**	**Value of state per km² (elephant population density times likelihood of HEC)**
1	Low (0.2 elephants)	Low (10 crop raids/elephant)	2
2	Low (0.2 elephants)	Medium (20 crop raids/elephant)	4
3	Low (0.2 elephants)	High (30 crop raids/elephant)	6
4	Medium (2 elephants)	Low (10 crop raids/elephant)	20
5	Medium (2 elephants)	Medium (20 crop raids/elephant)	40
6	Medium (2 elephants)	High (30 crop raids/elephant)	60
7	High (4 elephants)	Low (10 crop raids/elephant)	40
8	High (4 elephants)	Medium (20 crop raids/elephant)	80
9	High (4 elephants)	High (30 crop raids/elephant)	120

As the DBN is probabilistic (i.e., each state has a probability associated with it), the total HEC is a sum of each combination times the probability that the combination occurs, for all combinations:

$$Total\ HEC^{5} = 1a + 2b + 3c + 4d + 5e + 6f + 7g + 8h + 9i$$

Where a is the probability that state 1 occurs, b is the probability that state 2 occurs, c is the probability that state 3 occurs, etc.

In the DBN the 'Total HEC' node is deterministic, with the value of the 9 states known with certainty (100%) given its parents. The deterministic (100%) probability values are given in the node's CPT in Table 11:

Table 11: Deterministic probability values for the 'Total HEC' node.

	Elephant population	Low			Medium			High		
	Likelihood of HEC	Low	Med	High	Low	Med	High	Low	Med	High
'Total HEC' states	**1**	1	0	0	0	0	0	0	0	0
	2	0	1	0	0	0	0	0	0	0
	3	0	0	1	0	0	0	0	0	0
	4	0	0	0	1	0	0	0	0	0
	5	0	0	0	0	1	0	0	0	0
	6	0	0	0	0	0	1	0	0	0
	7	0	0	0	0	0	0	1	0	0
	8	0	0	0	0	0	0	0	1	0
	9	0	0	0	0	0	0	0	0	1

It should be noted that the efforts to quantize the variables 'Elephant population density,' 'Likelihood of HEC,' and 'Total HEC' within a 1 km² conceptual landscape do not necessarily represent accurate numbers. Like with the DBN's other nodes whose qualitative

[5] *Given limitations of the software used to create the DBN, GeNIe, these calculations were computed and graphed in Excel. GeNIe cannot support equation-based nodes with a temporal plate.*

states have corresponding quantitative intervals, these numbers were used to more tangibly ground the DBN in a realistic setting.

3.2.12 ADDITIONAL LIMITATIONS OF THE DBN

The DBN contains several limitations that were deemed acceptable for the scope of this dissertation but are critical to acknowledge. For instance, because some nodes in the DBN contain qualitative states with no quantitative intervals referenced, the DBN is a necessarily descriptive model of HEC. As mentioned in the research objectives in Section 1.1, this is acceptable for a proof of principle model.

Another simplification of the influence diagram is that the 'Farm-to-forest ratio' node is not linked directly to 'Water availability,' even though a direct increase in farmers' water availability would imply that they expand the area of their farms, a premise that was confirmed by the survey responses from HEC experts (see survey results in Appendix A). However, the influence diagram does not represent this causal relationship, and the 'Farm-to-forest ratio' node is instead independent of 'Water availability.' This was done primarily to reduce the size of the node's CPT; the 'Farm-to-forest ratio' can still reflect an increase in farmland area through its 'Encroachment scenario' contemporal parent node.

3.3 CONCEPTUAL MODEL SCENARIOS

The contemporal nodes of the DBN were set under a combination of scenarios to predict total HEC in the context of socio-environmental change. Table 12 shows 5 combinations of inputs into the DBN for which the model was run. These combinations reflect baseline conditions (e.g., contemporary conditions in Sri Lanka) where there is complete '*No change*' scenarios for the contemporal nodes, positive elephant conservation conditions, negative elephant conservation conditions, predicted realistic conditions, and conditions of antagonistic combinations. The positive conservation conditions are meant to reflect the least harmful impacts to elephant conservation (i.e., total HEC is minimised and elephant population increases). The negative conservation conditions are meant to reflect the most harmful impacts to elephants (i.e., total HEC increases and elephant population decreases). The predicted realistic conditions reflect expected socio-environmental changes in Sri Lanka (see Section 2.1.2). Antagonistic combinations depict HEC drivers and mitigation actions interacting conflictingly, such as an increase in irrigation but a decrease in precipitation.

Table 12: Combinations of DBN inputs for which the model was run.

Combination	DBN inputs (contemporal node scenarios)
1 – Baseline / contemporary conditions	- 'No change' ('Irrigation change scenario' node) - 'No change' ('Encroachment scenario' node) - 'No change' ('Precipitation change scenario' node) - 'No change' ('Use of electric fence change scenario' node) - 'No change' ('Use of firecrackers change scenario' node) - 'No change' ('Shooting change scenario' node) - 'No change' ('Other forms of lethal action change scenario' node)
2 – Positive conservation conditions	- 'Decrease irrigation' ('Irrigation change scenario' node) - 'Reforest' ('Encroachment scenario' node) - 'Decrease precipitation ('Precipitation change scenario' node) - 'Increase use' ('Use of electric fence change scenario' node) - 'No change' ('Use of firecrackers change scenario' node) - 'Decrease use' ('Shooting change scenario' node) - 'Decrease use' ('Other forms of lethal action change scenario' node)
3 – Negative conservation conditions	- 'Increase irrigation' ('Irrigation change scenario' node) - 'Increase mosaics ('Encroachment scenario' node) - 'Increase precipitation ('Precipitation change scenario' node) - 'Decrease use' ('Use of electric fence change scenario' node) - 'Decrease use' ('Use of firecrackers change scenario' node) - 'Increase use' ('Shooting change scenario' node) - 'Increase use' ('Other forms of lethal action change scenario' node)
4 – Predicted realistic conditions	- 'Increase irrigation' ('Irrigation change scenario' node) - 'Increase cropland ('Encroachment scenario' node) - 'Increase precipitation ('Precipitation change scenario' node) - 'No change in use' ('Use of electric fence change scenario' node) - 'Increase use' ('Use of firecrackers change scenario' node) - 'No change in use' ('Shooting change scenario' node) - 'Increase use' ('Other forms of lethal action change scenario' node)
5 – Antagonistic combinations	- 'Increase irrigation' ('Irrigation change scenario' node) - 'Increase cropland ('Encroachment scenario' node) - 'Decrease precipitation ('Precipitation change scenario' node) - 'Decrease use' ('Use of electric fence change scenario' node) - 'Increase use' ('Use of firecrackers change scenario' node) - 'Decrease use' ('Shooting change scenario' node) - 'No change in use' ('Other forms of lethal action change scenario' node)

3.4 ADDITION OF A FEEDBACK LOOP

In the conceptual DBN, farmers' behaviours are not dynamic in response to conflict (see results in Section 4.1). For instance, in Figure 13, total HEC increases but plateaus because the likelihood of conflict decreases. With less HEC occurring, the elephant population density might increase. In this context, the Sri Lankan elephant population might 'run away,' that is, it will continue to increase to maximum extremes.

This pattern does not necessarily reflect real-world circumstances, as farmers' tolerances for conflict will decrease as conflict increases. Logically, farmers might begin employing extreme mitigation actions: shooting and using explosives to kill elephants as conflict increases. Conversely, they might decrease shooting and other forms of lethal action as conflict decreases. Regardless, either of these scenarios will have an impact by either allowing the elephant population to grow with minimal human interference, or by directly decreasing the elephant population.

Thus, a feedback loop was introduced into the DBN between the nodes 'Total HEC' and 'Shooting' and between 'Total HEC' and 'Other forms of lethal action.' Figure 11 shows

these changes to the DBN. New temporal arcs were created, at an order of 2. This order of 2 represents a small delay in 'Shooting' and 'Other forms of lethal action' falling increases or decreases to 'Total HEC.' The delay was necessary in the model, as farmers start out at time *t=0* with *a priori* behaviours for use of 'Shooting' and for use of 'Other forms of lethal action' that are later modified depending on total HEC.

Because new arcs were added to the DBN, the CPTs of the 'Shooting' and 'Other forms of lethal action' nodes were updated to reflect the following assumptions:

- Shooting and other forms of lethal action are higher when conflict is higher.
- Shooting and other forms of lethal action are lower when conflict is lower.

These assumptions are encoded into the 'Shooting' and 'Other forms of lethal action' nodes' CPTs (Appendix F).

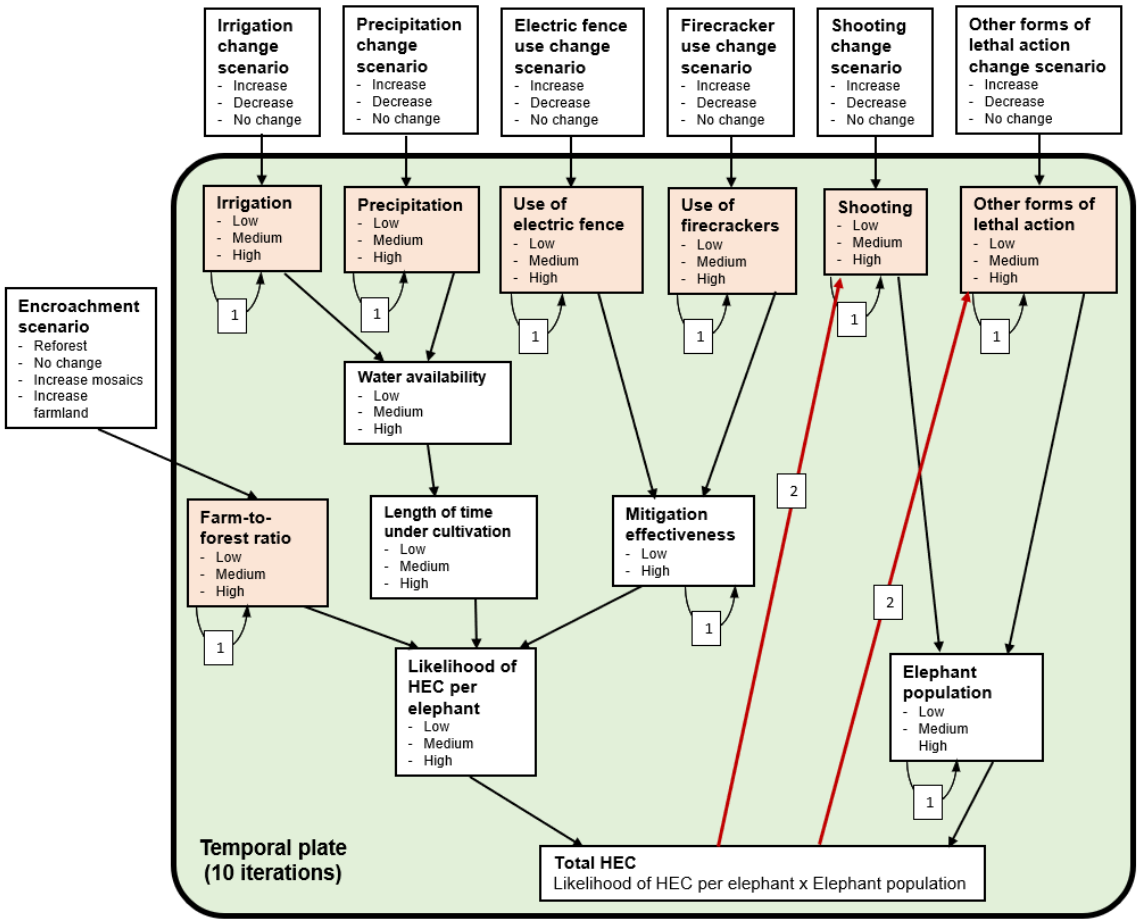

Figure 11: The influence diagram with feedback loops. The new temporal arcs from 'Total HEC' – 'Shooting' and 'Total HEC' – 'Other forms of lethal action' are shown in red, at temporal order 2.

The feedback-loop DBN was run under combinations 1, 2, and 3 in Table 12. However, for these three combinations, note that the 'Shooting change scenario' and 'Other forms of lethal action change scenario' are set to the state '*No change*'; this was done

because the additions of the feedback loop account for changes in ‘Shooting’ and ‘Other forms of lethal action.’

4 RESULTS

The following section presents results for the conceptual DBN and the feedback-loop DBN run under various scenarios to show future socio-environmental change in Sri Lanka might affect the HEC system.

4.1 CONCEPTUAL MODEL

4.1.1 BASELINE CONDITIONS

Figure 12 shows the outputs of the model under baseline conditions. The probabilities of the node ‘Total HEC’ (plotted on secondary y-axis) and the states for the nodes ‘Elephant population density’ and ‘Likelihood of HEC’ are plotted over the DBN’s 10 iterations of time.

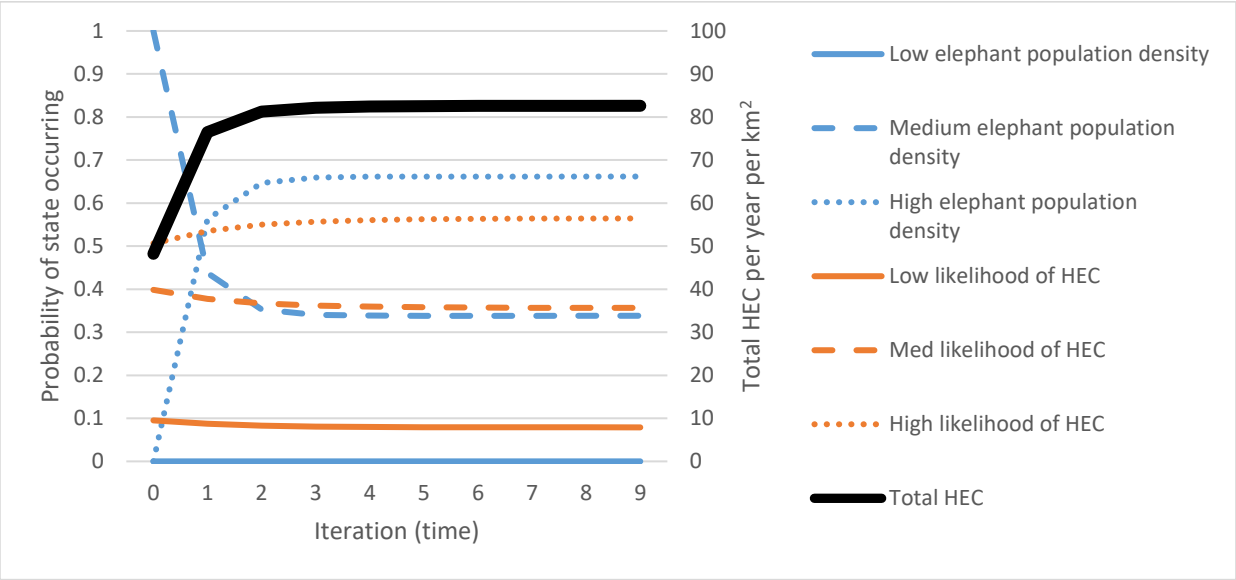

Figure 12: Results of the conceptual DBN under baseline conditions. All states are per km². see Appendix E for additional results of the HEC drivers and mitigation actions, which do not change with time).

4.1.2 POSITIVE CONSERVATION CONDITIONS

Figures 13 shows the outputs of the model (‘Total HEC,’ ‘Elephant population density,’ and ‘Likelihood of HEC’) under positive conservation conditions. Figure 14 shows

the temporal dynamics of the underlying HEC physical drivers and mitigation action variables set for these positive conservation conditions in Table 12.

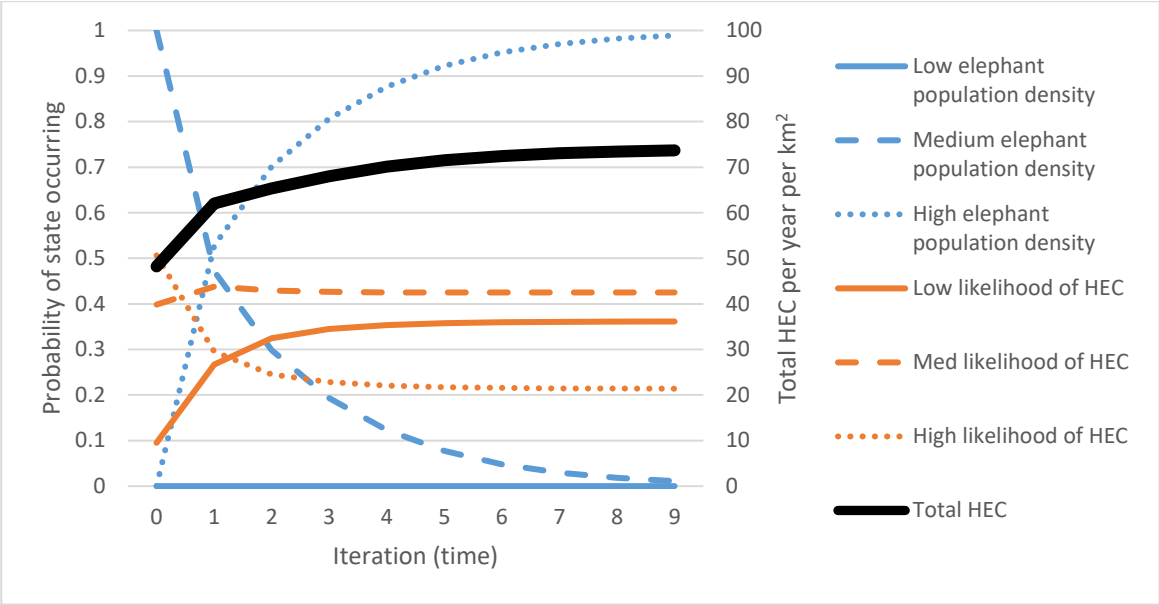

Figure 13: Results of the conceptual DBN under positive conservation conditions in Sri Lanka, showing total HEC and states for the nodes 'Elephant population density' and 'Likelihood of HEC'. All states are per km².

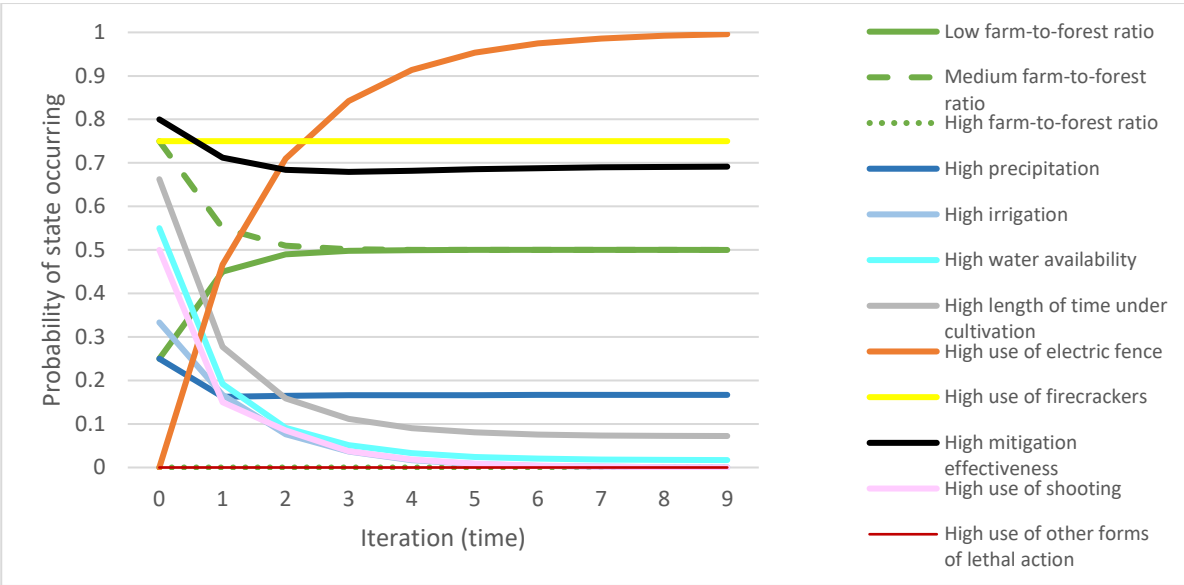

Figure 14: HEC drivers and mitigation strategies of the conceptual DBN under positive conservation conditions in Sri Lanka. Note that the 'Low' and 'Medium' states are not included for some of the nodes for ease of visibility in the plot (see Appendix E). All states are per km².

4.1.3 NEGATIVE CONSERVATION CONDITIONS

Figures 15 shows the outputs of the model ('Total HEC,' 'Elephant population density,' and 'Likelihood of HEC') under negative conservation conditions. Figure 16 shows

the temporal dynamics of the underlying HEC physical drivers and mitigation action variables set for these negative conservation conditions in Table 12.

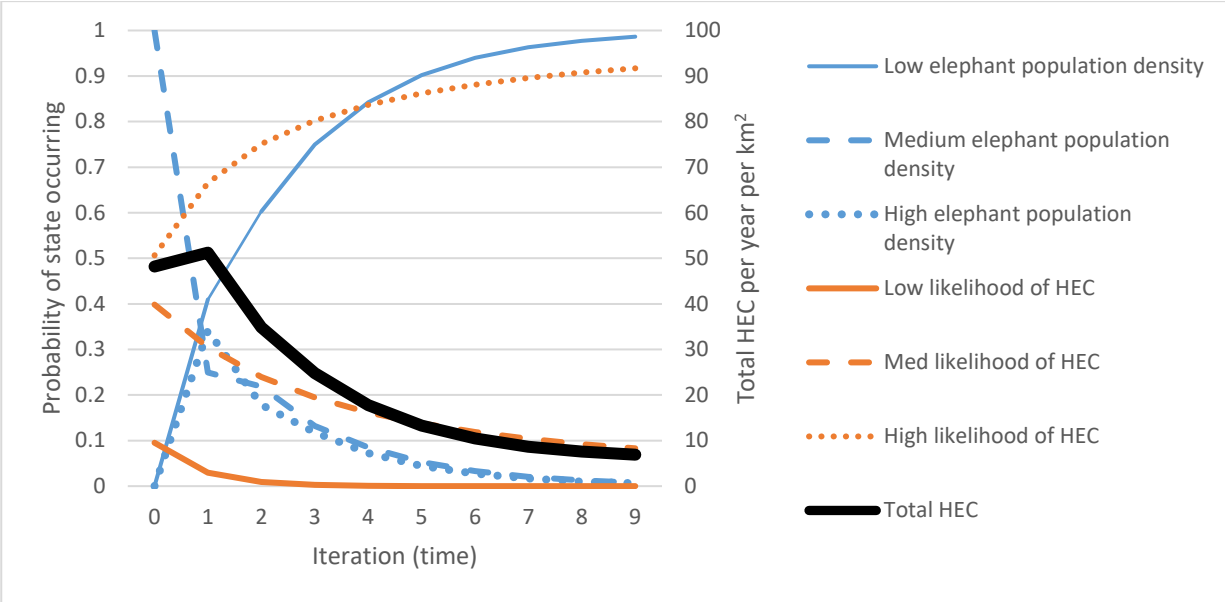

Figure 15: Results of the conceptual DBN under negative conservation conditions in Sri Lanka, showing total HEC and states for the nodes 'Elephant population density' and 'Likelihood of HEC'. All states are per km².

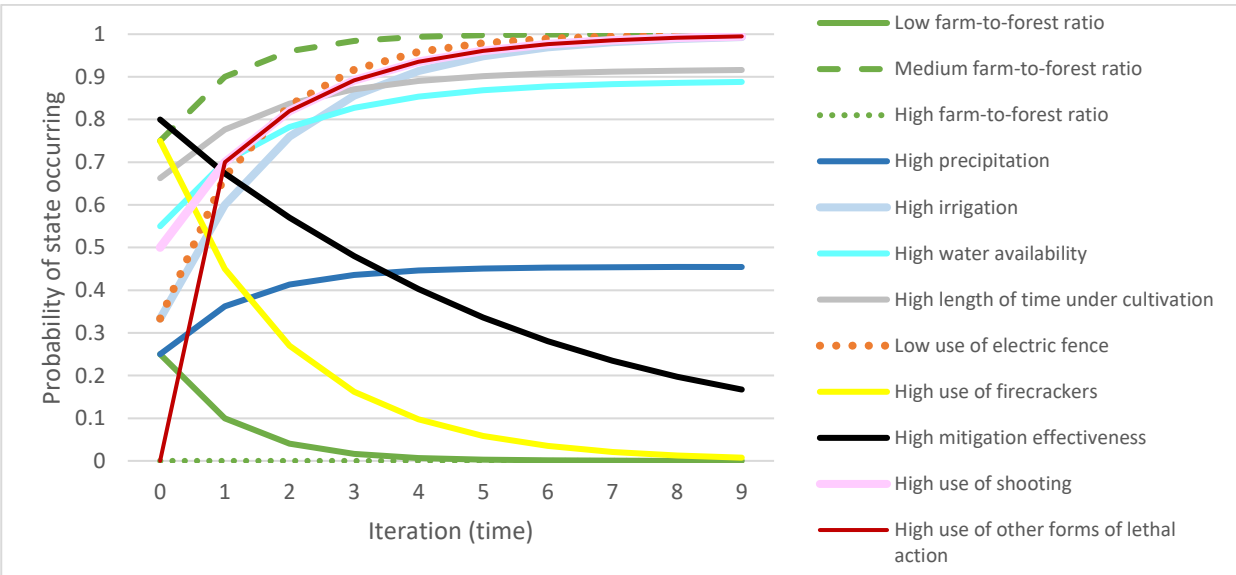

Figure 16: HEC drivers and mitigation strategies of the conceptual DBN under negative conservation conditions in Sri Lanka. Note that the 'Low' and 'Medium' states are not included for some of the nodes for ease of visibility in the plot, with the exception of 'Low use of electric fence' (as 'High use of electric fence' did not change for this negative conservation conditions). All states are per km².

4.1.4 ADDITIONAL CONDITIONS

The results for the conceptual model was run under predicted realistic conditions as well as antagonistic combinations (combinations 4 and 5 in Table 12) are given in Appendix

E. The predicted realistic conditions resemble the results of the negative conservation conditions, as their scenarios are not very different. The DBN was run under antagonistic to show the model's fitness-of-purpose in that it can be used to demonstrate how antagonistic and/or synergistic variables interact to influence total HEC (see Section 2.1.2).

4.2 FEEDBACK LOOP

4.2.1 BASELINE CONDITIONS

Figure 17 shows the outputs of the feedback loop model under baseline conditions. The probabilities of the node 'Total HEC' (plotted on secondary y-axis) and the '*High*' states for the nodes 'Elephant population density,' 'Likelihood of HEC,' 'Shooting,' and 'Other forms of lethal action' are plotted over the DBN's 10 iterations of time.

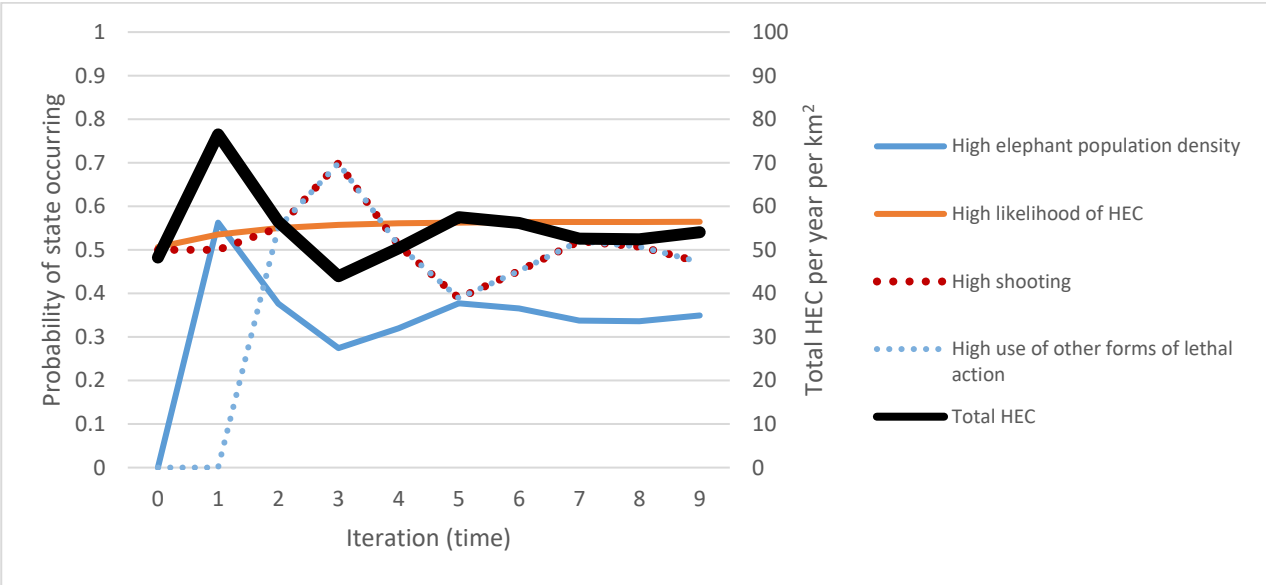

Figure 17: Results of the feedback-loop DBN under baseline conditions, showing total HEC and the 'High' state for the nodes 'Elephant population density' and 'Likelihood of HEC' (see Appendix F for supplementary results of the nodes' other states). All states are per km².

4.2.2 POSITIVE CONSERVATION CONDITIONS

Figure 18 shows the outputs of the feedback loop model under baseline conditions. The probabilities of the node 'Total HEC' (plotted on secondary y-axis) and the '*High*' states for the nodes 'Elephant population density,' 'Likelihood of HEC,' 'Shooting,' and 'Other forms of lethal action' are plotted over the DBN's 10 iterations of time.

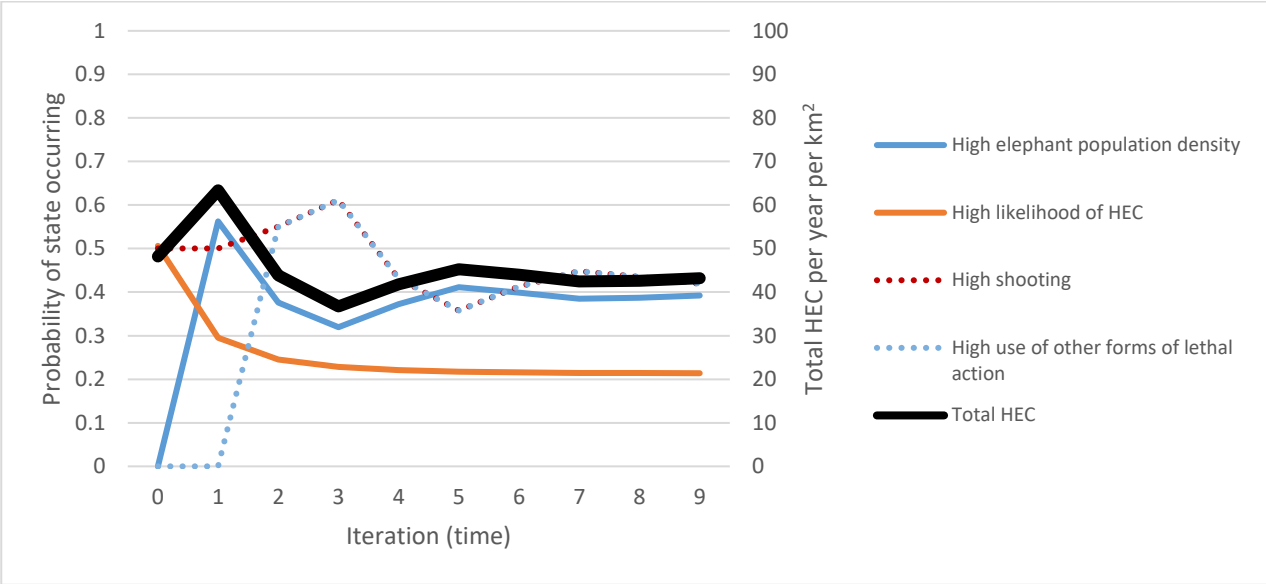

Figure 18: Results of the feedback-loop DBN under positive conservation conditions, showing total HEC and states for the nodes 'Elephant population density' and 'Likelihood of HEC' (see Appendix F for supplementary results of the nodes' other states). All states are per km².

4.2.3 NEGATIVE CONSERVATION CONDITIONS

Figure 19 shows the outputs of the feedback loop model under baseline conditions. The probabilities of the node 'Total HEC' (plotted on secondary y-axis) and the '*High*' states for the nodes 'Elephant population density,' 'Likelihood of HEC,' 'Shooting,' and 'Other forms of lethal action' are plotted over the DBN's 10 iterations of time.

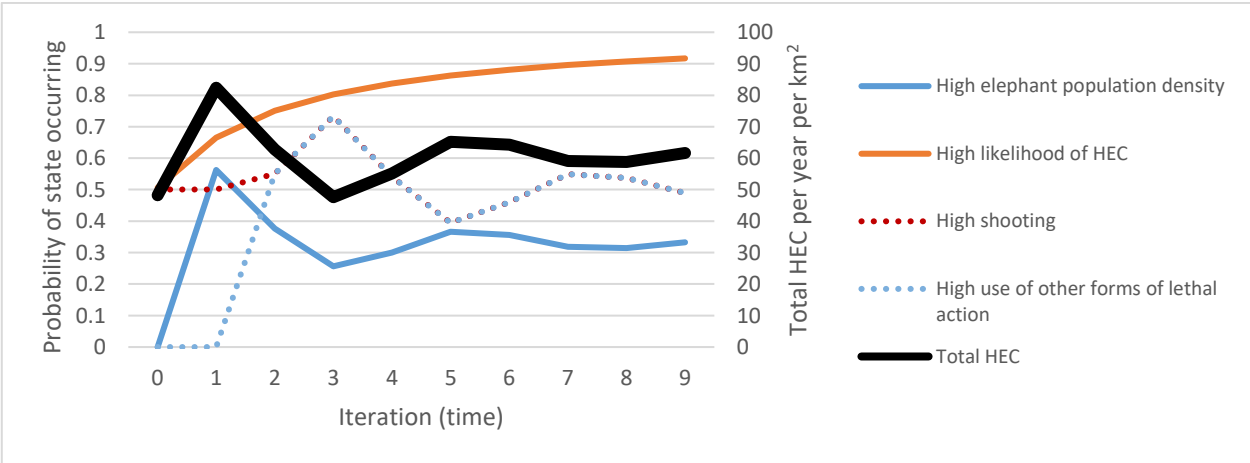

Figure 19: Results of the feedback-loop DBN under negative conservation conditions, showing total HEC and states for the nodes 'Elephant population density' and 'Likelihood of HEC' (see Appendix F for supplementary results of the nodes' other states). All states are per km².

I discuss the implications of these results from the conceptual DBN and from the feedback-loop DBN in the following section.

5 DISCUSSION

The DBN created in this dissertation was designed as a proof of concept model that reflects qualitative knowledge, intuitions, and assumptions about the HEC system in Sri Lanka. This qualitative knowledge was encoded via probabilities into each node's CPT, resulting in model outputs that quantitatively (through probabilities) express how HEC and its physical drivers and mitigation actions might change in time under certain socio-environmental conditions. The results of the model runs under different scenarios show that incomplete and qualitative knowledge can be used to create a proof of concept model and demonstrate that the DBN approach can be used to explore how various drivers and mitigation strategies of HEC interact, both synergistically and antagonistically (see Section 4.1.4)

More detailed implications of the results from the conceptual DBN versus from the feedback-loop DBN are discussed in the following section.

5.1 OVERVIEW OF FINDINGS

The model outputs of the conceptual DBN in Figures 12 through 16 reflect several of the encoded intuitions and assumptions about HEC. First, under contemporary conditions in Sri Lanka, which are expressed via the priors of the DBN's first-order temporal nodes, total HEC increases through time and plateaus at a near-maximum value (Figure 11). This is due to an encoded assumption in the node's CPT: the contemporary elephant population increases despite conflict resulting in a number of elephant deaths per year (see Figure 1). Total HEC plateaus in Figure 11 when the elephant population density also plateaus, reaching a quasi-carrying capacity.

In the positive conservation conditions depicted in Figure 13, total HEC is slightly lower than the 'no change' conditions in Figure 11. This is because even though the elephant population density is higher than in Figure 11, the likelihood of HEC is also lower, thus resulting in fewer conflicts. Under negative conservation conditions shown in Figure 15, both the likelihood of HEC and the elephant population density plummet despite an a priori assumption encoded into the DBN that the elephant population growth rate is positive. This results in total HEC decreasing throughout time, because there are fewer elephants with which humans can come into contact with.

The feedback-loop DBN is an adoption of the conceptual DBN to reflect a change in human behaviour, whereby humans have a direct impact on elephant population by employing lethal HEC mitigation actions. The results presented in Figures 17, 18, and 19 demonstrate that with a HEC-elephant population feedback loop, total HEC is greatest under

negative conservation conditions, approaching 60 conflicts per year per km^2 in Figure 21. Total HEC approaches 55 conflicts per km^2 per year under the 'No change' scenario in Figure 19, and total HEC is lowest under the positive conservation conditions in Figure 20, approaching 43 conflicts per year per km^2.

Neither the conceptual DBN nor the feedback-loop DBN are incorrect, but they demonstrate how a small modification using a Bayesian approach can result in two very different scenarios of how a HEC system can be modelled. In the former, human behaviours are pre-determined in time, due to setting '*Increase*' and '*Decrease*' scenarios of the 'Shooting' and 'Other forms of lethal action' nodes, whether or not HEC has increased or decreased over time. This may result in counterintuitive outcomes; for instance, under positive conservation conditions total HEC increases over time but 'Shooting' decreases and 'Other forms of lethal action' stay constant (Figure 13).

In contrast, the feedback-loop DBN allows human behaviours underlying the usage of 'Shooting' and 'Other forms of lethal action' to dynamically respond to increases and decreases in total HEC through time. This illustrates how farmers' tolerance for HEC is eroded when conflict increases, and they respond by shooting at elephants and/or using other forms of lethal action. The results of the feedback-loop DBN that depict quasi-equilibria states for 'Elephant population density,' 'Shooting,' and 'Other forms of lethal action' are still naturally simplifications of the real-world system. However, the results demonstrate that the DBN approach can encode different kinds of behaviours that affect HEC.

The model outcomes in Figures 12 to 16 show that the assumptions and intuitions of HEC from literature and expert elicitation were correctly encoded into the DBN. For instance, conflict increases in mosaic areas, use of electric fences and firecrackers deteriorate with time and are not very effective strategies to begin with, and the length of time a farm is under cultivation causes conflict to increase.

Additional information on HEC in literature, as well as comments from survey participants (Appendix A), validate the DBN's results. The patterns shown in the feedback-loop DBN have also been reported qualitatively in literature: 'Elephants destroy crops, damage houses, and at times even kill people. Irate farmers in return retaliate by shooting, wounding or killing elephants with home-made weapons. Hence, the tolerance traditionally shown to the elephant appears to be gradually weakening in farming communities when the elephant interferes with agriculture' (Santiapillai et al., 2010). Thus, the results from the feedback-loop DBN provide a proof of principle.

Additionally, in a study of HEC in Uganda, Chiyo et al. (2005) found that HEC was related to temporal patterns, with crop raiding peaking when crop availability was high. The model outcomes reflect this finding, as likelihood of HEC increases when the length of time a farm is under cultivation also increases (compare Figures 15 and 16). In another study on

African elephants, Graham et al. (2009) found that ‘the greater the amount of smallholder land within an elephant’s range, the more it was utilized, with consequent implications for conflict.’ The DBN results correspond to this finding: agricultural expansion increases the likelihood of conflict, as elephants thus have greater spatial opportunities to raid crops.

Finally, the results in this dissertation echo Fernando et al. (2018)’s argument that human-elephant conflict must be shifted into a human-elephant coexistence model if the Sri Lankan elephant population is to persist long term. Both the conceptual and feedback-loop DBNs depict bleak future prospects for elephant conservation. All results shown from Figures 12 to 19 show that the proximity of elephants and humans readily lead to conflict and/or elephant population decline. Thus, within the DBN, elephant conservation outcomes can be more positive only if additional variables are included (e.g. a variable that shows that financial compensation is effective at mitigating conflict, a dubious assumption) or if the assumptions and knowledge encoding the nodes’ CPTs change.

5.2 LIMITATIONS AND FUTURE DIRECTIONS

It should be noted that the DBN includes several limitations and simplifications that were deemed acceptable for this proof of concept model. Most significantly, the model does not provide exact numbers of total HEC. Rather, the quantitative components of the DBN (e.g. precipitation data, total HEC per km^2 per year, elephant population density) are numerical representations of what data on the variables in the DBN could conceivably resemble. These numbers are used to demonstrate that the DBN can integrate both quantitative and qualitative data that are uncertain and incomplete. Moreover, the CPTs were not populated by exact amounts, but as qualitative descriptors of the assumptions outlined, highlighting how intuitions and assumptions can still be encoded into the DBN.

These shortcomings of the DBN also provide opportunities to improve the model in future research, particularly by integrating quantitative data, provided the data exist. For example, the states of all nodes could be quantitatively defined in an explicit manner, and quantitative data could be used to calibrate CPTs. In future directions, the DBN can be expanded to include more nodes and arcs, including non-physical drivers of HEC, as well as spatially explicit and intra-annual phenomena (see Section 3.1.1). In its current state, the scope of the DBN was conceptually applied to a 1 x 1 km landscape, but the model could be made spatially explicit by hybridising the Bayesian approach with GIS modelling, an approach that has been used for other applications in biodiversity conservation (Stelzenmuller et al., 2010; Smith et al., 2007). The original simplifications of the DBN (see Section 3.1.1) and the other relevant correlates of HEC (see Table 1) could also be addressed in future work by incorporating additional nodes, such as socioeconomic

variables (e.g. poverty, crop prices, financial compensation), human belief variables (e.g. communication of elephant conservation initiatives), and other mitigation strategies (e.g. placement of wildlife corridors).

Finally, formal model validation could be undertaken in future research. Empirical data were not available to validate the DBN, and as such, the DBN contains high uncertainty (Chen and Pollinio, 2012). However, as a proof of concept model, the DBN has adequate fitness-of-purpose, serving its intentions by qualitatively encoding assumptions and knowledge of the HEC system. In future work, spatiotemporal data could validate that the model operates according to reality. This might involve acquiring HEC occurrence data over time from a variety of areas in Sri Lanka that reflect the DBN's different model scenarios (e.g. positive vs negative conservation conditions) to validate conflict patterns against socio-environmental changes.

6 CONCLUSIONS

This dissertation presents a proof of concept dynamic Bayesian model of human-elephant conflict, developed from a combination of literature reviews and expert elicitation. It is important to understand that the influence diagram in this dissertation does not represent all conflict correlates, but the framework presented addresses an important analytical gap and has flexible scope for further modelling. This work demonstrates that a DBN approach can be used to model a complex coupled natural-human system for which empirical, quantitative data is difficult to obtain. The DBN of HEC illustrates how the Bayesian approach is useful to create a model that incorporates different sources of data (quantitative, qualitative, etc.), as well as incomplete data. Although the DBN did not incorporate exact data, it was still able to probabilistically express proof of principle. Furthermore, as demonstrated by the 'Precipitation' and 'Farm-to-forest ratio' nodes, real existing quantitative data can be integrated into the DBN.

Although Bayesian networks have been used in environmental management, they have not been widely applied specifically to wildlife conservation studies (Uusitalo, 2007; Hamilton et al., 2015; Marcot et al., 2001). This dissertation highlights steps towards how a Bayesian network can be used to model socio-environmental systems in conservation. Finally, the model serves as a framework to use a Bayesian approach to model HEC and could be applied to other regions where HEC is prevalent.

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APPENDICES

Appendix A – Survey questions and responses sent out to experts with knowledge of HEC in Sri Lanka. 4 participants completed the survey. (Questions 1-8 were related to information and privacy notice for survey participants).

9 What part of Sri Lanka do you have knowledge about human-elephant (HEC)?

Showing all 4 responses	
Island-wide	500643-500634-49556671
The entire island	500643-500634-49564935
The entire country	500643-500634-49602706
South-central (Udawalawe and surroundings)	500643-500634-49654378

10 How would you describe your knowledge of HEC in your area?

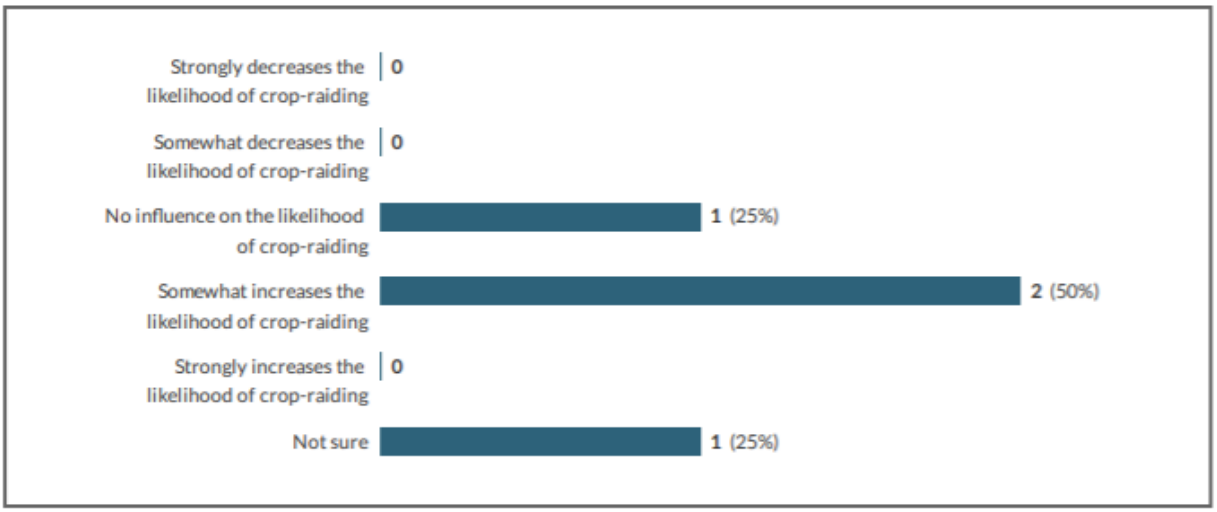
10.a If you selected Other, please specify:

No responses

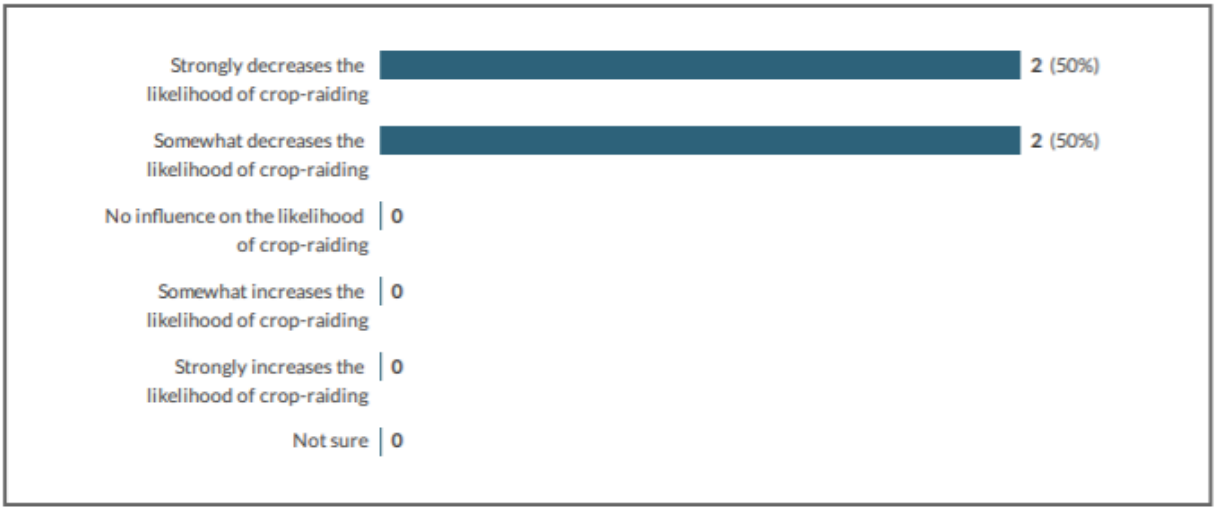
11 Additional comments (optional):

Showing 1 response	
I have been working on HEC issues in Sri Lanka and in Asia for the last 15 years	500643-500634-49602706

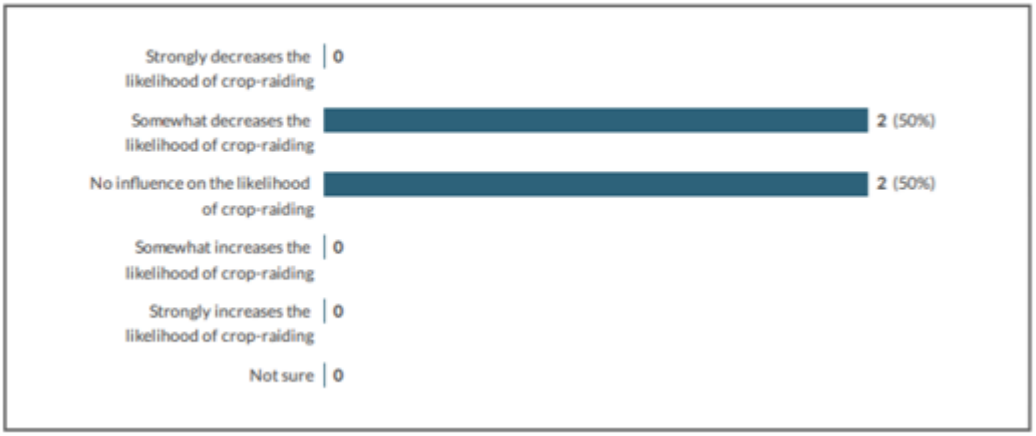
12 Increase the land area of a farm



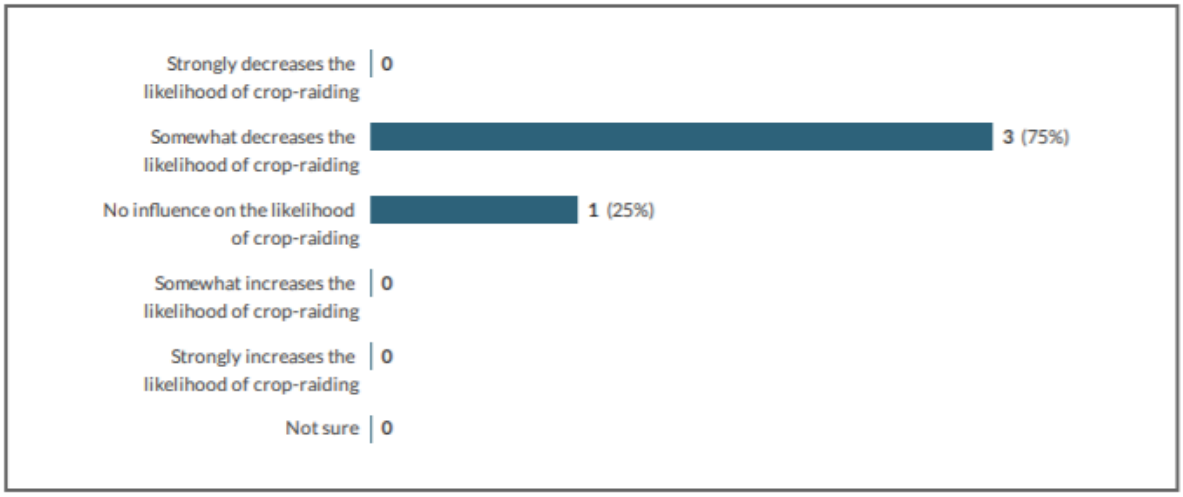
13 Employ a sufficient physical barrier or electric fence around a farm



14 Human uses firecrackers if an elephant approaches farmland / property



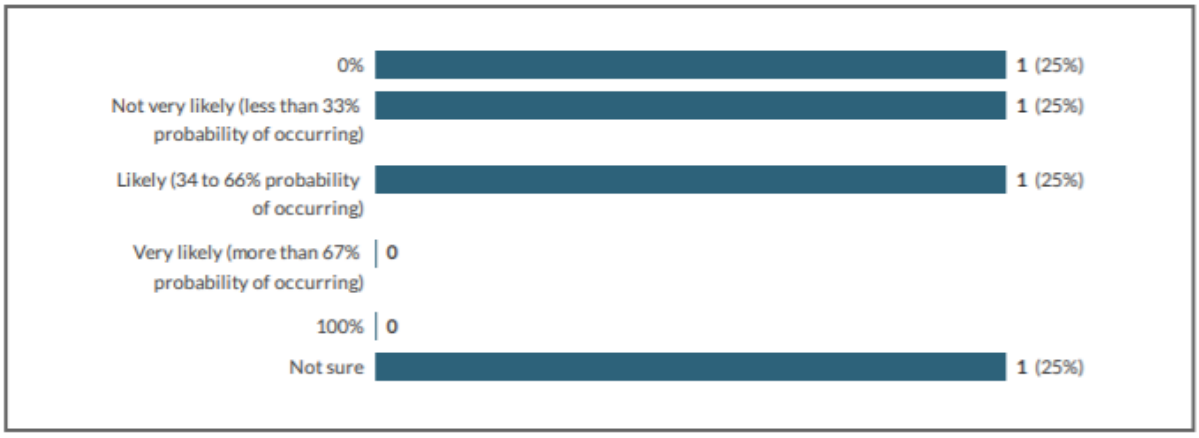
15 Human uses a gun to shoot at the elephant if it approaches farmland / property



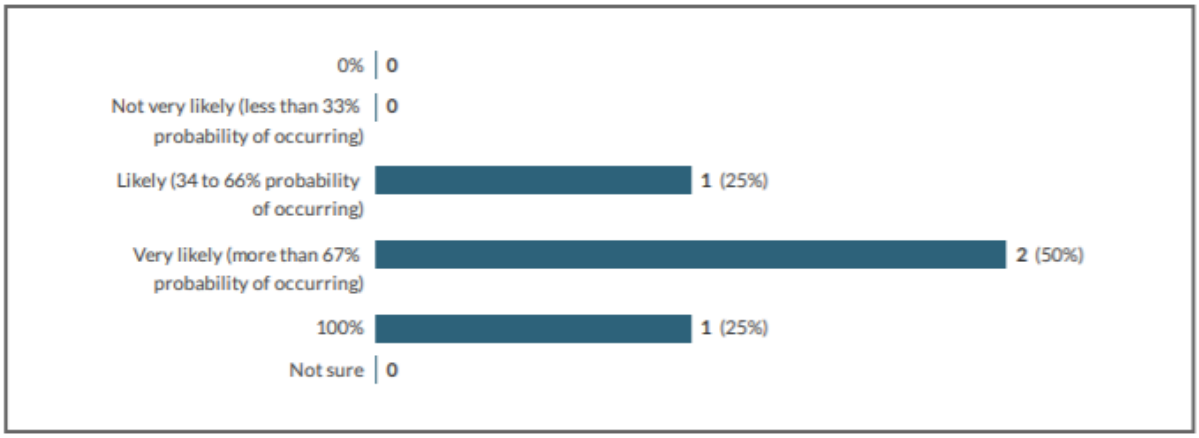
16 Additional comments (optional):

Showing all 3 responses	
Electric fences only work in the right situation, correctly built and maintained properly - which is not easy!	500643-500634-49556671
Any of the factors or methods mentioned depends on the local situation.	500643-500634-49564935
Electric fences are an effective barrier only if it located at the right place. Basically on the ecological boundary and not on administrative boundaries. The use of fire-crackers and guns are a short term deterrent because elephants get used to it over time and also it makes elephants more aggressive towards humans, thereby increasing the conflict.	500643-500634-49602706

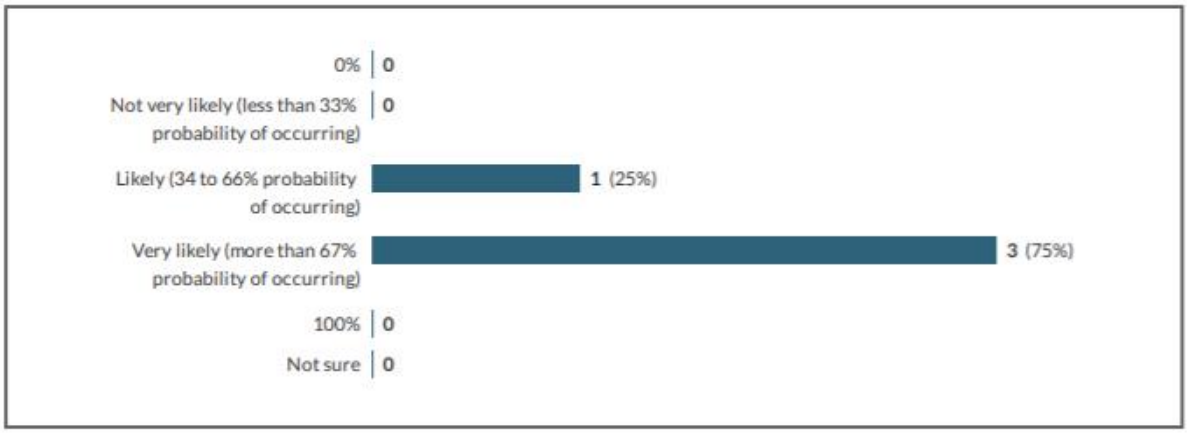
17 A landscape of 100% forest



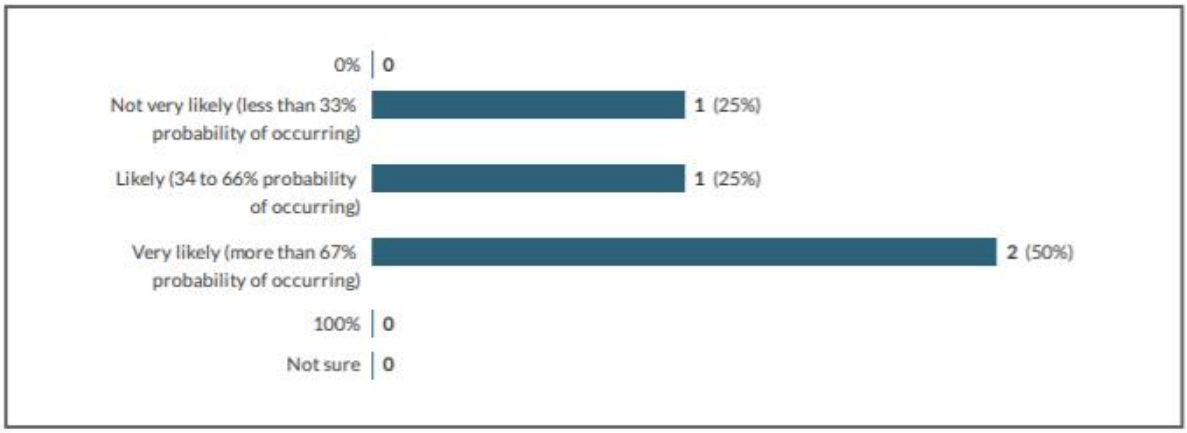
18 A landscape of 25% farmland and 75% forest



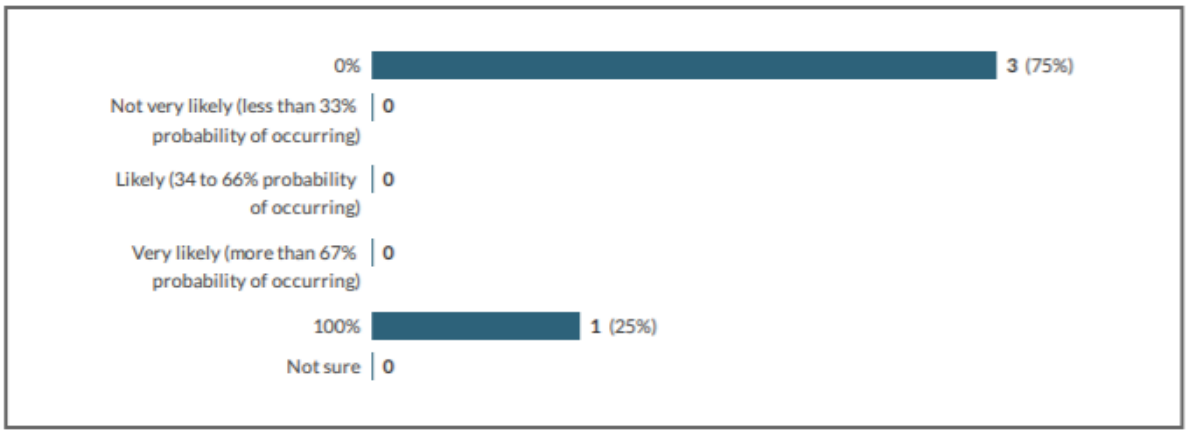
19 A landscape of 50% farmland and 50% forest



20 A landscape of 75% farmland and 25% forest



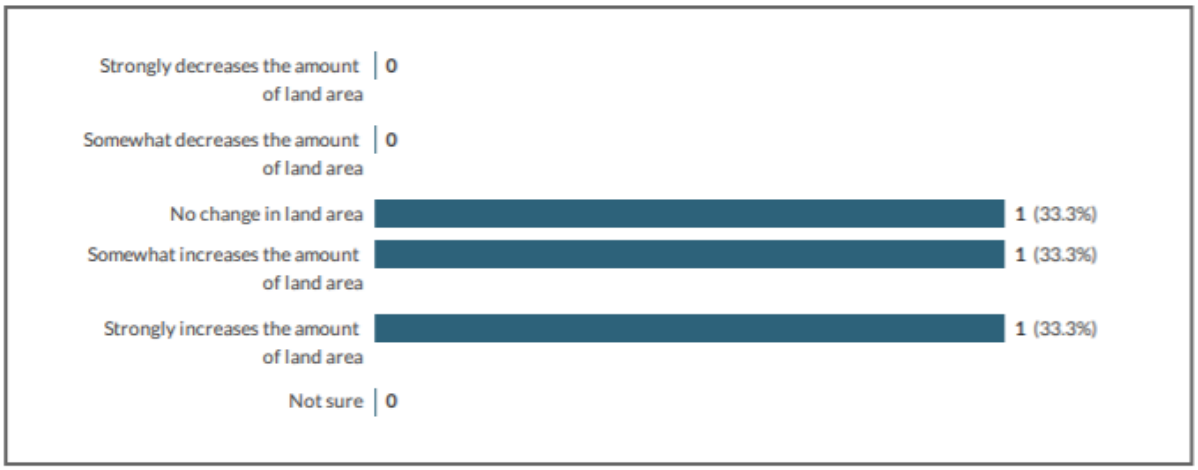
21 A landscape of 100% farmland



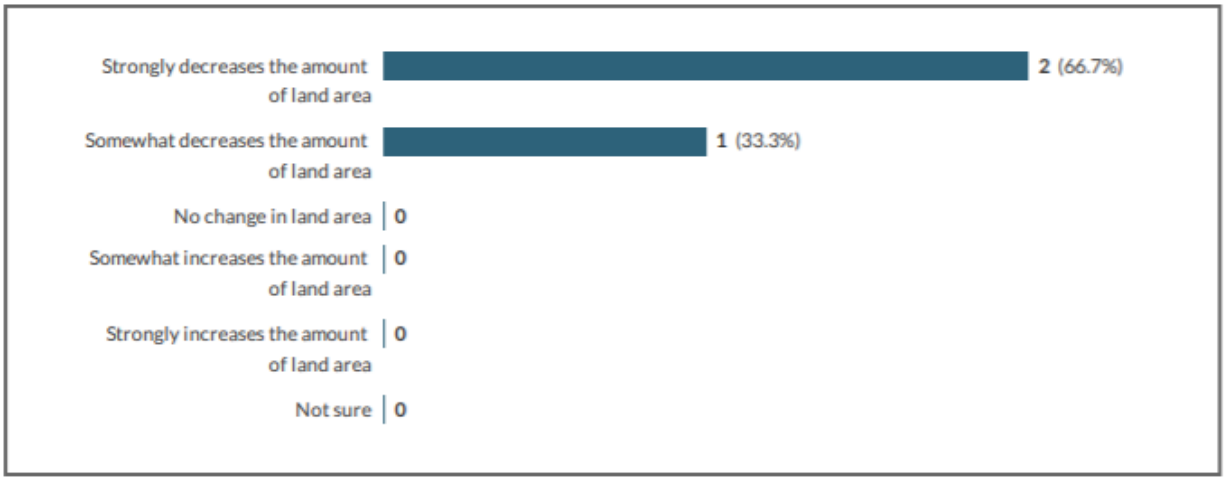
22 Additional comments (optional):

Showing all 3 responses	
It depends how fragmented it is - to ask like this makes little sense	500643-500634-49556671
At this time there is no 100 forest cover left for elephants in Sri Lanka. Practically all elephant populations in Sri Lanka in contact with humans.	500643-500634-49564935
The best elephant habitat is degraded forest. So 100% forest can accommodate a low density of elephants ~ 0.2-0.3 elephants per square km whereas grasslands and scrub jungle can accommodate up to 3 elephants per sq. km. So if there is a large elephant population, and a lot of forest land--particularly primary forest, there is a significant likelihood that elephants will raid crops.	500643-500634-49602706

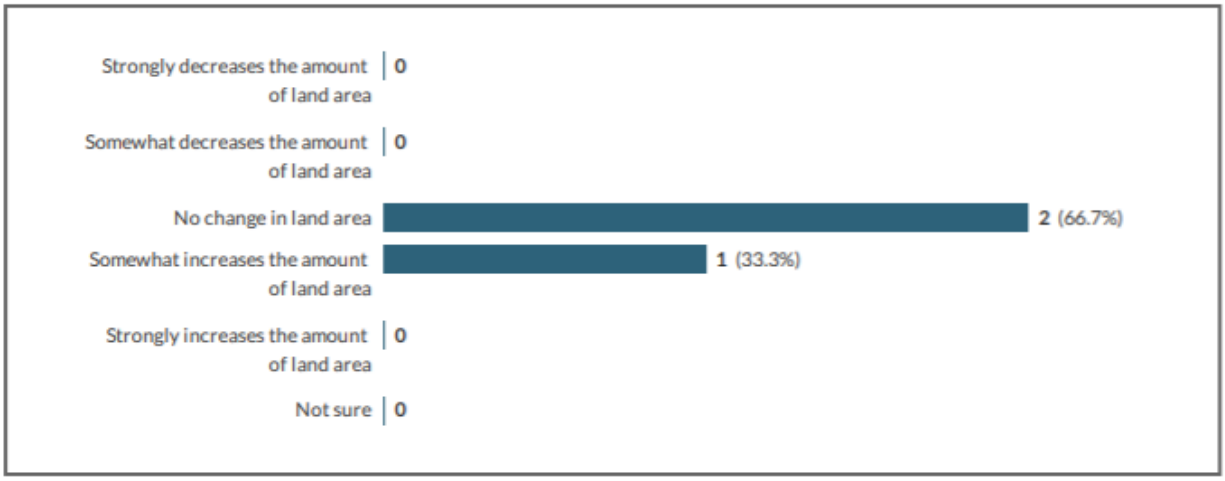
23 Precipitation INCREASES substantially from the yearly average (e.g. an increase from a typical/historically expected yearly average to 1 standard deviation above average)



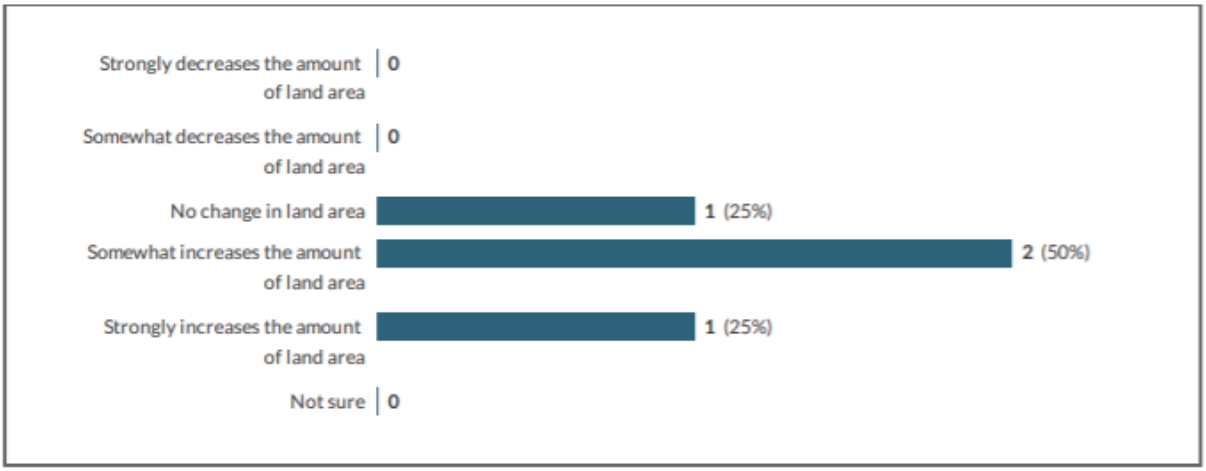
24 Precipitation DECREASES substantially from the yearly average (e.g. a decrease from a typical/historically expected yearly average to 1 standard deviation below average)



25 Precipitation remains the same as 'typical'/historically expected levels



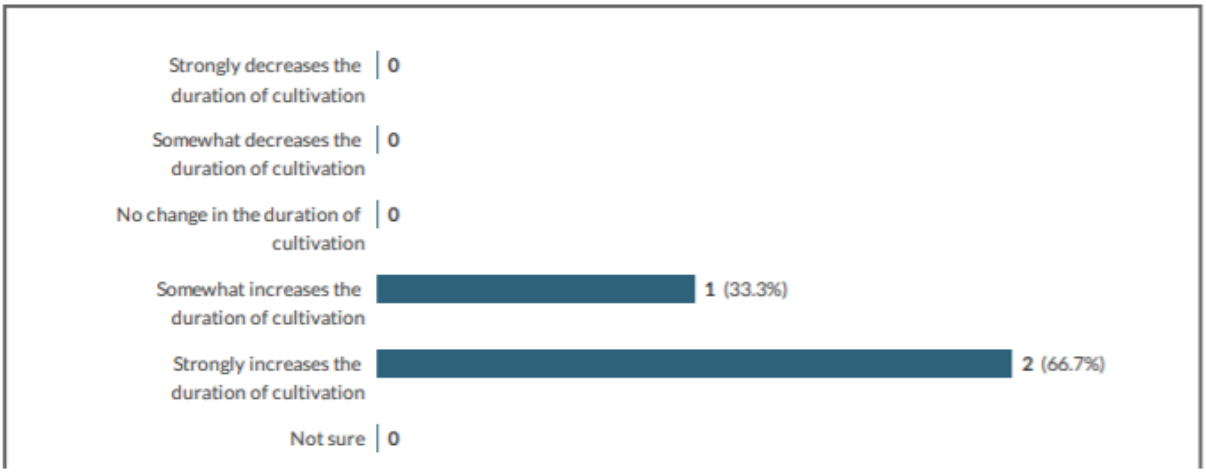
26 Farmer has access to irrigation infrastructure



27 Additional comments (optional):

Showing all 3 responses	
I don't know what you mean with increlase/decrease by 1 standard deviation. Precipitation the same? The last two years it was very low. So not clear which level is "the same"	500643-500634-49556671
Availability of irrigation water is vital for cultivation and does play a major role in how land is used.	500643-500634-49564935
Sri Lankan farmers do not focus on increasing the yield from a unit area of land. The farmers tend to increase the land area cultivated to increase yield. As a country we need to improve productivity of existing land but there are minimal efforts made in regard to that. If productivity is increased, there will be less elephant habitat encroached.	500643-500634-49602706

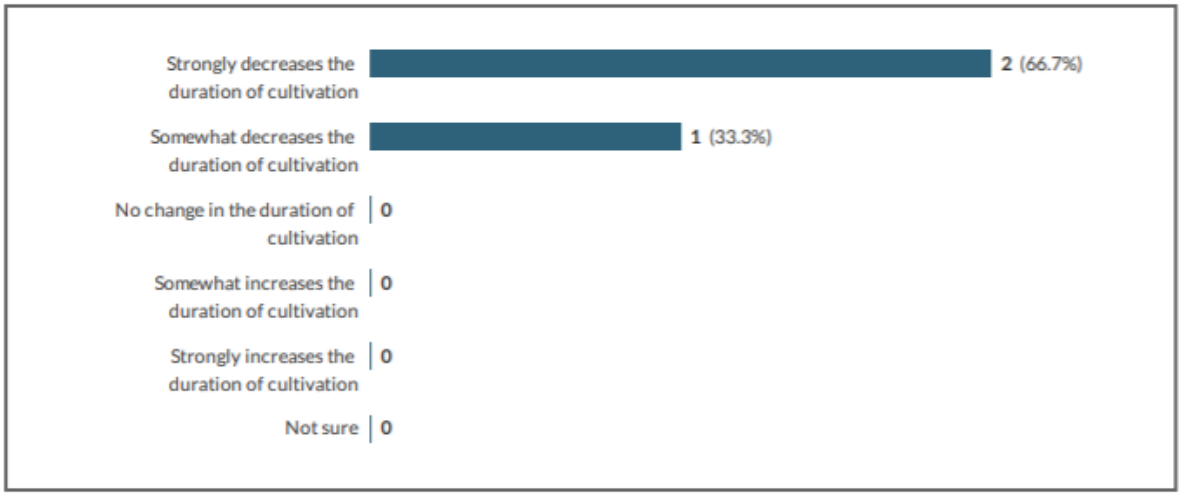
28 Precipitation INCREASES from the yearly average to 1 standard deviation above average



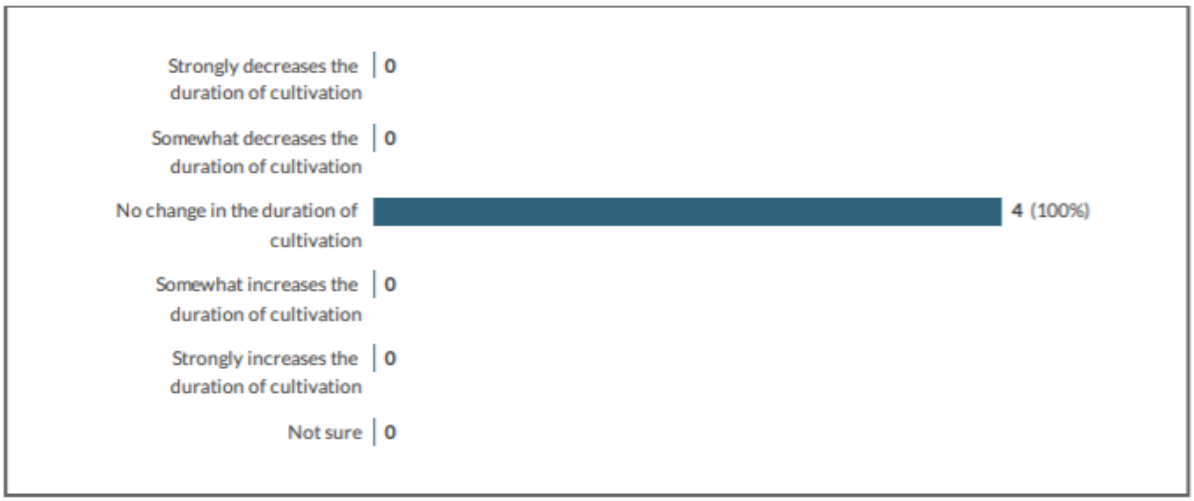
28.a By how many months do you think it would change?

Showing all 3 responses	
Generally there are two cultivation seasons in Sri Lanka. If there is excessive rains farmers are known to cultivate a third season as well. This adds another 3 months of cultivation	500643-500634-49564935
by about 4 months	500643-500634-49602706
3	500643-500634-49654378

29 Precipitation DECREASES from the yearly average to 1 standard deviation below average



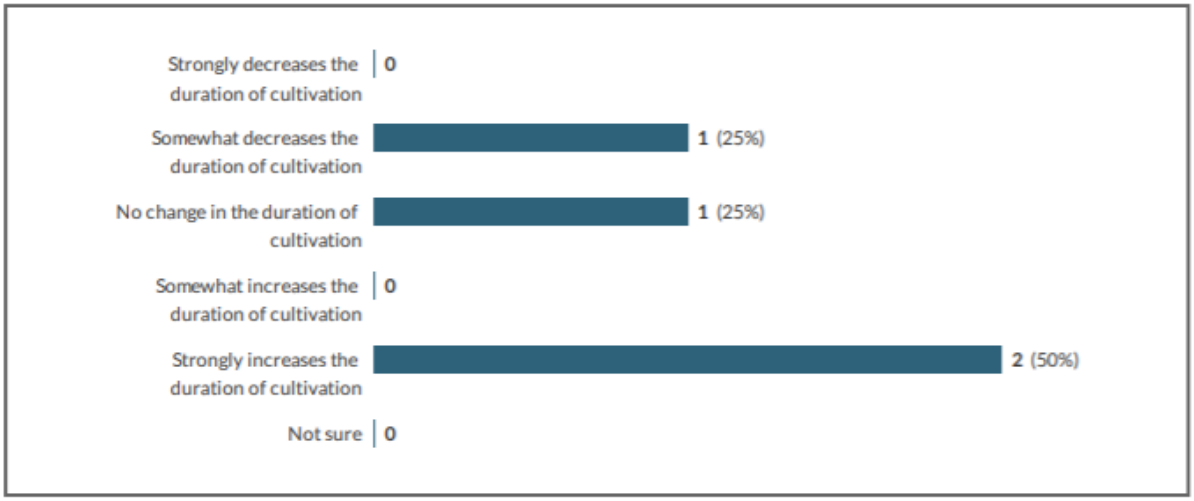
30 Precipitation remains the same as it is currently



30.a By how many months do you think it would change?

Showing all 2 responses	
If rain fall patterns remain the same then farmers will adhere to the two cultivating seasons. No change in months	500643-500634-49564935
none	500643-500634-49602706

31 Farmer has access to irrigation infrastructure

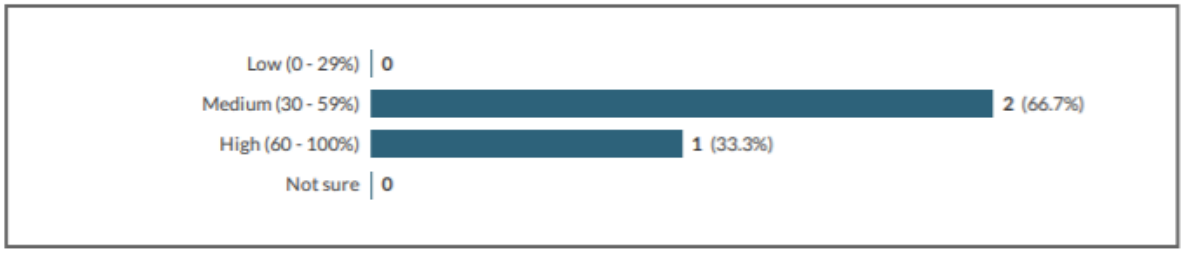


Showing all 4 responses	
they want all year round - again, how much is the irrigation making possible?	500643-500634-49556671
Farmers will follow attempt to cultivate throughout the year. This will add another four to 6 months.	500643-500634-49564935
4 months	500643-500634-49602706
3	500643-500634-49654378

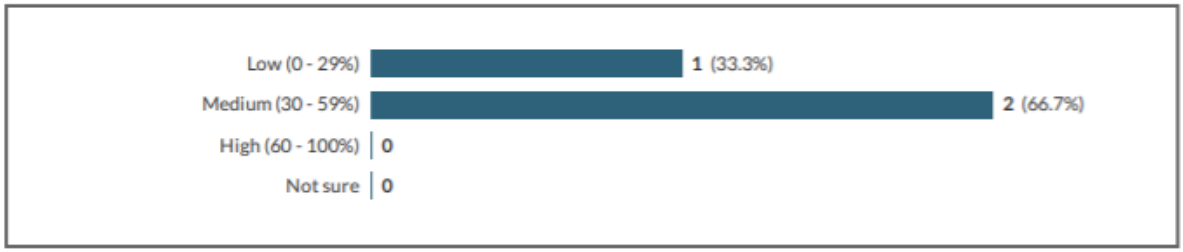
32 Additional comments (optional):

Showing all 2 responses	
Already now it is very variable as the rains are not every year the same	500643-500634-49556671
Crops are planted for one season in the dry zone where there are a predominance of elephants, due to water availability. But if there is additional water, there could be 2 crops planted.	500643-500634-49602706

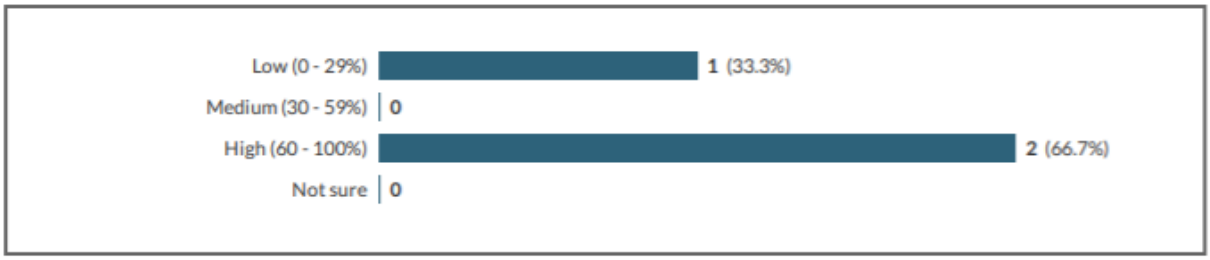
33 For people affected by HEC in your area of expertise, approximately what percentage of peeople use some irrigation when growing crops?



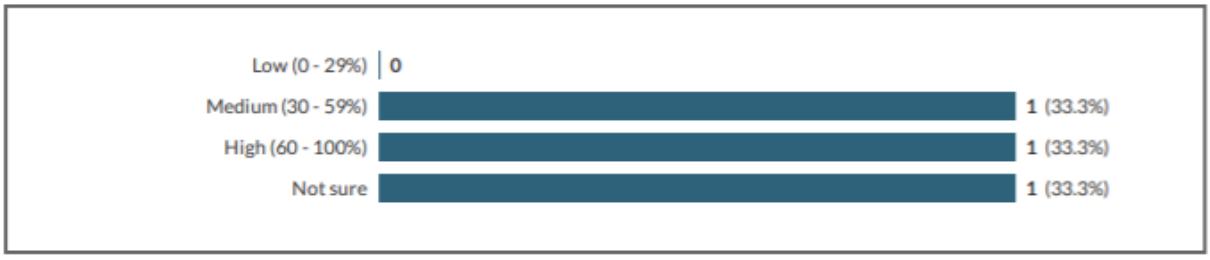
34 For people affected by HEC in your area of expertise, approximately what percentage of people employ a physical barrier (e.g. electric fence, live fence)?



35 For people affected by HEC in your area of expertise, approximately what percentage of people use firecrackers if an elephant approaches farmland / property at any time of day?

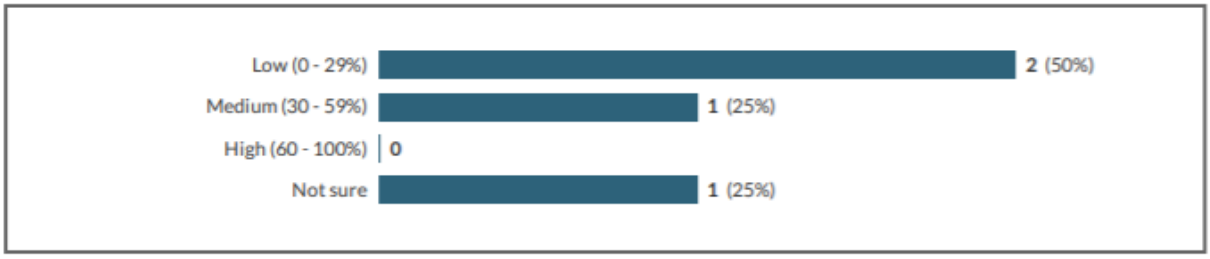


36 For people affected by HEC in your area of expertise, approximately what percentage of peeople use a gun to shoot at the elephant if it approaches farmland / property at any time of the day (not including a gun or firecrackers)?

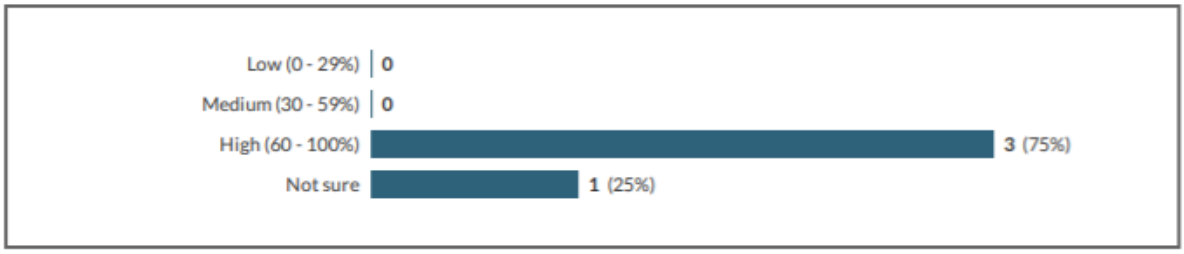


37 For people affected by HEC in your area of expertise, approximately what percentage of peeople use some form of lethal control (e.g. explosives, poison, etc.) at the elephant if it approaches farmland / property at any time of the day (not including a gun or firecrackers)?

38 What is the likelihood of killing an elephant when shooting?



39 What is the likelihood of killing an elephant when using explosives, poisons, or some other form of lethal control (not including shooting)?



40 Additional comments (optional):

Showing all 2 responses	
Farmers will not admit to using any lethal measure to control elephants. Elephants that have been subjected to lethal measures will succumb to their injuries far from where they received them. So overall it is rather difficult collect data on such practices and measure their impacts on elephants	500643-500634-49564935
319 elephants were killed as a result of the conflict in 2018, which is the first time the increasing trend of elephant deaths exceeded 300, therefore, the means used by people to kill elephants is quite effective.	500643-500634-49602706

Appendix B – Average monthly precipitation data for Sri Lanka, for historic (1901-2016) and predicted future conditions (World Bank Group, 2019). Data were used to calculate the 'Precipitation' node's prior and posterior probabilities.

Average monthly rainfall from 1901-2016 (mm/mo)	
Jan	118.14
Feb	80.86
Mar	84.87
Apr	151.52
May	126.54
June	73.66
Jul	72.38
Aug	87.55
Sept	113.14
Oct	256.72
Nov	303.51
Dec	225.07
Average	141.1633
Standard dev	78.25033
-1 std dev	62.913
+1 std dev	219.4137
# months 1 std. dev. below average	0
# months at average	9
# months 1 std. dev. above average	3

Future predicted rainfall for 2080-2099 (mm/mo)			
Month	Lower end of 10-90% confidence interval	Median	Upper end of 10-90% confidence interval
Jan	67.69	120.49	177.52
Feb	36.96	72.67	107.98
Mar	42.4	70.02	95.35
Apr	95.07	144.94	171.83
May	61.67	106.69	159.69
June	6.86	72.45	172.96
Jul	46.95	95.09	186.38
Aug	43.32	141.22	289.31
Sept	82.89	163.05	291.18
Oct	278.63	363.38	465.92
Nov	275.45	387.24	517.45
Dec	179.85	264.04	380.95
# months 1 std. dev. below average	6	0	0
# months at average	4	9	7
# months 1 std. dev. above average	2	3	5

Appendix C – Conditional probability tables for all temporal nodes in the DBN.

'Precipitation' node at time *t=1*

Precipitation change scenario	Decrease			No change			Increase		
Self (t-1)	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.62	0.4	0.3	0	0	0	0	0	0
Medium	0.213333	0.45	0.5	0.75	0.75	0.75	0.8	0.7	0.4
High	0.166667	0.15	0.2	0.25	0.25	0.25	0.2	0.3	0.6

'Irrigation' node at time *t=1*

Irrigation change scenario	Decrease			No change			Increase		
Self (t-1)	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.62	0.4	0.3	0	0	0	0	0	0
Medium	0.213333	0.45	0.5	0.75	0.75	0.75	0.8	0.7	0.4
High	0.166667	0.15	0.2	0.25	0.25	0.25	0.2	0.3	0.6

‘Farm-to-forest ratio’ node at time *t=1*

Encroachment change scenario	Reforest/Afforest			No change			Increase mosaics			Increase farmland		
Self (t-1)	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.6	0.4	0.5	0.25	0.25	0.25	0.4	0	0.5	0.1	0.15	0.05
Medium	0.4	0.6	0.5	0.75	0.75	0.75	0.6	1	0.5	0.5	0.55	0.05
High	0	0	0	0	0	0	0	0	0	0.4	0.3	0.9

‘Water availability’ node at time *t*

Irrigation	Low			Medium			High		
Precipitation	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	1	0.5	0.6	0.7	0	0	0.2	0	0
Medium	0	0.5	0.3	0.3	0.7	0.3	0.5	0.2	0
High	0	0	0.1	0	0.3	0.7	0.3	0.8	1

‘Length of time under cultivation’ node at time *t*

Water availability	Low	Medium	High
Low (0-4 months)	0.75	0.25	0
Medium (4-8 months)	0.25	0.5	0
High (8-12 months)	0	0.25	1

‘Use of electric fence’ node at time *t=1*

Electric fence change scenario	Decrease			No change			Increase		
Self (t-1)	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	1	0.5	0.3	0.33	0.33	0.33	0.3	0.2	0
Medium	0	0.5	0.7	0.66	0.66	0.66	0.3	0.3	0
High	0	0	0	0	0	0	0.4	0.5	1

‘Use of firecrackers’ node at time *t=1*

Firecrackers change scenario	Decrease			No change			Increase		
Self (t-1)	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	1	0.9	0.2	0	0	0	0	0	0
Medium	0	0.1	0.2	0.25	0.25	0.25	0	0.4	0
High	0	0	0.6	0.75	0.75	0.75	1	0.6	1

‘Mitigation effectiveness’ node at time *t=1*

Electric fence	Low						Med						High					
Firecrackers	Low		Med		High		Low		Med		High		Low		Med		High	
Self (t-1)	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Low	0.99	0.2	0.7	0.2	0.85	0.2	0.9	0.2	0.5	0.2	0.7	0.2	0.5	0.2	0.4	0.2	0.6	0.2
High	0.01	0.8	0.3	0.8	0.15	0.8	0.1	0.8	0.5	0.8	0.3	0.8	0.5	0.8	0.6	0.8	0.4	0.8

‘Likelihood of HEC’ node at time *t*

Length of time under cult	Low						Med						High					
Mitigation effectiveness	Low			High			Low			High			Low			High		
Farm-to-forest ratio	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.7	0	0.5	0.99	0	0.8	0.2	0	0	0.6	0	0	0	0	0	0.3	0	0
Med	0.3	0.5	0.5	0.01	0.8	0.2	0.8	0.2	0.7	0.4	0.5	1	0.6	0.01	0.5	0.7	0.3	0.8
High	0	0.5	0	0	0.2	0	0	0.8	0.3	0	0.5	0	0.4	0.99	0.5	0	0.7	0.2

‘Shooting node’ at time *t=1*

Shooting change scenario	Decrease			No change			Increase		
Self (t-1)	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	1	0.6	0.4	0	0	0	0	0	0
Med	0	0.2	0.5	0.5	0.5	0.5	0	0.6	0
High	0	0.2	0.1	0.5	0.5	0.5	1	0.4	1

‘Use of other forms of lethal action’ node at time *t=1*

Other forms of lethal action change scenario	Decrease			No change			Increase		
Self (t-1)	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	1	0.6	0.4	0.5	0.5	0.5	0	0	0
Med	0	0.4	0.5	0.5	0.5	0.5	0	0.6	0
High	0	0	0.1	0	0	0	1	0.4	1

‘Elephant population node at time *t=1*

Shooting	Low									Medium									High								
Other forms of lethal action	Low			Medium			High			Low			Medium			High			Low			Medium			High		
Self (t=0)	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0	0	0	0	0	0	0.9	0.55	0.35	0	0	0	0	0	0	0.95	0.55	0.35	0	0	0	0	0	0	1	0.6	0.4
Med	0.7	0.6	0	0.25	0.25	0.25	0.1	0.2	0.5	0.3	0.3	0.3	0.4	0.4	0.4	0.05	0.2	0.5	0.8	0.7	0.1	0.35	0.35	0.35	0	0.2	0.5
High	0.3	0.4	1	0.75	0.75	0.75	0	0.25	0.15	0.7	0.7	0.7	0.6	0.6	0.6	0	0.25	0.15	0.2	0.3	0.9	0.65	0.65	0.65	0	0.2	0.1

‘Total HEC’ node at *t* (deterministic node)

Elephant population	Low			Medium			High		
Likelihood of HEC	Low	Med	High	Low	Med	High	Low	Med	High
1	1	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0
6	0	0	0	0	0	1	0	0	0
7	0	0	0	0	0	0	1	0	0
8	0	0	0	0	0	0	0	1	0
9	0	0	0	0	0	0	0	0	1

Appendix D – Conditional probability tables for the ‘Shooting’ and ‘Other forms of lethal action’ nodes under the feedback-loop DBN

‘Other forms of lethal action’ node at time *t+2*

Other forms of lethal action scenario	Decrease/No change/Increase																										
Self t=0	Low									Medium									High								
Total HEC (t+1)	2	4	6	20	40	60	40	80	120	2	4	6	20	40	60	40	80	120	2	4	6	20	40	60	40	80	120
Low	1	1	1	0.333333	0	0	0	0	0	1	1	1	0.333333	0	0	0	0	0	1	1	1	0.333333	0	0	0	0	0
Medium	0	0	0	0.333333	0.333333	0.5	0.666667	0.333333	0	0	0	0	0.333333	0.333333	0.5	0.666667	0.333333	0	0	0	0	0.333333	0.333333	0.5	0.666667	0.333333	0
High	0	0	0	0.333333	0.666667	0.5	0.333333	0.666667	1	0	0	0	0.333333	0.666667	0.5	0.333333	0.666667	1	0	0	0	0.333333	0.666667	0.5	0.333333	0.666667	1

‘Shooting’ at time *t+2*

Other forms of lethal action scenario	Decrease/No change/Increase																										
Self t=0	Low									Medium									High								
Total HEC (t+1)	2	4	6	20	40	60	40	80	120	2	4	6	20	40	60	40	80	120	2	4	6	20	40	60	40	80	120
Low	1	1	1	0.5	0	0	0	0	0	1	1	1	0.5	0	0	0	0	0	1	1	1	0.5	0	0	0	0	0
Medium	0	0	0	0.5	0.5	0.7	0.8	0.5	0.2	0	0	0	0.5	0.5	0.7	0.8	0.5	0.2	0	0	0	0.5	0.5	0.7	0.8	0.5	0.2
High	0	0	0	0	0.5	0.3	0.2	0.5	0.8	0	0	0	0	0.5	0.3	0.2	0.5	0.8	0	0	0	0	0.5	0.3	0.2	0.5	0.8

Appendix E – Supplementary results from model outputs of the conceptual DBN that show states of nodes not in Section 4.1.

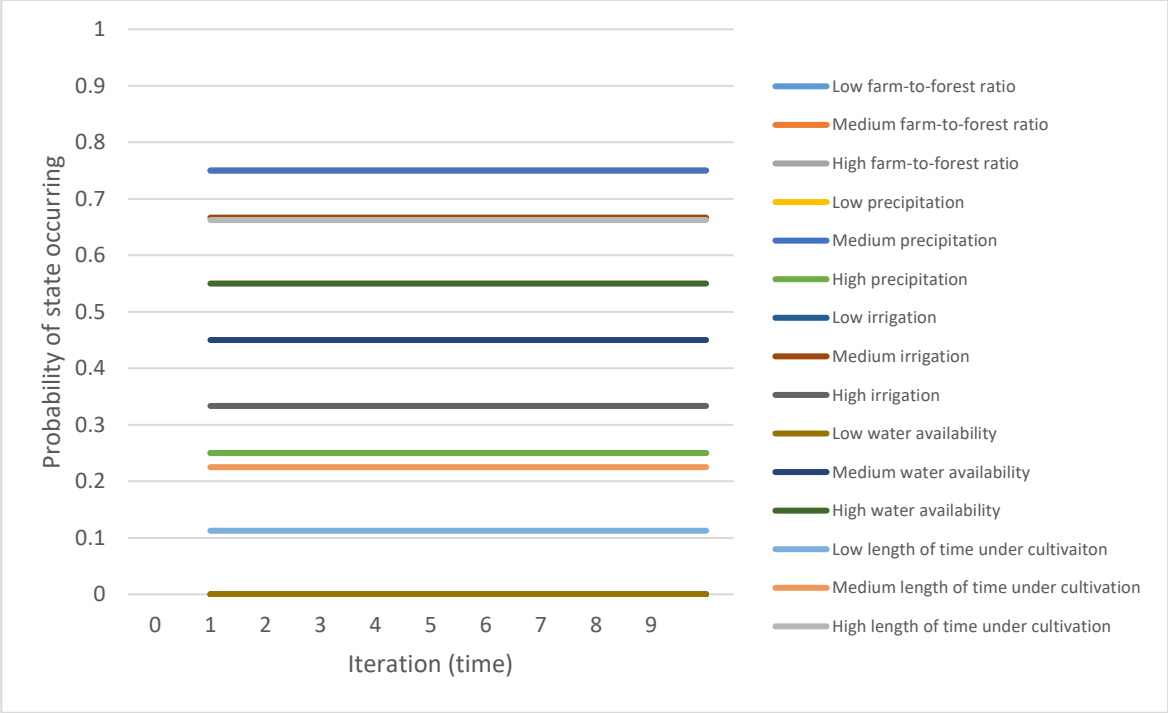


Figure 20: Additional results of HEC drivers for the conceptual model – 'No change' setting. As the probabilities of these nodes do not change, they reflect the priors.

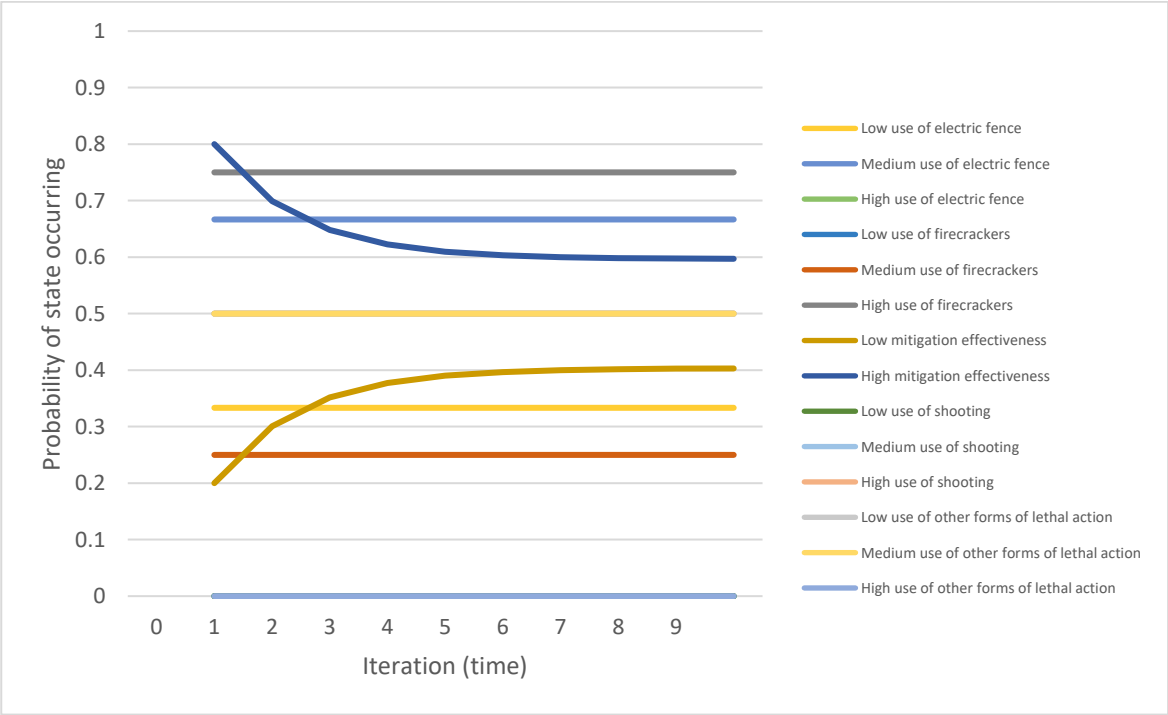


Figure 21: Additional results of HEC mitigation actions for the conceptual model – 'No change' setting.

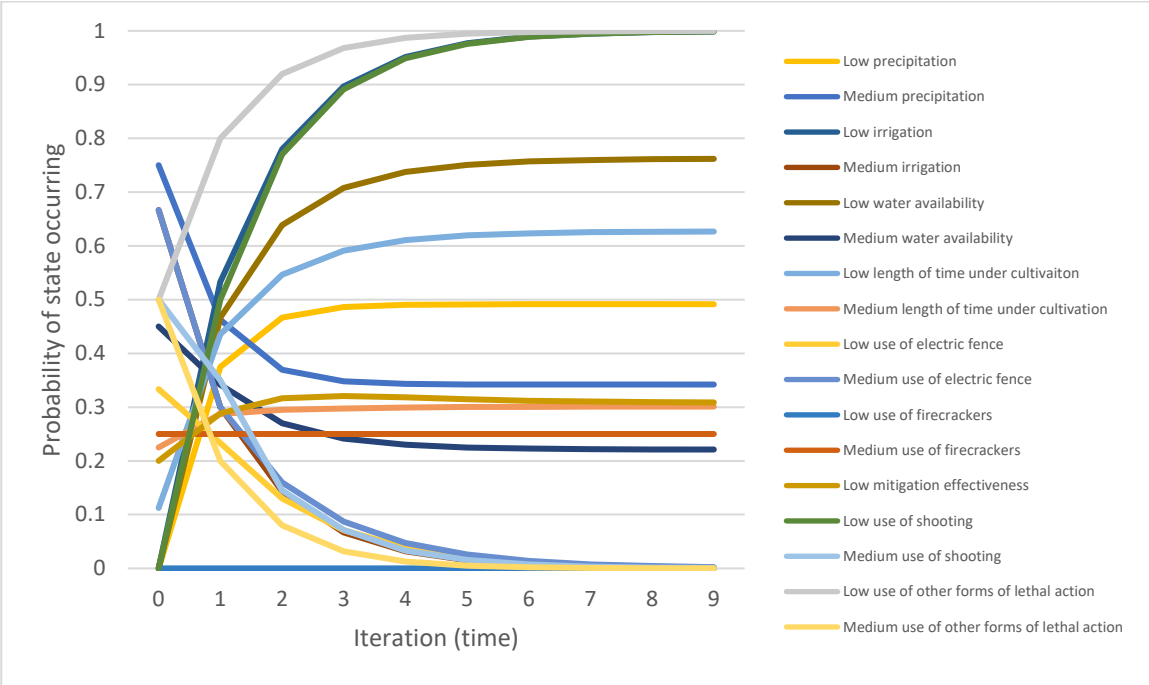


Figure 22: Additional results not shown in Figure 13 of states for HEC drivers and mitigation actions for the positive conservation setting.

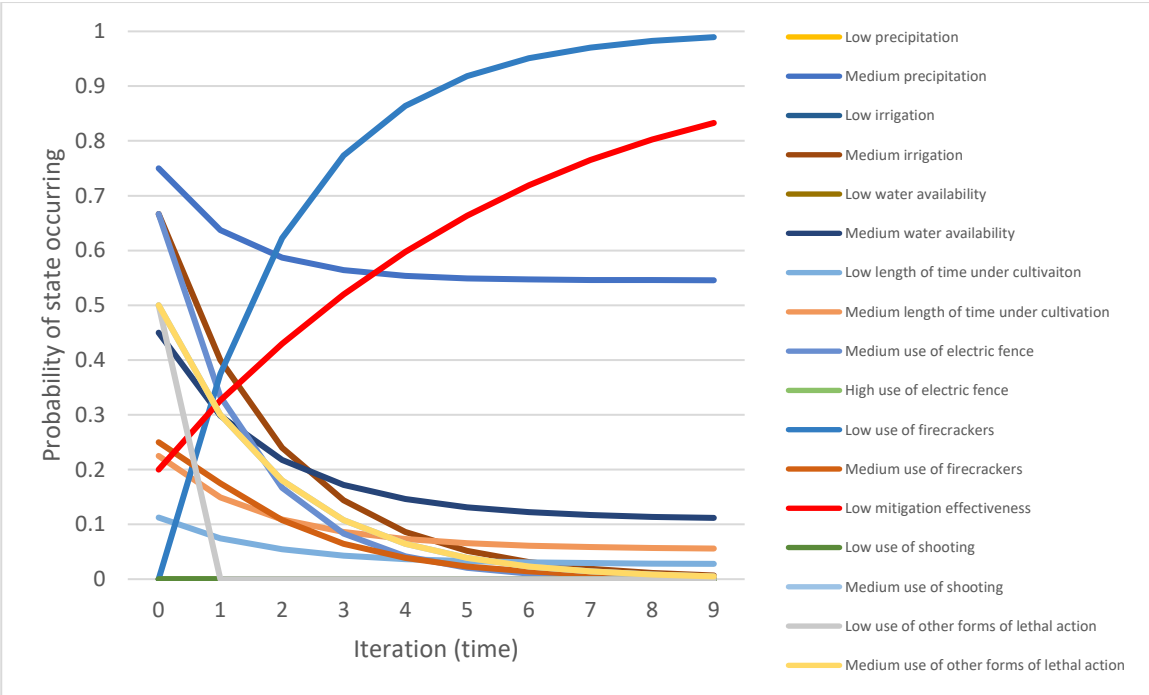


Figure 23: Additional results not shown in Figure 15 of states for HEC drivers and mitigation actions for the negative conservation setting.

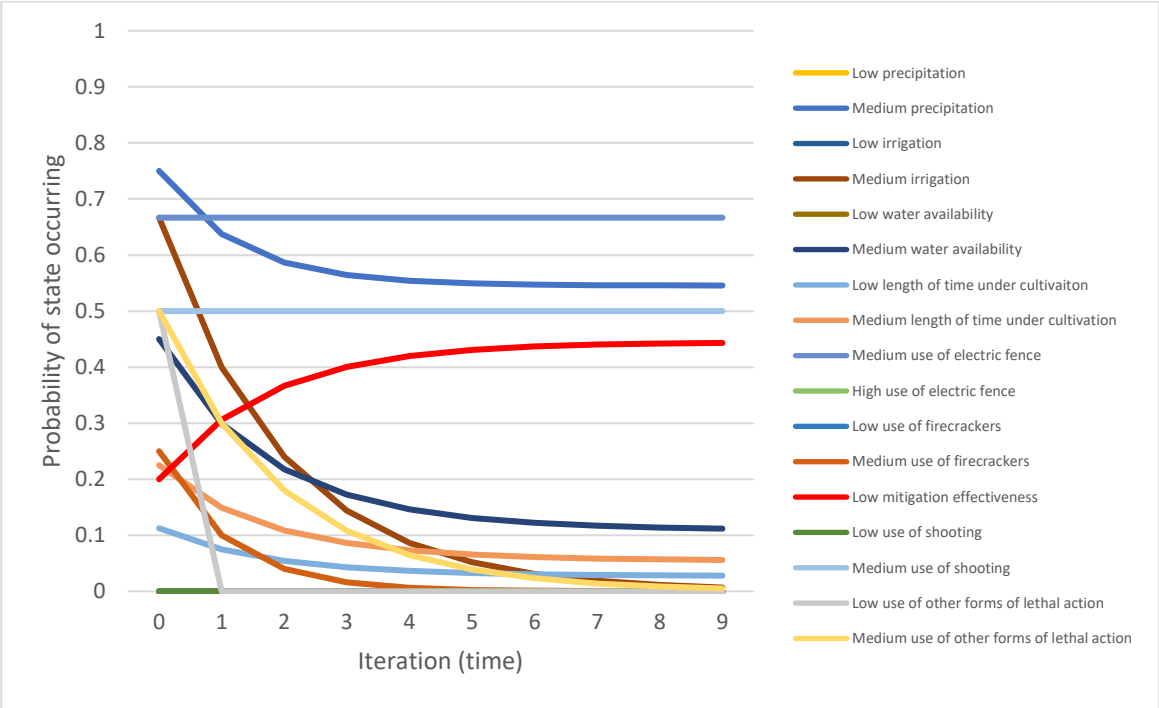


Figure 24: Additional results not shown in Figure 17 of states for HEC drivers and mitigation actions for the realistic future predicted setting.

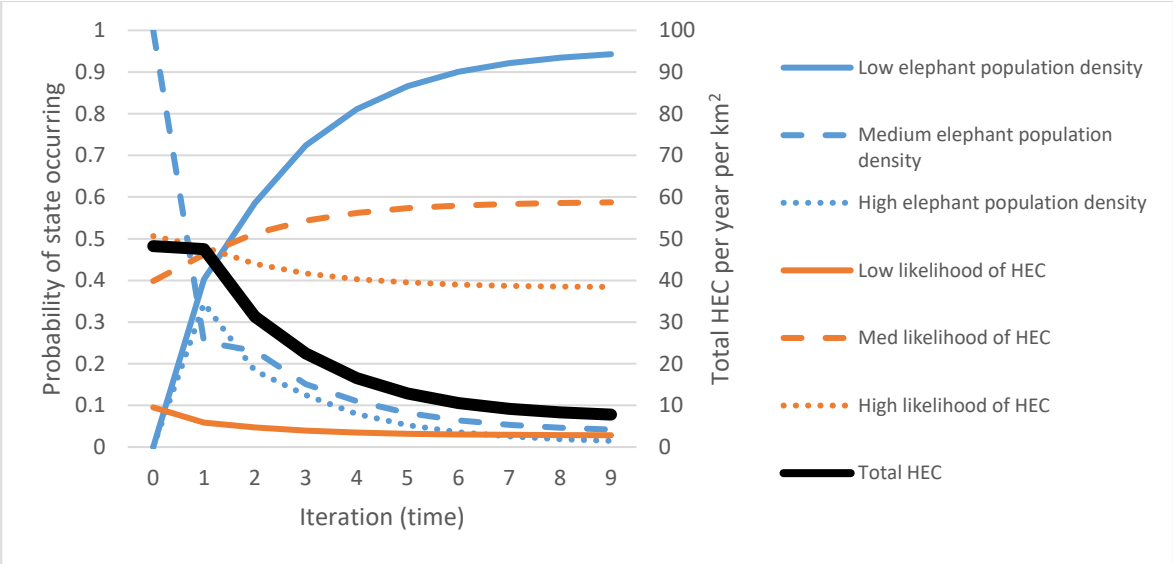


Figure 25: Results of the DBN under a realistic predicted future setting in Sri Lanka, showing total HEC and states for the nodes 'Elephant population density' and 'Likelihood of HEC'. All states are per km^2.

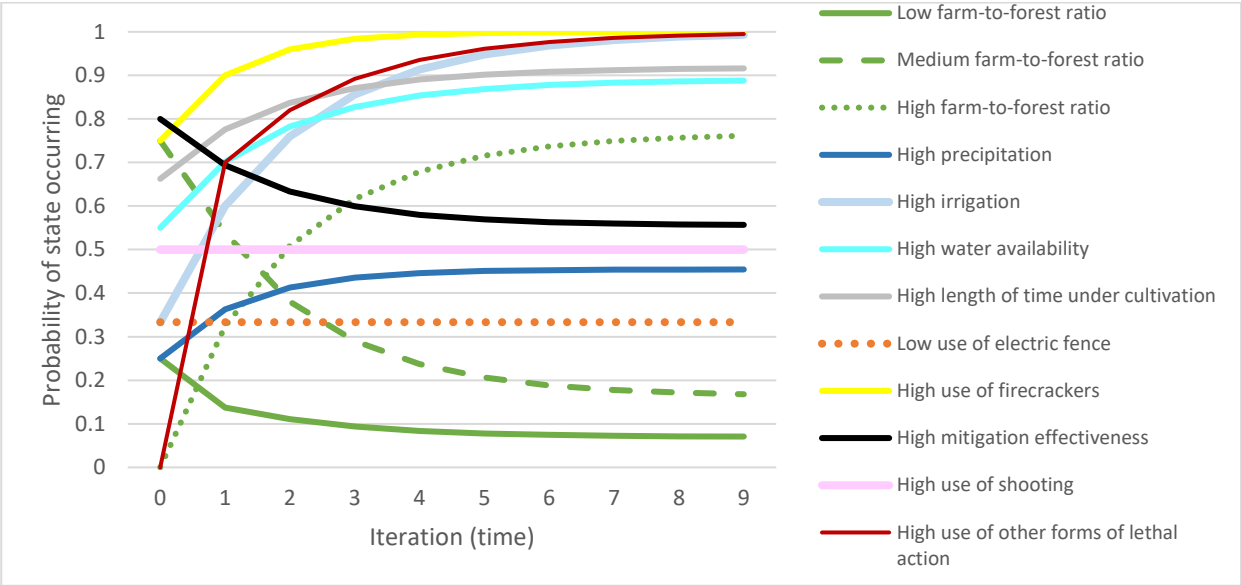


Figure 26: HEC drivers and mitigation strategies of the DBN under a realistic predicted future setting in Sri Lanka. Note that the 'Low' and 'Medium' states are not included for some of the nodes for ease of visibility in the plot, with the exception of 'Low use of electric fence' (as 'High use of electric fence' did not change for this negative conservation conditions). All states are per km².

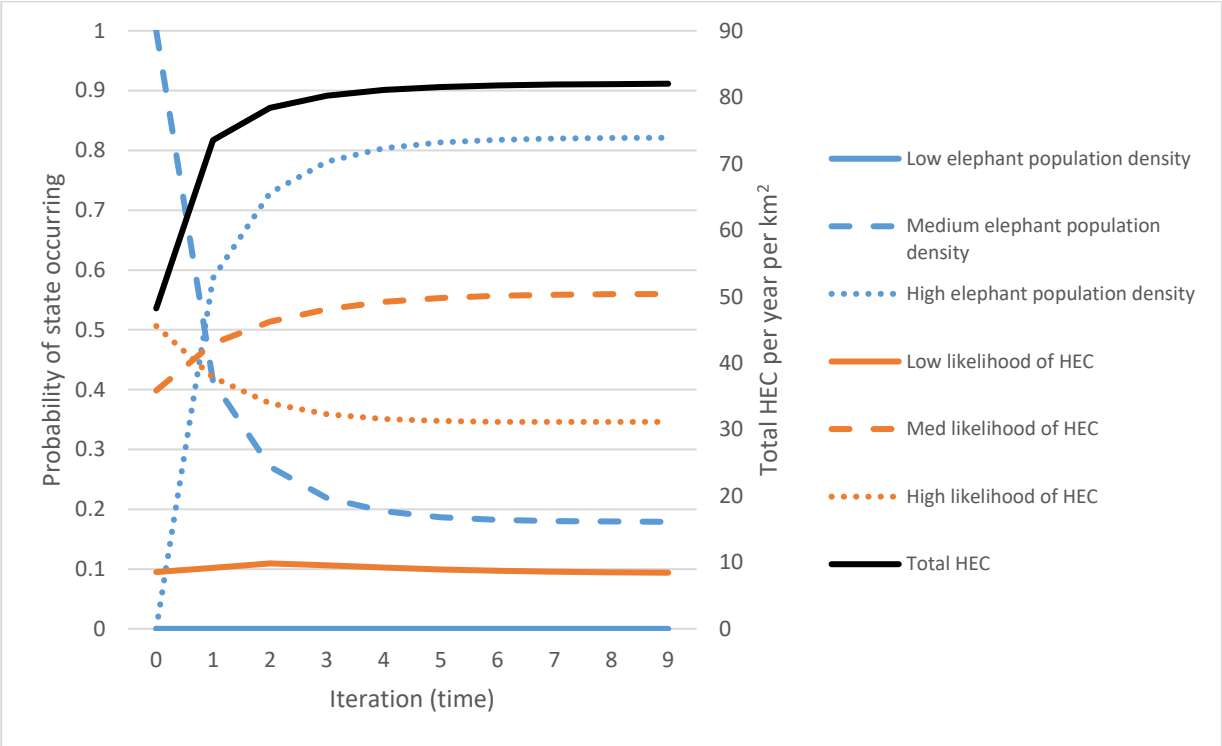


Figure 27: Results of the DBN under antagonistic combinations, showing total HEC and states for the nodes 'Elephant population density' and 'Likelihood of HEC'. All states are per km².

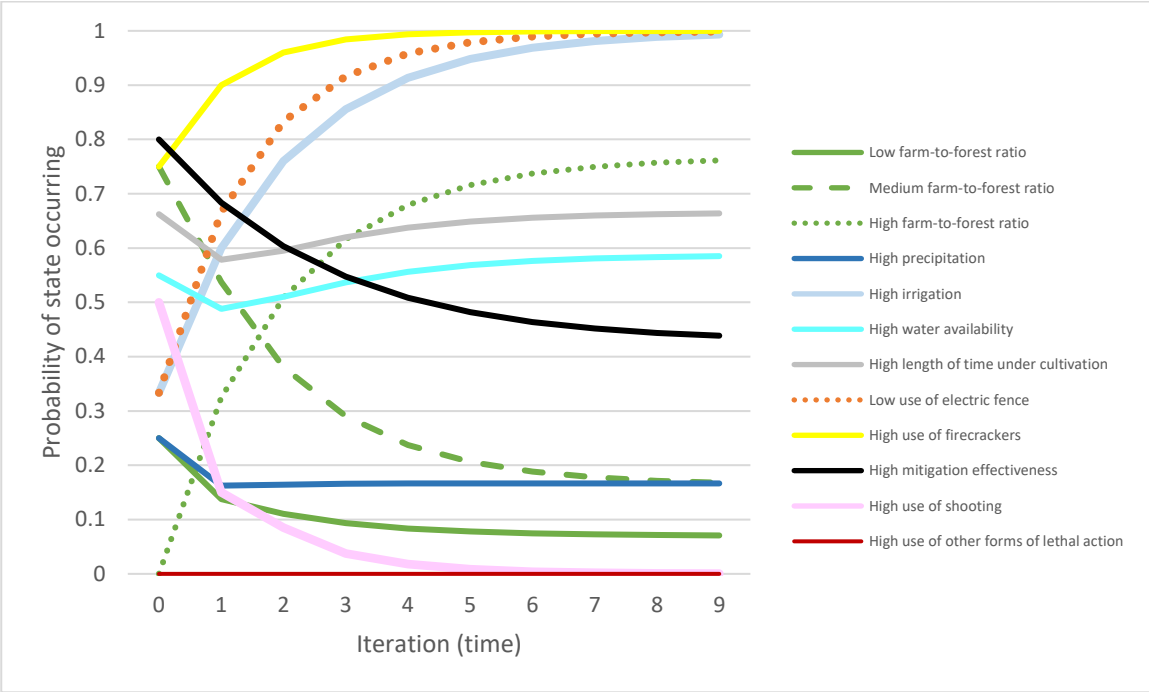


Figure 28: HEC drivers and mitigation strategies of the DBN under a realistic predicted future setting in Sri Lanka. Note that the 'Low' and 'Medium' states are not included for some of the nodes for ease of visibility in the plot, with the exception of 'Low use of electric fence' (as 'High use of electric fence' did not change for this negative conservation conditions). All states are per km².

Appendix F – Supplementary results from model outputs of the feedback-loop DBN that show states of nodes not in Section 4.2.

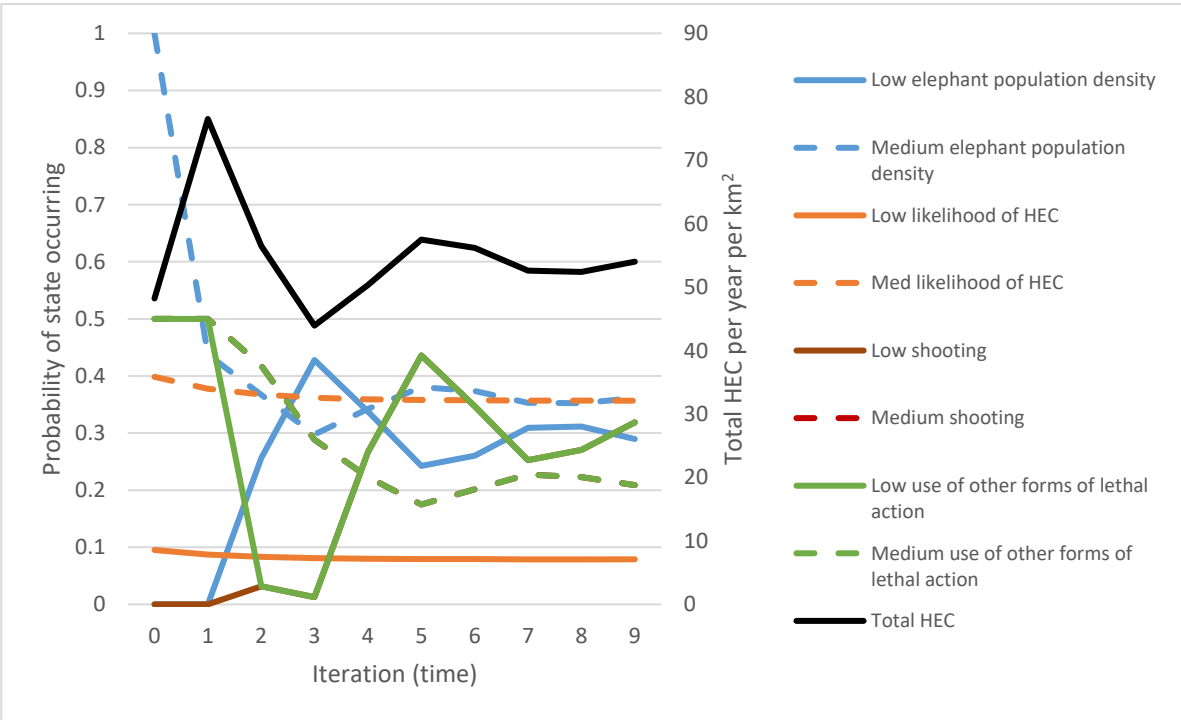


Figure 29: Additional results under a 'No change' scenario for all contemporal nodes, for the feedback-loop DBN.

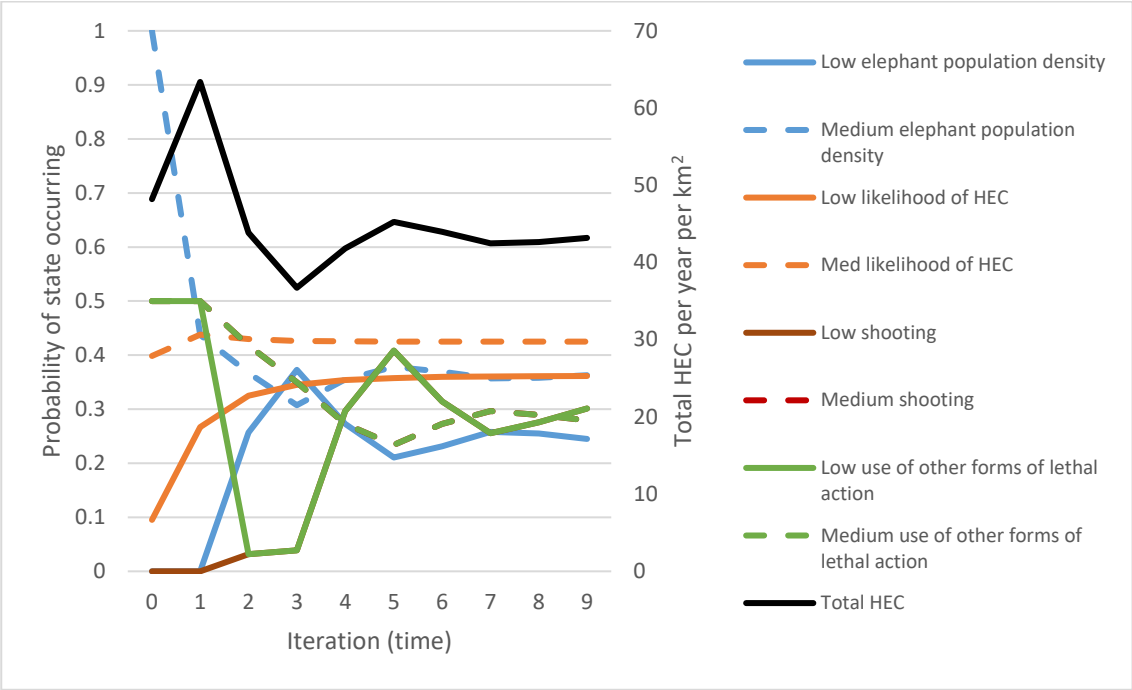


Figure 30: Additional results under positive conservation conditions for the feedback-loop DBN.

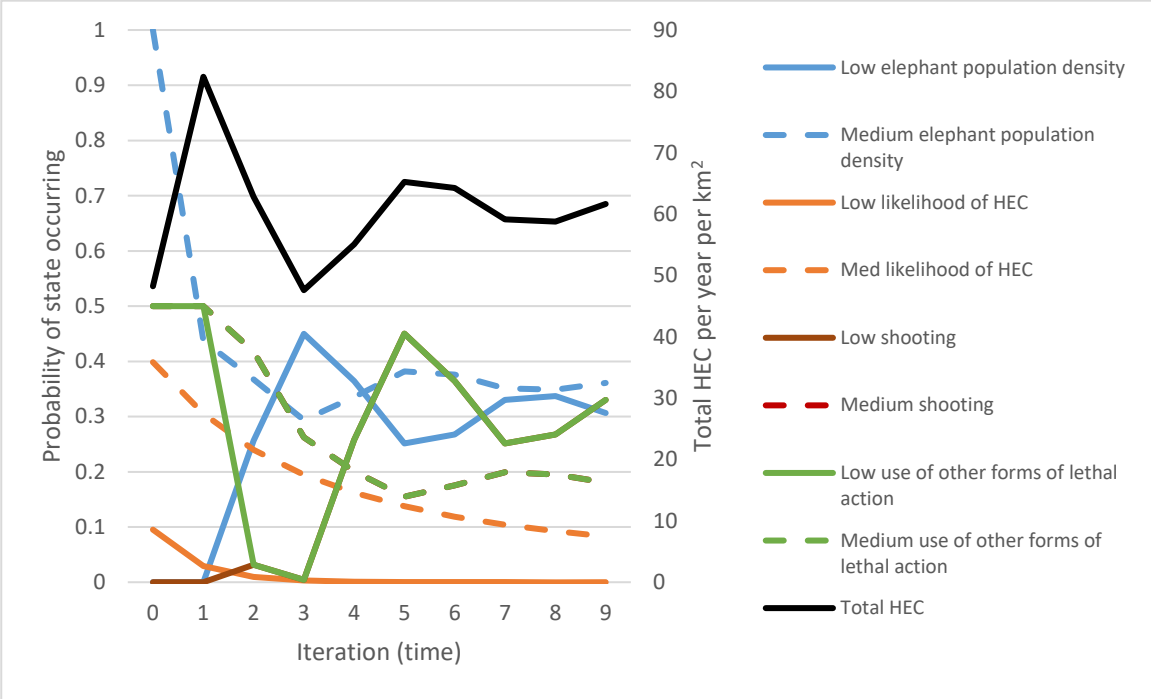


Figure 31: Additional results under negative conservation conditions for the feedback-loop DBN.