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Human-elephant conflict risk assessment under coupled climatic and anthropogenic changes in Thailand

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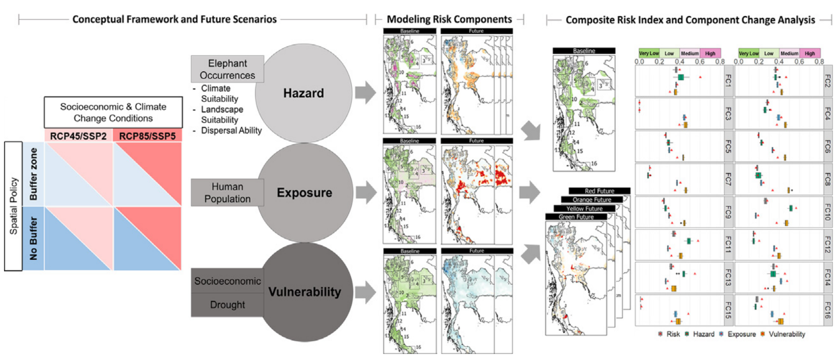
HIGHLIGHTS

- Long-term planning in human-wildlife conflict benefits conservation and human safety.
- We proposed a framework to assess HEC risk under climate change and human pressure.
- A spatial shift in HEC risk toward higher latitude and altitude was projected.
- HEC vulnerability was predicted to increase from drought, despite less exposed humans.
- Lower habitat quality was predicted to alter HEC hazard where most elephants occur.

GRAPHICAL ABSTRACT



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ABSTRACT

As natural resources decrease, competition between humans and large endangered wildlife increases, hindering the sustainability of animal conservation and human development. Despite the multi-dimensional nature of such interactions, proactive assessments that consider both the biosphere and anthroposphere remain limited. In this study, we proposed a human elephant conflict risk assessment framework and analyzed the spatial distribution of risk at the baseline (2000–2019) and in the near future (2025–2044) for Thailand, so that it may address the multifaceted characteristics and impending effects of climate change. Future scenarios were based on the combination of RCP45/SSP2 or RCP85/SSP5 and spatial policy, with or without elephant buffer zones. The composite risk index, comprised of hazard, exposure, and vulnerability, was constructed using the geometric mean, and validation was performed with the area under the curve (AUC). Our results projected a shift with increasing future risk toward higher latitudes and altitudes. Increasing future risk (average +1.7% to +7.4%) in the four forest complexes (FCs) in northwestern regions was a result of higher hazard and vulnerability from more favorable habitat conditions and increasing drought probability, respectively. Reduction in future risk (average −3.1% to −57.9%) in other FCs in lower regions was mainly due to decreasing hazard because of decreasing habitat suitability. Our results also highlight geographically explicit strategies to support long-term planning of conservation resources. Areas with increasing future risk are currently facing low conflict; hence it is recommended that future strategies should enhance adaptive capacity and coexistence awareness. Conversely, areas with lowering future risk from a decrease in habitat quality are recommended to identify buffer strategies around protected areas to support existing large elephant populations.

1. Introduction

Human-wildlife conflict (HWC) occurs when the behaviors of wildlife and humans negatively affect one another. Such negative interactions are

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common where agriculture and natural landscapes intersect, especially near protected areas. HWCs occur when wildlife damage crops, kill livestock, and cause harm to humans, or when humans encroach on wildlife habitats. Threats related to wildlife are perceived as small yet frequent events and are commonly neglected in risk assessment and subsequent management policies (Gaillard et al., 2019). Nevertheless, they usually accumulate and erode society's ability to handle hazardous incidents and achieve sustainable development (UNISDR, 2015).

Although species of varying sizes are found to have conflict with humans, large body-sized endangered species are disproportionately concerning (Dickman, 2010). The Asian elephant (*Elephas maximus*) is the largest terrestrial herbivore in Asia and is a subject to conflict with humans, known as the human-elephant conflict (HEC) (IUCN, 2017). The HEC mechanism was driven by multiple reciprocal factors. Physiological requirements for daily energy intake caused Asian elephants to forage over large areas with home ranges varying from less than 100 km^2 to 800 km^2 (Alfred et al., 2012; Sukumar, 2003), while heterogeneous habitat preferences led them near the forest edges (Wadey et al., 2018). In recent decades, an increase in human population and socioeconomic pressures have fueled the demand for agricultural land, which has led to pervasive forest conversion and encroachment into elephant habitats (Crist et al., 2017; Nyhus, 2016). Degraded and fragmented habitats among agricultural matrices cause elephant's ranging pattern to become overlap with agricultural activities, resulting in increasing HEC. The spatial configuration of available resources, especially mature crops adjacent to natural habitats, can also attract elephants (Artelle et al., 2016; Branco et al., 2019). In HEC-prone areas, human perception and tolerance of wild elephants can lead to an array of behaviors ranging from poaching and retaliatory killing to acceptance (Bruskotter and Wilson, 2014; Kansky et al., 2014).

Although land conversion is currently the leading cause of biodiversity deterioration, climate change is projected to become the dominant driver (IPBES, 2019). Climate change is expected to shift suitable species ranges, alter physical tolerance, and cause phenological asynchrony between animals and their food sources (Bellard et al., 2012). Consequently, as climate change exacerbates human-elephant competition for scarce resources and suitable habitats, HEC is expected to intensify (Abrahms, 2021; Shaffer et al., 2019). This is particularly relevant during dry and drought periods (Chan et al., 2022; Kitratporn and Takeuchi, 2019). Moreover, as future economic growth and drought intensification are projected, countries with Asian elephants are likely to face the coupling effects of anthropogenic pressures and climate change. As rural livelihood depends on agriculture activities, deforestation from agriculture expansion within the Southeast Asia intact forest would continue with an estimated 5.2 mha forest cover loss in 2050 under the worst-case scenario (Estoque et al., 2019). Increasing future drought due to drying soil moisture and reduced precipitation were predicted using ensemble models within the region (Dai, 2013). Hence, the simultaneous consideration of future climate and land change is important, as emphasized by Foden et al. (2019) and Titeux et al. (2016).

A flexible framework is necessary to allow the long-term countrywide evaluation of HEC that incorporates multidimensional future projections. Risk assessment is common in disaster and climate change risk analyses, and is essential for making informed decisions. A risk assessment framework in which risk is expressed as a function of hazard, exposure, and vulnerability was employed in the United Nations Office for Disaster Risk Reduction (UNISDR) guidelines (UNISDR, 2015), the Intergovernmental Panel on Climate Change (IPCC) Special Report (IPCC, 2012), and the IPCC Fifth Assessment Report (IPCC, 2014). This risk framework also incorporates scenario planning, which allows decision makers to explore plausible futures and develop relevant long-term actions (Mahmoud et al., 2009).

By framing HEC similarly to a disaster event, we demonstrated the application of a risk framework with climate change scenarios to estimate the spatial distribution of HEC risk at the baseline (2000–2019) and in the near future (2025–2044) in Thailand. Our study addressed the impacts of climate change on HEC by incorporating future projections from the climatic domain (temperature and precipitation), the socioeconomic domain (human population and gross domestic product), and the combined effects on land cover.

2. Materials and methods

2.1. Study area

Thailand has approximately 3000–4000 wild elephants, of which large populations are concentrated in terrestrial forest complexes (FC) located in the western and eastern regions (Fig. 1). The country faced significant deforestation due to the 1970s timber demand, the government-led policy to allow settlement in unoccupied land, and the expansion of commercial agriculture (ICEM, 2003). Nowadays 56% of the country's area was used for agriculture to grow rice, sugarcane, cassava, maize, rubber, and oil palm as major crops, while forest, urban, water, and other land types covered around 33%, 6%, 3%, and 3%, respectively (LDD, 2016). Thailand has a population of almost 70 million people, with nearly half of the population remaining in rural areas and still involved in the agriculture sector (World Bank, 2020). Despite a slow annual population growth, which fell from 3% in the 1970s to 0.5% in the 2010s, urban and agriculture expansion continued (World Bank, 2020). Consequently, wild elephants in Thailand occurred in fragmented and degraded habitats (IUCN, 2017; Leimgruber et al., 2003). Although Thai elephants do not have long distance migration, they were observed to disperse into the surrounding agriculture land, eating crops and accessing human-made water points (Htet et al., 2021; van de Water and Matteson, 2018). During the HEC, households in some areas spent an average of 212 nights annually guarding crops against elephant-raiding, and the HEC-induced cost was significant compared to the average household income (Jarungrattanapong et al., 2017). Climate change will likely affect potential crop yield and increase extreme events for floods and drought in the country (Kiguchi et al., 2021). These variations in climatic patterns coupled with the demand for production land, urbanization, and depopulation trend likely influences the future HEC.

2.2. Risk framework and future scenarios

The proposed HEC risk framework is illustrated in Fig. 2. HEC risk was defined as wild elephant occurrence (hazard) in areas overlapping with the rural human population (exposure) who possess various vulnerable conditions (vulnerability). We first prepared the underlying climatic and landscape data relevant to the HEC for the baseline and future scenarios. The attributes of the risk components, including hazard, exposure, and vulnerability sub-indicators, were then calculated. Finally, the composite risk index was computed using the geometric mean with equal weighting.

Climate change scenarios combining representative concentration pathways (RCPs) and shared socioeconomic pathways (SSPs) provide projections of climate radiative forcing and the relevant underlying socioeconomic factors (van Vuuren et al., 2014). The RCP/SSP scenarios have benefited research communities in a wide range of topics (O'Neill et al., 2020). RCP45/SSP2 assumed a slow reduction of emissions corresponding to government efforts proposed for the Paris Agreement, while RCP85/SSP5 assumed high development in economic and human capital with a strong reliance on fossil fuels (O'Neill et al., 2017; van Vuuren et al., 2014). Combining RCP45/SSP2 and RCP85/SSP5, hereafter environmental-focus and development-focus, respectively, with the HEC spatial policy of the 12 km buffer zone around protected areas with known elephant populations, four future scenarios were evaluated (Table 1). The 12 km distance was chosen based on the observation of elephants' movement outside of the Khao Yai-Dong Phayayen FC as reported by park rangers. The colour code associated with each of the four scenarios represents the range from the most to the least environmentally and elephant-friendly pathways.

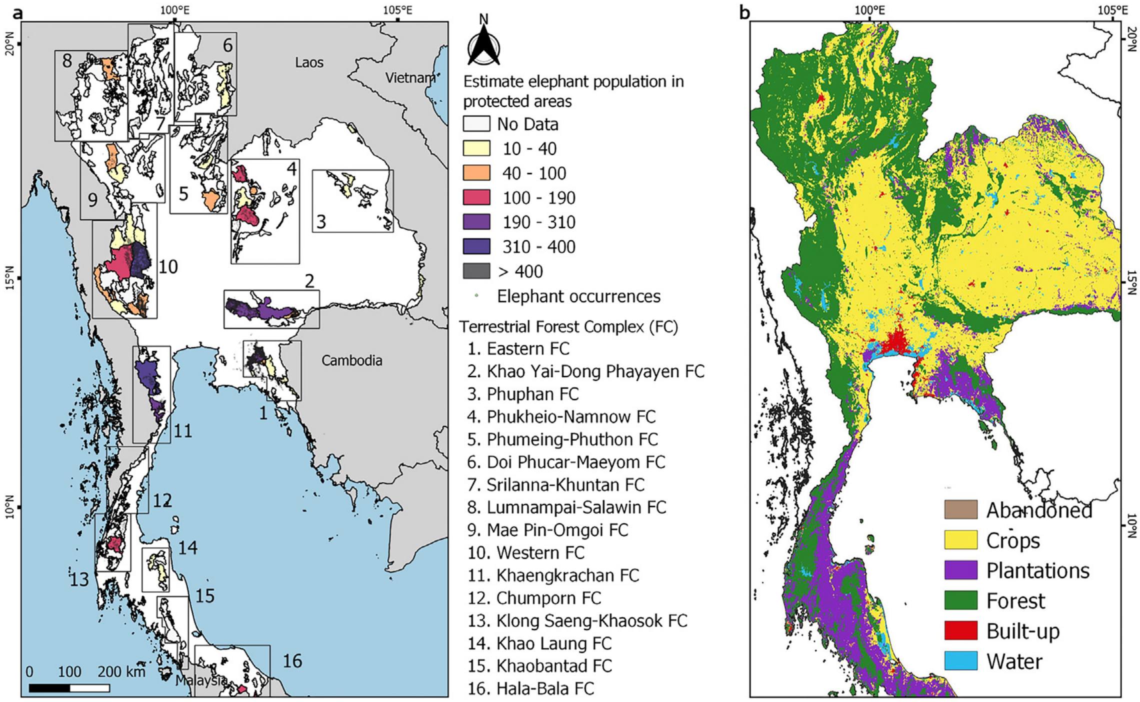

Fig. 1. Map of the study area. **a.** Distribution of the terrestrial forest complex (FC) and estimated number of wild elephant populations within each protected area in Thailand. **b.** Thailand's land cover at the baseline period.

2.3. Dataset and pre-processing

Since climate influences processes on a large scale and the climatic niche of the species might be inadequately captured when modeling within small spatial extents (Fournier et al., 2017; Sirami et al., 2017), we applied two scales of analysis. Regional coverage across all 13 countries was considered when modeling climatic suitability, whereas areas within the boundary of Thailand were considered when modeling landscape suitability for elephant distribution. Various data layers were used to represent the risk components with different spatial units based on data availability (Table S1). For the final analysis, all data were resampled to 500 m spatial resolution using bilinear interpolation to provide consistency with the land-cover map. Data processing was done using R version 4.0.2 with the "raster," "rgeos," and "sf" packages for raster/geospatial data processing and "stats" package for the statistical analysis. Satellite imagery for land cover classification was preprocessed and classified using the random forest algorithm on the Google Earth Engine platform (Gorelick et al., 2017). The future land-cover projection map was computed using the CLUE-S model (Verburg et al., 2002).

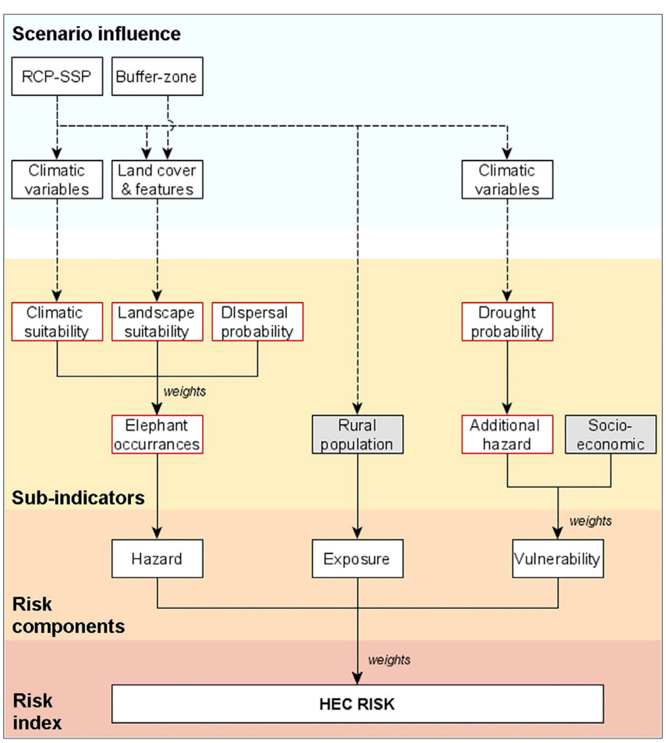

Fig. 2. Diagram illustrating the HEC risk framework. Boxes with red-borders highlight sub-indicators that were simulated in this study, while gray boxes indicate sub-indicators that were obtained from ancillary data.

2.3.1. Climatic data

The minimum and maximum temperatures, and precipitation data from the ECMWF ERA5 reanalysis product and NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) Coupled Model Intercomparison Project Phase 5 (CMIP5) product were used for the baseline and near future scenarios, respectively. ERA5 showed consistent improvements over its predecessors (Hersbach et al., 2020), while NEX-GDDP provided higher resolution and accuracy than the original global climate models

Table 1
Four future scenarios evaluated in this study with the colour-coded naming which ranges from the most to the least environmental and elephant-friendly pathways: environmental-focus with buffer-zones (Green Future), environmental-focus without buffer-zones (Yellow Future), developmental-focus with buffer-zones (Orange Future), and developmental-focus without buffer-zones (Red Future).

Climate change		HEC spatial policy	Scenario
Environmental focus (RCP45/SSP2)	Developmental focus (RCP85/SSP5)	Buffer zones	
x		x	Green Future
x			Yellow Future
	x	x	Orange Future
	x		Red Future

(GCMs) (Thrasher et al., 2012). Five GCMs, CanESM2, CESM1-BGC, IPSL-CM5A-MR, MIROC5, and MPI-ESM-MR, were chosen to represent the ranges of potential future climatic conditions, following the guidelines of Sanderson et al. (2015).

Climatic data were used to calculate bioclimatic variables and drought indicators. Bioclimatic variables provide biologically meaningful indices that are commonly used in ecological modeling (Hijmans et al., 2005). Drought indicators were derived from the Keetch-Byram Drought Index (KBDI) (Keetch and Byram, 1968), which reflects the net effect of evapotranspiration and precipitation in producing cumulative moisture deficiency in the deep duff and upper soil layers. Bioclimatic variables were calculated for the study period, while the KBDI was calculated at daily time steps:

$$KBDI = KBDI^{t-1} + \frac{\left[800 - KBDI^{t-1}\right]\left[0.968e^{(0.0486\times T_{max})} - 8.3\right]\times 10^{-3}}{1 + 10.88e^{(-0.0441\times Pr_{annual})}} - (100\times Pr) \tag{1}$$

where $KBDI^{t-1}$ is the previous day's $KBDI$; T_{max} is the daily maximum temperature; Pr is the daily precipitation; and Pr_{annual} is the average annual precipitation. Drought day (D_{day}) was identified when the standard anomaly of KBDI, $\frac{\text{KBDI}-\mu}{\sigma}$ was over 1.5, while drought event (D_{event}) was defined as when at least seven consecutive D_{day} were measured. The drought intensity (2) and frequency (3) for the baseline and future periods were then calculated, where $KBDI_{Dday}$ and day_{Dday} refer to the value of KBDI and the number of days identified as D_{day}.

$$Drought\ Intensity = \frac{\sum KBDI_{Dday}}{\sum day_{Dday}} \tag{2}$$

$$Drought\ Frequency = \sum D_{event} \tag{3}$$

We assessed the accuracy of the chosen climatic dataset with observations from Thai weather stations (Table S2) and compared our KBDI results with existing products (Fig. S1).

2.3.2. Landscape data

The landscape dataset comprised landscape features and land cover classes. The landscape features included topography, accessibility to water, and human disturbance, which were represented by the terrain roughness index (TRI) calculated using the Shuttle Radar Topography Mission (SRTM) (USGS, 2004); the Euclidean distance to rivers and water points were calculated using HydroSHED (Grill et al., 2019) and the European Commission Joint Research Centre (JRC) yearly water classification version 1.2 (Pekel et al., 2016); and the Euclidean distance to transport networks was calculated using GRIP4 (Meijer et al., 2018) and Thai Railway. These landscape features were assumed to be static.

For land cover, five classes were selected following the Thailand Land Development Department (LDD) definition (Table S3): abandoned, crops, plantations, forest, built-up, and water. The baseline land cover was classified using remotely sensed satellite images available during 2014–2016. The data sources, spectral reflectance and indices, and classification methods are described in Supplementary Note 1. The resulting land cover achieved an overall accuracy of 0.89 and a Kappa value of 0.83 (Table S4). To simulate future land cover, land demand and spatial allocation were required. For the land demand projection, the following assumptions were made: the water areas were assumed to remain constant from the 2015 baseline to the future. The built-up cover for 2040 was based on Gao and O'Neill (2020). Forest areas were assumed to gradually increase based on the recent trend (2010–2019) of increasing protected areas in Thailand and the National Forestry Strategy, which aimed for 40% forest cover (RFD, 2017). Land demand for crops and plantations was assumed to be a function of production demand and yield (Alexandratos and Bruinsma, 2012; Stehfest et al., 2019). After obtaining the land demand, the CLUE-S model was employed to perform spatially explicit allocation under future scenarios (see Supplementary Note 1). The performance was assessed by comparing the simulated land cover map in 2015 with the land cover classification result, which showed an 81% agreement. The model was then applied to simulate four future land cover maps (Fig. S2).

2.3.3. Asian elephant data

Asian elephant presence data were used under the hazard component as an input for the species distribution modeling (SDM) technique, in which the location of known species presence is used to fit the statistical relationship with ecologically relevant environmental layers, and its output provides a relative probability ranging from 0 (no chance of presence) to 1 (high relative probability of presence). Two sets of locations were used. For the climatic suitability model, elephant presence was obtained from the Global Biodiversity Information Facility (GBIF) and the existing literature (Bi et al., 2016; Naha et al., 2019; Sampson et al., 2019). The (derived GBIF dataset 2022) with low-accuracy coordinates, unsuitable data sources, and dates before 1995 were removed. For the landscape suitability model, elephant presence was digitized from the Department of Thailand National Parks, Wildlife, and Plant Conservation (DNP). Spatial filtering was applied to reduce potential autocorrelation among the presence points (Fourcade et al., 2014). A total of 328 and 3018 presences were used for climatic and landscape modeling, respectively.

2.4. Hazard modeling and projection

A hazard refers to the potential occurrence of events that may cause harm (IPCC, 2014). Here, hazard was represented by the probability of wild elephant presence, which was governed by habitat suitability and whether the locations were reachable by the species. Three sub-indicators were selected: climatic suitability, landscape suitability, and elephant dispersal probability from protected areas. The two suitability sub-indicators were computed using the SDM. We used R version 4.0.2 with "ENMEval," "usdm," and "biomod2" package (Thuiller et al., 2020) to compute ensemble of six SDM algorithms including Generalized Linear Modeling, Generalized Additive Modeling, Generalized Boosted Modeling, Multivariate Adaptive Regression Spline, Random Forest, Maximum Entropy.

Predictor variables known to affect the distribution of Asian elephants were chosen (Chen et al., 2016; Deb et al., 2019; Estes et al., 2012; Kitratporn and Takeuchi, 2019; Naha et al., 2020; Wato et al., 2016; Wilson et al., 2015). The environmental factors under the climatic suitability model included six bioclimatic and three drought variables: annual mean temperature, diurnal range, isothermality, temperature seasonality, annual precipitation, precipitation seasonality, drought intensity, drought frequency, and KBDI in the dry quarter. Nine factors were considered for landscape models: forest cover within 6 km, percent food cover (forest and crop land cover) within 6 km, distance to crop, distance to forest, distance to plantation, distance to transport, distance to urban area, distance to water, and TRI. Multicollinearity was checked by removing variables with $r > |0.75|$ and VIF > 10. Multiple sets of pseudo-absences were then randomly generated and combined with presence data, and the combined dataset was then replicated and split in a 70/30 ratio for training/testing, respectively (Fig. S3). Model performance was evaluated using the true skill statistic (TSS) and area under the curve (AUC) of the receiver operating characteristic (ROC). Models with TSS > 0.6 were included in the final ensemble calculation using the weighted mean based on their TSS values.

The dispersal probability was calculated using the Euclidean distance from the protected areas with a known elephant presence. The inverse function was then applied to place a higher value on areas closer to the boundary of elephant habitats. Additionally, the distance was restricted to 50 km, beyond which the threshold likelihood was zero.

2.5. Exposure modeling and projection

Exposure refers to the presence of assets that may include, but are not limited to, people, livelihoods, properties, environmental functions, and services that may be affected by hazards (IPCC, 2014). Here, exposure is represented by the number of rural populations, as projected by Gao

(2020). Available data for the baseline and future periods were obtained. Because the spatial distribution of the population was skewed, a natural log was applied to the data prior to further processing.

2.6. Vulnerability modeling and projection

Vulnerability refers to the characteristics or tendencies that are affected (IPCC, 2014). Vulnerability is represented by socioeconomic conditions and the probability of drought. Three socioeconomic variables that reflect the capacity of people to cope when exposed to hazards were used: households with internet access, workforce with higher secondary education, and average household monthly income. The finest available data at the provincial level from years as close to 2015 as possible were obtained from the National Statistic Office of Thailand (NSO, 2020). Accessibility to information and technology was suggested to strengthen the HEC-affected community (Nyirenda et al., 2018). The same study also found that the education level allowed access to alternative sources of income and increased the ability to implement more effective crop protection measures (Nyirenda et al., 2018). Lastly, high income enabled households to mitigate conflict and suffer less from wildlife-induced loss (Inskip and Zimmermann, 2009).

Additional natural hazards can aggravate the vulnerability of the human population. Drought was chosen because it is expected to cause a large yield reduction in the future (Leng and Hall, 2019). The drought probability was calculated to represent the added pressure on the communities exposed to HEC:

$$Drought\ Probability = \frac{\sum D_{event}}{N} \tag{4}$$

where the number of D_{event} in a location and the maximum number observed from the entire region (N) over a 20-year period were used.

2.7. Composite index and validation

A composite index was generated based on guidelines provided by United Nations (United Nations, 2019). Sub-indicators were first checked for multicollinearity. Min-max normalization was then applied, followed by geometric mean calculation:

$$I_i^{'} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{5}$$

$$\left(\prod_{i=1}^{n} {I_i^{'}}^{w_i}\right)^{\frac{1}{\sum_{i=1}^{n} w_i}} = \sqrt[n]{{I_1^{'}}^{w_1} {I_2^{'}}^{w_2} \cdots {I_n^{'}}^{w_n}} \tag{6}$$

where X_i is the value of sub-indicator i while X_{min} and X_{max} are the minimum and maximum values, respectively, within the range of the sub-indicator i. $I_i^{'}$ refers to normalized sub-indicator i and w_i represents weighting power. Owing to uncertainty in determining the level of influence from each sub-indicator, equal weighting was applied. We performed the analysis in R version 4.0.2 using the "Compind" package. The risk score and underlying components ranged from 0 to 1. A 5-class equal interval classification was applied, from very low to very high.

Validation of HEC risk requires long-term historical data of HEC events and related information (e.g., loss quantity and compensation records), but such data have not been tracked systematically for Thailand. Alternatively, we performed validation using the locations of 803 HEC events from the Khaoyai-Dong Phayayen FC(2) with 60 sets of randomized HEC pseudo-absences (Fig. S4a). These HEC records were collected with GPS coordinates from two studies: Wongram and Salee (2017) in 2012–2017 and DNP in 2019. The area under the receiver operating characteristic curve (AUC), a threshold-independent metric, was generated from the true positive (sensitivity) and false positive (1-specificity).

3. Results

3.1. Baseline and future hazard levels

The high level of baseline hazard (>0.8) was concentrated close to protected areas, especially near the eastern FC(1), Khao Yai-Dong Phayayen FC(2), Phukieo-Namnow FC(4), western FC(10), Khaengkrachan FC(11), and Klong Saeng-Khaosok FC(13) (Fig. 3a), which corresponded to the current areas estimated to host a large number of elephant populations (Fig. 1). However, these locations were projected with an overall decreasing hazard level across future scenarios. Contrarily, Lamnampai-Salawin FC(8), west of Mae Pin-Omgoi FC(9), west of Western FC10, Phumieng-Phuthon FC(5), and north of FC2 were estimated to have higher future hazards (Fig. 3a).

Across all scenarios, the general pattern of higher future hazards in the northwest direction was a result of similar climate projections. However, localized differences among scenarios were a result of projected land cover variations and buffer-zone policies. The increasing future hazard to the west of FC10 under the developmental-focus scenario (orange and red) was from higher landscape suitability due to the change in agricultural land cover (Fig. 3a, S2, and S5). The areas north of FC8 and FC2 showed differences in future hazards, where restrictions were imposed within buffer zones, as shown under the green/yellow and orange/red scenarios (Fig. 3a and S5).

3.2. Baseline and future exposed rural population

The baseline exposure was lower in locations closer to protected areas, whereas higher values were estimated in the central region, northeastern plain, and areas south of Khao Laung FC(14), where a high density of human population resides (Fig. 3b). In future scenarios, many locations adjacent to protected areas were projected with a slight increase in exposure (<5%). A large reduction in future exposure has been projected in locations near areas with a high baseline human population. This decrease in exposure level was due to the combination of urban expansion and lower rural population, with an overall greater reduction in the number of exposed persons under developmental-focus (orange and red), −38%, compared to environmental-focus (green and yellow), −21% (Table 2). This larger reduction in the exposed population under developmental-focus scenarios corresponded to the demographic trajectory of SSP5, a relatively low population growth and fertility with high migration and urbanization (O'Neill et al., 2017).

3.3. Baseline and future vulnerability levels

Baseline vulnerability was low, with an average of 0.34 countrywide. Under future scenarios, an overall higher vulnerability was projected for most locations, of which the largest increase (>100%) was estimated in the northern region near FC8 and FC9 (Fig. 3c). Despite an increase in lower magnitude, south of FC14, central of FC10, FC11, and north of FC2 areas still showed an above-average increase in future vulnerability compared to other locations. Since three socioeconomic sub-indicators were assumed to be static in all future scenarios, the increase in vulnerability was solely due to a higher drought probability. Although all projections under developmental-focus scenarios had slightly higher drought probabilities than the environmental-focus scenarios, they were very close, without clear differences in spatial distribution.

3.4. Baseline HEC risk and future changes in Thailand

The validation of baseline HEC risk from FC2 showed an average AUC of 0.71 with 0.01 standard deviation (Fig. S4b), which is considered a good predictive performance.

The baseline HEC risk in Thailand was very low to low (0.0–0.4) in most locations and increased to moderate and high (0.4–0.8) closer to the protected areas (Fig. 4a). The top five FCs with the highest average baseline HEC risk were FC1, FC2, FC14, FC11, and FC13. Despite the reduction in

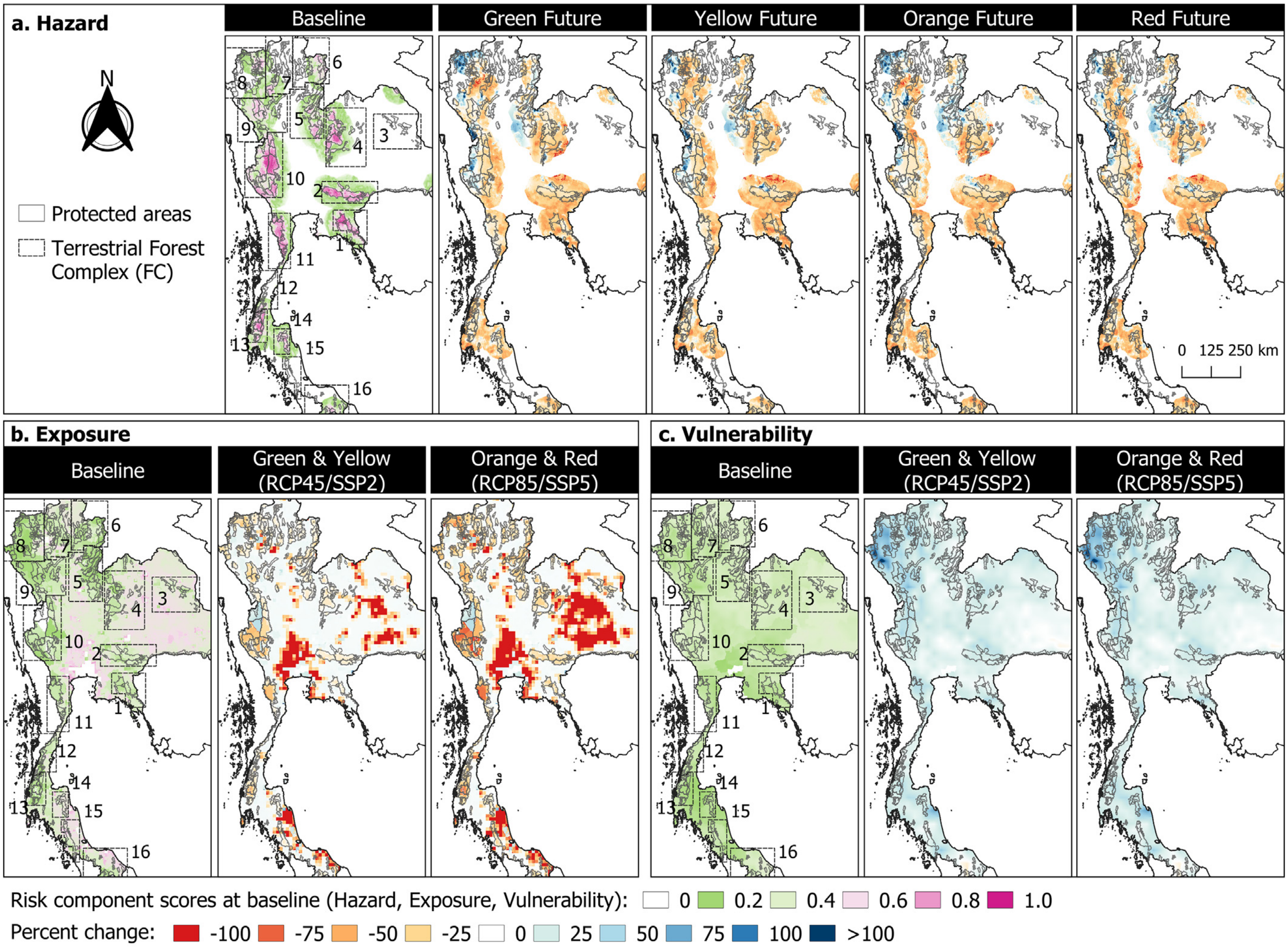

Fig. 3. Spatial distribution of baseline risk components including Hazard, Exposure, and Vulnerability and their average change in percentage under future scenarios. **a.** Hazard is expressed as the probability of elephant presence under four scenarios: environmental-focus with elephant-zones (Green Future), environmental-focus without elephant-zones (Yellow Future), developmental-focus with elephant-zones (Orange Future), and developmental-focus without elephant-zones (Red Future). **b.** Exposed human population and **c.** vulnerability were evaluated under two RCP/SSP scenarios without considering the effect from buffer zones.

future risk, these FCs were projected to remain in the top five under future scenarios. Areas with increasing future risk were FC8, FC9, areas surrounding FC5, and north of FC2. The complete elimination of future HEC risk was rarely predicted in areas coinciding with patterns of decreasing exposure from urban expansion. Across future scenarios, the overall spatial patterns were similarly estimated, with a few locations where clear variations were identified. Under environmental focus (green and yellow), larger spatial coverage of decreasing risk was projected to the west of FC10, with increasing risk on the east side adjacent to the FC boundary. HEC buffer zones can cause both negative and positive impacts, as is visible in the green and orange scenarios. For example, the areas near FC8 and FC9 showed an increasing HEC risk, but those immediately adjacent to protected areas north of FC2 showed decreasing results.

On average, the HEC risk levels for 69% of FCs ($n = 11$) were projected to be reduced under future scenarios (-3.1% to -57.9%), while 25% ($n = 4$) were identified with an increase (1.7% to 7.4%) (Fig. 4b). By inspecting risk components (Fig. 4b), hazard was projected to decrease in 13 FCs, increase in two FCs (FC8 and FC5), and remain stable with zero hazard in FC3. 85% of FCs with decreasing hazard levels were projected with over -10% change, of which FC15 and FC1 were estimated to have over -30% reduction. Exposure in and around all FCs was estimated to decrease with an average change of -9.15% (-3.2 to -26.5%), where the largest decrease was projected in the southern region, including FC16, FC15, and FC14, owing to urban expansion. In contrast, vulnerability across all FCs was projected to increase by 24.2% on average (8.8 to 48.7%), with three northern FCs (FC8, FC9, and FC7) showing the largest change of over $+30\%$.

Although the total number of exposed populations potentially affected by hazards was projected to reduce across four future scenarios, the population within each hazard level was estimated to have a higher level of vulnerability (Table 2). Under very high hazard conditions, approximately 332,000 exposed persons were estimated at the baseline period, but decreased to around 19,000, 15,000, 11,000, and 11,000 individuals in the Green, Yellow, Orange, and Red future scenarios, respectively. Across all hazard levels, the pattern of larger reductions under developmental focus (orange and red) compared to environmental focus (green and yellow) was similarly projected. However, the reduction gaps became smaller as the hazard moved from very high to low.

4. Discussion

This study applied a risk assessment framework to estimate the HEC risk under baseline and future climate change scenarios in Thailand. Our results identified different degrees and directions of changes in future HEC risk and highlighted the underlying influences of the hazard, exposure, and vulnerability components. Our projections suggested a higher future HEC risk

Table 2
The population (in 1000 person) with different levels of vulnerability that were exposed to varying levels of hazard under a baseline for environmental-focus with elephant-zones (Green Future), environmental-focus without elephant-zones (Yellow Future), developmental-focus with elephant-zones (Orange Future), and developmental-focus without elephant-zones (Red Future).

Hazard	Vulnerability	Exposed population (1000 person)				
		Baseline	Green Future	Yellow Future	Orange Future	Red Future
Very high	Moderate	9	18	14	10	11
	Low	323	1	1	0.3	0.3
	Very low					
Total very high hazard		332	19	15	11	11
High	Moderate	115	613	613	468	480
	Low	1286	176	204	86	117
	Very low	0.1				
Total high hazard		1401	789	817	554	597
Moderate	Moderate	213	1290	1228	1296	1121
	Low	1963	468	498	334	395
	Very low	25				
Total moderate hazard		2201	1758	1727	1630	1516
Low	Moderate	537	2280	2057	1992	1881
	Low	3553	1421	1399	1332	1270
	Very low	66				
Total low hazard		4156	3701	3457	3314	3151
Very low	Moderate	7029	19,605	19,894	15,103	15,377
	Low	24,146	5362	5325	3790	3749
	Very low	374	42	42	36	36
Total very low hazard		31,549	25,010	25,261	18,928	19,161
Total overall		39,638	31,276	31,276	24,436	24,436

toward the northwest region, which resulted in an average increase of 1.7%–7.4% for the four FCs in the northern region, while FCs at lower latitudes showed a decreasing future HEC risk of −3.1% to −57.9% on average. More broadly, our findings attested to the importance of climate change considerations in conservation planning, which has been shown to impact both wild elephants and humans. Although the complete elimination of risk from wildlife conflict is unlikely, mitigation and adaptation strategies to alleviate potential impacts can be implemented when the influences of risk components can be identified (Gaillard et al., 2019).

4.1. HEC effects due to climate change

The increase in future HEC risk in the mountainous regions of northern Thailand aligns with the reported changes in the distribution of suitable ranges toward higher latitudes and elevations for various species, including Asian elephants (Kanagaraj et al., 2019; Scheffers et al., 2016). Similar to the findings of Kanagaraj et al. (2019), climate change caused an increase in human pressure from urbanization and an increase in evaporative demand owing to higher temperatures at lower latitudes. Along with a higher hazard due to more favorable conditions for elephants, the northern region was also projected to face an increase in vulnerability to drought. Such climate-induced vulnerability is expected to reduce the capacity of people exposed to bare HEC damage in the future. Local observations have identified changes in weather patterns that have caused a decrease in crop yield, intensified extreme events, and escalated resource competition (Savo et al., 2016).

Although generally showing similar patterns across the four future scenarios, localized differences in the future outlooks between

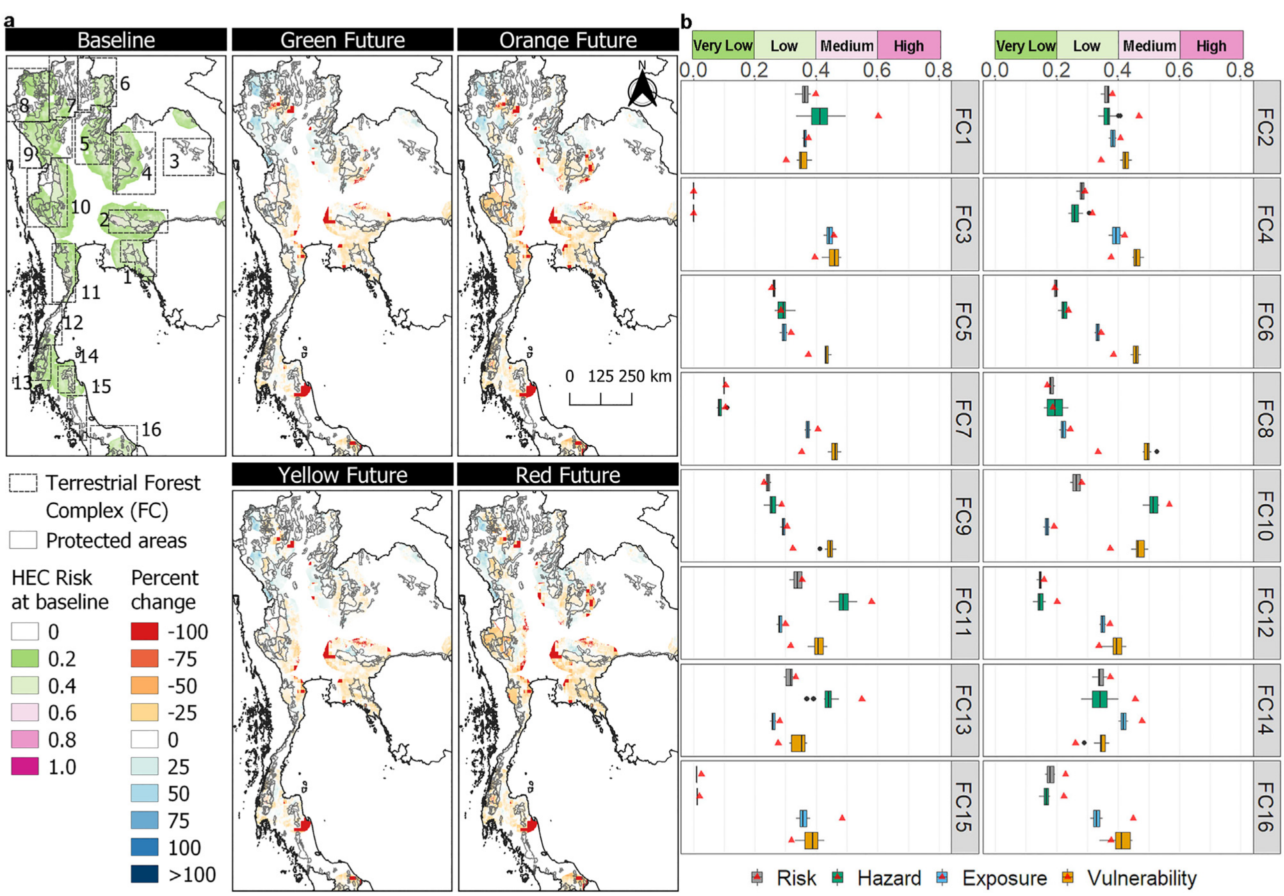

Fig. 4. Projected HEC risk at the baseline (2000–2019) and near future scenarios (2025–2044) for the Thailand forest complex (FC). **a.** The baseline risk and future percent change under four scenarios: environmental-focus with elephant-zones (Green Future), environmental-focus without elephant-zones (Yellow Future), developmental-focus with elephant-zones (Orange Future), and developmental-focus without elephant-zones (Red Future). **b.** Boxplots of the future HEC risk for 16 FCs and the underlying components including *Hazard*, *Exposure*, and *Vulnerability*. The circle symbol shows outliers. The triangle symbol (▲) represents the baseline values.

environmental- and developmental-focus climate change scenarios were observed. A more exposed rural population was expected under the environmental-focus projection due to slower urban expansion. Additionally, the introduction of elephant buffer zones seemed to foster a higher HEC risk. Therefore, choosing a greener pathway will likely result in a higher risk of HEC.

4.2. Implications for HEC management

Although northern FCs currently host relatively low wild elephant populations and face very low levels of HEC risk (Fig. 4b), climate-induced vulnerability was expected. For these FCs, various strategies to enhance adaptive capacity and coexistence can be considered, such as improving educational attainment (O'Neill et al., 2020), and behavioral change training (van Eeden et al., 2018). Because these areas are still not fully developed, land use planning can also be applied to selectively minimize access to potential habitats. Although a reduction in HEC risk was estimated for 11 FCs in the southern, eastern, and lower western regions of Thailand, the top five FCs with the highest future HEC remained, specifically FC1, FC2, FC14, FC11, and FC13. These FCs currently host large elephant populations (Fig. 1), but existing favorable habitat conditions are expected to decline, resulting in a lower hazard (Fig. 3a). Since population responses usually lag behind disturbances (Kuussaari et al., 2009), the reduction in habitat suitability would not immediately lead to a decrease in elephant numbers and subsequent HEC hazards but can cause extinction debts. FCs with less favorable habitat conditions may retain a high number of elephants for a period of time, but their long-term survival is likely to be affected by increasing localized extinction rates (Figueiredo et al., 2019). Therefore, management actions must be identified to buffer future impacts, which may include the establishment of protected area networks (Maron et al., 2015), increasing existing carrying capacity through habitat improvements (Bonebrake et al., 2018), and translocation of populations to more suitable locations (Bonebrake et al., 2018). Concurrently, immediate on-the-ground investigations are necessary to increase community tolerance.

4.3. Modeling limitations and future improvements

Future applications and interpretations of this framework should recognize its limitations. First, although our study used multiple GCMs to cover ranges of plausible climate, the results of future projections still are inherently uncertain (Sanderson et al., 2015). Second, bias could be present in the elephant presence-only data used for suitability modeling, which may or may not represent the fundamental niche of the species(Faurby and Araújo, 2018). We used established databases and official records; however, the subsequent hazard may change if the species has a broader niche than that captured by the available data. Third, large agricultural areas in this study were projected to be converted into abandoned lands, but the conversion of this land cover for other uses was not considered. Abandoned land may support either bioenergy production or reforesting, (Chen et al., 2020) which likely differs in the distribution of HEC risk. Lastly, owing to the limitation of HEC records, the validation data were obtained from one FC in the northeastern region, which may or may not represent the nature of conflict in other locations.

We also identified possible future research directions to enhance the proposed framework. Because species demography and behavior, phenology of food resources in agriculture and natural land, and human perception and tolerance are crucial determinants of human-wildlife coexistence (Philip J. Nyhus, 2016; Branco et al., 2019; ; Struebig et al., 2018), methods to incorporate such data as sub-indicators could be explored. Although we modeled HEC risk for Asian elephants in Thailand, this framework is scalable beyond the borders of a single country. Hence, further studies could assess the impacts of climate change scenarios on the transboundary population of elephants in mainland Southeast Asia. In addition, the framework can be tested on other species.

5. Conclusion

To offer a proactive approach in addressing wildlife-induced conflicts, this study proposes a risk assessment framework that enables the future projection of HWC risk and underpinned components requiring management interventions. Asian elephants are a cornerstone species for tropical dry forest and a conservation flagship in South and Southeast Asia, yet they face with increasing HEC. Unlike South Asia, majority of elephant conservation in Thailand and the neighboring countries in Southeast Asia have been focused on a few sites, lacking large-scale assessment. The specific use case of the proposed framework on HEC in Thailand cover countrywide assessment which suggests a shift in future HEC risk toward areas at higher latitudes and altitudes. We recommend that management focus on capacity building for communities within four FCs in the northern region and habitat improvement for 11 FCs at lower altitudes, especially those with existing large elephant populations. Further on-the-ground work is necessary to observe current HEC situations and determine specific actions; however, our results can support evidence-based allocation of conservation resources in anticipation of plausible future changes. This framework can be adopted by both scientific and conservation communities to assess the range of relevant factors, diverse spatial policies, and different locations and species worldwide.

CRediT authorship contribution statement

Nuntikorn Kitratporn: Conceptualization, Methodology, Software, Formal analysis, Investigation, Validation, Data curation, Visualization, Writing – original draft. **Wataru Takeuchi:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.155174.

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