Doctoral Dissertation

博士論文

Assessment of Asian elephant status and human-elephant conflict risk under climate change scenarios

(気候変動シナリオの下でのアジアにおける人間とゾウの軋轢の評価)

ナンティコーン　キットラットポン

Nuntikorn KITRATPORN

Doctoral Dissertation
博士論文

Assessment of Asian elephant status and human-elephant conflict risk under climate change scenarios

(気候変動シナリオの下でのアジアにおける人間とゾウの軋轢の評価)

Candidate:
Nuntikorn Kitratporn
ナンティコーン　キットラットポン

Thesis advisor:
Dr. Wataru Takeuchi

Committee:
Dr. Akira Maeda
Dr. Daiju Narita
Dr. Takehito Yoshida
Dr. Yasuki Kansha

A thesis submitted in fulfillment of the requirements
for the degree of Doctor of Philosophy
in the

Graduate Program in Environmental Sciences
School of Arts and Sciences

The University of Tokyo

Dissertation Abstract

論文の内容の要旨

Assessment of Asian elephant status and human-elephant conflict risk under climate change scenarios

(気候変動シナリオの下でのアジアにおける人間とゾウの軋轢の評価)

ナンティコーン　キットラットポン
Nuntikorn Kitratporn

Asian elephant (*Elephas maximus*) occurs in 13 range countries occupying heavily fragmented landscapes surrounded by human-dominated activities. Negative interactions between wild elephants and humans through crop depredation, property damages, and fatality, impact the quality of life of local communities and also hammer the species conservation outlook. As economic development and human population growth in this region are expected to continue, Human-Elephant Conflict (HEC) will likely become more frequent and emerge as the national challenge. Nevertheless, HEC management remains mostly reactive with localized assessment and lack of long-term planning. Therefore, a study on landscape-scale assessment of HEC distribution that incorporates future scenarios can benefit the species conservation, but has yet to be done. This dissertation aims to develop assessment framework for HEC that covers large spatial scale and considers climate change scenarios. Expected outputs from the proposed framework would quantify current and future HEC distribution at country-level by utilizing open-access data, spatio-temporal coverage of remotely-sensed products, ecological modeling, and climate change assessment techniques. To construct the framework and identify needed key variables for analysis, the following three sets of questions were raised: (i) What are the main priority for Asian elephant conservation in each range country? and which country is the most concern for HEC? (ii) Within the country of most concern, how did HEC distribution change over time? and what are the important variables influencing its change? Lastly, (iii) within the country of most concern, how HEC will change in the future, and which spatial locations should be given priority?

Chapter 2 categorizes range countries based on possible relationship of changes in wild elephant population to key landscape and socioeconomic factors. The long-term changes in land cover and landscape were analyzed within elephant home ranges based on remotely-sensed ESA CCI land cover product from three time periods: 1990, 2003,

and 2015. GHSL human settlement and socioeconomic factors (Human Development Index, GDP, and Control of Corruption index) were also considered as candidate variables in sustaining large wild elephant population. Based on the best model with the lowest AICc (28.77) and good pseudo-R^2 (0.68), four key drivers were identified from multiple logistic regression, namely area of the largest forest patch, land cover diversity, forest fragmentation, and average number of human population within elephant home range. Principle Component Analysis and K-means clustering were then applied on the linear trend coefficient of the elephant population and its cross-correlation coefficient to the four key selected drivers. The results indicated four possible groups with the following characteristics: (i) Cambodia, Laos, and Vietnam experienced a decrease in elephants with high forest loss and fragmentation, implying priority in halting habitat loss. (ii) Indonesia and Myanmar had a decrease in elephants even with remaining large forest patch as a possible result of illegal forest encroachment and poaching respectively, implying necessity for effective conservation law enforcement. (iii) Protection of key forest habitat was identified in Bhutan, India, and Nepal which should be further expand in other areas within the country. Lastly, (iv) a stable or increasing elephant population despite human disturbance and varying level of unfavorable conditions were identified in Bangladesh, China, Malaysia, Thailand, and Sri Lanka, implying the likelihood of overlapping resource usage and HEC. Within this group, Thailand was positioned as a potential leading country on the development pathway of forest transition theory, especially within Southeast Asia. The country showed an increasing elephant population despite highly developed landscape and deteriorating conditions of all key variables. This same situation will likely become that of many neighboring countries. Therefore, Thailand was chosen on which further analysis of HEC situation was performed.

Chapter 3 identifies governing factors of HEC by modeling its distribution in Eastern Thailand, a region with high number of reported HEC. To overcome data limitation due to the lack of official HEC records, news reports in online platform were collected from 2009 to 2018. The time-calibrated species distribution modeling (SDM) with maximum entropy (MaxEnt) was applied to model the relative probability of HEC in wet and dry seasons. The environmental dynamic over the 10-year period was represented by remotely sensed vegetation (MOD09A1), meteorological drought (KBDI), topographical (SRTM), and human-pressure data (human population, transport network, and distance to protected habitats). Results were classified into HEC zones using the proposed two-dimensional conflict matrix. The models yielded good predictive performance with AUC>0.78. The results showed that although HEC probability varied across seasons, overall HEC-prone areas expanded in all provinces from 2009 to 2018. High HEC-prone areas were estimated to cover 5,381 and 8,806 km^2 in the wet and dry season during 2018, which were double and triple that of 2009 estimation. The largest HEC areas were estimated during dry seasons with Chanthaburi, Chonburi, Nakhon Ratchasima, and Rayong provinces being the HEC hotspots. Direct human pressure caused a more gradual increase of HEC probability around protected areas, while resource suitability showed large variation across seasons. The top importance variables from direct human pressure (forest cover percent, drought level, and distance to forest) and resource suitability (distance from protected habitats, and human density) were identified. The evaluation from Eastern Thailand also highlighted climate-induced HEC impacts in which drought variations greatly alter HEC distribution.

In Chapter 4, the IPCC risk framework was adopted to assess spatial distribution of HEC risk under baseline (2000-2019) and near future (2025-2044) for Thailand. HEC risk is defined as the probability of wild elephant occurrence (hazard) in overlapping areas with human population (exposure) who possess different vulnerable levels (vulnerability). Four future scenarios were based on the combination of Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs) with 12km buffer-zone (BZ) policy: A1 (RCP4.5-SSP2-BZ), A2 (RCP8.5-SSP5-BZ), B1 (RCP4.5-SSP-no BZ), and B2 (RCP8.5-SSP5-no BZ). Climatic data included ERA5 (baseline) and NEX-GDDP (5 selected future GCMs). MOD09A1, ALOS-PALSAR yearly composite, and SRTM were used for land cover supervised classification at baseline period. Future land cover were simulated from land demand projection and location suitability. Derived land cover maps together with HydroSHED, ERA-JRC surface water, transport network, and topography represented landscape conditions. Elephant occurrences were obtained from existing literature, GBIF database, and Thailand national park report. Elephant habitat suitability and dispersal probability were then modeled for hazard. Exposed rural human population were available from existing study as proxy of exposure, while vulnerability was represented by socioeconomic factors and drought probability. Composite HEC risk was then calculated using geometric means with equal weighting. The validation indicated an average AUC of 0.71 ± 0.01 for baseline HEC risk map. The findings suggested a northward shift in future HEC risk which resulted in an average of 1.7% to 7.4% increase for four forest complexes (FC) in northern region and an average reduction of -3.1% to -57.9% for other FCs in lower latitude. Climate-induced changes were estimated to prominently alter HEC risk through deteriorating habitat conditions and increasing drought probability. Although land cover changes had overall lower effect, future conversion to abandoned land holds potential for conservation. HEC buffer zones created both positive and negative effects depending on locations. Many of the FCs projected with future unfavorable habitat conditions currently host large elephant population. Hence, habitat improvement is their likely priority to buffer the effects of climate change. On the other hand, FCs with expected increase in HEC risk hold lower elephant population and is surrounded by less developed human activities. Capacity building and limited access to future habitats maybe beneficial for communities in these locations.

Lastly, Chapter 5 discusses the contribution of this research which is two-fold. First, the proposed framework improves the assessment of HEC to cover large spatial scale, multi-dimensional analysis, and climate change impacts. The approaches used in this study utilize open-access dataset which support evident-based assessment in data-poor locations and can be applied across different species. Second, the findings of the proposed framework highlighted the areas that needed management attention. Allocation of limited conservation resources, thus, can be systematically planned. Caveats and recommendations to further the applicability of the proposed framework were also discussed.

Acknowledgements

I would like to express my deepest thank to all who journeyed with me during this PhD study. Many have given support and encouragement that enable me to reach this milestone.

First and foremost, my advisor, Prof. Wataru Takeuchi, whom I worked with for 5 years since my Master study. Throughout my time in Takeuchi lab, he continuously encourages me to strive for higher goals, while provides the space for me to explore various aspects in my academic interest. His valuable suggestions helped foster not only the work I undertook, but also my research attitude. I also would like to thank the dissertation committee for their comments that provide fresh perspectives and improvements to my thesis as well as their time and encouraging words during our individual discussions. I would also like to express my thank to Dr. Pantip, Dr. Tanakorn, Ms. Nin, and Mr. First from Suranaree University of Technology for their support during field visit.

I am sincerely grateful to the Royal Thai Government Scholarship which provided financial support for my studies at the University of Tokyo. Also, I must mentioned the tremendous assistance from the Office of Education Affairs at the Royal Thai Embassy in Tokyo, especially during difficult times. They never hesitate to provide their time and give all the help necessary to smoothen my stay in Japan. I also would like to acknowledge the kind assistance from GPEAK office in academic procedures and thesis submission.

I appreciated all the friends in Takeuchi Lab. Not only their great suggestions and academic discussion have helped me throughout my study, but also their lively spirit. The bonds I developed here will forever stay with me. I am specifically grateful for the day-to-day support, especially during my 3rd year, from Ms.Han and Mr.Fujiwara. I would have never survived my stay in Japan without the kindness from Ms. Yoshimura and her extended family. She is always willing to assist our lab members. In all my difficult times, she never failed to offer help, even beyond her responsibilities, and strengthen my moral.

Lastly, this journey would not be possible without the unconditional love and support from my parents and those who I love dearly. Their selfless sacrifices and never-fading trust have made me who I am today.

Contents

List of Figures

List of Tables

List of Abbreviations

AIC	Akaike Information Criterion
ALOS	Advanced Land Observing Satellite
AUC	Area Under the Curve
BCSD	Bias Corrected Spatial Downscaling
BZ	Buffer Zones
CC	Control of Corruption indicator
CCI	Climate Change Initiative
CLUE	Conversion of Land Use and its Effects modelling framework
CMIP	Coupled Model Intercomparison Project
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellite Program
DNP	Department of National Parks, Wildlife, and Plants Conservation
ECMWF	European Centre for Medium-Range Weather Forecasts
ESA	European Space Agency
ESA-JRC	ESA-Joint Research Centre
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization of the united Nation
FC	Forest Complex
GCM	Global Circulation Models
GDP	Gross Domestic Product
GHSL	Global Human Settlement Layers
GIS	Geo-spatial Information System
GSMaP	Global Satellite Mapping of Precipitation
HDI	Human Development Index
HEC	Human Elephant Conflict
HWC	Human Wildlife Conflict
IIASA	International Institute for Applied Systems Analysis
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services

IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
IUCN/SSC	IUCN Species Survival Commission
KBDI	Keetch-Byram drought index
LCCS	Land Cover Classification System
LPI	Largest Patch Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MTSAT	Multi-functional Transport Satellites
NASA	National Aeronautics and Space Administration
NDBI	Normalized Different Built-up Index
NDWI	Normalized Different Water Index
NDVI	Normalized Different Vegetation Index
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
NP	National Parks
NSO	National Statistical Office of Thailand
PALSAR	Phased Array L-band Synthetic Aperture Radar
PD	Patch Density
PDSI	Palmer Drought Severity Index
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
ROC	Receiver Operating Characteristic
RS	Remote Sensing
SD	Standard Deviation
SDM	Species Distribution Modeling
SHEI	Shannon Evenness Index
SRTM	NASA Shuttle Radar Topography Mission
SSP	Shared Socioeconomic Pathways
TRI	Terrain Roughness Index
UNDP	United Nations Development Programme
UNDRR	United Nations Office for Disaster Risk Reduction
USGS	United States Geological Survey
VIIRS	Visible Infrared Imaging Radiometer Suite
WDPA	Word Database on Protected Areas
WGI	Worldwide Governance Indicators
WS	Wildlife Sanctuaries

Chapter 1

Introduction

1.1 Background

Anthropogenic activities transformed large extent of the earth land surface, degrading and extirpating habitats, which triggered the on-going sixth mass extinction of organism globally (Chapin et al., 2000). The extinction rates are estimated to be over 1,000 times greater than the likely natural background (Pimm et al., 2014). Between 1900 to 2015, all of the 177 mammals species being studied loss at least 30% of its geographical ranges, while 40% of these species experienced severe habitat shrinkage of over 80% (Ceballos, Ehrlich, and Dirzo, 2017). The loss of species and associated biodiversity may go unnoticed at the immediate present, but can certainly cause significant impacts to ecosystem and human health in long-term. The persistence of wild species, especially of large herbivores and carnivores (megafauna), affects ecosystem physical structure, trophic structure (abundance and composition of animals community) and ecosystem biogeochemistry (Malhi et al., 2016). The extinction of one megafauna species will not only cause co-extinctions (Galetti et al., 2018), but also degrade the health of ecosystem functions and services which are fundamental for human survivals (Cardinale et al., 2012).

Despite the evidences in support of nature and wildlife conservation, the rate of habitat loss, habitat degradation, and number of threatened species accelerated (IPBES, 2019). With the projected growth of human population, the 2019 world population of 7.7 billion people will reach 9.7 billion by 2050 and 10.9 billion by 2100 (United Nations, 2019b). The continuation of development is necessary to ensure equal opportunity and quality of life for the global citizen. The agenda to conserve nature while support growing human population is challenging. The increase in human population comes with associated surges in demand for resources, especially for food. Agricultural land already covered around 38% of the earth terrestrial surface (FAO, 2016) and its expansion contributed to 40% of tropical deforestation during 2000 and 2010 (FAO and UNEP, 2020).

The expansion of agricultural land caused not only the direct increase in habitat loss and fragmentation (Veach, Moilanen, and Minin, 2017), but also the agricultural frontiers that stimulates resource competitions and interactions between human and wild species (Nyhus, 2016). This unavoidably leads to conflict over wildlife-induced damages. Such situations can negatively impact people through crop and livestock depredations, damages to property and even the loss of lives (Dickman, Marchini, and Manfredo, 2013). In response, human developed hostility and resorted to retaliation killing of the problem species (Mateo-Tomás et al., 2012). Although human-wildlife conflict (HWC) occurred mostly in communities at close proximity to forest, conflict is escalating near urban-fringe (Anand and Radhakrishna, 2017). Therefore, HWC phenomena is fast becoming one of the must-addressed issues to further the success of conservation and the sustainability of human livelihood (Distefano, 2005; Inskip and Zimmermann, 2009). Figure 1.1 showed an exponential increase in the numbers of scientific papers on HWC in the last two decades which reflected the raising priority and interest of this issue (Nyhus, 2016).

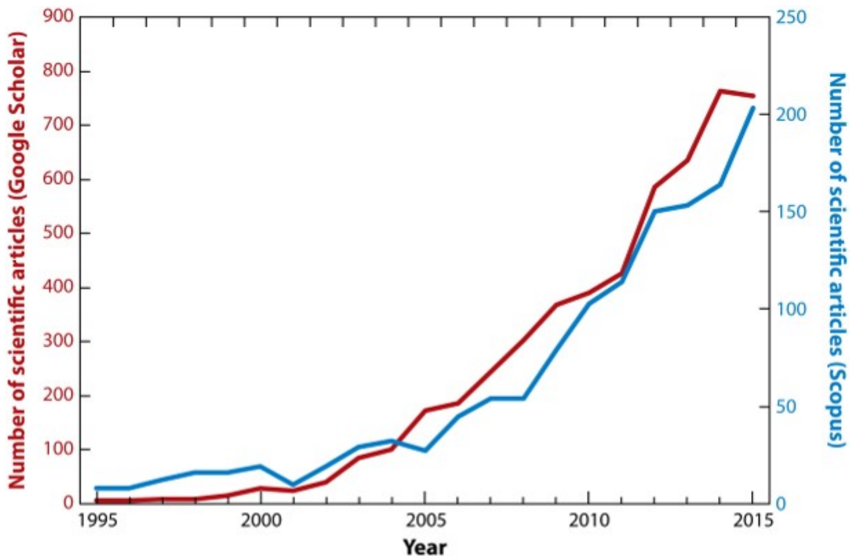


Figure 1.1: The number and growth of scientific papers covering human-wildlife conflicts during 1995 to 2015 with red referring to the exact usage of the word 'human-wildlife conflict' or 'human wildlife conflict' in Google Scholar and blue representing a combination of 'human' and 'wildlife' with 'conflict' in Scopus database (Nyhus, 2016)

Although species of varying sizes were found in conflict with human, large endangered species are disproportionately caused concerns (Dickman, 2010). The number of threatened large herbivores are concentrated in South and Southeast Asia, while intensive human pressure were also observed in the same region (Figure 1.2). Moreover, most countries in this region remain within developing category where the problems of HWC is believed to be particularly challenging (Seoraj-Pillai and Pillay, 2017). With high number of large species, existing pressure from human activities, and projected growth in economic development, this region is likely to face with intensified conflicts between human and nonhuman species.

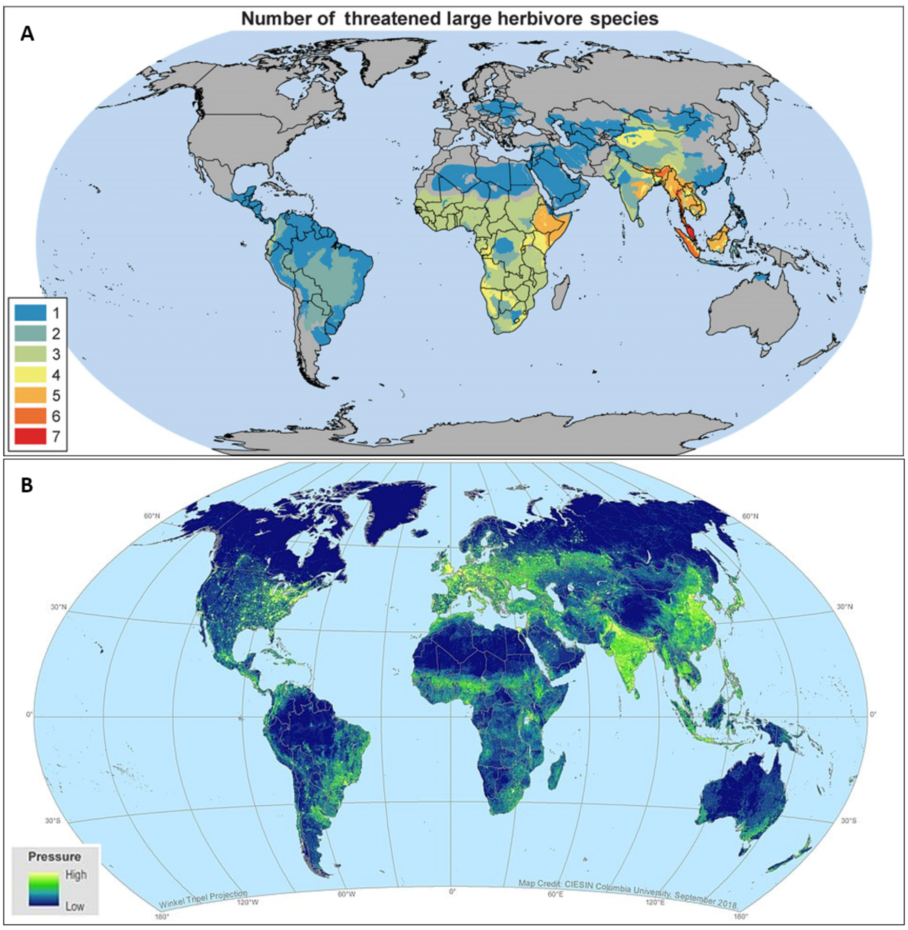


Figure 1.2: Global distribution of the threatened larger herbivores total number (Ripple et al., 2015) (A) and the level of human pressure measured by Human Footprint Index in 2009 (Venter et al., 2016) (B)

Asian elephants (*Elephas maximus*) is the largest terrestrial herbivore in Asia. The species is a subject of intense HWC which is usually referred to as human-elephant conflict (HEC). Hosting the largest population of wild elephants, the HEC situation in India is causing the death of approximately 400 people and 100 elephants each year (Rangarajan et al., 2010). In Thailand, 70% of the protected areas estimated with wild elephant are facing HEC (Noonto, 2009). In China, HEC is officially listed as the leading damages from wildlife despite small elephant population (Li et al., 2017). Evidences of HEC in varying degrees were reported from all countries where Asian elephants occur (IUCN/SSC Asian Elephant Special ist Group, 2017). Approximately 10-15% of total agricultural output in many areas located close to elephant habitats can be damaged by wild elephants (Barua, Bhagwat, and Jadhav, 2013). Therefore, the management of HEC became the central focus of Asian elephant conservation.

HEC is a reciprocal complex system involving various components that ranges among elephant ecology, geopolitic, socio-economic, human perception, and resource distribution. Among existing mitigation strategies, landscape-scale planning is regularly emphasized together with the fostering of human tolerance (Hoare and Du Toit, 1999; Sitati et al., 2003; Neupane, Johnson, and Risch, 2017; Shaffer et al., 2019). However, landscape-scale assessment remained limited and urgently needed (Gubbi et al., 2014). The researches on HEC are normally localized covering a single protected area or few surrounding villages. Besides logistics difficulty and resource limitations, the reasons for such local-scale focus usually arise from the observations that HEC is context-specific. Although an in-depth understanding of the conflict characteristics within a particular area is invaluable, the lack of landscape-scale consideration and planning led to incomplete awareness of the situation and short-sighted decision-making (Athreya et al., 2013; Goswami and Vasudev, 2017). Therefore, assessment of Asian elephant conservation and related conflicts at larger scale, despite lessen in detailed information, are critical and should be pursue.

When assessing and monitoring large habitats, the use of geo-spatial and satellite remote sensing (RS) tools together with modeling techniques became an invaluable complementary to traditional in-situ data. The most commonly used RS data is land cover products, while continuous measurements, such as vegetation indices and climatic data, are being increasingly utilized (He et al., 2015; Radeloff et al., 2019). The integration of RS and ecological modeling enhance the monitoring and assessment of species and believed to be the way forward (Randin et al., 2020). In addition, the application of RS data not only expands spatiotemporal coverage of monitoring but also provides standardized products and techniques allowing comparative assessment across continents (Skidmore et al., 2015). Hence, the integration of RS products, geo-spatial techniques, and ecological modelings also likely enable the evaluation of HEC at landscape-scale.

Accordingly, in the following sections I provided details on Asian elephant conservation status, then reviewed literature on the mechanism of HEC and current situations in Asia, the concept of coexistence, landscape conservation and scenario planning, and lastly the application of remote sensing and geospatial tools.

1.2 Literature review

1.2.1 Asian elephants

Asian elephants historical range comprised over 9 million km^2; stretched from West Asia to Southeast Asia and reached as far west as Yangtze-Kiang river in China (Sukumar, 2003). However, its current range contracted and comprised of sparsely fragmented habitats covering 486,800 km^2 (Blake and Hedges, 2004). As a long-lived species with late reproduction, this severe habitat destruction occurred rather rapidly within roughly two to three generations of many populations. The 13 countries hosting the remaining Asian elephant population include Bangladesh, Bhutan, Cambodia, China (Yunnan province), India, Indonesia, Laos, Malaysia, Nepal, Sri Lanka, Thailand and Vietnam (Figure 1.3). Elephant population in Asia has been estimated at 40,000 to 50,000 individuals and listed under endangered status since 1990 (IUCN, 2015). In fact, many experts believed the actual number is likely lower because range countries mostly lacked systematic range-wide population assessment (Blake and Hedges, 2004; Calabrese et al., 2017). Unlike their African counterpart, Asian elephants do not face extensive risk of poaching, but habitat conversion and conflict with humans are severely prominent (Sukumar, 1989; Fernando et al., 2005; Choudhury et al., 2008; Fernando and Pastorini, 2011; IUCN/SSC Asian Elephant Special ist Group, 2017).

Asian elephants are regarded as an ecosystem engineer and a keystone species. Elephants influence the structure of ecological communities and processes through various foraging behaviors (Blake and Inkamba-Nkulu, 2004; Hawthorne and Parren, 2000). The trampling and breaking by forest elephants open up dense vegetation to create forest gaps enabling light to reach the forest floor, which creates productive ground layer and benefits various ground species of plants and vertebrates (Terborgh et al., 2016). These behaviors also filter tree recruitment and allow higher carbon storage effecting climate regulation (Berzaghi et al., 2019). Asian elephants are also one of the most crucial long-distance seed dispersal agent (Harich et al., 2016). As a seed disperser, elephants maintain tree diversity and some native plants developed to solely rely on them for spreading seeds

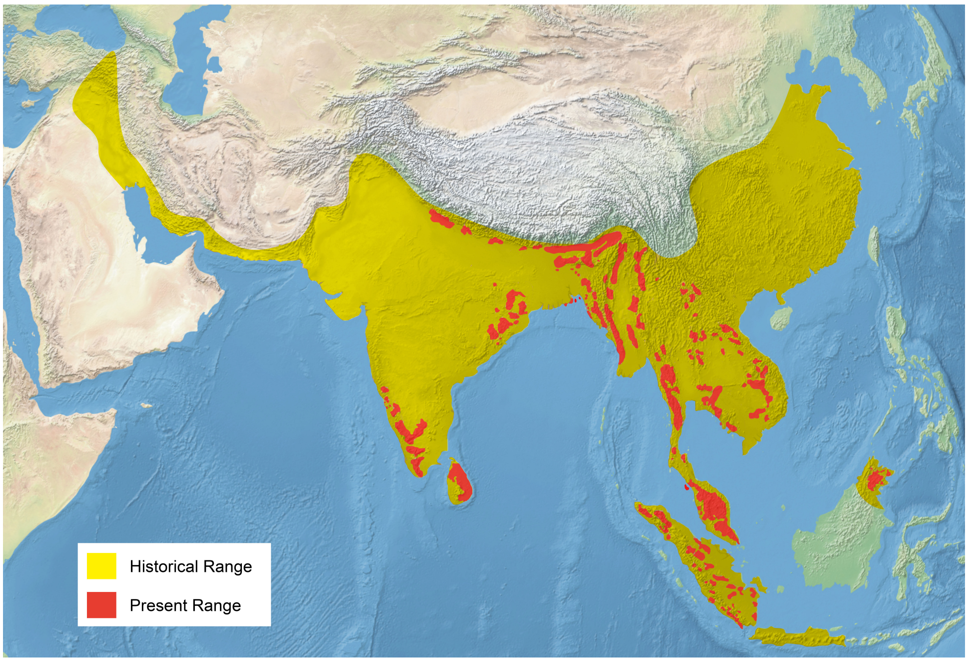


Figure 1.3: The estimated historical and present distribution of Asian elephants (Sukumar, 2003)

(Campos-Arceiz and Blake, 2011). Moreover, elephants are considered as an umbrella species. Because their conservation requires the protection of wide-ranging areas, the safeguarding of elephant habitats consequently preserve habitats for other species and serve a greater biodiversity protection (Branton and Richardson, 2011; Epps et al., 2011). For conservation community, elephants are also viewed as a flagship species because their charismatic appearance and nature which help bringing public attention and awareness (Barua, Tamuly, and Ahmed, 2010).

Beside their ecological importance, the species also holds a cultural role in their range countries and has long been in intricate relationship with humans. Historical records mentioned elephants in association to gods, kings, a mechanism of wars, a mode of transport, a token of peace, a source of fears and much more (Sukumar, 1992). In Hinduism and Buddhism, elephants are associated with deity and prosperity (Bandara and Tisdell, 2003). In Thailand, for example, white elephant was perceived as a national pride and once printed on the country's flag as a national symbol (Vinitpornsawan and Sirimanakul, 2014).

Nonetheless, over time economic and technological development shifted human perception of forest and wildlife within it. Forest and wild elephants became assets when benefits can be directly reaped, such as during the peak of logging, but burden otherwise (Laohachaiboon, 2010). The estimated home range of wild elephants now lies in heavily fragmented landscapes and is surrounded by human-dominated activities (Leimgruber et al., 2003). Since wild elephant population decreased and their sightings became disproportionate, the bonds and knowledge of locals about the species faded (Vinitpornsawan and Sirimanakul, 2014). The shifting in perceptions and the localized increase in elephants' use of human-dominated land led to a growing in likelihood of negative interactions between human and wild elephants which resulted in HEC.

1.2.2 Human-elephant conflict (HEC)

Adapted from the International Union for Conservation of Nature (IUCN)'s definition of HWC, HEC can be defined as situations when needs and actions of wild elephants caused recurring threats, both actual and perceived, to the livelihood of people, leading to the persecution of elephants (IUCN/SSC Human Wildlife Conflict Taskforce, 2020). HEC incidents in Asia are believed to be increasing and caused concerns across all range countries. For example, Desai and Riddle (2015) approximated 500,000 to 1 millions households in India as being affected by damages related to wild elephants. Even one of the smallest population located in China were involved in conflict causing the deaths of 12 humans in 2019 and a yearly estimate of 4.5 million dollars losses (Jia and Wei, 2020). Although monetary and spatial quantity of damages are relatively small at a national level, affected communities were usually either among the least privileged or disproportionately bare the cost beyond their capacity (Barua, Tamuly, and Ahmed, 2010). In addition, intangible costs of conflict such as the inability to travel caused by fear of roaming elephants, loss of time and deterioration of health during night guarding, and other opportunity costs can greatly affect the livelihood of those who co-habit elephants range (Jadhav and Barua, 2012; Barua, Bhagwat, and Jadhav, 2013; Kansky and Knight, 2014).

Mechanism of conflicts

Conflict between human and wildlife, including HEC, is complex and driven by numerous reciprocal factors. Various scholars suggested that HWC should be viewed as coupled systems and sometimes referred to as *coupled human and nature systems (CHANS)* (Carter et al., 2014), *socio-ecological systems (SES)* (Lischka et al., 2018) or *coupled human-environmental systems* (Turner et al., 2003). Despite these varying terminologies, the general concepts are similar. Such systems comprised of biophysical (nature) and social (human) elements with interactions at multiple spatial, temporal, and organizational scales that are controlled in dynamic and complex ways (Liu et al., 2007; Redman, Grove, and Kuby, 2004). Ostrom (2009) suggested multidisciplinary approach to understand such integrated systems and emphasized its importance for sustainability. Similar suggestion was stressed for HWC (Pooley et al., 2017). Based on these concepts, the alternation of one component can trigger changes in others and even cause a shift in the system stage. Hence, it is crucial to understand the holistic picture of HEC system.

Based on existing literature, I reviewed and grouped HEC components into two categories: (i) proximate elements and (ii) ultimate factors. The overall interaction between each component was summarized in Figure 1.4. HEC was shown as hexagon. Proximate actions were drawn in rectangle, while ultimate factors were represented with ellipsoid.

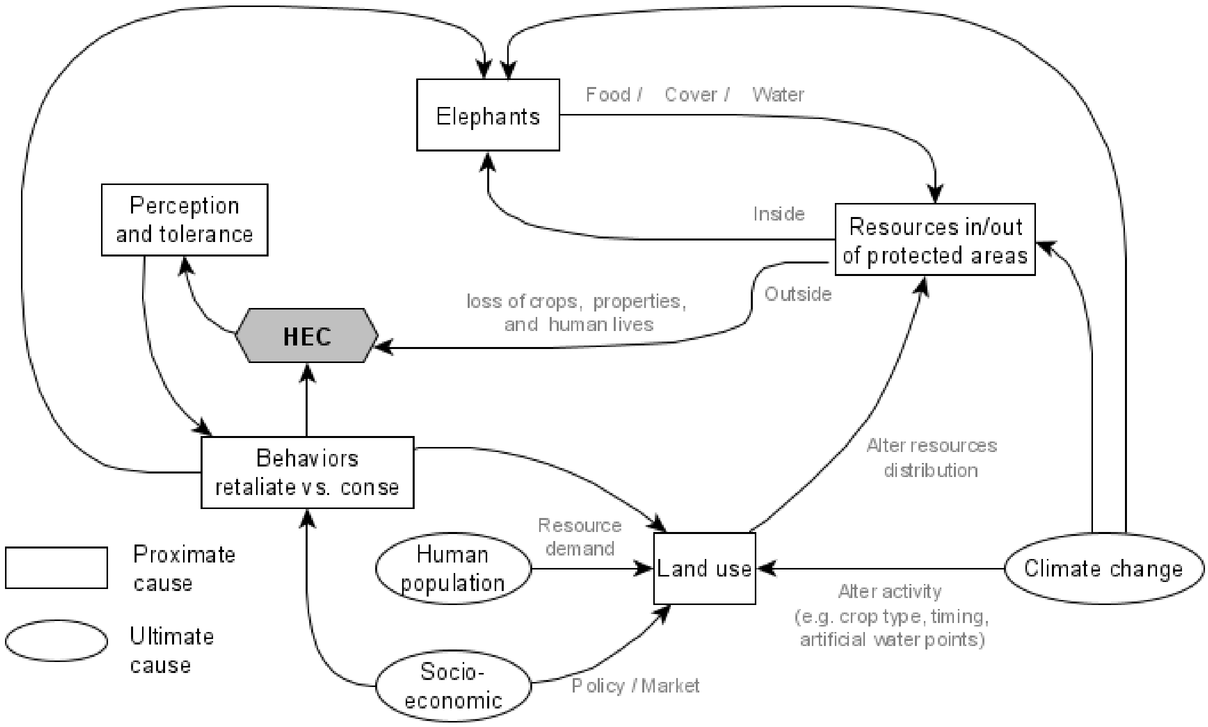


Figure 1.4: The general summary of the components and their associated relationships within HEC system which included ultimate causes represented in oval and proximate factors represented in rectangular symbols

Proximate factors

Proximate factors cause immediate effects and directly influence HEC situations. Three main factors were summarized namely, elephant ecology, human perception and tolerances linking to human behaviors, and land use induced resource distribution.

Elephant ecology: To support their physiological and energy requirements, elephants need to daily consume around 10% of their body weight, or approximately 150 kilograms of food and 190 liters of water (Sukumar, 2003). Consequently, elephants tend to forage over large area, sometimes extending beyond formal protected habitats. Despite disruption from human structures, seasonal movement and migration were reported within many ranges, covering 100-10,000 km^2 of areas depending on resource availability (Fernando and Leimgruber, 2011). Moreover, elephants are edge-specialist and prefer matrix of land cover which is often occurring near the forest edges (Wadey et al., 2018). The optimal foraging theory (Stephens and Krebs, 1986), individuals seek for the most energy at the lowest cost, was also believed to influence crop-raiding by elephants. Sukumar (1989) suggested a "high risk, high gain" strategy in which richer nutrients and mineral salts in cultivated crops maximize nutrient intake better than natural vegetation. Pokharel et al. (2019) confirmed higher productivity and dietary quality in human-production land surrounding elephant habitats and also measured lower faecal glucocorticoid metabolite (fGCM) levels, an indicator of stress, from elephants habituate agricultural lands. These requirements and preferences led the species to forage near the forest edge and human-dominated lands which increases the likelihood of interactions and conflicts.

Human perception, tolerance, and behavior: Perception reflects how individuals perceived themselves to be at risk which socially and culturally constructed through personal experiences (Hill, 2004). Tolerance here indicates how much ones can accept negative impacts caused by wildlife (Kansky, Kidd, and Knight, 2016). Tolerance is influenced by perception along with individual economic conditions (Nsonsi et al., 2017), social connections (e.g. institutional trust) (Bruskotter and Wilson, 2014) as well as frequency and extent of damages (Sampson et al., 2019). Direct tangible losses cannot always indicate the level of tolerance toward wildlife. In spite of high costs induced by wildlife, some communities maintained positive attitude toward conservation, while other refused to compromise with much smaller losses (Kansky, Kidd, and Knight, 2016). Specifically, tolerance toward wild elephants varied greatly among studies and, in some cases, high tolerance were observed (Kansky, Kidd, and Knight, 2014). Such aspects of human cognition were recognized to translate into expression of behaviors and acknowledged among the key to conservation success (Chapron et al., 2014; Bruskotter and Wilson, 2014).

Resource distribution and land use: Previously, the distribution of resources were mainly governed through natural factors, but human adaptation and recent technological advancement allowed rapid spatial and temporal alteration of resources. Agriculture land conversion was suggested to associate with elephant conflicts (Hoare, 1999). Crop types and location of certain palatable trees in relation to residential areas increased the likelihood of HEC (Neupane, Johnson, and Risch, 2017). Moreover, the availability of mature crops adjacent to protected areas during a period of low vegetation productivity within natural habitats influenced elephants' movement and raiding pattern (Branco et al., 2019). Timing and availability of food were a stronger indicator associated with an increase in conflicts, not the abundance of species or number of problem individuals (Artelle et al., 2016). Analysis of GPS collar and long-term sighting showed that the locations and available of resources together with associated risk influence elephants movement and distribution (Chamaillé-Jammes et al., 2013; Krishnan et al., 2019). Consequently, managing spatial and temporal distribution of shared resources was proposed as a key to long-term HEC management (Shaffer et al., 2019) .

Ultimate factors

The ultimate factors are considered as root-causes and act at large scale, such as regional, and global. These factors are usually problematic to directly manage, but essential indirect drivers of proximate factors. Human population, socio-economic demands and climate change are the main forces under this category.

Human population: The growth of human population was directly linked to the negative impacts on nature, especially through increase in land demand (Crist, Mora, and Engelman, 2017). In South and Southeast Asia, increasing in land demand resulted in pervasive forest conversion, with less than half of its original forest remained (Sodhi et al., 2004). Besides influencing land configuration which consequently alter resource distribution, human population also created direct pressure for wildlife through predator effects.

Socioeconomic demands and market trends: Along with human population growth, socioeconomic demands largely impact food production. Food consumption and waste, for example, can heighten land demand beyond simple linear relationship to the number of human population. The boom of palm oil as low-cost ingredient in various products is one example of how market demand influenced local farmer or government decision to promote certain land use (Meijaard et al., 2018). Suba et al. (2017) identified oil palm conversion which showed an increase of over 400% during 2006-2010, as the single biggest cause of HEC in north Kalimantan, Indonesia. Besides being an indirect driver of land conversion, socioeconomic trends can also influence human behavior both through government regulations or individuals decision, such as growing movement in elephant-friendly tea plantation in India or rubber plantation in China (Liu et al., 2017).

Climate change: Although land use is currently the number one cause of biodiversity deterioration, climate change is fast becoming more prominent and believed to surpass land use in the future (IPBES, 2019). As climate change causes fundamental shift in precipitation, temperature, and extreme events, existing habitat of Asian elephants may become unsuitable. Changes in climatic conditions can either cause direct physical impacts on elephants, such as that of thermal regulation, or indirectly through alteration of food and water availability (Kanagaraj et al., 2019). Silva et al. (2020) suggested overall future contraction of Asian elephant range areas with some localized range expansion especially at higher altitude. This projection suggested range shifting which may trigger migration through human-dominated landscape and consequently increase the probability of HEC. Moreover, climate change will likely impact crop yield and crop suitability resulting in land use alteration (Zhao et al., 2017) which also link to elephant-human resource distribution.

Common mitigation and success uncertainty

Various mitigation strategies have been implemented. Most of which are founded in fear conditioning and physical separation that include deterrents (e.g. creating loud noises through drumming or firecrackers), guarding (e.g. watchtower, patrolling), and physical barriers (e.g. fences, elephant-proof trenches) (Desai and Riddle, 2015). Some mitigation aim to directly alter elephant population, such as domestication, culling, and translocation of problem individuals (Shaffer et al., 2019). Others aim to increase human tolerance through compensation (DeMotts and Hoon, 2012). More proactive methods were also attempted, such as tracking the movement of problem individuals with the use of GPS collaring (Salim, 2019), and the implementation of government insurance schemes (Nuntatripob, 2019). New technology and innovation are also being explored, such as advance early warning technologies based on the detection of infrasonic sounds used by elephants (Zeppelzauer, Hensman, and Stoeger, 2015), and the image recognition of live camera installed in elephants paths (Ramesh et al., 2017; Zeppelzauer and Stoeger, 2015).

Despite the various methods, the effectiveness and success of mitigation strategies varied greatly between communities. Some techniques are expensive to maintain or facing low uptake by local communities (Hoare, 2015). Moreover, elephants possess behavioral flexibility which allow them to adapt and become habituate to deployed mitigation reducing its effectiveness over time (Mumby and Plotnik, 2018). More often than not, the implementation of mitigation within one location merely shift HEC problems to adjacent areas due to the lack of landscape consideration (Osipova et al., 2018). Mumby and Plotnik (2018) suggested that commonly employed mitigation only reduce conflict symptoms, but overlook the underlying causes.

1.2.3 Coexistence

The traditional conservation approach of complete separation became impractical as natural landscape decreased. Carter and Linnell (2016) conceptualized the definition of coexistence as “a dynamic but sustainable state in which humans and large [species] co-adapt to living in shared landscapes where human interactions with [species] are governed by effective institutions that ensure long-term [species] population persistence, social legitimacy, and tolerable levels of risk”. The concept emphasized the long-term perspective and the ability to co-adapt by both human and wildlife to share the key overlapping resources. Spatial arrangement of resources in shared landscape and their accessibility at multiple scales are, thus, fundamental to HWC management (Carter et al., 2012).

1.2.4 Landscape conservation and scenario planning

Although protected areas will retain its central role in conservation, human activities and interactions with wild species in landscape beyond their boundaries will influence management options (DeFries et al., 2007). Landscape approach, with the integration of socioeconomic needs and environmental effects, allows holistic evaluation of trad-off and synergies between conservation and development for various stakeholders (Palomo et al., 2014; Reed et al., 2016). Morzillo, Beurs, and Martin-Mikle (2014) emphasized the impacts of landscape-scale characteristics and spatial changes on HWC. Traditional conservation plannings frequently rely on localized historical records; however, they are unlikely to cope with rapidly changing and uncertain future at landscape level (Peterson, Cumming, and Carpenter, 2003).

Scenario plannings, on the other hand, allow decision-makers to explore plausible futures and develop relevant alternative actions (Mahmoud et al., 2009). Foden et al. (2019) emphasized the importance to evaluate future climate impacts on species in order to identify needed modifications to conservation strategies. Titeux et al. (2016) suggested that future scenarios in ecological modeling should consider climate change, as well as inter-related climate and human-induced land cover changes. Similarly, future climate and anthropogenic change are expected to alter resource dynamic over shared landscape requiring both humans and elephants to adapt (Shaffer et al., 2019).

Landscape scale scenario planning that incorporated future scenarios were conducted for elephant distribution (Kanagaraj et al., 2019; Li et al., 2019) and population response (Boult et al., 2019a), but yet to directly address HEC. Limited study on HEC that somehow evaluated future scenario mostly considered historical trend in land cover only (Naha et al., 2019).

1.2.5 Geospatial and remote sensing application

HEC is a spatial phenomena requiring the investigation of spatially explicit factors (Smith and Kasiki, 2000). Dublin and Hoare (2004) also emphasized the necessity of spatial analysis of HEC and highlighted that much more remained to be done. Since then multiple HEC studies attempted to utilize geospatial techniques together with RS data. Sitati et al. (2003) provided spatial prediction of HEC at coarse resolution (25-km^2). Graham et al. (2010) analyzed HEC pattern at various spatial scale based on intensive collection of crop damage data. Chen et al. (2016) predicted HEC hotspot in Southwest China using detailed HEC compensation records with land cover and distance to key landscape features.

Advancement in computational power and increasing availability of satellite RS products enabled more landscape details, larger spatial coverage, and finer spatiotemporal resolution to be incorporated. Duffy and Pettorelli (2012) identified positive relationship between satellite-derived Normalised Difference Vegetation Index (NDVI) and African elephant densities. Boult et al. (2019b) utilized NDVI as a proxy of resource availability which govern elephants' movement decision beyond protected areas. Additionally, the timing of vegetation productivity in agricultural land influenced raiding pattern of crop depredation by elephants (Branco et al., 2019).

Nevertheless, there remain limitations among existing studies which commonly arise from the lack of underlying HEC records and the spatial and temporal coverage of the analysis. These limitations may be addressed with data integration combining available data from multiple sources including RS, geospatial, socioeconomic, and ecological data (Randin et al., 2020).

1.3 Motivation of this study

Despite the advancement of spatial analysis on Asian elephant habitats and HEC, most studies remain limited in their spatial coverage and consideration of future outlook. Landscape assessment are fundamental to provide holistic decision-making which enable limited conservation resources to be delegated appropriately. Although widely recognized and already observed in many locations, climate change-induced impacts on wildlife conflicts has yet been systematically incorporated in long-term HEC management. A study on landscape-scale assessment incorporating climate change scenario can benefit Asian elephant conservation. Therefore, analytical framework that enable such assessment should be studied and practical suggestions should be put forward.

1.4 Objective of this study

Taking the argument in the previous sections, the objective of this study is to develop assessment framework for HEC that covers large spatial scale and considers climate change scenarios. Consistent risk framework, in which risk is expressed as a function of hazard, exposure, and vulnerability, was employed in United Nations Office for Disaster Risk Reduction (UNSDRR) guideline (UNISDR, 2015) as well as Intergovernmental Panel on Climate Change (IPCC) Special Report (IPCC, 2012) and Fifth Assessment Report (IPCC, 2014). This framework potentially holds characteristics necessary to support HEC assessment as it provides flexibility in utilizing data upon availability, spatially explicit outputs, multi-dimensional analysis, and scenario planning consideration. Specifically, to adapt this framework to HEC assessment and identify needed key variables for analysis, this study address the following three sets of questions:

1. What are the main priority for Asian elephant conservation in each range country considering long-term historical changes in elephant population and key driving factors within elephant home ranges?, and which country is the most concern for HEC? (Chapter 2)

2. Within the country of most concern, how did HEC distribution change over time? and what are the important environmental variables influencing changes in HEC? (Chapter 3)

3. Within the country of most concern, how HEC will change in the future, and which location should be given priority? (Chapter 4)

1.5 Contribution and novelty of this study

The contribution of this research is two-fold. First, the proposed framework improves the assessment of HEC to cover large spatial scale, multi-dimensional analysis, and climate change impacts. The approaches used in this study utilize open-access dataset which support evident-based assessment in data-poor locations. The framework also aim to provide flexibility that allow it to be applied across different locations and targeted species. Second, the findings of the proposed framework highlighted the areas that needed management attention. Allocation of limited conservation resources, thus, can be systematically planned. Specifically, novelty of this study include:

1. Being the first study to adopt risk framework from IPCC and UNSDRR to assess HEC risk

2. Providing quantitative spatial distribution of current and future HEC risk at country-level by incorporating Representative Concentration Pathways (RCP), Shared Socioeconomic Pathways (SSP), and spatial policy.

1.6 Thesis outline

This thesis is divided into five chapters. Chapter 1 (current chapter) introduced Asian elephants conservation status with a review HEC mechanism, coexistence, landscape conservation and scenario planning followed by motivation, objective, contribution and novelty of the research. The main body of this dissertation is divided into three chapters. Each chapter covers background and relevant literature, the data and methodology used, results, discussion and conclusion. Chapter 2 describes cross-country assessment of Asian elephant habitats and subsequent categorization of country characteristics by analysis its population dynamic with environmental changes in 1990, 2003, and 2015. Chapter 3 covers the modeling of HEC distribution in Eastern Thailand to identify spatio-temporal trend of HEC and important drivers. Chapter 4 discusses the application of risk framework with future scenario projection of HEC risk at country-scale for Thailand. Finally, Chapter 5 summarizes the outcomes of this research, recommendations, limitations and future works. Figure 1.5 shows the general flow and order of chapters.

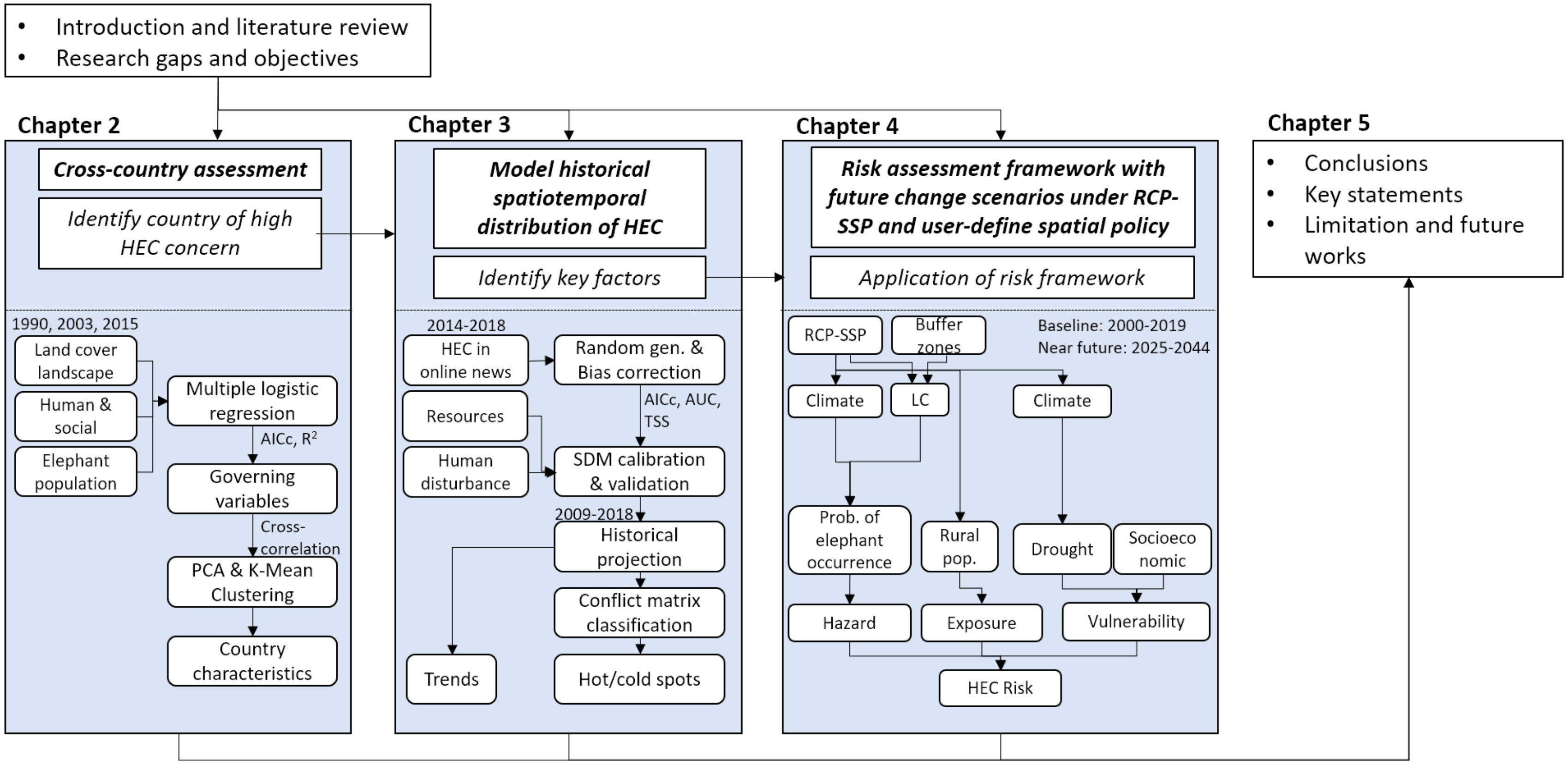


Figure 1.5: The overview of flow and the main outcomes under each chapter for this study.

Chapter 2

Country-level comparative assessment of Asian elephant population dynamic and environmental changes

2.1 Introduction

The Asian elephant (Elephas maximus) is listed as endangered species in the IUCN Red List of Threatened Species (IUCN, 2015). Its range in 2000s has significantly reduced over four times that of early 1900s (Fernando and Pastorini, 2011). The main reason affecting the Asian elephant population is habitat loss and fragmentation due to growing human population and competition for resources (Leimgruber et al., 2003; Madhusudan et al., 2015). Other factors that contributed to Asian elephant population reduction are poaching (Diana Vollmerhausen, 2014), capturing of live elephants (Doyle et al., 2010), and human-elephant conflicts (HEC)(Fernando and Leimgruber, 2011). Despite its endangered status and well-known ecological importance for conservation, the baseline data on Asian elephant population and habitat quality are severely sparse. Although it is the priority to improve the quantity and quality of such data, careful utilization of existing data to guide conservation remain essential despite its limitations.

Elephants are the largest terrestrial mammal and can weight over 1,000 kilograms. With such large body size, the wild Asian elephants forage over wide habitat areas to support their physical requirements. To monitor the conditions of habitats in such large-scale, networks of standardized in-situ observations are necessary, yet lacking due to logistic difficulty and restricted resources. Consequently, satellite remote sensing has been a vital alternative. Many studies utilized satellite-derived land surface information ranging from such products as land cover, vegetation productivity, and digital surface model. Together with elephant presences collected either from field observation or GPS telemetry, satellite-derived dataset can be used to model habitat preference and suitability. Despite the commonality of researches that incorporated satellite dataset (Aini et al., 2017; Duffy and Pettorelli, 2012; Liu et al., 2016; Rood, Ganie, and Nijman, 2010; Zhang et al., 2015), such studies are performed at the local-scale within a single park level or province-level.

Limited studies evaluated cross-country status of Asian elephants and their habitats. Leimgruber et al. (2003) quantified the level of fragmentation and the availability of undisturbed wild land within known elephants home ranges. In their study the satellite-derive land cover and fire location from Advanced Very High Resolution Radiometer (AVHRR) satellite were used together with other spatially explicit ancillary data. Calabrese et al. (2017) further incorporated socio-economic indicators, such as Gross Domestic Product (GDP), corruption level and environmental performance. Despite the importance and usefulness of their results, these two studies were performed at a static time period. For long-live species like elephants, long-term monitoring and assessment are critical for conservation purposes, where drivers of change in species population and demography can be identified and then adequately managed. Additionally, since Asian elephants face various threats, the long-term cross-country assessment is important to inform government and support appropriate allocation of resources.

2.1.1 Objectives

To address the gap of limited temporal assessment and elucidate country-specific conservation priority, this chapter aims to review long-term and cross-countries factors that impact Asian elephant population dynamic. The outputs are also expected to address the first set of research questions raised in Chapter 1 and support the country selection for further HEC analysis. Since habitat alteration is believed to be a prominent factor effecting the species population, this study focused on the land cover and landscape changes together with some key social indicators. The specific objectives are to:-

1. assess the land cover and landscape within range countries and available home range around 1990, 2003, and 2015

2. identify significant drivers and their correlation with the dynamic of Asian elephant population over time

3. categorize range countries based on characteristics of change in selected key drivers and elephant population over time

2.2 Methodology

2.2.1 Study location and flowchart

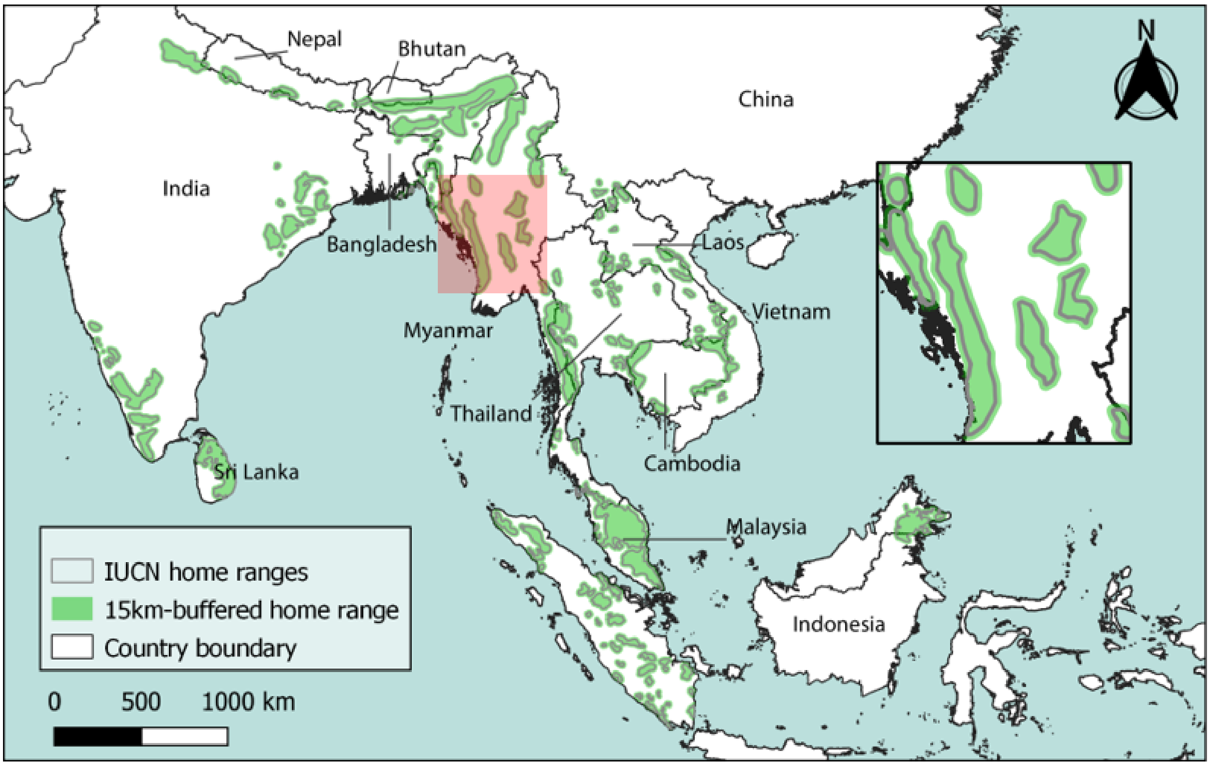


Figure 2.1: Study area shows home ranges of the wild Asian elephants and the 15km-buffered areas with an excerpt zooms-in over Myanmar.

The home ranges where wild Asian elephants occur with certainty are provided in digital format from IUCN (WWF, 2015). A 15-km buffer was generated as shown in Figure 2.1, and any overlapping home ranges were joined. This buffer rule was based on the observation of Asian elephant average daily movement in zoo (9.05 ±0.6 km/day) (Rowell, 2014) as well as the average large daily travel distance in the wild (Fernando et al., 2012). Moreover, since the home range data was generated in early 2000s, the buffer assisted to cover the uncertainty of past home range in 1990. Because elephant population data is at the country-level, any cross-border home ranges are intersected using country boundary and assigned to relevant countries. All land cover and landscape metrics for this study were generated only within this specified home range. Figure 2.2 provides the overview of the dataset and the methodology used.

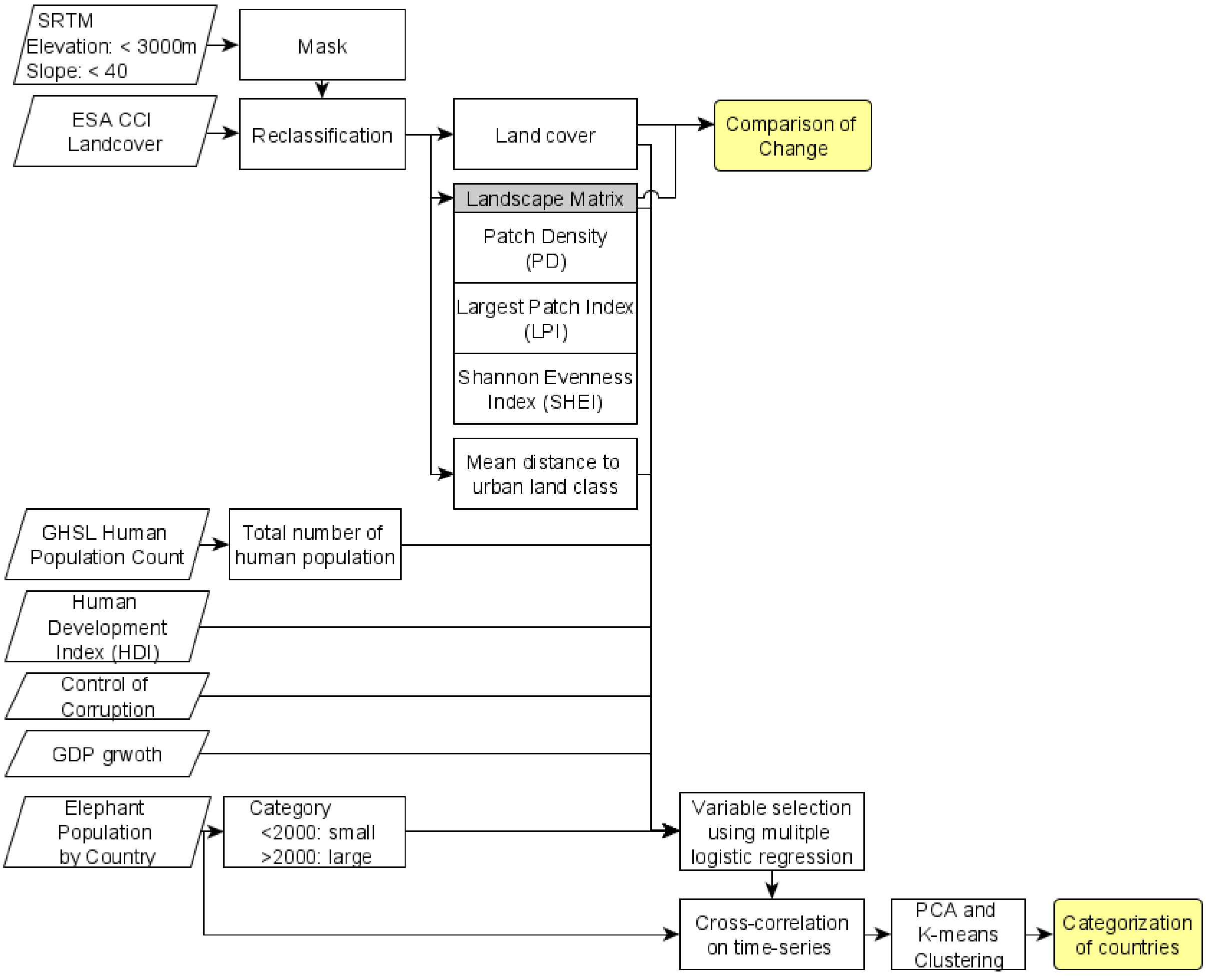


Figure 2.2: Flow chart of this study

2.2.2 Datasets

This study used records of Asian elephant population in 1990, 2003 and 2015. Other datasets which represent environmental and social conditions were retrieved as closely as possible to these three period. The available data covered around 25 year period. Even though the importance of longer monitoring period is recognized, the duration covered in this study closely represents one generation change of elephant population (Turkalo, Wrege, and Wittemyer, 2018) and is also adequate to identify changes in land cover. Table 2.1 described the data used for this study.

Table 2.1: The data used in this study as proxies for environmental and social conditions

Data	Source	Temporal Coverage	Original Resolution
Land cover	ESA CCI-Land	1992/2003/2015	300m
Elevation	SRTM	2000	90m
Human population	GHSL	1990/2000/2015	250m
GDP growth rate	United Nations	1990/2003/2015	country-level
Human Development Index	UNDP	1990/2003/2015	country-level
Control of Corruption	WGI	1996/2003/2015	country-level

ESA CCI-Land: European Space Agency Climate Change Initiative-Land cover, SRTM: Shuttle Radar Topography Mission, GHSL: Global Human Settlement Layers, UNDP: United Nations Development Programme, WGI: Worldwide Governance Indicators.

Asian elephant population

The Asian elephant census is not regularly reported. Large-scale reporting of population census were publicly available from 1990 (Santiapillai and Jackson, 1990), 2003 (Choudhury et al., 2008), and 2015 (IUCN/SSC Asian Elephant Special ist Group, 2017). The total populations have been estimated at around 50,000 elephants since 1990 with only a slight decline. However, at individual range country, the population illustrated apparent differences. Some countries experienced a drastic reduction in elephant population, while others showed continuous increase (Figure 2.3).

Land cover variables

To capture the change of land cover and landscape throughout the selected period, consistent land cover maps with classification that reflect elephants' preference are needed. Due to the large extent of the study area resulting in the lack of ground truth data, the existing land cover products were used instead of re-performing the classification myself. The European Space Agency (ESA) Climate Change Initiative (CCI) land cover maps, hereafter CCI-Land, were selected. This product provides moderate spatial resolution at 300 m and an annual temporal resolution from 1992 to 2015. CCI-Land applied United Nation Land Cover Classification System (UN-LCCS). Its predecessor version was evaluated to be suitable for climate modeling, global forest change assessment as well as global agriculture monitoring (Tsendbazar, Bruin, and Herold, 2015). CCI-Land from the year 1992, 2003 and 2015 were used because of their temporal proximity to the study period.

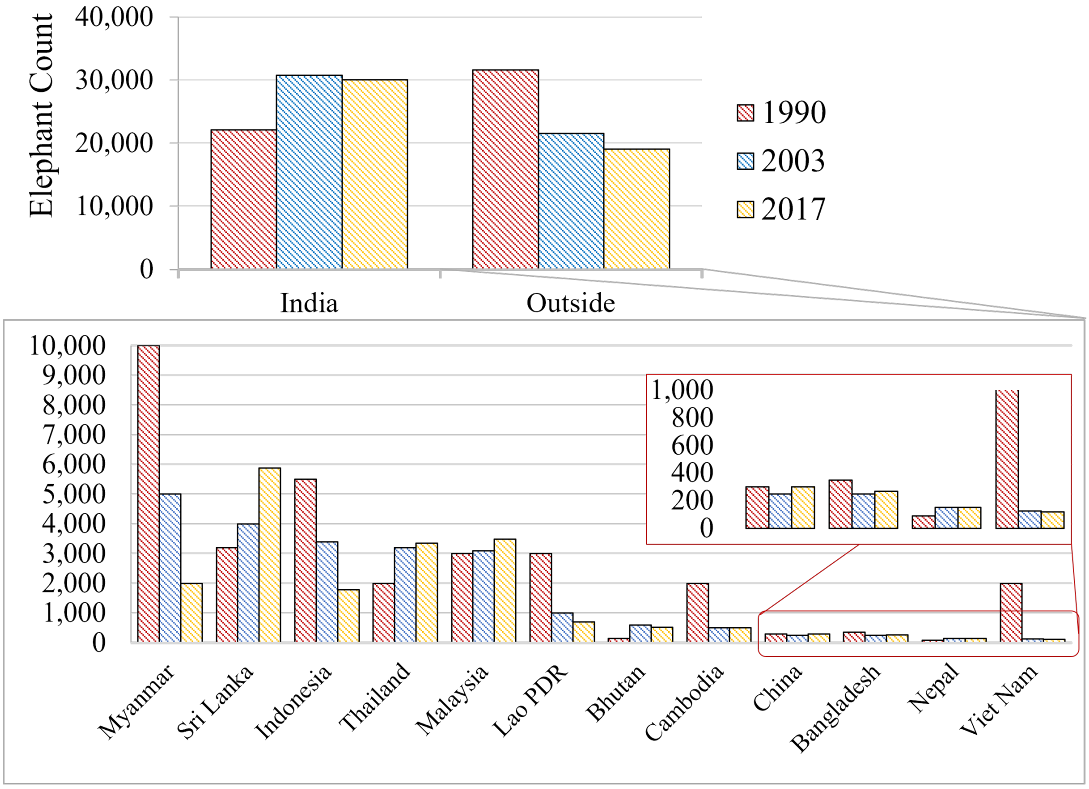


Figure 2.3: Officially estimated number of Asian elephants in 1990 (Santiapillai and Jackson, 1990), 2003 (Choudhury et al., 2008) and 2015 (IUCN/SSC Asian Elephant Special ist Group, 2017) from each of the thirteen range countries

Based on the use of various land cover type by elephants (Sukumar, 2003), original UN-LCCS classes were reclassified to eight classes including crop, forest, shrub and grass, other vegetation, urban, bare land, water and snow. Table 2.2 mapped the reclassified land cover types from 22 UN-LCCS classes to that used in this study. Land cover reclassification was performed and downloaded from Google Earth Engine (Gorelick et al., 2017). Further analysis was done in R version 3.5.3 (R Core Team, 2019).

Landscape metrics

Landscape metrics quantitatively describe the spatial patterning of the ecosystem (O'Neill et al., 1988; Turner, 1989) and various indicators had been generated to evaluate the interconnection between spatial heterogeneity and ecological processes (Turner, 2005). The landscape metrics must be considered because the amount of land cover type alone do not provide adequate insight into the landscape structure. Herbivores, including elephants, response to patchiness of foraging resources, in which the dominant scale

Table 2.2: The eight reclassified land cover types used in this study and their associated classes from that of Climate Change Initiative land cover map (CCI-land).

Land Cover Reclassification	Original ESA CCI-Land Cover Classes
Crop	Cropland, rainfed
	Cropland, irrigated or post-flooding
	Mosaic cropland (>50%/ natural vegetation (<50%)
	Mosaic natural vegetation (>50%)/ cropland (<50%)
Forest	Tree cover, broadleaved, evergreen (>15%)
	Tree cover, broadleaved, deciduous (>15%)
	Tree cover, needleleaved, evergreen (>15%)
	Tree cover, needleleaved, deciduous (>15%)
	Tree cover, mixed leaf type
	Mosaic tree and shrub (>50%)/ herbaceous cover (<50%)
Grass/Shrub	Mosaic herbaceous cover (>50%)/ tree and shrub (<50%)
	Shrubland
	Grassland
Other Vegetation	Lichens and mosses
	Sparse vegetation (<15%)
	Tree cover, flooded, fresh or brakish water
	Tree cover, flooded, saline water
	Shrub or herbaceous cover, flooded, fresh/saline/brakish water
Urban	Urban areas
Bare land	Bare areas
Water	Water bodies
Snow	Permanent snow and ice

and intensity of spatial heterogeneity can explain the variance in elephant occurrences (Murwira and Skidmore, 2005). In addition, fragmentation also negatively influences elephant habitat utilization (Leimgruber et al., 2003). Goossens et al. (2016) illustrated that the level of fragmentation restricted the population size due to the available of resources and can also lead to isolation between herds which negatively impact gene pool and genetic diversity. Based on previous researches regarding the relationship of landscape and elephant distribution (Gaucherel et al., 2010; Leimgruber et al., 2003; Neupane et al., 2019), the following landscape metrics were chosen: Patch Density (PD), Largest Patch Index (LPI), and Shannon Evenness Index (SHEI). The mathematical formula for PD, LPI and SHDI were shown in Equation 2.1, 2.2 and 2.3 respectively.

$$PD = \frac{n_i}{A} \tag{2.1}$$

$$LPI = \frac{\max_{j=1}^{n}(a_{ij})}{A} \times 100 \tag{2.2}$$

$$SHEI = \frac{-\sum_{i=1}^{m}(P_i \ln P_i)}{\ln m} \times 100 \tag{2.3}$$

PD represents the number of patches of type i per landscape area A. LPI reflects the percentage of the landscape comprised by the largest patch of type i. LPI reaches 100 when the largest patch occupies 100% of the landscape. Different from PD and LPI, which are of a class-level, SHEI measures heterogeneity at a landscape-level considering all land classes. It calculates the distribution of area among patch types. P_i represents the proportion of class i, while m refers to the number of classes. SHEI value ranges from 0 to 100 where 0 indicates no diversity when the landscape contains only one patch. In this study, only vegetation classes (crop, forest, grass/shrub, and other vegetation) were considered in SHEI calculation.

Prior to calculating landscape metrics, the elevation above 3,000 m and the slope over 40°, extracted from Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) product, were used to masked the land cover maps. Topographic characters can act as natural barriers and prevent habitat utilization. Previous Asian elephants habitat suitability studies identified unlikely occurrences above these thresholds. All calculation was done in R using 'landscapemetrics' package (Hesselbarth et al., 2019).

Human disturbance variables

Human presence and activities showed significant impact to landscape and wild elephant distribution and movement (Hoare and Du Toit, 1999; Aini et al., 2017; Krishnan et al., 2019). To incorporate human influence, the averages euclidean distance to urban land cover type within the home ranges of each country were computed. Additionally, spatially explicit count of human population from the Global Human Settlement Layers (GHSL) population grid for 1990, 2000, and 2015 were also used. This data utilized the estimates by Gridded Population of the World (GPW) v.4 in aggregation with density of built-up map for more accurate distribution of human population and provide number of people at 250 m resolution (Freire et al., 2016). The sum of human population within home ranges of individual countries were computed.

Human socioeconomic variables

As suggested by Calabrese et al. (2017) and De Boer et al. (2013), socio-economic factors influence conservation performance and correlate with presence of elephants. In this study, GDP annual growth rate (GDP-growth, World Bank 2020b), Human Development Index (HDI, United Nations Development Program 2020) and Control of Corruption (CC, World Bank 2020a) were used. GDP-growth infers the consumption of resources to produce goods and services of a country which believes to limit wildlife conservation, especially in developing nations that rely heavily on agriculture sectors (Czech, 2000). HDI is an aggregated indicator that measures the progress in three basic dimensions, knowledge, health and per capita income, and was shown to have positive relationship with population trend of wildlife within protected areas (Barnes et al., 2016). HDI ranges from 0 to 1 in which the value approaches 1 when human development is high. Lastly, the level of corruption was shown to be a predictive indicator of elephant population status (Calabrese et al., 2017). CC is a composite indicator reflecting governance performance and ranging from -2.5 (weak) and 2.5 (strong).

2.2.3 Quantification of land cover and landscape changes

The land cover and landscape changes were calculated in three periods which include the overall changes between 1992 to 2015, the changes in epoch1 covering 1992 to 2003, and the changes in epoch2 between 2003 and 2015. The overall land cover changes within each country and its elephant home range were compared. The conversion matrix was then calculated for elephant home range of each country to quantify the area of land converted between different classes during epoch1 and epoch2. To visualize these land conversions, sankey diagram was generated for the elephant home range of each country. The sankey diagram is commonly applied to analyze energy or material flows to and from nodes in a network (Schmidt, 2008). For land cover, sankey diagram depicts changes from multiple intervals with chronicle flow from left to right and with thickness of the flows representing the proportion of land type being converted (Cuba, 2015).

2.2.4 Identification of drivers of elephant population changes

To identify key variables effecting elephant population changes, the logistic regression was applied with elephant population at country level as a dependent variable (n=39, 13 countries from 3 year) and various social and environmental factors as independent variables. Because the population data is based on educated guess, previous studies have highlighted concern on the accuracy of such rough estimation that the direct use of census data can mislead the results (Calabrese et al., 2017). Hence, The elephant population data was simplified into large or small population. I assigned each country to a population category namely, category 1: large population of ≥ 2000 elephants, and category 2: small population of 2000 individuals. This threshold was adapted from a previous research (Santiapillai, 1997).

Based on the land cover analysis, forest and crop land cover area were chosen among other classes for further analysis as together they contributed over 75% of home range areas for each country. The area of the largest forest patch was also used. Natural log transformation was applied to area variables and human population variable. To reduce the effect of multicollinearity, variables with high correlation, $r \geq |0.75|$ and variance inflation factors (VIF) > 10, were removed. After removing highly correlated variables, nine variables remained: four land-related variable (*PDcrop, LPIcrop, SHEI, Ln.largestForest*), two human disturbance variables (*Ln.humanPop, distance.urban*), and three human socioeconomic status (*CC, HDI, GDP.growth*).

Rather than using automatic model selection, the model candidates were identified based on priori knowledge. Previous studies suggested land-related variables, especially forest cover, to determine level of elephant population (Leimgruber et al., 2003; Choudhury et al., 2008; Calabrese et al., 2017). Therefore, candidate models were first built with land-related variables and *Ln.largestForest* was used as a base variable for all models. After the best-fit land-related model was identified, the human disturbance and socioeconomic variables were considered. Akaike's Information Criterion corrected for small sample sizes (AICc) was used to rank candidate models. A final model was selected based on the smallest AICc where the AICc difference ($\Delta AICc$) equaled to zero. McFadden pseudo R^2 was calculated to evaluate model fit. The variables from the final model were then select as key drivers which increase the likelihood of having large elephant population. All calculation was performed in R program using 'glm' function in 'stats' package.

2.2.5 Categorization of country-level status

To assess changes of selected key variables in relation to elephant population dynamic within elephant home range of each country over time, the change in elephant population along with the correlation between elephant population and selected key drivers were calculated. Since each country initial elephant population in early 1990s differed and proportional changes were more meaningful for comparison, natural log transformation was applied to the raw elephant population before further analysis. The overall change of elephant population within each country was obtained from linear regression with time, following equation 2.4. Cross-correlation coefficients with no lag were also calculated between selected variables and elephant population for each range country, following equation 2.5.

$$\beta = \frac{\sum[(x_t - \bar{x})(t - \bar{t})]}{\sum(x_t - \bar{x})^2} \tag{2.4}$$

$$r_t^{xy} = \frac{\sum[(x_t - \bar{x})(y_t - \bar{y})]}{\sqrt{\sum(x_t - \bar{x})^2 (y_t - \bar{y})^2}} \tag{2.5}$$

where x_t is elephant population variable at year t, and y_t is key selected variables at time t. The coefficient value of this linear trend model (β) and cross-correlation coefficient (r_t^{xy}) were then used. The magnitude and direction of the associations from correlation coefficient provided general information of how situations within each range country varied. Principle Components Analysis (PCA) were then applied on these coefficients to identify clusters of country with similar changes over time. Using K-means clustering on PCA scores, each country was assigned to different category. PCA and K-means clustering calculation was also performed in R program with 'stats' package.

2.3 Results

2.3.1 Land cover and landscape changes

The proportion of area by land cover type over the whole country and that with the country's elephant home range are shown in Figure 2.4. India holds the largest home range area, followed by Myanmar, Malaysia and Thailand, while over 50% of Sri Lanka land area fell within Asian elephant home range (Table 2.3). Except for Indonesia, a higher proportion of forest land cover were observed within elephant home ranges compared to that of the whole country throughout all the three years. Table 2.3 also highlighted the net gain of crop and urban cover within Asian elephant home ranges for all countries between 1992 to 2015. The loss of forest cover was prominent in Cambodia, Vietnam and Indonesia. On the other hand, an increase in forest were identified in Bhutan and Yunnan (China) which expanded around 10% of the home range area. A slight increase in forested area of around 3% were also identified in Myanmar. Other countries showed either rather stable or loss of forest cover over the years.

Table 2.3: The area of home range (with 15km-buffer), the percent change within home range to total country change, and the net loss/gain of each land cover type within the elephant home range between 1992 and 2015 for each country.

Country	Home range km^2 (%)	Home range to country change (%)	Net change between 1992 to 2015 (km^2)						
			Crop	Forest	Grass/Shrub	Other vegetation	Urban	Water	Bare land
Bangladesh	22,139 (15%)	20%	664.6	102.4	(610.7)	(29.3)	41.0	(169.6)	1.5
Bhutan	11,979 (29%)	76%	7.6	1,495.3	(1,505.2)	0.5	1.8	-	-
Cambodia	47,801 (27%)	44%	7,154.5	(6,851.0)	(337.0)	(0.8)	33.2	1.1	-
China	17,332 (4%)	10%	122.9	1,739.2	(1,913.7)	1.3	50.7	(0.4)	-
India	339,685 (10%)	22%	5,202.4	4,069.0	(10,867.4)	21.0	1,241.0	133.5	200.6
Indonesia	16,2805 (9%)	15%	10,970.1	(11,314.7)	0.6	212.4	126.5	5.0	-
Laos	71,995 (31%)	36%	2,315.3	775.6	(3,211.4)	(1.3)	10.8	111.1	-
Malaysia	133,590 (43%)	38%	49.0	(900.0)	5.9	329.6	468.4	47.0	-
Myanmar	224,936 (33%)	42%	2,739.4	6,715.9	(9,757.2)	100.6	121.7	79.5	0.1
Nepal	22,095 (14%)	16%	570.3	(505.4)	(72.0)	-	34.6	-	(27.5)
Sri Lanka	42,772 (68%)	73%	1,710.5	(2,393.0)	607.1	5.9	52.4	17.1	-
Thailand	111,538 (22%)	35%	1,741.4	(1,656.1)	(365.5)	109.4	87.0	83.8	-
Vietnam	31,812 (10%)	16%	2,569.7	(3,188.9)	545.3	17.0	16.7	40.1	-

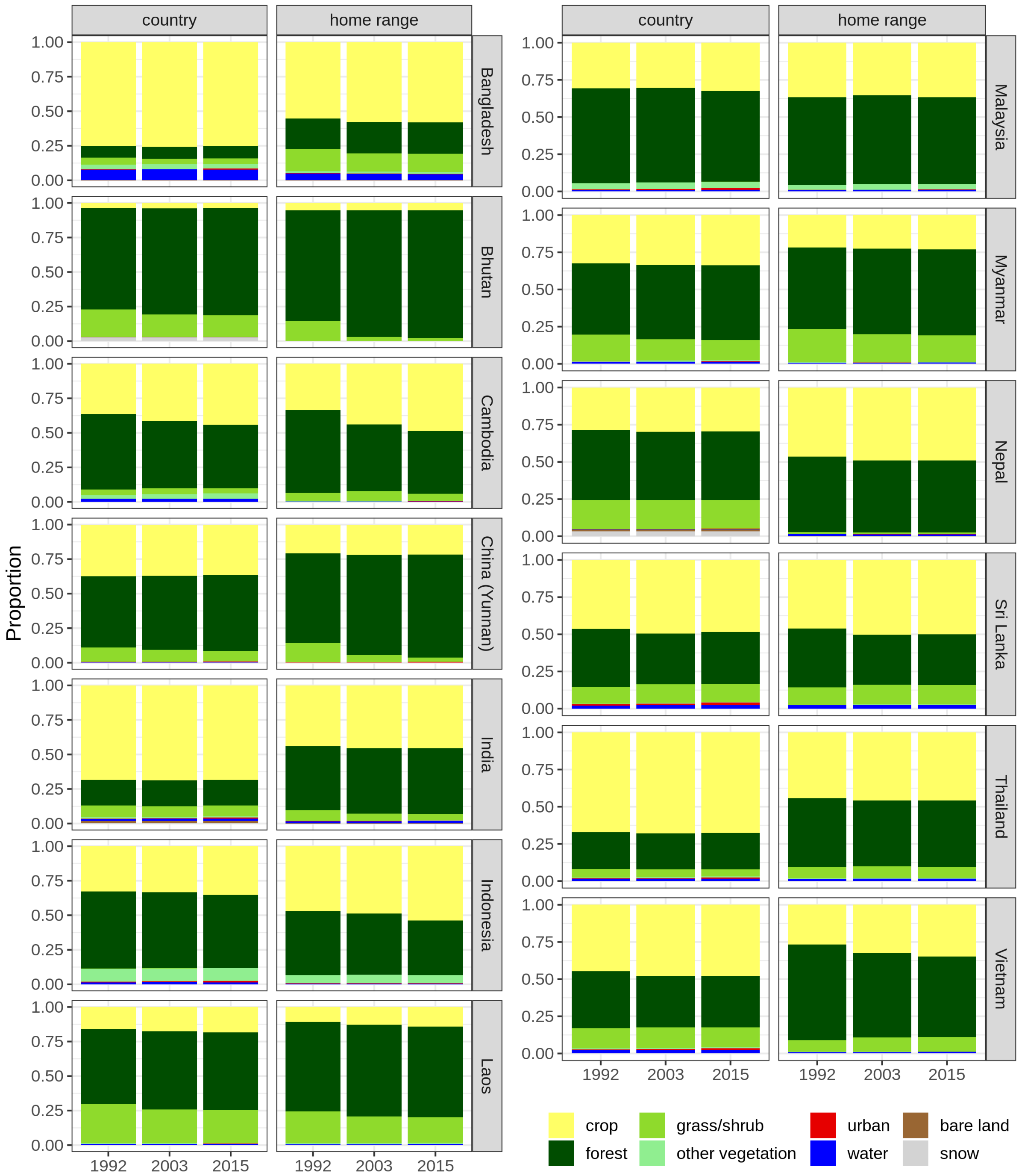


Figure 2.4: Proportion of land cover types within each range country and its Asian elephant home range in 1992, 2003 and 2015 showed over all expansion of crop areas across all countries.

Figure 2.5 illustrated the conversion among land cover types within the elephant home range in 1992, 2003 and 2015. Within elephant home ranges, the most common converted land cover class were crop, forest, and grass/shrub. Different change patterns were observed and three examples were also highlighted in Figure 2.6. Most countries had larger land conversions during epoch1 (1992-2003) of which Cambodia had the largest forest conversion. Only Indonesia showed a higher area conversion in epoch2 (2003-2015), specifically a change from forest cover to cropland. Cropland was commonly expanded into forested areas. On the other hand, forest cover expansion was usually contributed by grass/shrub land cover and less likely from other land classes. While it was uncommon for cropland to reverted into forest, it happened in Malaysia during epoch1. In Bhutan and Yunnan (China), a clear increase in forest cover as a result of grass/shrub conversion was identified. Although some countries (e.g. Bhutan) showed stable or even increasing forest cover, growing urban areas crept ever closer to forested areas.

The changes of landscape structure within the elephant home ranges are shown in Figure 2.4. The PD value for crop cover decreased for most country which can be inferred that cropland became larger and more connected. Cambodia had the highest increase in forest PD reflecting severe forest fragmentation. A decrease in fragmentation of grass/shrub was observed for all country except Vietnam which showed slight increase. For LPI, the decrease in its value indicates that the largest patch of that particular class becomes smaller. For crop cover, most country showed an increase in LPI which indicated a larger patch of crop cover. Only in Yunnan (China) where a clearly smaller LPI was identified. On the other hand, the largest decrease in forest LPI was in Sri Lanka, followed by Cambodia. The grass/shrub patch becomes smaller with an exception of that in Thailand and Vietnam. Although SHEI did not change much for most countries, Bhutan and Yunnan (China) showed large reduction of 24% and 50% respectively. The increase/decrease of SHEI reflects the increase/decrease in equal distribution among patch type. Hence, the large reduction can imply more dominant patch type occurred, which in the case of Bhutan and Yunnan are likely a result of forest expansion.

2.3.2 Possible drivers of Asian population dynamic

The best AICc model using land-only variables was built with *Ln.largestForest*, *SHEI*, and *PDforest* (Table 2.5) with the lowest AICc of 32.40 and McFadden's R^2 of 0.56. The best AICc model after considering both human disturbance and socioeconomic variables showed an improvement in McFadden R^2 (0.68) and lower AICc (28.77) compared to land-only model. The final selection of key variables comprised of *Ln.largestForest*, *SHEI*,

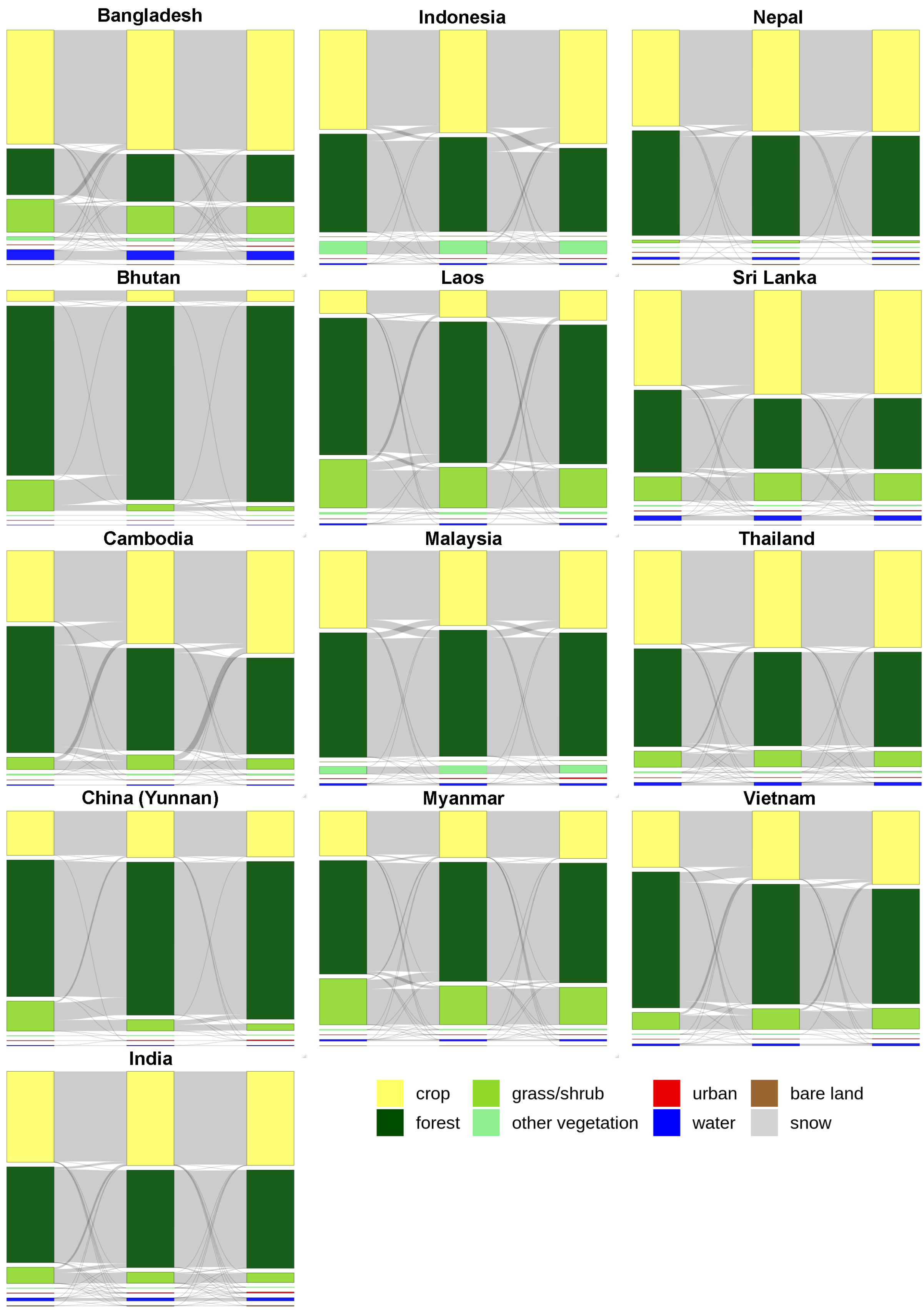


Figure 2.5: Conversion between land cover types within Asian elephant home range for each country from 1992 to 2003 and 2003 to 2015 represented from left to right.

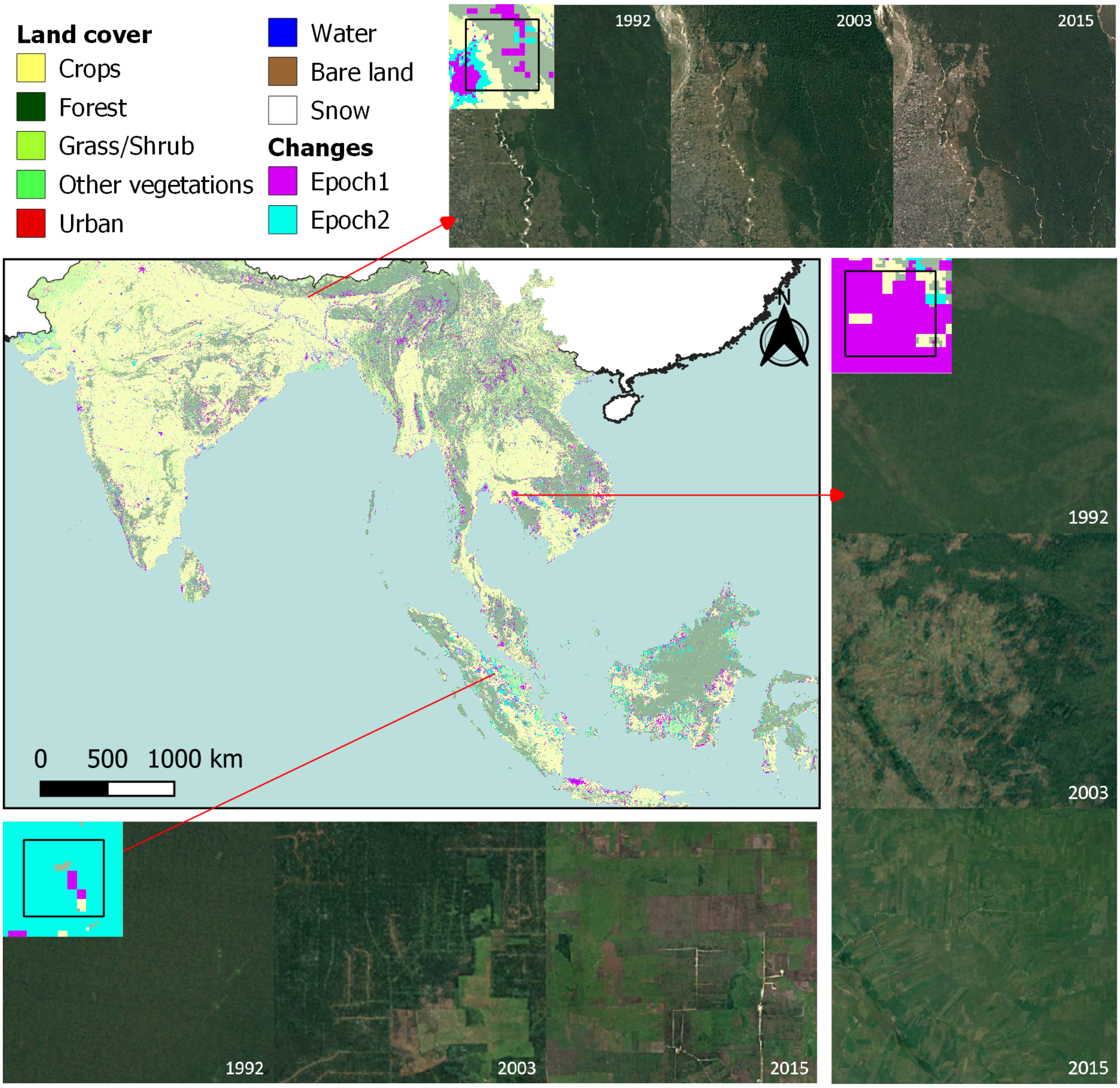


Figure 2.6: Land cover changes in epoch1 (1992-2003) and epoch2 (2003-2015) were highlighted in three regions with different change patterns. Nepal-Bhutan border (top) showed stable forest cover with continuous expansion of urban areas in close proximity. Cambodia (right) illustrated large conversion to cropland in epoch1, while Sumatra-Indonesia (bottom) showed the conversion continued in epoch2.

Table 2.4: Percentage change of Patch Density (PD), Largest Patch Index (LPI) and Shannon's Evenness Index (SHEI) between 1992 and 2015

Country	Period	PD Crop	PD Forest	PD Grass	LPI Crop	LPI Forest	LPI Grass	SHEI
Bangladesh	'92-'15	(6.7)	(5.2)	(9.3)	(0.7)	1.9	(6.3)	(4.1)
Bhutan	'92-'15	(6.4)	(40.0)	(29.1)	22.5	15.9	(98.5)	(50.0)
Cambodia	'92-'15	(43.4)	169.2	(1.8)	46.2	(40.2)	(22.1)	2.6
China	'92-'15	1.5	(20.8)	(32.6)	(34.2)	13.7	(87.3)	(26.0)
India	'92-'15	(6.1)	(3.4)	(9.3)	5.0	5.1	0.0	(7.1)
Indonesia	'92-'15	(19.0)	23.7	-	10.2	4.1	-	(0.9)
Laos	'92-'15	(8.2)	10.3	(2.2)	82.1	(7.7)	(59.7)	0.3
Malaysia	'92-'15	(26.7)	9.1	-	29.1	2.4	-	1.0
Myanmar	'92-'15	(5.6)	(6.1)	(9.8)	0.8	13.6	(3.3)	(2.9)
Nepal	'92-'15	(17.6)	9.1	0.0	5.7	5.5	(65.3)	(1.5)
Sri Lanka	'92-'15	(7.3)	18.5	(1.2)	4.8	(47.0)	72.6	0.7
Thailand	'92-'15	(15.2)	7.4	(2.0)	4.8	(13.9)	139.6	(0.1)
Vietnam	'92-'15	4.3	53.6	4.6	96.3	(12.1)	13.8	10.6

PDforest, and *Ln.humanPop*. Signs of the coefficient estimates from the best model indicated that probability of large elephant population increase with higher *Ln.largestForest*, *SHEI*, and *Ln.humanPop*, and lower *PDforest* (Table 2.6). Ranking of variables showed *Ln.largestForest* as the most important predictor following closely by *SHEI*, *Ln.humanPop* and *PDforest* respectively.

2.3.3 Range countries categorization

The changes over the three period of elephant population (log-transformed), along with the selected four key drivers are shown in Figure 2.7. The coefficient of linear trend in elephant population and its cross-correlation coefficient to key drivers were used for PCA and K-means clustering analysis. PCA results illustrated that the first two principle components explain 86% of the variation observed between countries. On Figure 2.8, *ElephantPop* is the coefficient of proportional elephant population over time, while other variables were the correlation coefficient between that variable and the elephant population. The first component (PC1) explained 47.5% of variation and had correlation with changes in landscape components, namely correlation coefficient of the largest forest area, PD forest, and SHEI. Component 2 (PC2, 38.8% variation) was a function of

Table 2.5: List of top 5 candidate models under land-only variables (m1-m5) and combining the AICc-best land-only model with disturbance and socioeconomic variables (m1a-m1e). AICc, McFadden's R^2, and ΔAICc were calculated with bold indicated final selection.

Variables	AICc	R^2	$\Delta AICc$
Land-only			
largestForest, SHEI, PDforest	**32.40**	**0.56**	**0.00**
Ln.largestForest, SHEI	32.95	0.51	0.55
Ln.largestForest, SHEI, PDforest, PDcrop	33.64	0.59	1.24
Ln.largestForest, SHEI, PDforest, LPIcrop	34.27	0.57	1.87
Ln.largestForest, SHEI, LPIcrop	34.95	0.51	2.55
Land/Disturbance/Socioeconomic			
Ln.largestForest, SHEI, PDforest, Ln.humanPop	**28.77**	**0.68**	**0.00**
Ln.largestForest, SHEI, PDforest, Ln.humanPop, CC	29.78	0.71	1.00
Ln.largestForest, SHEI, PDforest, Ln.humanPop, GDP.growth	30.32	0.70	1.55
Ln.largestForest, SHEI, PDforest, CC	30.73	0.64	1.96
Ln.largestForest, SHEI, PDforest, Ln.humanPop, dist.Urban, CC	31.25	0.73	2.48

Table 2.6: Coefficient estimates, standard error, and P-value for the best model with lowest AICc, where (**) P-value <0.01, (*) P-value <0.05, (.) P-value < 0.1.

Variable	Estimate	Std.Error	P-value
(Intercept)	-60.2052	22.0461	**
Ln.largestForset	2.233	1.0214	*
SHEI	0.3562	0.1643	*
Ln.humanPop	2.0811	1.0182	*
PD forest	-270.695	139.1338	.

changes in population including trend in elephant population and correlation coefficient of human population.

Projections of range countries onto principle components and application of K-means clustering revealed four groups among thirteen range countries (Figure 2.8). *Group A* is composed of the countries with reduction in proportion of elephant population (located at opposite to *ElephantPop* vector) along with increasing human population (negative correlation to elephant population), decreasing in areas of largest forest (positive coefficient correlation with elephant population), and increase in forest patches (negative coefficient correlation of forest PD and SHEI to elephant population). *Group B* includes range countries which have an increase in proportion of elephant population together with increasing human population, while area of largest forest patch slightly increased with a decrease in fragmentation especially from *SHEI* reduction. Majority of range countries were under *Group C* which show a stable or increasing trend in proportion of elephant population with a positively correlated changes in largest forest area, but varying degree of change in human population and forest fragmentation among countries. Lastly, the reduction in elephant population with increasing human population despite the increase in area of the largest forest constituted *Group D*.

2.4 Discussion

2.4.1 Habitat conditions as shown from long-term land cover changes

Although elephant home range within different range countries faced varying degree of change, majority commonly experienced loss in forest cover and large expansion of cropland. Only Bhutan and China (Yunnan) showed relatively stable crop land areas with an increase in forest cover. The decline in native food supplies due to the loss of natural habitat together with expansion of high nutrient cropland was believed to exacerbate human-elephant conflict (HEC) (Desai and Riddle, 2015). Elephants were more reliance on cropland for forage in many range areas (Chen et al., 2016; Naha et al., 2020). Since elephant utilized mixed of land cover, changes of a single land cover type may not directly impact population and a combination of land cover maybe more informative (Sukumar, 2003). Similar situation can be implied from this current study in which forest loss and gain did not simply translate into the decrease or increase of elephant population. Sri Lanka, for example, reported a continuous increase in Asian elephant population, but its

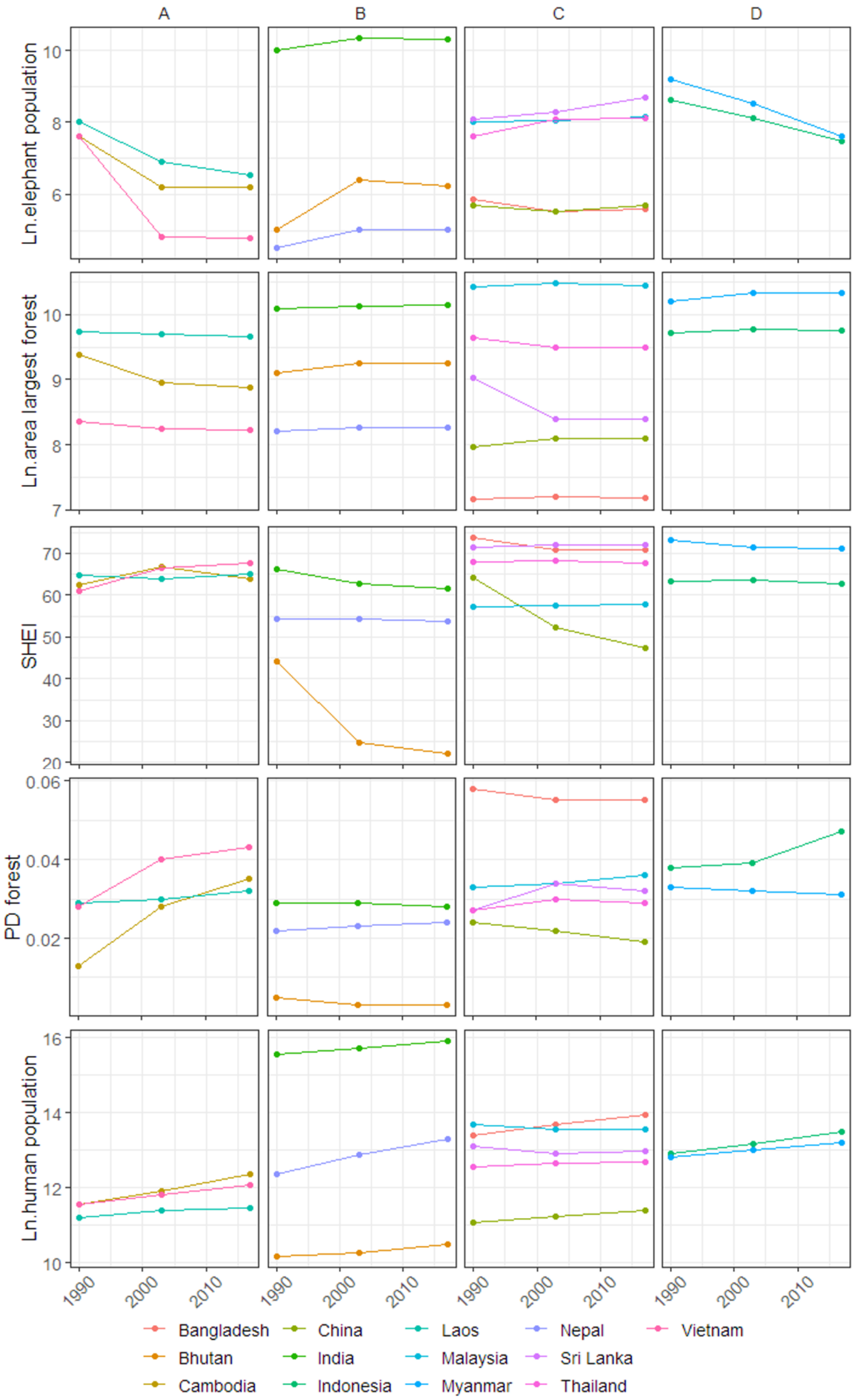


Figure 2.7: The changes of natural-log transformed elephant population (*Ln.elephant population*), as well as the four selected drivers are shown.

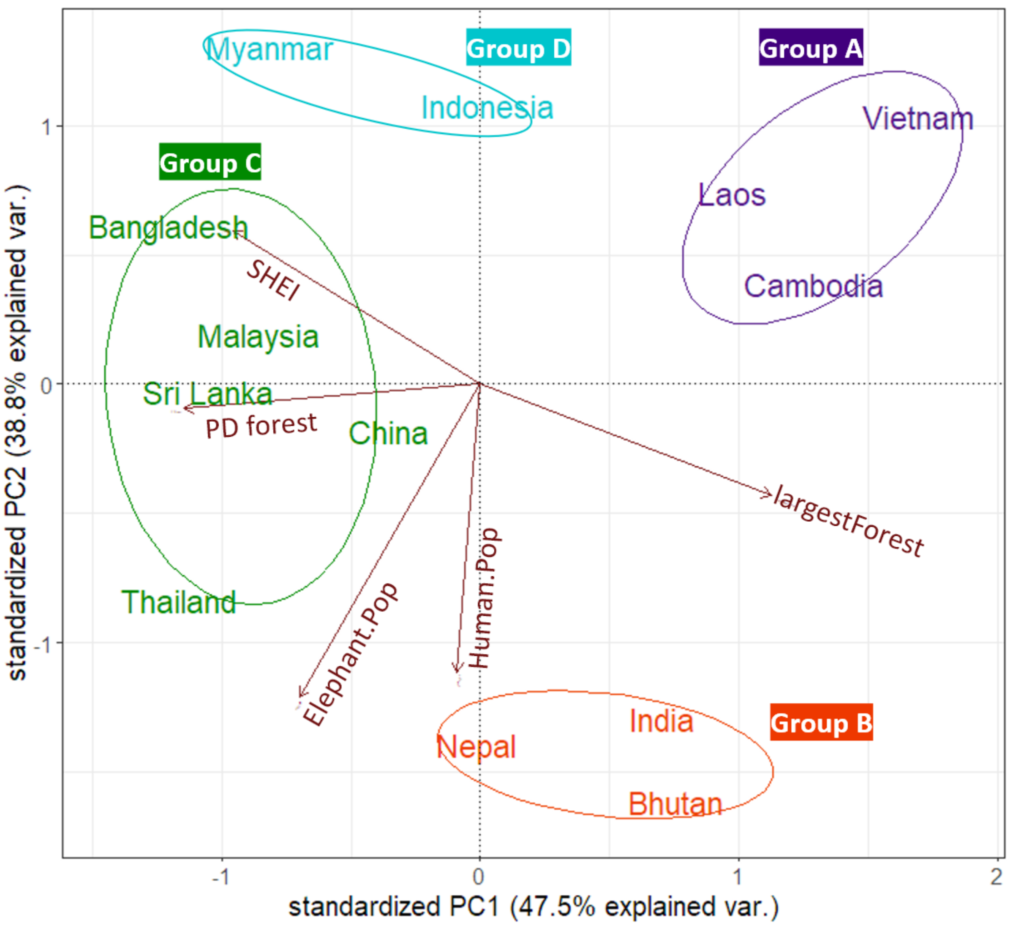


Figure 2.8: Biplot of Principle Component Analysis with K-mean clustering results for range countries showed four groups based on pattern of changes in elephant populations and associated correlation of key drivers.

land cover change illustrated a dominant conversion of forest area. As the continuous loss in forest cover and expansion of cropland were identified across epoch1 and 2, it is possible to say that this trend will likely to continue in the future. In addition, with projected growth in human population within these countries, the situation for wild elephant may be further exacerbated. Hence, continuous monitoring together with future projection based on historical trend of key drivers are critical for the planning of landscape-level management for Asian elephant population. However, habitat loss is not the only threads or the main threat for all the countries. Myanmar, where a drastic drop of elephant population was reported, showed a net gain of forest from 1990 to 2015. Therefore, it is also important to elucidate the prominent threads and prioritize appropriate conservation

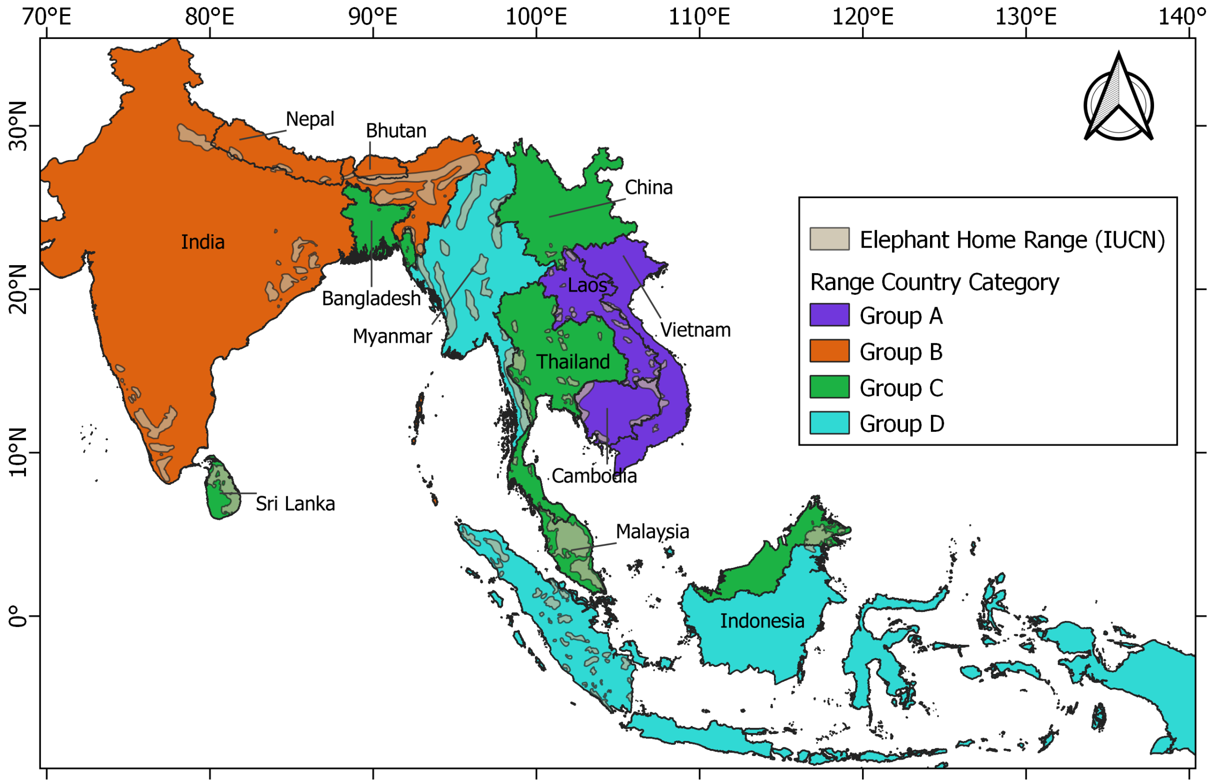


Figure 2.9: The map of range countries classified into four groups showed most countries under Group B in which HEC situation was expected as primary conservation concern.

actions.

2.4.2 Key drivers of large Asian elephant populations

The key variables in the final model selected for logistic regression indicated that substantial Asian elephants population can persist in highly diverse landscape along side human population when a large patch of forest with less fragmentation were maintained. The most important driver was the areas of largest forest patch which agreed with the initial expectation. Similarly, forest cover was identified as positively associated with occupancy (Jathanna et al., 2015; Liu et al., 2016) and the probability of step selection in Asian elephant (Suksavate, Duengkae, and Chaiyes, 2019). SHEI, representing land cover diversity, was the second most influential variable in this study. The result suggested that larger SHEI increased the likelihood of maintaining large elephant population. Land cover diversity was also previously identified as a key feature preferred by Asian elephants (Calabrese et al., 2017; Huang et al., 2019; Neupane et al., 2019). Sukumar (2003) and

Fernando and Leimgruber (2011) observed that elephants benefit from a mixed of habitats where elephants can switch between grazing and browsing depending on the season. In addition, forested areas can provide refuge and cover, while agricultural mosaic supply high nutrient forage and grazing opportunities. Nevertheless, the forest-agriculture mosaic must also be balanced by level of forest fragmentation as the increase in forest patch density (PDforest) caused a reduction in probability of having large elephant population. Fragmented landscape leads to the increase in human-elephant conflicts which is one of the leading cause in the decline of Asian elephant (Leimgruber et al., 2003). Three main socioeconomic factors were considered, yet none was selected in the final model. This may suggest that habitat-related and human disturbance cause a more direct influence on elephant population. Although good governance was suggested as an important predictor in Asian elephant abundance (Calabrese et al., 2017), CC was not selected in the current study. Nevertheless, the variable was part of most top competing models which indicated its potential predictive power.

2.4.3 Conservation implications from change patterns of key drivers

This study assessed the proportional change in elephant population and the corresponding changes in four key selected variables, namely (i) areas of largest forest patch (*LargestForest*), (ii) land cover diversity (*SHEI*), (iii) forest fragmentation (*PDforest*), and human population (*HumanPop*). The range countries can be, firstly, looked at in term of changes in elephant population. Large proportional reduction in elephant population was identified in *Group A* and *Group D* which comprised of Cambodia, Laos, Vietnam, Indonesia, and Myanmar. the other two group, *Group B* and *Group C* mainly showed an increase (Bhutan, India, Nepal, Thailand, Sri Lanka, and Malaysia), then stable (China), and low reduction (Bangladesh).

Among the countries with decreasing elephant population, *Group A* was categorized with corresponding reduction in the area of the largest forest, while forest patch density, land cover diversity, and human population increased. Countries within this group, hence, faced with severe loss of key habitat and forest fragmentation. Countries under *Group A* included Cambodia, Laos and Vietnam. Although forested areas over the whole country were increasing, Vietnam showed a decrease in forest cover within elephant home range. The transition to reforestation program in many areas of Vietnam displaced deforestation to neighboring countries, Cambodia and Laos (Meyfroidt and Lambin, 2009; Ingalls et al., 2018). In fact, Cambodia showed the second largest reduction of forest cover within the elephant home ranges (Table 2.3). The country was also identified with one of the highest rate of deforestation in the world (FAO and UNEP, 2020). In addition, negative net change in forest cover were reported in many areas of Cambodia, Laos, and Vietnam (NYDF Progress Assessment, 2019). Consequently, the loss of key forested habitats, increasing forest fragmentation, and growing human population likely linked to the reduction of elephant population within this group. Halting the loss of key habitats along with protection and restoration of forested areas should be given a high priority.

Group D, on the other hand, showed a decreasing trend in elephant population despite an increasing in areas of the largest forest patch. Although both were placed within *Group D*, Myanmar and Indonesia showed slightly different characteristic in forest fragmentation. Indonesia was positioned at the opposite end crossing into Quadrant I, while Myanmar was in Quadrant IV as shown in Figure 2.8. Myanmar showed a positive correlation between elephant population and PD forest, hence a corresponding decrease in forest fragmentation was identified. In contrast, Indonesia with negative correlation between elephant population and PD forest, faced higher forest fragmentation. Unfragmented wildland remained in Myanmar (Leimgruber et al., 2003), but geographical distribution and population shrunk drastically Leimgruber et al., 2011. Intact forest, >80% canopy cover, in Myanmar declined in recent years and most forested areas are not formally protected (Bhagwat et al., 2017). In addition, disturbing rate of poaching for elephants' body parts were observed (Sampson, 2013). This may explain the large reduction even with the increase in key forest area and decrease in forest fragmentation within Myanmar's elephant home range. In Indonesia, encroachment to expand agricultural land was identified (Rood, Ganie, and Nijman, 2010) which likely caused the increase in PD forest. In addition, the country, especially Sumatra, experienced large expansion of oil palm and rubber plantation which can be difficult to distinguish from forest (Leimgruber et al., 2003; Menon and Tiwari, 2019). Despite slightly different characteristics, both Indonesia and Myanmar seemed to face with illegal human activities which likely impacted elephant population in their ranges. Therefore, high priority should be given to enforce conservation laws and establish protected areas.

Group B comprised of Bhutan, India, and Nepal where elephant population showed an overall proportional increase from early 1990s. India holds over half (nearly 30,000 individuals) of the total Asian elephant population, while Bhutan and Nepal only sustained less than 2.5% of the population occurred in India. However, these three countries illustrated corresponding increase in the area of the largest forest patch along with a decrease in land cover diversity within elephant home ranges. These implied that improvement of some key forest habitats positively influence the proportional change in elephant population. Two regions with the largest elephant population in India are located at the southern and north-eastern regions. The latter is bordering with Bhutan and Nepal, as well as fostering known trans-boundary elephant migrations (Menon and Tiwari, 2019). Bhutan and Nepal were reported to have high commitment in conservation program. Bhutan, specifically, established protected area networks covering over 50% of the country areas (Dorji, Rajaratnam, and Vernes, 2019). The northeastern regions of India together with Nepal and Bhutan trans-boundary landscape still retain adequate natural areas for mammal conservation with potential for future recovery (Dorji et al., 2018). These likely contributed to the results of this analysis. Close inspection, however, revealed differences in level of forest PD among these three countries. India, specifically, showed less correlation coefficient between forest PD and elephant population due to the heterogeneity across its large geographical areas. In fact, India faced severe habitat deterioration, especially at West and Central regions (Leimgruber et al., 2003). Priority should be given to strengthen the effectiveness of existing protected networks and restore key habitats in Bhutan, Nepal, and India, especially the northeastern regions. Nevertheless, careful consideration and additional analysis at regional level should be performed for India.

Group C showed proportional increase and rather stable in elephant population, but with varying characteristics of land cover and landscape changes within elephant home ranges. Countries in this group included Bangladesh, China (Yunnan), Malaysia, Sri Lanka, and Thailand. Except Malaysia, all countries had a reduction in the areas of the largest forest patch. Higher land cover diversity was identified for all countries. Forest fragmentation also became more severe across the countries with an exception in Yunnan. Human population within elephant home ranges increased in Bangladesh, China, and Thailand, while rather stable in Malaysia and Sri Lanka. Overall, it can be inferred that elephant population persisted despite recent development and fragmentation in their ranges within these countries. Consequently, negative interaction between human and elephant or HEC are expected. Different degree of HEC was reported in all range countries, of which Sri Lanka identified with high severity due to high number of elephants (IUCN/SSC Asian Elephant Special ist Group, 2017). India and Sri Lanka had been dealing with HEC and developed variety of studies and mitigation (Desai and Riddle, 2015). On the other hand, other countries in this group were less studied. Therefore, priority should be emphasized on the mitigation of HEC through knowledge-sharing from more experience range countries (i.e. Sri Lanka) and further enhanced the effectiveness in protected network.

2.4.4 Thailand's unique position

Thailand was the only country with the overall increase in proportion of elephant population despite the negative impacts from all four key drivers. The country showed a reduction in the largest forest area, a relatively high land cover diversity, high human population and overall increasing in forest fragmentation. Due to high timber demand during 1960s coupled with government-led policy to allow settlement of unoccupied land and expansion of cash crops, Thailand historically had the highest rate of deforestation in the region (ICEM, 2003). Despite the recent trend of slow forest recover, land cover in Thailand has been mostly developed and forested areas are restricted within fragmented protected areas. With finite resource, the interaction between humans and elephants are likely increased, leading to HEC. Based on the idea following environmental Kuznets curve and forest transition (Perz, 2007), countries are believed to follow development path where ecological degradation is first expected and later replenished. Therefore, Thailand in particular was likely position as a leading country on the development pathway based on forest transition theory, especially within Southeast Asia. This same situation will become that of many neighboring countries. In addition, compare to countries in South Asia, limited HEC evaluation was conducted in this region. Therefore, Thailand was chosen as representative case to further analyze its HEC situation.

2.4.5 Uncertainties based on current assumptions

To properly interpret and apply the results from this study, it is crucial to recognize the uncertainties and limitations of the approach employed here. First, the elephant population data used were mostly based on expert estimation, hence any uncertainties in the data would be presented in the analysis. Second, the long-term elephant population data was available at coarse geographical resolution of country-level. Consequently, the analysis was performed with a single representative result for each country. However, variations from different regions of the same country may be present in countries with large geographical areas, such as India, and Indonesia. Incorporating such differences would require more precise elephant population data, possibly, at the scale of a single home range. Such data would also support home range specific conservation recommendations. Third, I recognized that lager number of variables may impact Asian elephant population. Therefore, it may be possible that some important factors were missed. Such variables may include vegetation phenology, water availability, human value and traditions, etc. Lastly, with limited temporal availability of elephant population, a simple cross-correlation was performed assuming no lag time between changes in key variables and the corresponding changes in elephant population. However, depending on the type of changes on the landscape, there may be possible delayed in population response.

2.5 Conclusion

In this chapter, I aimed to perform a review of Asian elephant status in relation to land cover and socioeconomic changes at country-scale with three specific objectives: (i) to assess the land cover and landscape within range countries and available home range around 1990, 2003, and 2015, (ii) to identify significant drivers and their correlation with the dynamic of Asian elephant population over time, and (iii) to categorize range countries based on changes of drivers and elephant population over time

For the first objective, overall expansion of agriculture areas were the prominent cause of forest conversion, while continuous growth in urban areas were also common within elephant home ranges in all countries. In addition, most countries experience higher forest fragmentation represented by increasing forest patch density, while cropland showed more connectedness with growing area of largest crop patches.

As for the second objective, four key variables, namely area of largest forest patch, landscape diversity (SHEI), forest fragmentation (PD forest), and human population were identified as part of logistic regression model with lowest AICc and good pseudo $\boldsymbol{R}^2$. This model implied that substantial Asian elephants population can persist in highly diverse landscape along side human population when a large patch of forest with less fragmentation were maintained. Area of largest forest patch was the dominant predictor of having large elephant population which agreed with my expectation.

Based on the change in the proportion of elephant population and the correlation between that of key selected drivers, range countries can be categorized into four groups. This findings addressed the third objective. Cambodia, Laos, and Vietnam showed high forest loss and fragmentation with the corresponding reduction in elephant population; hence, halting habitat destruction should be given priority. Indonesia and Myanmar showed a decrease in elephant population despite the remaining largest forest patch. The two countries displayed different forest fragmentation characters which implied dissimilar underlying causes, with potential poaching for Myanmar and forest enroachment for Indonesia. Therefore, priority should be given to enforce conservation laws and establish protected areas. Bhutan, India, and Nepal maintained an increase in elephant population with improvement in largest forest and fragmentation. Majority of the countries (Bangladesh, China, Malaysia, Thailand, and Sri Lanka) hosted a stable and even increasing elephant population, while human disturbance and habitat deterioration were observed within their elephant home ranges. HEC was expected to become more frequent in such countries and mitigation should be given priority.

The cross-country analysis in the current study demonstrated that patterns and variations among countries can be identified using various satellite-based remote sensing products and comparison results may be useful to develop conservation applications. I attempted to incorporate many aspects of possible drivers, but recognized that more exhaustive list remains. In addition, the assumption of homogeneous characteristics within the country with large geographical areas (e.g. India) may biased the result and must be taken with caution. Further research can be performed to seek finer-resolution for both elephant population and environmental dataset, as well as to elucidate key selected factors in more detail.

In the future, growth in economic development and human population are expected in most regions of Asia which will fuel further land conversion placing human in closer proximity to Asian elephant habitat. This situation will increase the likelihood of HEC in many regions and negatively impact both human development and elephant conservation. Thailand, in particular, was positioned with unfavorable conditions from all key factors while retained an increasing elephant population. Land cover in Thailand is highly developed with remaining forest resided mainly in protected areas within matrix of human-modified land cover. This situation will likely be the future of many range countries. Hence, further analysis on HEC situation in Thailand was performed and discussed in later chapters, Chapter 4 and 5.

Chapter 3

Modeling spatiotemporal Distribution of Human-Elephant Conflict in Eastern Thailand

3.1 Introduction

Thailand is estimated to have 3,000-3,500 wild elephants in 68 areas, 41 of which are facing HEC, commonly in the form of crop depredation (Noonto, 2009). Historically, elephants have been recorded inside Bangkok, Thailand's capital city, and the surrounding provinces (Sukmasuang, 2015). Nowadays, the estimated home range of wild elephants in the country lies in heavily fragmented landscapes and is surrounded by human-dominated activities (Leimgruber et al., 2003). Consequently, interaction between wild elephants and humans became more frequent, increasing the likelihood of Human-Elephant conflict (HEC).

Across countries with presence of wild elephants, various mitigation strategies have been implemented that include guarding (e.g. watchtowers), deterrents (e.g. firecrackers), physical barriers (e.g. trenches and various form of fences: electric, chilies), translocation of elephants or humans, and compensation (Desai and Riddle, 2015). In Thailand, guarding, together with traditional deterrents, are the most common strategy (WCS Thailand, 2007). In high conflict areas, large fences and trenches were constructed by the government, but proved ineffective due to the lack of proper maintenance (Vinitpornsawan, 2012). Recently, more active approaches were employed, such as (i) GPS collaring of wild elephants known to forage outside protected areas to track their movement (Salim, 2019), and (ii) issuing of government insurance schemes for crop damage by elephants (Nuntatripob, 2019). Landscape planning is viewed as a potential long-term solution (Saif et al., 2019), but its implementation has not yet been established despite being mentioned in the draft of 20-year Master Plan for Elephant Conservation (Nuntatripob, 2019).

Apart from the negative human-elephant interaction, HEC also includes conflicting human objectives (Dickman, 2010; Redpath, Bhatia, and Young, 2015). Social factors, such as trust in authority, education, income, culture, and religion, influence community tolerance and willingness to coexist with elephants (Nyhus, 2016; Saif et al., 2019). Simultaneously, competition for scare resources between humans and wildlife in a shared landscape remains a fundamental cause of conflict (Morzillo, Beurs, and Martin-Mikle, 2014; Shaffer et al., 2019). Knowledge of the spatiotemporal variation of resources and its effect on the pattern of conflict is an important initial step toward a sustainable, long-term solution (Chen et al., 2016).

Studies in Thailand generally focus on social aspects of HEC, such as people' s attitudes and perceptions (Water and Matteson, 2018; Jenks et al., 2013), conservation and legal management (Parr et al., 2008; Thongjan et al., 2017). An existing study on the spatial distribution of wild elephants included only localized habitat suitability assessment in a single conservation area (Sukmasuang, 2015). Studies on spatiotemporal patterns of HEC across landscapes remain limited but they are crucial for appropriate decision making (Gubbi et al., 2014). Compared to African elephants, such studies are relatively few in Asia (but see Goswami et al. 2015; Chen et al. 2016; Li et al. 2018) and, to the best of our knowledge, no such study exits in Thailand.

Species Distribution Models (SDMs) are widely used in ecology to predict spatial patterns of species. SDMs are numerical models that quantify the relationship between ecological (e.g. species/population abundance) and environment variables (Elith et al., 2011). SDMs estimate the environmental similarity between locations to known ecological response and extrapolates from local samples to entire target landscapes. Their application has been seen in human-wildlife conflicts (Mateo-Tomás et al., 2012), but remains relatively few in HEC modeling.

Previous ecological studies on elephants have researched the seasonal variation in elephant movement and dispersal (Sukumar, 1992; Santiapillai, Chambers, and Ishwaran, 1984). Nevertheless, SDMs commonly employ environmental data that provide less dynamic information with often irrelevant temporal resolution between predictor and response variables. This is specifically true for meteorological time series, which are often interpolated from weather stations, introducing uncertainty due to uneven data distribution and availability in developing countries (Bedia, Herrera, and Gutiérrez, 2013). In contrast, remotely sensed satellite datasets can provide spatially explicit and continuous observation which are believed to enhance SDM accuracy (He et al., 2015). Previous studies highlighted model-performance improvement due to the utilization of remote sensing datasets, such as vegetation phenology (Tuanmu et al., 2011), and human activities (Albabia et al., 2016). In addition, a generic assumption in SDMs is that ecological response can be described by a single function, which results in over-simplification (Naves et al., 2003), reducing the ability to identify drivers of response (Bleyhl et al., 2015). Specifically in habitat modeling, a single function SDM will overlook certain management areas (e.g. sink-like habitat) when key factors that determine the occurrences are not positively correlated (De Angelo et al., 2013). Therefore, modeling occurrences based on two SDMs from the perspective of different key factors allows for a more informative assessment (De Angelo et al., 2013; Bleyhl et al., 2015; Romero-Muñoz et al., 2019). HEC in particular, depends on two prominent physical variables; resource suitability and human pressure. Such a two-dimensional approach has not yet been applied in HEC modeling.

3.1.1 Objectives

The aim of this study was to estimate the recent trend of HEC and identify the physical factors that potentially govern its spatial distribution. The findings from this section will address the second set of research questions raised in Chapter 1. Eastern Thailand region was chosen as a study area as it was reported with high HEC incidents. Given the large landscape extent and the dynamic spatiotemporal variation of environmental and physical factors, I utilized remotely-sensed satellite data and quantified the spatiotemporal HEC distribution over 10-year period. The specific objectives were to

1. model the potential spatial distribution of seasonal HEC from 2009 to 2018 with the use of time-calibrated SDMs
2. identify and distinguish the contribution over time of important modeling factors (resource suitability and direct human disturbance)
3. prioritize the areas that require targeted management and increased intervention

3.2 Methodology

3.2.1 Study location and flowchart

This study was carried out in two forest-dominated areas or forest complexes of Eastern Thailand (Figure 3.1) covering eight eastern and two north-eastern provinces. The area has a tropical monsoon climate. The monsoon season occurs from mid-May to mid-October with an average rainfall of 1,400 mm, while the area during dry season receives about 400 mm of rainfall (Thailand Meteorological Department, 2015; Nounmusig, 2018). The region has nine national parks (NP) and wildlife sanctuaries (WS) hosting elephants (Sukmasuang, 2015). Khao Angruenai-WS, for example, experiences high density of wild elephants, approx. 0.2 elephant/km^2 (Vinitpornsawan et al., 2013). In addition, a constantly low elevation in the central region enabled elephants to easily disperse into agricultural land. Consequently, this area is suspected to be a HEC hotspot. Agriculture is the dominant land cover. Five most important crops in planting areas are rice, cassava, rubber plant, sugarcane, and maize. Orchards and plantations commonly spread out in the southern areas. To limit the modeling boundary to only those potentially accessible by elephants, a 20km buffer was created from the boundary of protected areas and village location with reported HEC. The seasonal models were set according to the monsoon pattern with May to October as the wet season and November to April of the following year as the dry season.

HEC occurrences were collected from online news reported between 2014 to 2018. Based on this data, I built the models using environmental variables temporally matched with each occurrence and modeled spatial distribution of HEC across the study area for the period 2009-2018. The maps of HEC category were then developed. The flow chart of this study is shown in Figure 3.2. The procedures comprised of three parts including the preparation of input data, the model construction and evaluation of HEC probability, and the classification of HEC category and trend analysis.

3.2.2 Dataset used

HEC occurrences

Until March 2019 when elephant-induced damages were first included in farmers insurance schemes, HEC was neither compensated nor insured by the Thai government (Nuntatripob, 2019). Consequently, official records were not consistently maintained across protected areas. Although elephants' locations outside of protected areas were sometimes documented, elephants presence is not always equivalence to HEC. Reporting from news sources usually happens when negative outcomes occur, and this better reflect HEC occurrences. Therefore, HEC incidences were retrieved from online news sources. '*Wild elephants*' in Thai language was used as a search keyword from the News section of Google

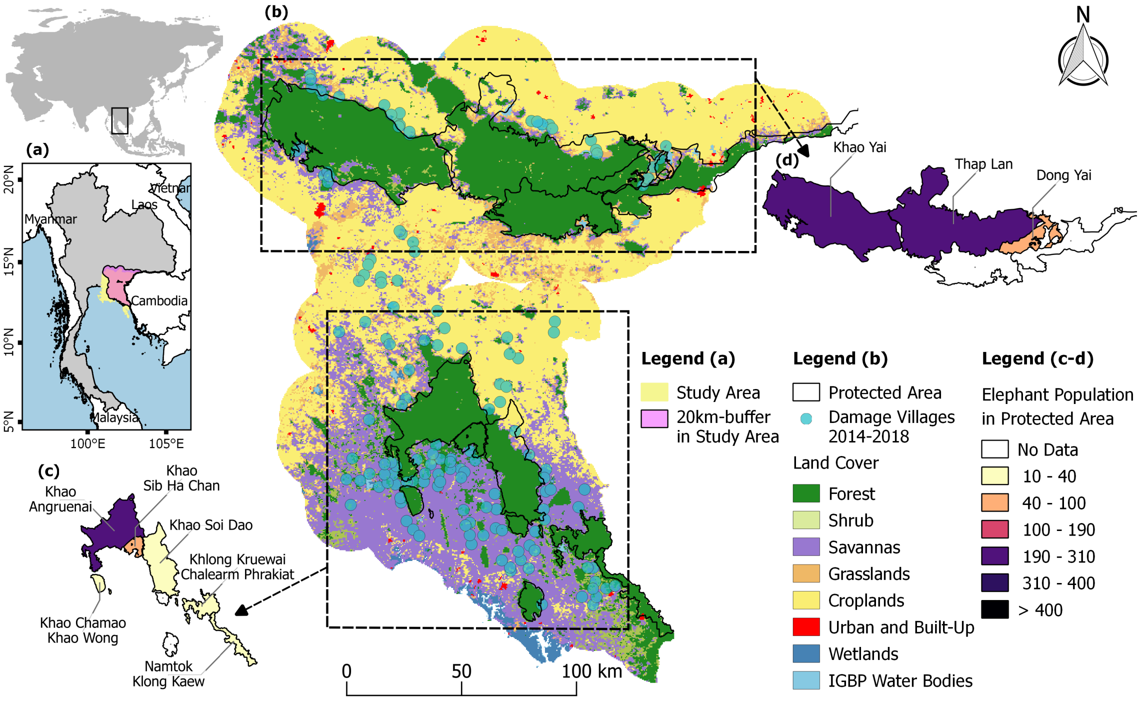


Figure 3.1: The study area in Eastern Thailand (a). The area is dominated by croplands and savannas, while the damaged villages are located near the forests (b). Human-elephant conflict was modeled within 20-km buffers generated around the nine protected areas (c, d), which are natural habitats for elephant populations.

Search Engine. A customized time period was set between 2014 to 2018. Each search output was investigated manually to exclude duplicated reports of the same incident.

The news reports, however, did not mention the precise locations of HEC occurrence but only the village names. To overcome this lack of exact occurrence locations, I simulated the occurrence locations using conditional random sampling method. The sampling boundaries were restricted within a 3km-buffer around the center of each mentioned village, excluding areas that fall within the protected areas, large water bodies (e.g. reservoirs), and major road networks. I excluded locations with the aforementioned features because HEC are unlikely to occur within them. The numbers of random occurrence points were generated according to the numbers of damage incidents reported within each village. A total of 124 incidents occurred in the wet season; a combination of 7, 12, 14, 31, and 60 incidents from 2014 to 2018 respectively. The dry season had 122 reports in total; 5, 20, 20, 20, and 57 of which occurred respectively.

Five sets of random occurrences were generated. A Wilcoxon-Mann-Whitney test

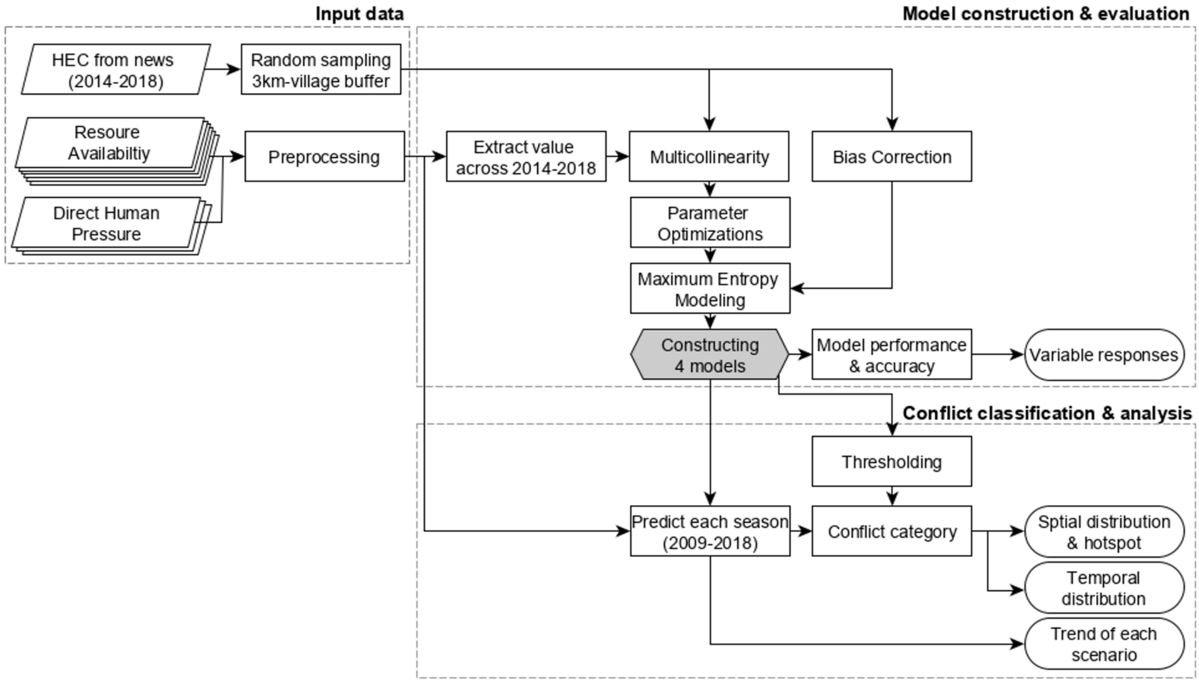


Figure 3.2: Flow chart of the study showed that two models for each season under resource availability and direct human pressure were constructed to identify governing environmental variables, HEC spatiotemporal distribution, and trends.

(Fay and Proschan, 2010) was performed to compare the distribution profile of each independent variable to that of the other four sets of simulated occurrence records. The p-value of over 0.05 indicated no significant difference between each set. I then selected one set for model constructions.

Environmental variables

Thirteen variables were analyzed. I grouped the predictors into two scenarios: (i) resource suitability and (ii) direct human pressure. Resource suitability comprised of vegetation productivity (Enhanced Vegetation Index - EVI), seasonal vegetation changes (EVI slope, and EVI standard deviation), landscape composition (EVI homogeneity), meteorological drought condition (Keeetch-Byram Drought Index), refuge locations (Forest percent cover, Distance to forest), and topographic condition (Terrain Roughness Index-TRI). Direct human pressure included distance to lit-up area, to main roads, to protected habitats, and human population density. Indirect human pressures, such as sociopolitical factors, were not considered in this study. All the predictors were re-projected to the

WGS 84/UTM zone 47N (EPSG:32647) and resampled to a 500m resolution using bilinear interpolation. Pre-processing was performed using Google Earth Engine (Gorelick et al., 2017) and R version 3.5.3 (R Core Team, 2019). Table 3.1 shows each variable together with the data source, the original resolution, and the temporal period used.

Resource suitability variables

Normalized Difference Vegetation Index (NDVI) was found to be an effective proxy of forage availability (Pettorelli et al., 2005). Dispersal of African elephants was shown to coincide with the greening-up measured by NDVI (Bohrer et al., 2014). For this study, I utilized the Enhanced Vegetation Index (EVI). Despite being similar to NDVI, EVI improved saturation in high biomass regions, corrected for aerosol influence, and reduced noise from soil background (Liu and Huete, 1995). Following (Huete, 1997), EVI was calculated from MODerate Resolution Imaging Spectroradiometer (MODIS) Terra product (MOD09A1) as:

$$EVI = 2.5 \times \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{(\rho_{\mathrm{NIR}} + 6 \times \rho_{\mathrm{Red}} - 7.5 \times \rho_{\mathrm{Blue}} + 1)} \tag{3.1}$$

where ρ_{NIR}, ρ_{Red}, and ρ_{Blue} represent the reflectance of the near-infrared, red, and blue bands respectively. Only the pixels under *clear* cloud state and *no cloud shadow* were used.

I first calculated the monthly median of EVI for each month from 2009 to 2018. The missing monthly pixels were filled using the 10-year averaged EVI value in the same pixel location of the same month. From the monthly EVI data, I then calculated the mean EVI for each season which represents vegetation productivity. Next, the EVI slope, representing the rate of change in vegetation condition (e.g. crop senescence), was calculated by applying pixel-wise linear regressions over the monthly EVI within each season. A standard deviation of the monthly EVI values within each season was calculated next which represents fluctuation in vegetation dynamic. These EVI variables can also be linked to different characteristics of land cover types. For example, a high EVI with a EVI slope near zero and low standard deviation usually associate with tropical forest land cover (Figure 3.3). Lastly, a spatial homogeneity of EVI was generated using the Gray Level Co-Occurrence Matrix (Haralick, Shanmugam, and Dinstein, 1973).

Drought influences surface water availability and vegetation quality, which govern elephant habitat use (Sukumar, 1992). The Keetch-Byram Drought Index (KBDI) estimates dryness of soil layers. The KBDI product was computed using the precipitation data derived from the Global Satellite Mapping of Precipitation (GSMaP) and land surface

Table 3.1: List of predictor variables including data source, spatial resolution, and temporal scale in which data was prepared.

Variable	Source	Resolution	
Resource-related			
Keetch-Byram Drought Index (KBDI)	KBDI from Takeuchi et al. 2015	4000 m	Seasonal
Enhance Vegetation Index (EVI)	MOD09A1	500 m	Seasonal
EVI change slope	MOD09A1	500 m	Seasonal
EVI standard deviation	MOD09A1	500 m	Seasonal
EVI landscape heterogeneity	MOD09A1	500 m	Seasonal
Distance to forest	MCD12A1	500 m	Annual
Forest percent cover	MCD12A1	500 m	Annual
Distance to Water	Global Water Surface product	30 m	Annual
Terrain Roughness Index (TRI)		90 m	Static
Direct human pressure			
Distance to lit-up areas	Intercalibrated DMSP and VIIRS	1000 m	Annual
Human population density	Landscan product	1000 m	Annual
Distance to main roads	Thailand Bureau of Highway	vector	Static
Distance to protected habitats	WDPA	vector	Static

MOD09A1: MODerate Resolution Imaging Spectroradiometer (MODIS) Terra Version 6, MCD12Q1: MODIS Land Cover Type Version 6, DMSP: Defense Meteorological Satellite Program (Night-time light), VIIRS: Visible Infrared Imaging Radiometer Suite (Night-time light), WDPA: World Database of Protected Areas.

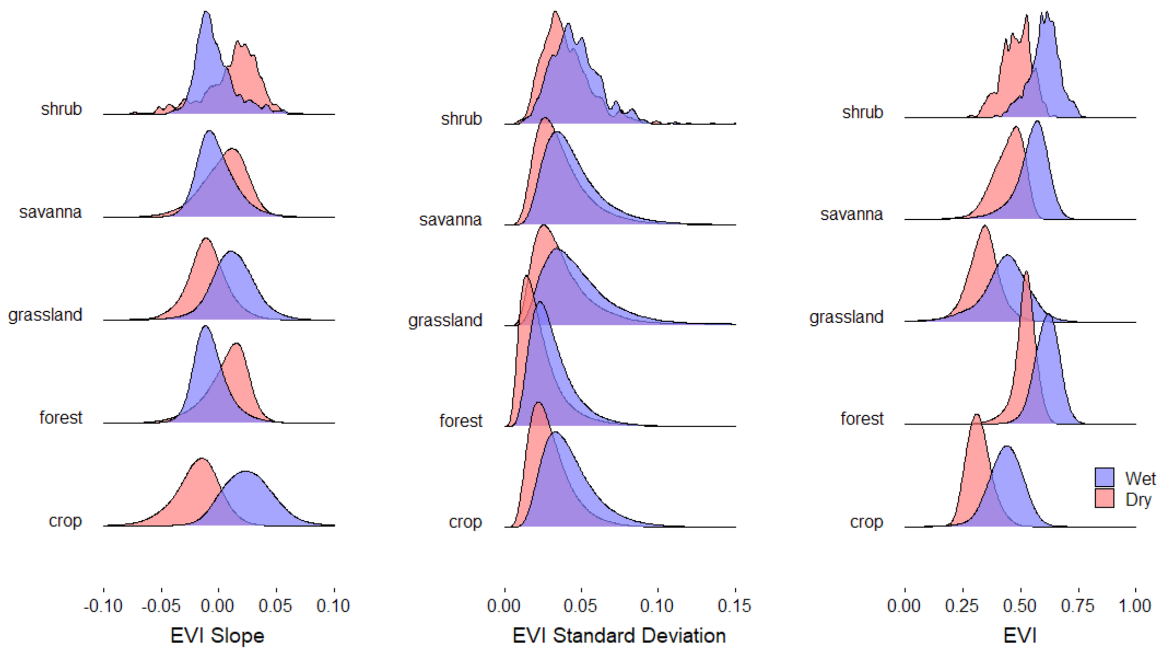


Figure 3.3: Histograms of three EVI properties (EVI slope, EVI standard deviation, mean EVI) from different vegetation land covers in wet and dry seasons during 2014-2018, y-axis shows number of pixels.

temperature (LST) data from Multi-functional Transport Satellite (MTSAT) (Takeuchi et al., 2015). The value of KBDI ranges from 0 (no moisture deficit) to 800 (extreme drought). The daily data from 2009 to 2018 was averaged by season. Additionally, wild elephants were observed to move toward inland areas during the dry season as waterhole in coastal regions dried up (Santiapillai, Chambers, and Ishwaran, 1984). To capture accessibility to water, locations of surface water were obtained from the monthly historical Landsat Global Water Surface Product (Pekel et al., 2016). Within a single year, pixels detected with water for at least 3 months were marked as water and Euclidean distance to them were calculated.

Forest is considered a natural habitat and represents a potential refuge location. Forest land cover classes from the MODIS land-cover product (MCD12Q1) was used. MCD12Q1 provides annual land cover in 500m resolution. Since the study area was dominated by dry evergreen forest (90% of all forest classes), I reclassified all forest types to a single land cover class. According to an interview with park rangers conducted by the authors, 6km was suggested to be a one-way distance traveled by wild elephants between patches of the forest outside the protected areas. Two variable were calculated, a mean Euclidean distance from each pixel to forest and a percentage of forest cover within

6km-buffer around each pixel. Lastly, I calculated terrain ruggedness index (TRI) from the Shuttle Radar Topography Mission data (SRTM) (USGS, 2004). The TRI represents the relative change in elevation from a center cell and eight surrounding cells. The higher TRI value indicates more rugged areas.

Direct human disturbance variables

Direct human disturbance was measured based on human population density as well as Euclidean distance to protected habitats, to main roads, and to lit-up areas. Density of human population also influences alteration of landscape and intensity of anthropocentric activities, which may not be captured by using only the proxy of urban areas. Hence, mean human population density was computed using yearly estimations from LandScan. Main roads were obtained in vector format from Thailand Bureau of Highway and only highway and primary roads were extracted for euclidean distance calculation. Vectors of protected areas recognized by IUCN was downloaded from the World Databased of Protected Areas (WDPA).

To detect lit-up areas, the pixels detected with light or the lit-up pixels were computed from satellite-derived night time light data. The Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and the Suomi National Polar-orbiting Partnership satellite's Visible Infrared Imaging Radiometer Suite (VIIRS) were the main sources of night-time light product. DMSP operation was committed from 1996 and then succeeded by VIIRS in 2012. Due to different specification of sensors on board the satellites through out operational time, calibration among OLS sensors, as well as between OLS and VIIRS was necessary. I applied a second-order regression model from (Elvidge et al., 2014) for the calibration among OLS sensors. For OLS and VIIRS inter-calibration, I first created VIIRS annual composite following (Wu and Wang, 2019) and then applied a combination of power function and Gaussian low pass filter (Li et al., 2017).

$$x_{ij} = ax_{i\,j}^{b} \tag{3.2}$$

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp^{-\frac{x^2+y^2}{2\sigma^2}} \tag{3.3}$$

$$x'''_{i\;j} = \begin{cases} s & \text{if } x''_{i\;j} > s \\ x''_{i\;j} & \text{otherwise} \end{cases} \tag{3.4}$$

The pixel value of i-th row and j-th column of DMPS image denoted as x_{ij} was processed first with Equation 3.2. A 2-D Gaussian kernel of window size w with a standard deviation σ was then applied on the whole image. Next, the produced pixel value $x''_{i\ j}$ was adjusted using Equation 3.4 with a threshold s. In this study parameter $a, b, \sigma andw$ were identified using step-wise analysis and the initial values were set following (Li et al., 2017). Final optimal value were 11.4, 0.43, 9 and 0.52 respectively. Same as Li et al. (2017), threshold s was set to 50. The images from 2012 were used. The calibrated result showed r and RMSE of 0.892 and 5.345. The example of calibrated result in Figure 3.4 showed the digital number of the original DMSP and the simulated DMPS from VIIRS in 2011. With calibrated time-series of night time light ready, the pixels with digital numbers of over 20 were used as delineate locations with anthropocentric activities. The Euclidean distance from extracted pixels were then calculated.

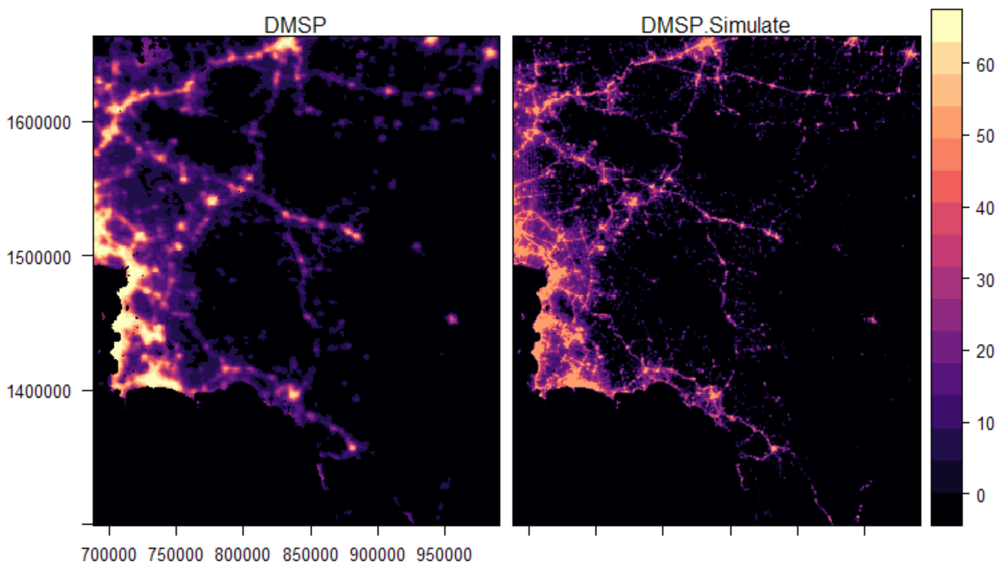


Figure 3.4: The night-time light result of DMSP-OLS (left) and the simulated DMSP-OLS based on VIRRS (right) from 2012. DMSP-OLS: efense Meteorological Satellite Program' s Operational Linescan System, VIIRS: Visible Infrared Imaging Radiometer Suite.

3.2.3 Model construction and evaluation

Bias correction

HEC incidences from online news sources are opportunistically collected and not randomly sampled. Such datasets often contain sampling bias wherein more reporting are made from easily accessible locations or well-known hotspots (Kramer-Schadt et al., 2013). With sampling bias, it is hard to determine whether occurrences were reported due to preferable conditions in that locations or concentration of search effort. When relative search effort across the landscape is known, sampling bias can be directly modeled and provided as prior distribution during SDM construction (Merow, Smith, and Silander, 2013; Phillips et al., 2009). Alternatively, the effect from sampling bias can be partially accounted for by subsampling the training dataset or adjusting the background selection (Elith, Kearney, and Phillips, 2010; Kramer-Schadt et al., 2013; Fourcade et al., 2014). Due to low occurrences in our study, we applied background selection method which nullifies bias by generating a similar bias in the background (Phillips et al., 2009). Bias grids were produced by deriving a Gaussian kernel density map of the village locations weighted by the average number of duplicated reports within each village. The bias values were re-scaled from 1 to 20, following (Elith, Kearney, and Phillips, 2010) to avoid extreme values, and used as probability in sampling background points. I sampled a total of 10,000 points, a combination of 2,000 each year from 2014 to 2018. The generated background points were later used as pseudo-absences in model construction.

Modeling HEC occurrence probability with Maximum Entropy

The Maximum Entropy algorithm from MaxEnt (Phillips, Anderson, and Schapire, 2006) was used. MaxEnt is a machine-learning technique that estimates the unknown distribution of suitability by contrasting the values of predictors at occurrence locations with the overall distribution of these predictors (Merow, Smith, and Silander, 2013). A detailed explanation and related equations can be found in (Phillips, Anderson, and Schapire, 2006). MaxEnt had shown a high performance even with few occurrence records and was least affected by errors of occurrence location (Merow, Smith, and Silander, 2013). It also outperformed other methods (Elith and Graham, 2009). All our models were constructed using dismo package in R with MaxEnt 3.3.4 version (Hijmans et al., 2017). The logistic link function was used to derive a relative probability of potential HEC occurrence ranging between zero (low probability) and one (high probability) (Phillips, Anderson, and Schapire, 2006).

A time-calibrated method (Sieber et al., 2015) was applied in which each occurrence point was matched with environmental predictors from the relevant season during which HEC was reported. This resulted in time-independent models which allowed comparability across the study period. MaxEnt requires background points as pseudo-absent. The 10,000 background samples previously generated in section 3.2.3 was used.

Prior to model construction, multicollinearity among predictors was evaluated. High Pearson correlation ($r < |0.75|$) and Variables that had Variance Inflation Factors (VIF) greater than 10 were removed. To identify variable for removal, stepwise VIF was performed. Since feature classes and regularization multiplier (RM) impacted modeling results (Merow, Smith, and Silander, 2013), parameter optimization was conducted using EMNeval package in R (Muscarella et al., 2014). Product and Threshold features were excluded in our models. Product-feature tends to over-fit and complicates interpretation of variable responses (Liu, Newell, and White, 2016). Threshold-feature should be used when a drastic cut-off exists in species' response to environmental factors, but no such cut-off has been identified for Asian elephants. Therefore, only Linear/Quadratic/Hinge combinations were selected and k-fold cross-validation was performed with RM value from 0.5 to 5 at 0.5 increment. Akaike Information Criterion (AIC) was used for optimal parameters selection. Other settings were left with default values which included 500 iteration maximum and convergence thresholds.

After optimal parameters were identified, the models were constructed using k-fold cross validation (k=5) and evaluated with Receiver Operating Characters (ROC) with average Area Under the Curve (AUC) from all replicas. In addition, a jackknife test was used to identify important predictors. Responses for each variable were also generated. A total of four models were constructed, one model for each season under the two high-level scenarios (resource suitability and direct human pressure). I identified the differences between environmental predictors from each season to those used for model construction using Multivariate Environmental Similarity Surface (MESS) and limiting factors (Elith, Kearney, and Phillips, 2010). The negative MESS score indicated a novel condition in variables used for prediction which implies possible uncertainty. I then estimated relative probability of HEC across the landscape for 20 seasons by applying the constructed models on the predictors from 2009-2018.

Conflict classification

The probability of HEC occurrence for each group was then categorized in three classes (High, Low, Very Low). Two thresholds were used, (i) 10th percentile of presence locations and (ii) maximum training sensitivity plus specificity (maxSS). The first threshold allowed omission of 10 percent of occurrences which reduces sensitivity to extreme localities (Radosavljevic and Anderson, 2014), while the second threshold was evaluated as an effective threshold value for presence-only modeling (Liu, White, and Newell, 2013). Probability lower than the first threshold was set as *Very Low* class. I then applied the

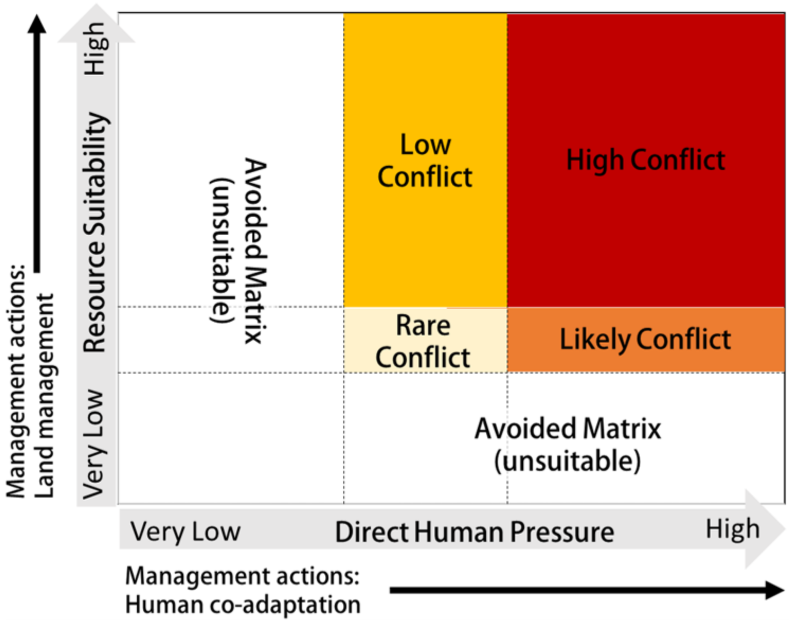


Figure 3.5: The proposed conflict classification matrix generated by overlaying between probability of resource suitability and direct human disturbance.

second threshold where the probability lower than maxSS was set as *Low*, and those higher or equal to maxSS was set as *High*. Interpretation of resource suitability is straight forward in which high HEC probability occurred in a more suitable condition. Conversely, the high HEC probability of human pressure captured the disturbance level in which conflict peaked. In reality, high human disturbance beyond the peak level existed, but likely restricted occurrence of elephants resulting in low predicted HEC probability.

Each classified maps from different scenario in the season were then overlaid into a two-dimensional HEC categorical map (Figure 3.5). these categorical classification contained:-

- *Avoid matrix*: at least one very low class from either scenario
- *Rare conflict*: low resource suitability and low human pressure
- *Low conflict*: high resource suitability but low human pressure
- *Likely conflict*: low resource suitability and high human pressure
- *High conflict*: high resource suitability with high human pressure

By using two-dimensional classification, two main key management-relevant actions related to each group of factors can be identified. First, management actions associated with resource suitability are linked to natural resource and land management (e.g. land-use policies, establishing elephants corridors) (e.g. Neupane, Johnson, and Risch 2017; Goswami and Vasudev 2017). Second, HEC occurrences are also governed by level of human disturbances which can be associated with different management actions directed more toward human co-adaptation (e.g. insurance schemes, behavioral adjustment in crop husbandry) (e.g. Chen et al. 2013; Treves et al. 2006).

3.2.4 Analysis of HEC distribution and trends

For each year during 2009-2018, two HEC maps (a wet season map and a dry season map) were generated. Areas of different HEC levels were calculated by summing the number of pixels within each category and multiplying that by the pixel size. The affected areas for each HEC classes were calculated by season from 2009 to 2018 both for the whole region and separately by provinces. Distribution of conflict hotspots, which are the areas repeatedly predicted with the same conflict category across the years, were identified. The change in probability of HEC occurrence under resource suitability and direct human pressure scenario over 10 years was calculated by fitting pixel-wise linear regression on predicted probability from 2009 to 2018.

$$Y_i = \beta_0 + \beta_1 t + \varepsilon_i \tag{3.5}$$

The slope coefficient (β_1) of the fitted regression indicated the rate and direction of change in HEC probability. The intercept (β_0) represented the baseline probability in 2009.

3.3 Results

3.3.1 Model performance and variable responses

The p-value of all simulated HEC occurrences were greater than 0.19. The mean cross-validated AUCs were 0.81 for resource suitability/wet season, 0.73 for resource suitability/dry season, 0.78 for direct human pressure/wet season, and 0.77 for direct human pressure/wet season. Jackknife analysis for the resource suitability scenario and direct human pressure scenario (both seasons) identified the same top three importance variables (Figure 3.6). Forest Percent Cover had the highest predictive contribution; together with KBDI, Distance to Forest, and EVI slope, these four predictors accounted for over

80% of the models' predictive power (Figure 3.6a). For the dry season model, KBDI had slightly less contribution, while distance to forest edge became more important. Under human pressure scenario (Figure 3.6b), Distance to Protected Habitats was the most influential variable for both season. The next important predictor for the wet season was Human Density, while Distance to Main Roads was for the dry season.

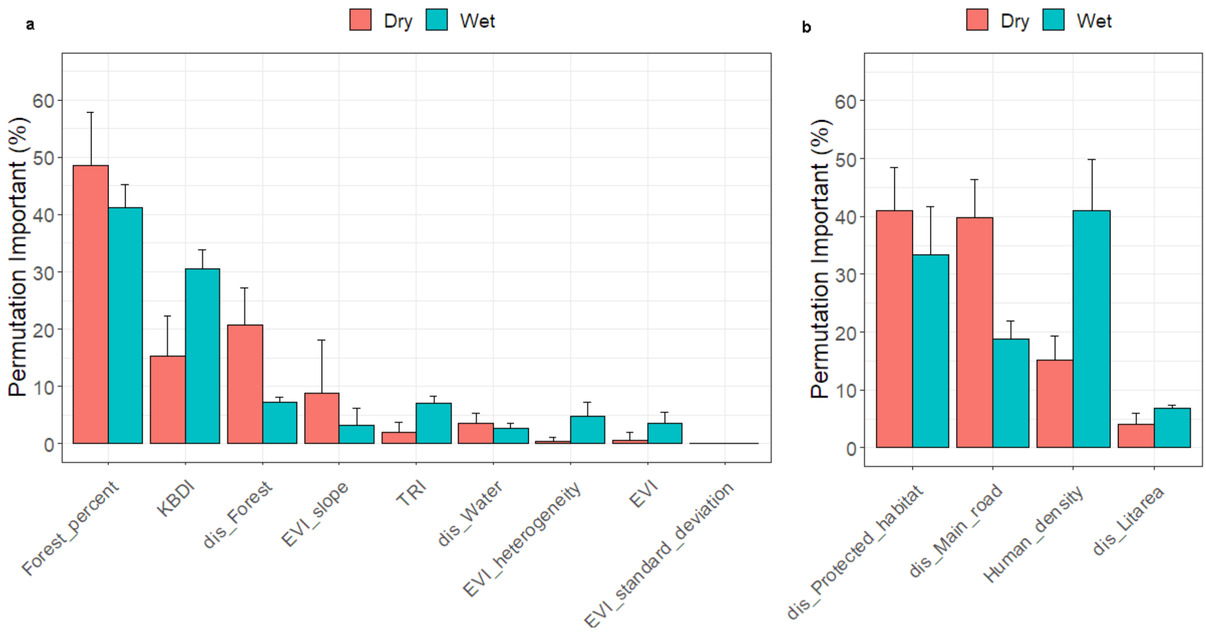


Figure 3.6: Permutation importance showed percentage of contribution from variables under (a) resource suitability and (b) direct human pressure.

Figure 3.7 shows how the HEC probability changes as each environmental predictor is varied, while keeping all other environmental variables at their average sample value. The response of Forest Percent Cover was similar for both seasons. In the highest and lowest forest densities, lower HEC probability was expected, while higher HEC probability was found in moderate forest densities. For KBDI, higher probability of HEC in wet season occurred at low KBDI, with a continuous reduction after KBDI of around 50. In dry season, however, HEC probability peaked at intermediate KBDI around 300-400 and decreased slowly. The response of EVI Slope for the wet season indicated that HEC was more likely to occurred where vegetation conditions were changing (diverted from zero), the highest HEC probability occurred when EVI was reducing over the season. In the dry season, however, probability of HEC was higher when EVI was relatively stable (EVI of zero) or increasing slightly (EVI of 0.05), indicating green-up of vegetation. The patterns of EVI slope from both seasons corresponded to the characteristics of EVI

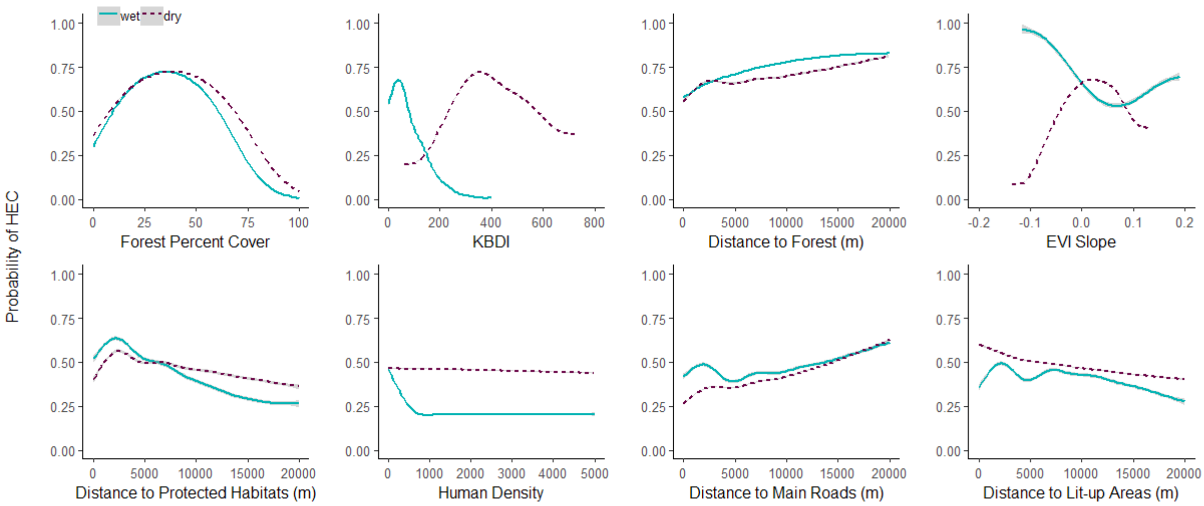


Figure 3.7: Relative probability of human-elephant conflict (HEC) occurrences for each environmental predictor, grouped based on resource suitability (top) and direct human pressure (bottom), while keeping all other predictors at average values. The predictors shown had a combined contribution greater than 80%. KBDI, Keetch-Byram Drought Index. EVI, Enhanced Vegetation Index.

slope from forest and savanna land cover (Figure 3.3). For human pressure, response of Distance to Protected Habitats, Distance to Main Roads, and Distance to Lit-up Areas had similar characteristics for both seasons. In dry season, a slower reduction in HEC probability was observed for Distance to Protected Habitat and Distance to Lit-up Areas as distance increased. For Human Density, HEC probability in the wet season reduced as density approached 1,000 person/km^2, but did not affect HEC probability in the dry season. Possible higher tolerance to high human pressure of elephants was captured in dry season.

MESS results indicated similarity of variables under the resource suitability scenario for the most part of the study period except slight dissimilarity in 2010 and 2014-2016. During those years, KBDI became prominent limiting factors, affecting large areas. Figure 3.8 showed examples of KBDI anomaly from which positive values observed in 2014-2016 indicated higher KBDI than the 10-year average values, while 2013 represented a relatively normal condition. For the direct human pressure scenario, dissimilarity with negative MESS was identified in 2012-2013 which I suspected was due to the use of different sensors for night-time light dataset.

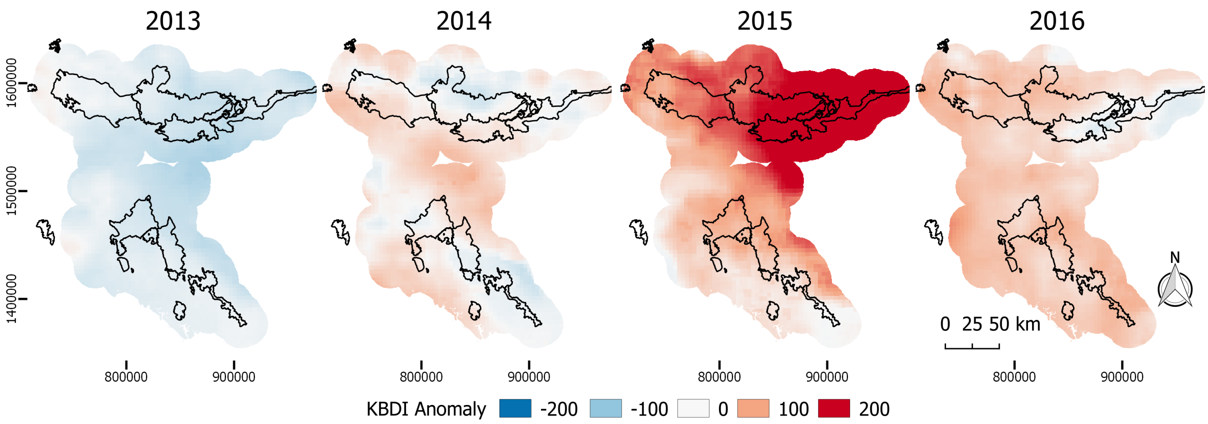


Figure 3.8: Anomaly of Keetch-Byram Drought Index (KBDI) showed large positive value in 2014-2016 compared to relatively normal condition in 2013. Positive KBDI anomaly indicated deficit of soil moisture which suspected to restrict availability of resource and alter potential HEC distribution.

3.3.2 Distribution of conflict and conflict hotspot

The potential for HEC occurrence was higher during the dry season; High and Low conflict areas were larger and more frequent. In contrast, during the wet season, the Likely and Rare conflict categories were more frequent, suggesting lower HEC potential. The hotspots of High conflict category were concentrated around the south and south-west of Ang Ruenai-WS in Chonburi, Rayong, and Chantaburi provinces (Figure 3.9). In the north, smaller clusters, especially near the protected areas, was predicted in Nakhon Ratchasima, Nakhon Nayok and Prachinburi provinces. The high HEC zones shrunk closer to the protected areas in the wet season and mainly located around Khao Chamao Khao Wong-NP at the border between Rayong and Chantaburi, east of Khao Soi Dao-WS in Chantaburi, and northwest of Khao Yai-NP in Nakhon Ratchasima. Additionally, the models estimated that many areas under High conflict category in the dry season changed to Likely conflict category in the wet season. This result implied that such locations have potentially experienced year-round HEC in different levels (e.g. intensity or frequency). Low conflict class was predicted in large areas in the dry season, affecting all provinces. Although less in frequency and intensity, in the wet season coldspots of Low and Rare conflict categories were concentrated around the main roads with some areas located are from protected areas.

During 2009-2018, overall areas of potential conflict were estimated to be increasing

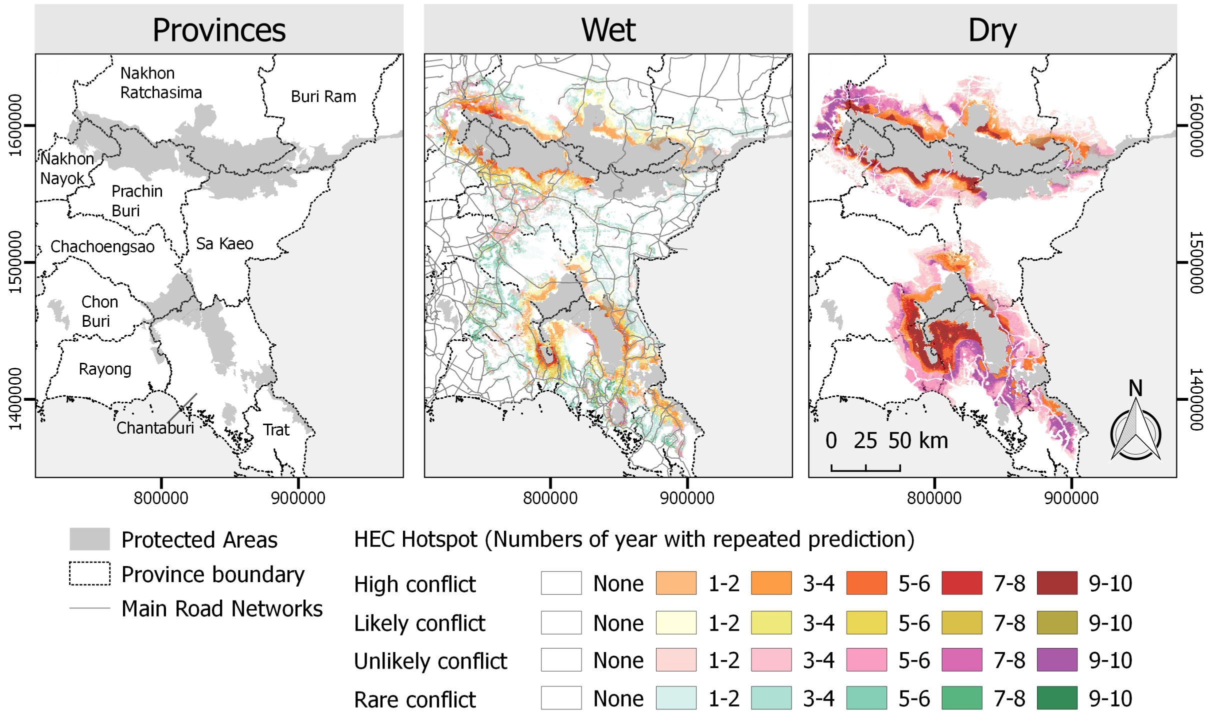


Figure 3.9: The sum of human-elephant conflict (HEC) classes over 10-year period (2009-2018) which indicated the number of years with repeated predictions of the same HEC class.

as shown in Figure 3.10. The increasing trend of High HEC was captured in both dry and wet season, although the peak values were lower in the wet season. Potential HEC areas expanded more than double between 2016 and 2017, of which areas with High conflict increased from 2,235 to 4,306 km^2 and 115 to 2,467 km^2 in the dry and wet season respectively. The dry season was dominated by two conflict categories, High and Low. On the other hand, similar trends were presented across all conflict categories in the wet season despite variations of affected areas among the years. For Likely conflict, the wet seasons had a similar increasing trend to that of the High conflict category. However, the dry seasons had relatively stable areas of the Likely and Rare HEC.

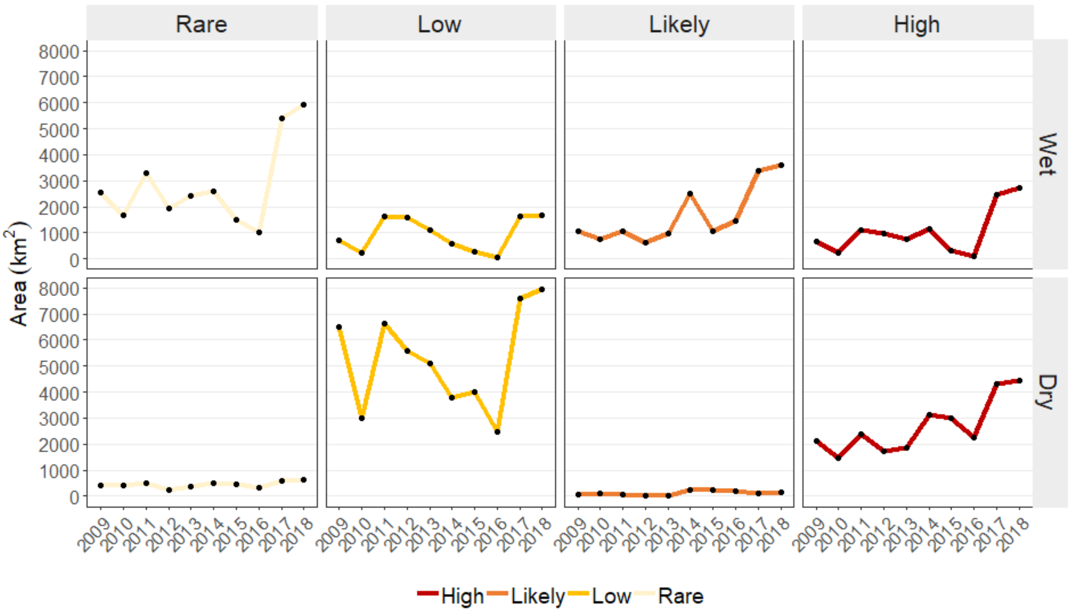


Figure 3.10: Total areas (km^2) of human-elephant conflict (HEC) under each category showed an overall increasing trend from 2009 to 2018.

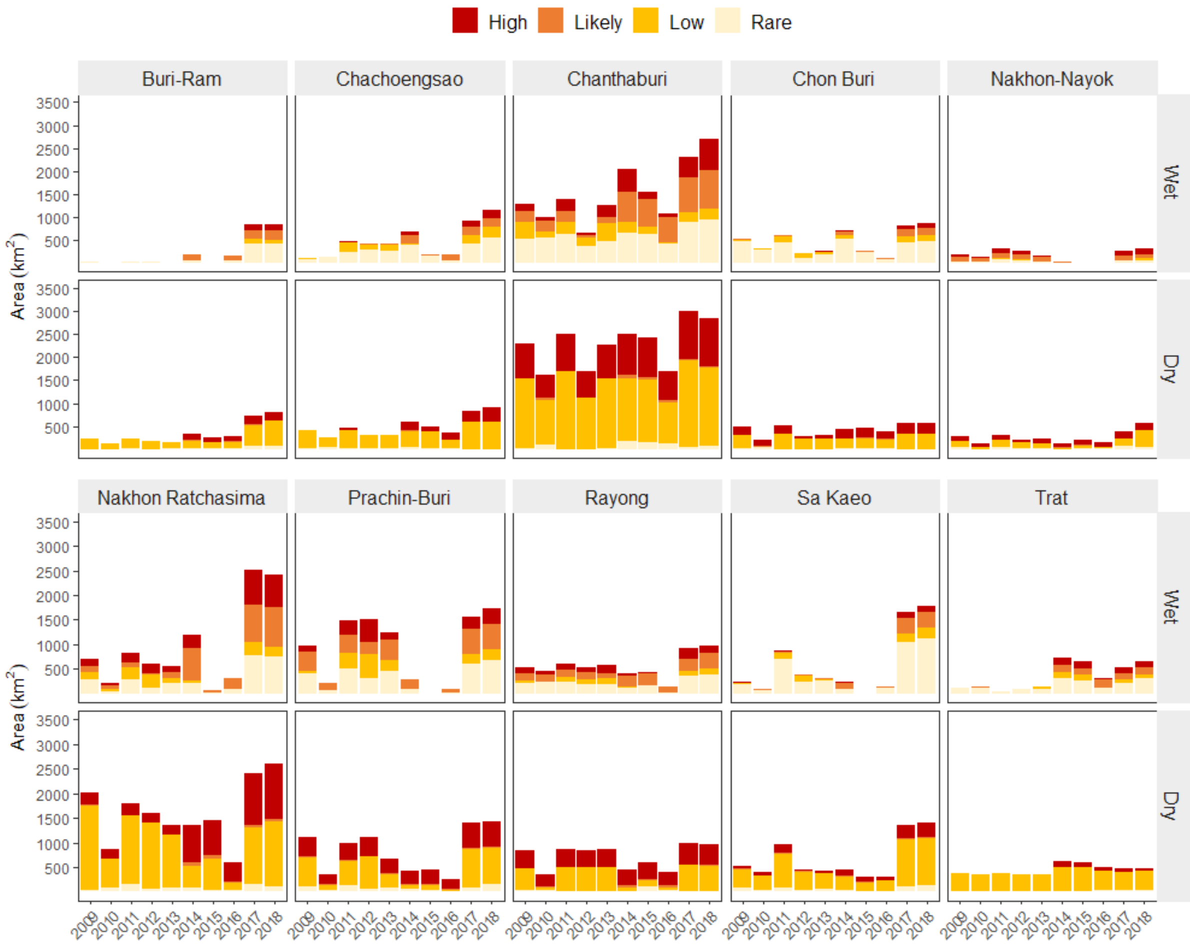


Figure 3.11: Areas of human-elephant conflict (HEC) under each category calculated by province from 2009 to 2018 showed that Chantaburi had the largest HEC areas.

Chantaburi was estimated to have the largest areas of HEC, followed by Nakhon Ratchasima (Figure 3.11). In Chantaburi, large areas of High HEC (approx. 900 km^2) were estimated in the dry season from the beginning of the study period. The province showed an increase in overall areas of conflicts, as well as the largest area expansion of High HEC captured in the wet season, from 170 km^2 in 2009 to 689 km^2 in 2018. Nakhon Ratchasima also had large HEC-prone areas, but the High conflict category showed a large increase only from 2014 onward. Similar to Nakhon Ratchasima, Buri-Ram and Chachoengsao were predicted with High HEC from 2014. Except Nakhon Nayok and Trat, all provinces were predicted to have a larger area of High conflict category during the dry season. HEC areas were increased more than double from 2016 to 2017 in Buri-Ram, Chachoengsao, Chantaburi, Nakhon Ratchasima, Prachinburi, Rayong, and Sa Kaeo. On the other hand, a decrease in the areas of HEC was identified in 2010 and 2014-2016 for most provinces.

3.3.3 Drivers of changes in HEC probability over time

We identified the contribution to changes of HEC by evaluating HEC probability from resource suitability and direct human pressure across the study period. From Figure 3.12a, HEC probability from direct human pressure scenario generally showed a gradual increasing trend with an exception of a drastic area expansion in both High (2,203 to 6,503 km^2) and Low (4,773 to 8,983 km^2) classes in 2014. This sudden increase was likely caused by lit-up areas increased as a result of improved night-time light sensor started from 2014 onward. For resource suitability scenario, a clear pattern cannot be observed. Hence, variation of predicted HEC category seen among different years were likely due to the dynamic changes in suitable resources. Areas of High and Low probability under resource suitability were reduced over half in 2010 and seemed to continuously decrease from 2012 to 2016. This reduction in HEC areas coincided with the high anomaly of KBDI period in Thailand.

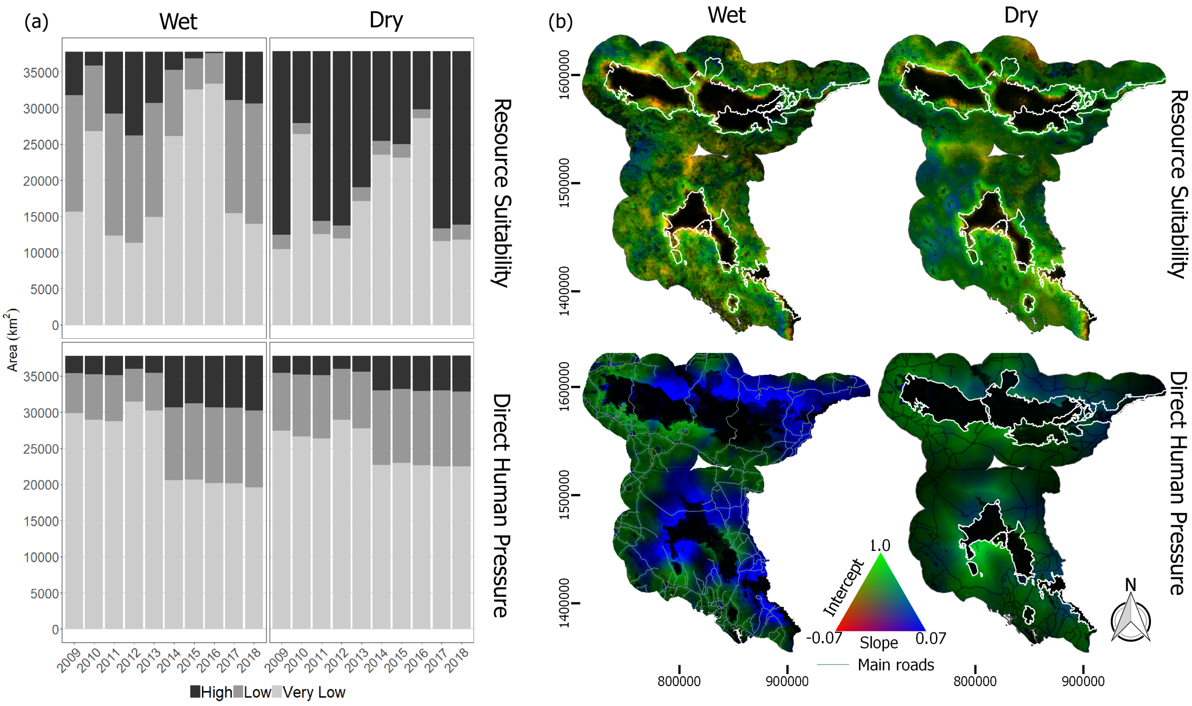


Figure 3.12: (a) Temporal distribution of areas predicted as High, Low, and Very Low category during 2009-2018.(b) Changes in HEC probability from 2009 to 2018 under resource suitability and direct human pressure scenarios. Each location presents two values, a slope and an intercept. The maps are visualized using RGB composite, Red: negative slope (decreasing trend), Green: intercept (baseline of HEC probability in 2009), and Blue: positive slope (increasing trend).

Figure 3.12b shows spatial distributions of changes in HEC probability from 2009 to 2018 under resource suitability and direct human pressure scenario. Each location on the maps conveys two information, (i) a regression slope (a rate and direct of change in HEC probability), and (ii) a regression intercept (a baseline of HEC probability in 2009). A decreasing trend is shown in red and an increasing trend in blue. A high 2009 baseline is shown in bright green, while a lower baseline is in darker shade.

In resource suitability maps, areas with orange color corresponded to a high baseline with moderate negative rate of change in HEC probability. This decreasing trend (-0.07 to -0.04 per year) in both wet and dry season was mainly predicted around the edge of the forests. Base on MODIS land cover (Figure 3.13), the reduction of HEC probability near the forest was due mainly to forest cover increased over the years. According to the predictors' responses in Figure 3.7, areas with high forest densities and nearer to forest were estimated with lower HEC probability. Positive trends (0.2 to 0.4 per year) was sparsely predicted in both wet and dry seasons on the west-side of Ang Ruenai-WS in Chachoengsao and Chantaburi provinces. Although we cannot specify a reason behind this increase, we observed from MODIS land cover that there was an expansion of the savannas land cover during 2017-2018, as well as increased of forest in those areas (Figure 3.13b). The high HEC probability of EVI slope corresponded to the characteristics of forest and savanna which may have heightened the predicted probability.

For direct human pressure scenario, large areas of increasing trend occurred in previously low and moderate HEC probability baseline in wet (a pure bright blue) and dry (a dark greenish-blue) season respectively. These areas were located around Ang Ruenai-WS, north-east of Khao Yai-NP, and north of Thablan-NP. Since the variables used under direct human pressure scenario only contain static and annual characteristic (Table 3.1), the differences observed between seasons were not the result of physical differences. The dissimilarities were due to seasonal differences of variable response that governed HEC prediction. In addition, the southern areas of Ang Ruenai-WS were predicted with constantly high HEC probability (around 0.7) from human pressure in the dry season. The increasing trend within the same areas in the wet season (a rate of 0.07 to 0.10 per year) likely caused a year-round HEC. The large positive trend from direct human pressure, when happen in areas with already high HEC probability predicted under resource suitability, may escalate HEC to a higher category. Lastly, spares areas in orange indicated a decreasing trend in HEC probability. These areas scattered in the west near the main roads. This is due to human population growth. The same was not predicted for the dry season because of the differences in variable response between the two models.

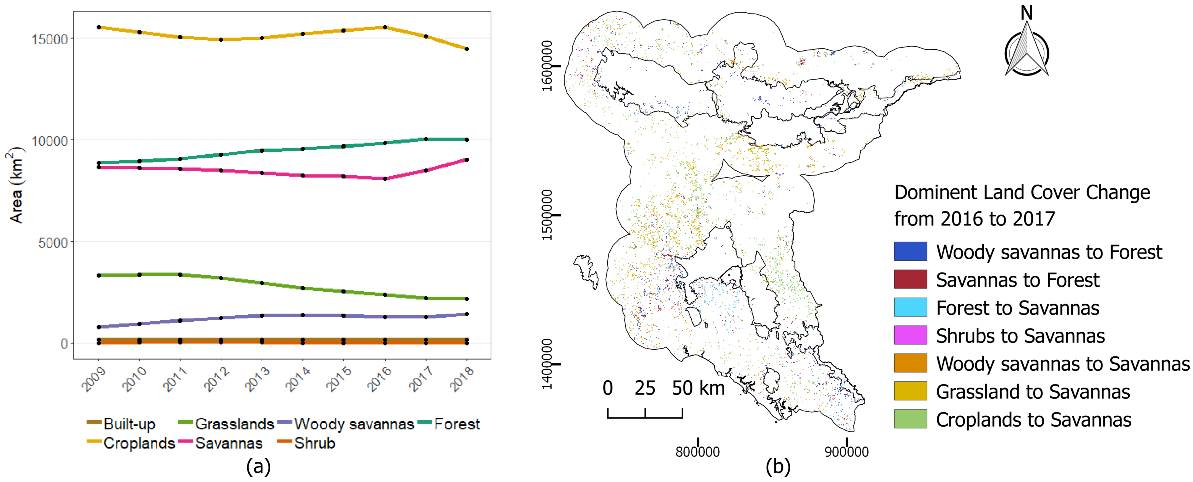


Figure 3.13: (a) Areas of different land cover types from 2009 to 2018 of the reclassified MODIS land cover classes (b) Dominant land cover changes detected between 2016 to 2017.

3.4 Discussion

3.4.1 Implication of the proposed models

Using two-dimensional classification together with time-calibrated SDM on remotely sensed satellite data, I predicted and compared potential HEC distribution in Eastern Thailand from 20 seasons across 10-year period. Making informed decision on where to allocate limited resources is crucial for government and conservation organizations alike (Bottrill et al., 2008). A two-dimensional classification approach has been used to identified management-relevant actions in habitat modeling (De Angelo et al., 2013; Bleyhl et al., 2015; Romero-Muñoz et al., 2019). Utilizing similar method, we recommended prioritization of HEC-zone dependent management actions. Two groups of management actions are considered, (i) natural resource/land management and (ii) promotion of human adaptation. High HEC zones must receive first priority with parallel emphasis on both land-use policies and human adaptation. Together with HEC-relevant land management, behavioral adaptation of those who live in the areas are important to reduce risky behaviors. In Likely HEC zones, certain land management actions are not necessary (e.g. permanent electric fences), but more focus should be put on community development. For areas with Low HEC category, the extensive change in human behavior may not be needed (e.g crop husbandry), but general knowledge on appropriate actions when encountering with wild elephants are potentially useful. In such areas, land use planning is more important in preventing further escalation of conflict. Lastly, Rare HEC zones were predicted sparsely and far from protected areas (Figure 3.9). Since these areas were concentrated closer to the main roads, management may focus on the risk of vehicle-elephant-collision. Further field investigation and data collection are necessary to pinpoint appropriate management actions.

3.4.2 Climatic and drought impacts on HEC distribution

Overall, the models predicted the occurrence of large HEC-conflict areas during the dry season which decreased both in term of spatial extent and intensity during the wet season. Chantaburi and Nakhon Ratchasima were predicted to have the largest HEC-prone areas. Drought-induced decrease in the distribution of suitable resources (base on KBDI index), resulted to a relevant decrease in the spatial extent of HEC. The high KBDI detected in 2010 and 2014-2016 (Figure 3.8) coincided with the El Nino phenomena that caused severe and prolonged drought in Thailand (NOAA/National Weather Service, 2019). This caused a decrease in the spatial HEC extent in some provinces, but HEC extent increased in other provinces. Previous studies in arid savannas showed that extreme drought can alter the distribution and abundance of elephants population, leading to mass starvation Wato et al., 2016; Foley, Pettorelli, and Foley, 2008. However, such extreme events is usually not considered during modeling. Considering that dry periods, and their associated extreme drought events, may occur more frequently due to climate change, HEC distribution may become unpredictable, causing critical management implications. Additional field investigation is required to examine whether or not a decrease in the spatial HEC extent in some areas may result to concentrated increase of elephant-induced damages in other locations.

3.4.3 Importance of forest and changes in land cover

The peak of HEC probability for forest percent cover, a variable with the highest predictive power, was identified at 25-45%. Forest land cover mainly entailed protected areas. Hence, HEC occurred in areas close to elephant natural habitats. Although high HEC occurrence near protected areas is expected, the peak probability implies that conflict incidents do not always locate directly adjacent to protected parks. Available patches of forest outside of protected areas, such as community forest, may assist in wild elephant dispersal as long as the composition with other land cover provide 25-45% cover within

6km. Further field study is necessary to identify the size of forest patches required by elephants outside of protected areas.

HEC hotspots along the southern and western of Ang Ruenai-WS were dominated by savannas land cover, a mixed tree and grass system. The peak in HEC probability as seen from EVI slope coincided with characteristics of MODIS savannas and forest land cover class. By comparing MODIS land cover with land use map from Land Development Department, Ministry of Agriculture and Cooperatives of Thailand, savannas land cover was generally rubber plantations and orchards. Available tree canopies in these land use, despite being sparse, may provide cover for elephants and assist in their movement. Studies in India and China identified proximity to forest edge and high-statue vegetation (e.g. eucalyptus and acacia) as important factors determining elephant occurrences outside of protected areas (Kumar, Mudappa, and Raman, 2010; Liu et al., 2016; Li et al., 2018). With large continuous extant of savannas within these hotspot, together with high HEC predicted across both season, elephants may already be frequent and even residing permanently in the areas.

3.4.4 Comparison of certain variables to existing studies

Although predictor responses were generally similar to studies from other Asian countries, some variable contributions were different. Distance to water has been identified as an important factor determining elephants distribution in China (Li et al., 2018), Indonesia (Evans, Asner, and Goossens, 2018), India (Lakshminarayanan et al., 2016), and Thailand (Meijer et al., 2018). In this study, however, it was not a prominent predictor. We expected the reason to be the coarse spatial resolution as we re-sampled the data from 30m to 500m. Consequently, small water bodies located in individual farmers' lands might not be captured. Although vegetation index was a good proxy for forage quality in (Pettorelli et al., 2005), the EVI variable had relatively lower predictive importance in our study. Usefulness of vegetation index depends highly on the types of habitat and the season (Borowik et al., 2013). In tropical forest, elephant forage abundance was unable to be mapped directly using average value of NDVI (Gautam, Arulmalar, and Kulkarni, 2019). Nevertheless, EVI slope had the highest predictive power among all EVI variables, implying possible importance of vegetation phenology. A study of crop raiding behavior in African elephants identified crop availability and ripening timing as important indicators for predicting crop damage (Branco et al., 2019). Therefore, variables related to crop types along with its phenology, which can be detected from remotely sensed satellite data, should be further studied.

3.4.5 Limitations and uncertainties of current assumptions

Overall our calibrated models had a good to very good predictive power with AUC ranging from 0.73-0.81. Nevertheless, this study still contains limitations and uncertainties. First, although bias correction was applied, we still cannot account for unreported locations where HEC occurred but not reported in the news. Second, different in variable responses were identified between wet and dry season, but the significance between predicted wet and dry HEC distributions remain to be evaluated. Having two separate HEC maps can support effective operational planning (e.g. seasonal patrol routes), but can also cause confusion for policy-level planning. Future study can evaluate models from key season similar to (Bleyhl et al., 2015) in which winter season was chosen. Third, additional variables can be included to provide better prediction of HEC occurrence. Besides potential use of cropping pattern and phenology, human tolerance and perception of risk should also be considered. These factors represent the possibility of coexistence between human and wildlife (Morzillo, Beurs, and Martin-mikle, 2019). Fourth, current mitigation efforts have not been included, but are essential as they can alter elephants' access to resources. Previous studies have shown that implementation of physical barriers shift HEC to new locations (Osipova et al., 2018). Such data on existing mitigation can be incorporated after to identify movement routes and potential corridors. Lastly, future study can include assessment of habitat quality within protected areas. Our models predicted an increase in potential HEC areas after prolong drought during 2014-2016. We cannot infer a conclusion based on our current study. However, extreme events can cause a change to land use and vegetation in the following years, impacting elephant's natural habitat and adjacent agricultural lands. Such information can elucidate root cause of conflict and enhance management decision.

3.5 Conclusion

This study utilized publicly available dataset and applied time-calibrated SDM with two-dimensional conflict classification to estimate time-series distribution of potential HEC in eastern Thailand. Three objectives were raised which included (i) to model the potential spatial distribution of seasonal HEC from 2009 to 2018, (ii) to identify and distinguish the contribution over time of important factors influencing HEC distribution, and (iii) to prioritize the areas that require targeted management and increased intervention.

As for the first objective, overall increasing trend of potential areas affected by HEC was predicted. HEC was projected to occur in both wet and dry season, with larger extend during the dry season. All provinces in the Eastern region experienced HEC at varying level across the seasons. In 2018, overall area of HEC under high category was estimated to cover 5,381 and 8,806 km^2 in the wet and dry season respectively. These were approximately triple and double the areas of high HEC in the wet and dry season during 2009. Chantaburi had the largest areas of HEC, followed by Nakhon Ratchasima. Nakhon Nakok, on the other hand, showed the smallest areas potentially affected by HEC. The reduction of conflict areas in 2010 and 2014-2016 were identified and likely explained by severe drought from El Nino events which was captured by KBDI. The increase of HEC areas noticeably from 2016 onward was possibly a result of land cover change.

For the second objective, the results suggested that variation in the probability and distribution of HEC was due to changes in resource suitability, while a more continuously gradual increase was observed from direct human pressure. Resource suitability was prominently governed by forest percent cover, drought condition, and distance to forest. This result implied that forested areas remained the source habitat and critical refuge for elephants, while drought seasonally alter resource distribution and the consequent changes in elephant presence and HEC. For direct human pressure, distance to protected habitat, level of human density, and distance to transport network were the key factors affecting HEC distribution.

Besides identifying HEC response to environmental characteristics, the findings can also support prioritization of conservation resources which answered the third objective. Based on the analysis, I proposed HEC-zone dependent management. Parallel emphasis on extensive land management and human co-adaptation should be performed in High HEC-zones. In Likely HEC-zones, more attention should be given to raise safe behaviors for communities. Land use policies in Unlikely HEC-zones should be strengthened with general awareness of appropriate actions when encountering wild elephants. Rare HEC-zones were scattered close to main roads, hence investigation to prevent vehicle-elephant collision should be given priority. Within each zone, more focus can be given to hotspots that estimated with repeated HEC. Lastly, this study highlighted the advantages of satellite-derived variables with high temporal resolution which can capture annual and seasonal variation.

In this chapter, the evaluation of HEC in Eastern Thailand was conducted in which increasing trend of spatial distribution from 2009 to 2018 was identified. Climate variations, specifically drought condition, was one of the key factors influencing alteration in HEC. With such increasing trend in recent years and imminent climate change impacts, consideration of future climate scenarios on HEC distribution can further improve long-term planning. In addition, the analysis in this chapter was confined only in Eastern region due to the lack of records of HEC incidents. However, whole country assessment is crucial for a holistic planning. Following the understanding gained and key variables identified in this chapter, Chapter 4, will propose assessment framework that enables whole country evaluation along with the incorporation of future climate scenarios.

Chapter 4

Countrywide HEC risk assessment under climate and land cover change scenarios in Thailand

4.1 Introduction

Human-Elephant Conflict (HEC) escalated in many countries and became an important issue for both elephant conservation and human development (Hoare, 2015). Among the countries hosting Asian elephant population, Thailand faced with increasing HEC incidents in most protected areas hosting elephant populations (Noonto, 2009). An average of 212 nights was annually spent by household in guarding crops against elephant-raiding and the HEC-induced cost is significant compared to average household income (Jarungrattanapong, Olewiler, and Nabangchang, 2017). Threats associated with wildlife, including HEC, is considered as small frequent events which are commonly neglected in risk assessment and consequent disaster risk management policies (Gaillard et al., 2019). Nevertheless, the impacts from small frequent events usually accumulate and massively erode society's ability to handle next hazardous incidents and achieve sustainable development (Wisner and Gaillard, 2009; UNISDR, 2015). Gaillard et al. (2019) emphasized the gap and necessity to reconcile human-wildlife conflict and disaster risk management as an integrated approach to broaden beyond managing conflict incidents.

The first step toward integration of risk reduction and HEC is to quantitatively measure HEC risk. Risk measurement is common in disaster and climate change risk analysis and essential for informed decision. Despite its initial parallel development, disaster risk reduction (DRR) and climate change adaptation (CCA) communities jointly adopt the same risk assessment framework (Birkmann and Welle, 2015; Sudmeier-Rieux et al., 2019). In particular, risk is defined as the probability of negative consequences from the interaction of hazards and the vulnerabilities of exposed elements (UNDP, 2010; IPCC, 2012). The framework had long been utilized in assessing natural disaster risk, such as floods, droughts, and earthquakes (UNISDR, 2015). It was recently also applied by the Intergovernmental Panel on Climate Change (IPCC) as part of its Special Report (IPCC, 2012) and the Fifth Assessment Report (IPCC, 2014). This risk assessment framework became an established practice to guide decision-making in government, business, and international organizations.

Traditional conservation plannings frequently rely on localized historical records; however, they are unlikely to cope with rapidly changing and uncertain future (Peterson, Cumming, and Carpenter, 2003). Scenario plannings, on the other hand, allow decision-makers to explore plausible futures and develop relevant alternative actions (Mahmoud et al., 2009). Foden et al. (2019) emphasized the importance to evaluate future climate impacts on species in order to identify needed modifications to conservation strategies. Titeux et al. (2016) addressed that future scenarios in ecological modeling should consider climate change, as well as inter-related climate and human-induced land cover change. Climate change causes a stronger impact on the spatial distribution of species at regional scale, while land cover changes influence more prominently at a finer-scale (Sirami et al., 2017). Similarly, future climate and anthropogenic change are expected to alter resource dynamic requiring both humans and elephants to adapt (Shaffer et al., 2019). However, it remains uncertain whether future changes will increase or decrease the likelihood of HEC. Hence, future scenarios should be incorporated to HEC risk assessment to support conservation planning for long term co-existence (Shaffer et al., 2019)

Some studies attempted to assess future changes of the interaction between humans and wildlife. Using Species Distribution Modeling (SDM) under future land use scenarios, Saito et al. (2016) projected higher conflict between humans and large mammals in Japan due to the estimated expansion of the studied species in 2028. Brambilla et al. (2016) also applied SDM technique and predicted potential conflict from the higher overlap between areas suitable for ski-pistes and those for high-elevation bird species based on various climate change scenarios in 2050. Schwartz et al. (2012) modeled four future scenarios of urban expansion and quantified the loss of key grizzly bear habitats within Greater Yellowstone Ecosystem. Specifically for HEC, Naha et al. (2019) applied SDM method and predicted the probability of HEC based on land cover in 2028 which was projected from historical land cover change trend. These studies, however, separately considered either changes in climate or land cover. In addition, the land cover scenarios were mainly based on historical trend and did not considered climate-induced effects. Socioeconomic factors, such as human population trend, were not considered, although conflict with wildlife is influenced by changes in socioeconomic aspects.

New set of future scenarios was developed based on the combinations of Representative Concentration Pathways (RCPs) and the Shared Socioeconomic Pathways (SSPs) (Vuuren et al., 2014). RCPs cover different trajectories of time-dependent projections of atmospheric greenhouse gas (GHG) concentrations which affect the climate radiative forcing and consequent warming of the planet (Vuuren et al., 2011). SSPs provide qualitative narratives and quantification of key socioeconomic variables which can alter the challenges to mitigation and adaptation to climate change, such as population growth, income, urbanization, agriculture production, among others (Riahi et al., 2017; O'Neill et al., 2017). The RCP-SSP scenarios were used in various future assessments, such as species range shift (Beyer and Manica, 2020), habitat loss in terrestrial vertebrate (Powers and Jetz, 2019), and costs of flood protection (Ward et al., 2017). The application of RCP-SSP is paramount for risk assessment. However, it remains limited in HEC especially at the national scale.

4.1.1 Objectives

In this chapter, I proposed and demonstrated the application of HEC risk assessment framework with RCP-SSP scenarios to estimate spatial distribution of HEC risk at baseline (2000-2009) and near future (2025-2044) in Thailand. The scenarios will evaluate the future changes in climate, related land cover, as well as HEC-based spatial policy. The specific objectives were to :-

1. assess the change in hazard sub-components between baseline and future scenarios
2. assess the change in exposure sub-components between baseline and future scenarios
3. assess the change in vulnerability sub-components between baseline and future scenarios
4. compare baseline HEC risk and quantify relative changes in the future

4.2 Methodology

4.2.1 Study location

In this study, Thailand was selected for analysis. Historically, wild elephants were sighted across the country even at the peripheral of Bangkok, the country's capital city (Sukmasuang, 2015). However, high timber demand during the 1970s led to large deforestation (Hirsch, 1990). Forest conversion was further exacerbated by government-led policy to allow settlement of unoccupied land, as well as the expansion of commercial agriculture (ICEM, 2003). Between 1980 to 1990, Thailand had the highest deforestation rate in the region with 2.6% annual forest loss (Hirsch, 1990). The 1989 nationwide ban on logging, which slowed down deforestation, was put in place following massive international campaigns and disastrous floods (Grainger, 2004). However, explosive growth in the economy continued to boost the demand for infrastructure development with various transport and dam construction projects. Despite slowing rate of deforestation and subsequent reforestation efforts, most forested area had already been lost with a remaining forest cover of 25% in 1993 compared to 53% in 1961 (Wannitikul, 2005).

Thailand's protected areas were first inaugurated in the 1960s and rapidly increased during the 1980s and 90s (ICEM, 2003). However, most land areas had already been developed and Thailand's protected areas were deemed too small to conserve biodiversity and sustain wide-ranging large species like elephants (Suksawang, 2018). As of 2015, there were 147 National Parks (NP) and 58 Wildlife Sanctuaries (WS) in Thailand, of which 68 hosted elephant populations (Suksawang and Mcneely, 2015; Noonto, 2009). Most elephant populations were confined within these fragmented protected areas surrounded by human-induced agriculture lands (Leimgruber et al., 2003). To facilitate more effective management of ecosystem within adjacent protected areas and surrounding lands, landscape-conservation units called forest complexes (FC) were designated (Suksawang, 2018). Three main groups of elephant population are currently located in the Western FC, the Khaengkrachan FC, and in Eastern region comprised of the Eastern FC and the Khao Yai-Dong Prayayen FC (Figure 4.1).

As discussed in Chapter 2, Thailand is likely leading the development path which other range countries in southeast Asia will follow. In term of HEC, this suggested Thailand as an interesting case study where forested areas are restricted among highly developed land cover. Additionally, growth in Thailand's urbanization and aging population are expected to induce a continuous reduction in rural population (World Bank, 2020b). Similar situation caused land abandonment and subsequent habitat recovery in depopulated rural areas of Japan (Tsunoda and Enari, 2020). If the same will occur in Thailand, the future of HEC situations is uncertain.

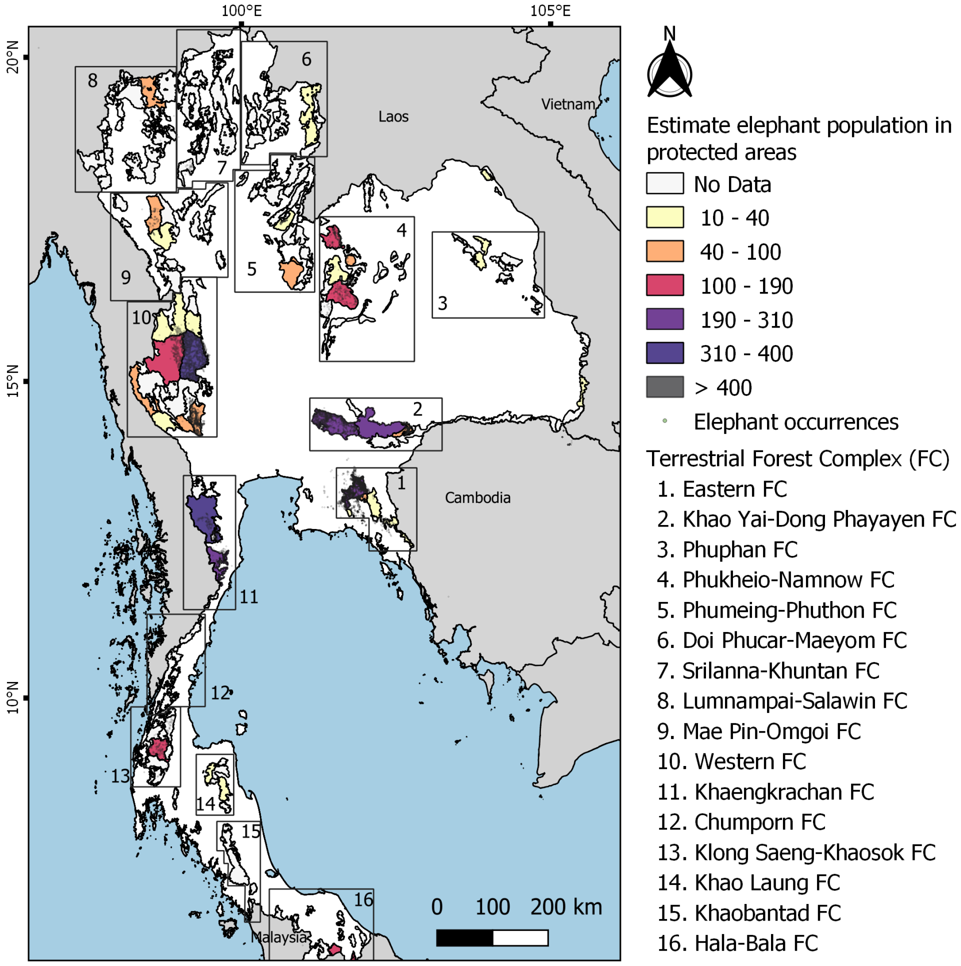


Figure 4.1: The map of the study location covering the whole of Thailand. The estimated elephant population is shown for each protected areas, while established forest complexes are numbered.

4.2.2 Definition of HEC risk and underlying components

Following IPCC (2012) definition, risk is defined as a function of hazard, exposure, and vulnerability. To adopt this framework for HEC, HEC risk is defined as the probability of wild elephant occurrence (hazard) in overlapping areas with human population (exposure) who possess different vulnerable levels (vulnerability). The implementation of HEC risk assessment required the selection of hazard, exposure, and vulnerability components. The overview of proposed HEC risk components was shown in Figure 4.2 and Table 4.1.

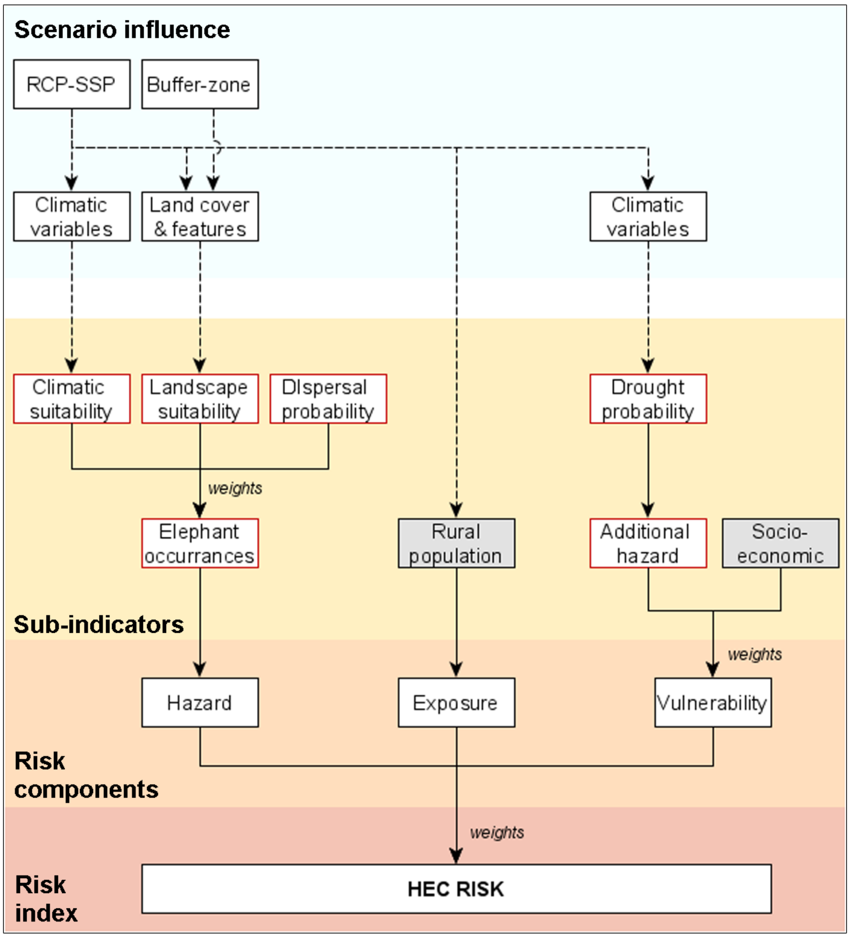


Figure 4.2: The overview of risk components in this study which comprised of hazard, exposure, and vulnerability. Highlighted in red-boxes are sub-indicators that must be calculated, while gray boxes were obtained directly from ancillary data or projections provided by other studies.

Hazard: Hazard refers to any phenomena that may cause negative impacts, such as damage to properties, injuries to human, or socioeconomic disruption (IPCC, 2012). In represent HEC hazard, the probability of elephant occurrence was chosen. Three sub-indicators must be obtained to determine this hazard probability. These three components included (i) climatic suitability for elephant, (ii) landscape suitability for elephants, and (iii) elephant dispersal probability from protected areas. The climatic and landscape suitability were modeled using SDM technique with relevant variables previously identified to influence elephant presence. The variables selected for modeling are discussed in detail under section 4.2.5. Dispersal probability was considered because the proximity to source habitats, such as protected areas, is the dominant factors in determining HEC

Table 4.1: The sub-indicators chosen for this study to represent *Hazard*, *Exposure* and *Vulnerability* are listed.

Indicators	Data	Baseline	Future
Hazard : the probability of elephant presence			
Climatic suitability	Calculate	X	X
Landscape suitability	Calculate	X	X
Dispersal probability	Calculate	X	-
Exposure : the number of population potentially affected by hazard			
Rural population	Gao 2020	X	X
Vulnerability : susceptibility of population to the loss from exposed hazard			
Technology	NSO[1]	X	-
Education	NSO[1]	X	-
Income	NSO[1]	X	-
Drought probability	Calculate	X	X

[1] Thailand National Statistic Office

(Chapter 3). The closer to protected areas, the more likely that HEC will occur.

Exposure: Exposure is defined as any assets (e.g. people, properties, etc.) that are present in the overlapping areas with hazards, and are thus subjected to potential loss (IPCC, 2012). The number of potentially affected human population was used to represent exposure in this study. Only rural population was considered because HEC incidents more commonly occur in rural areas close to elephant habitats. Spatially explicit dataset for rural population is available from Gao (2020) and was used.

Vulnerability: Vulnerability is the characteristics of assets, in this case rural population, that make them susceptible to the negative effects from hazards (IPCC, 2012). Human population exposed to the same level of hazards will response differently depending on their vulnerability level. The sub-indicators for HEC vulnerability can be divided into two groups, (i) the socioeconomic group representing human capital and (ii) the additional hazards group incorporating added pressure from other natural disasters. The socioeconomic sub-indicators were obtained from the National Statistic Office of Thailand (NSO, 2020). These sub-indicators intended to represent level of adaptive capacity in an event of HEC. Technology, education, and income level were previously identified to influence the vulnerable level of communities to wildlife threats (Nyirenda et al., 2018; Water and Matteson, 2018). Drought can further add to the vulnerable of human population and was considered under additional hazard sub-indicator. Drought was chosen as it historically disrupted Thailand agricultural sector (Prabnakorn et al., 2019) and expected to cause large yield reduction in the future (Leng and Hall, 2019).

4.2.3 Proposed future scenarios

Scenarios of plausible future allow an evaluation of potential outcomes which support suitable design of policies under interacting-complex system and uncertainties (Moss et al., 2010; Bai et al., 2016; Kebede et al., 2018). This section introduced climate change scenarios from RCP-SSP and HEC spatial policy represented by buffer zones that were chosen for the current assessment.

Combination of Representative Concentration Pathways and Shared Socioeconomic Pathways (RCP-SSP)

In this study, climate change scenarios were from existing global projections of potential changes in climate and socioeconomic aspects. Each RCP is a different scenario based on how quickly greenhouse gas (GHG) concentration in the atmosphere can be reduced. RCPs provide climate predictions. SSPs provide trajectories of how society, demographics and economics might change, especially those factors underlying climate change mitigation and adaptation. Various RCPs and SSPs are available (Vuuren et al., 2014), but two RCP-SSP combinations were used in this study. The characteristics of each chosen RCP and SSP were summarized in Table 4.2.

Table 4.2: The characteristics of Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs) chosen for this study. The color-coding showed the chosen RCP-SSP combinations, RCP4.5-SSP2 (light-shade) and RCP8.5-SSP5 (dark-shade).

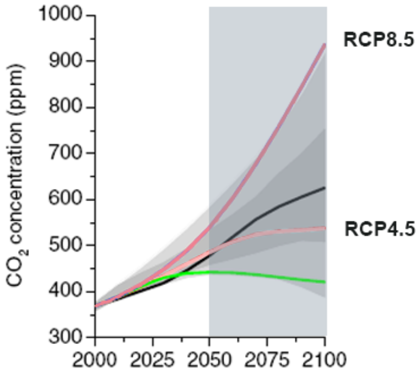
Pathway	**Key characteristics**	
RCP4.5	Radiative forcing 4.5 W m−2 by 2100 Very low baseline GHG emission with medium-low mitigation Medium air pollution	Slowly declining emission
RCP8.5	Radiative forcing 8.5 W m−2 by 2100 High baseline GHG emission Medium-High air pollution	Rising emission
SSP2	Medium population Medium urbanization Medium uneven economy Medium pace of tech change and productivity	Middle of the road
SSP5	Low-Medium population High urbanization High economy Rapid increase in productivity	High reliance on fossil fuel

The RCP4.5 is a trajectory for radiative forcing of $4.5Wm^{-2}$ corresponding to a global mean temperature of +1.8°C and considered as 'middle of the road' scenario where the emission is slowly declining (Thomson et al., 2011). The RCP4.5 assumed a slow start of emission reduction which corresponds to government efforts proposed for the Paris agreement (Van Hooidonk et al., 2016). On the other hand, RCP8.5 represents the high emission trajectory for radiative forcing greater than $8.5Wm^{-2}$ corresponding to +3.7°C (Moss et al., 2010). This scenario assumed the continuous reliance on fossil fuel with rising emission and is sometimes referred to as 'business-as-usual' scenario. Therefore, these chosen climate scenarios represent the likely future of whether emission reduction is committed (RCP4.5) or not (RCP8.5). The quantitative projections of the underlying GHG emission (Figure 4.3a) were used by experts to generate Global Circulation Models (GCMs) which estimate various climatic variables, such as temperatures and precipitation.

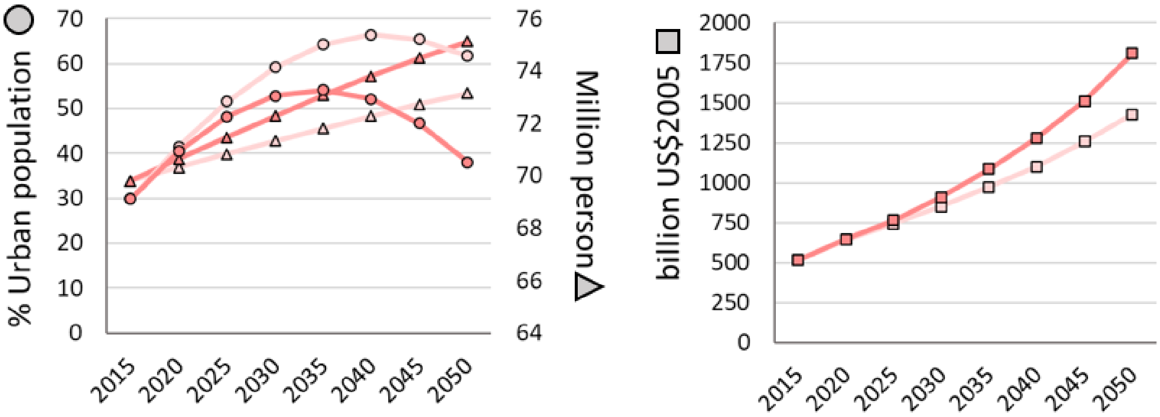
For socioeconomic trajectories, SSP2 and SSPs were selected. Vuuren et al. (2014) proposed scenario matrix which evaluated the possible combinations of RCPs and SSPs. It was suggested that RCP4.5 can be matched with SSP2, while RCP8.5 with SSP5. The same RCP-SSP combinations were adopted for the development of the next generation Coupled Model Intercomparison Projects or CMIP6 (O'Neill et al., 2016). SSP2 describes intermediate challenges mostly following historical pattern with heterogeneity within and across countries (O'Neill et al., 2017). SSP5 represents high development in economic and human capital with strong reliance on fossil fuels and the lack of environmental concerns (O'Neill et al., 2017). Along with the qualitative scenarios, the underlying key factors were quantitatively estimated as shown in Figure 4.3b. These data were used for land cover projection in this study.

HEC spatial policy around protected areas (buffer zones)

Buffer zone is one of the long-term conservation strategy where locations peripheral to protected areas are designated with special regulations. It is common that only ecologically low impact activities are allowed within the buffer zone, while communities are subsidized for possible costs, such as damages from wildlife (Wegge, Yadav, and Lamichhane, 2018; Lamichhane et al., 2019). Although having a buffer zone does not equate to the elimination or even a reduction of HEC (Sharma et al., 2020), the establishment of buffer zones is critical to allow application of land-use planning and relevant support to communities within the areas.



(a) RCP scenarios (Vuuren et al., 2011)



(b) SSP2 and SSP5 quantitative projection (Riahi et al., 2017)

Figure 4.3: The quantification of some underlying drivers for RCPs and SSPs is shown with color-coding corresponded to that shown in Table 4.2, RCP4.5-SSP2 (light-shade) and RCP8.5-SSP5 (dark-shade).

The appropriate formulation of buffer zones require on-the-ground information and participatory of local communities. I do not attempt to specify precise location of buffer zones, but rather evaluate the what-if scenarios where the implementation of buffer zones is considered. In this study, buffer zones were considered around protected areas with known elephant populations (Figure 4.1). A 12-km buffer from the boundary of such protected areas were chosen based on the average daily round-trip distance traveled by elephants from the forest edge to forage on agricultural lands and back (interview with park rangers at Khoa Yai National Parks on September 2019). I assumed that, within this 12-km buffer zones, no additional land conversion of any type is allowed.

Four future scenarios

Figure 4.4 illustrated the general narratives in this study where combination of RCP-SSP are matched with the spatial policy with and without buffer zones (BZ). The combination provided four possible future scenarios, namely A1 (RCP4.5-SSP2-BZ), B1 (RCP4.5-SSP2-noBZ), A2 (RCP8.5-SSP5-BZ), and B2 (RCP8.5-SSP5-noBZ). Based on narrative characteristics (Table 4.2), RCP4.5-SSP2 ('1'-scenario) is estimated with some demand reduction for agricultural land due to moderate development in yield productivity, while RCP8.5-SSP5 ('2'-scenario) is expected to have further reduction of agricultural land from both the grater advancement in technology and the combination of lower population growth with high shared of urban resident. '2'-scenario are expected to face higher change in temperature and precipitation which will likely impact level of drought. 'A'-scenarios include buffer zone consideration, while 'B'-scenarios do not.

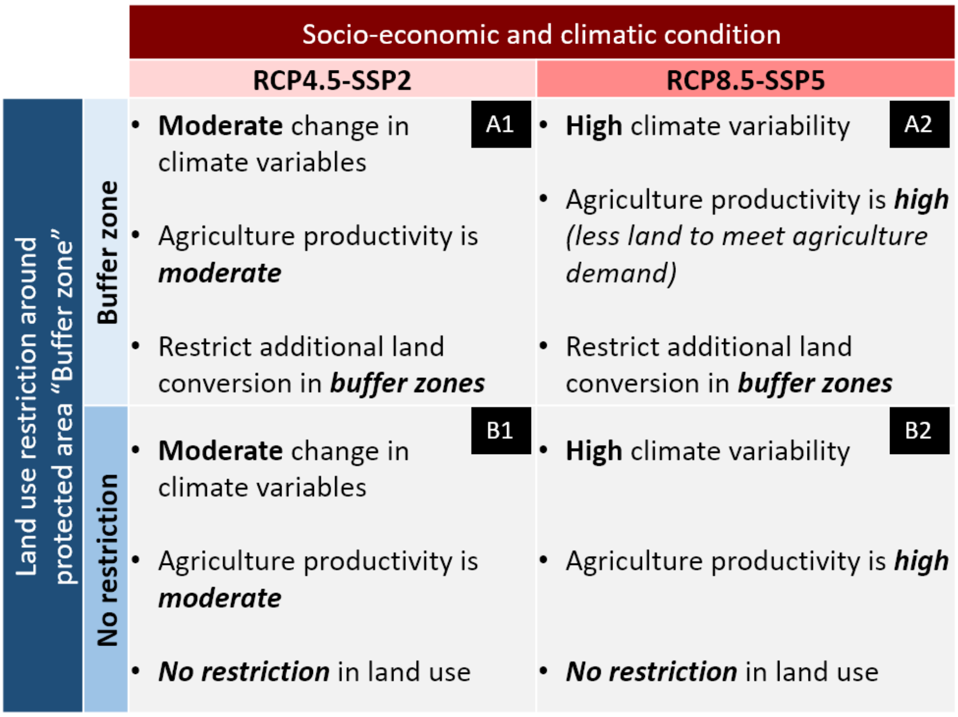


Figure 4.4: The proposed scenarios for this study considering RCP-SSP combination and the spatial policy to establish buffer zones around protected areas with elephant residents

4.2.4 Dataset

Climatic dataset

The climatic dataset used in this study are listed in Table 4.3. Minimum temperature, maximum temperature, and precipitation were obtained from ERA5 reanalysis product to represent baseline conditions, while the same from NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) were obtained for near future scenarios. ERA5 was developed under the European Centre for Medium-Range Weather Forecasts (ECMWF) and showed consistent improvements over previous products (Albergel et al., 2018). ERA5 was suggested to have high temporal advantage in modeling species distributions (Bütikofer et al., 2020). NEX-GDDP is a global bias-corrected and statistically downscaled products derived from Global Climate Models (GCMs) of the Coupled Model Intercomparison Project Phase 5 (CMIP5) under RCP 4.5 and 8.5 emission scenarios. NEX-GDDP product provided higher resolution and accuracy compared to the original GCMs by applying Bias-corrected/Spatial Disaggregation (BCSD) method (Thrasher et al., 2012). Accuracy assessment over South Asia suggested that NEX-GDDP performance surpassed regional simulations, COordinated Regional climate DOwnscaling Experiment (CORDEX, Giorgi et al., 2009), and provided realistic climate extremes (Jain et al., 2019). NEX-GDDP also well represented the mean temperature and precipitation in Southeast Asia at monthly scale (Raghavan, Hur, and Liong, 2018).

Table 4.3: The climatic dataset used in this study was obtained from ERA5 reanalysis product for baseline and bias-corrected downscaled NEX-GDDP product for future scenarios.

Dataset	Description	Spatial resolution	Temporal resolution
Baseline	ERA5 reanalysis product by European Centre for Medium-Range Weather Forecasts (ECMWF)		
Minimum temperature		~25km	Daily
Maximum temperature		~25km	Daily
Precipitation		~25km	Daily
Future	NEX-GDDP product by NASA based on bias-corrected downscaled GCM under CMIP5		
Minimum temperature		~25km	Daily
Maximum temperature		~25km	Daily
Precipitation		~25km	Daily

For future climate scenarios, five GCMs were selected to represent ranges of potential future climatic conditions. The selection of these GCMs followed the guideline from

Sanderson, Knutti, and Caldwell (2015) which provided an order for model selection based on stepwise model elimination procedure using model similarity information. The five selected GCMs included CanESM2, CESM1-BGC, IPSL-CM5A-MR, MIROC5, and MPI-ESM-MR.

To assess the accuracy of the chosen climatic dataset, Root Mean Square Error (RMSE) was calculated between ERA5 reanalysis data and the observed amount of daily precipitation, minimum temperature, and maximum temperature during 2015 from 124 weather stations in Thailand. The same was performed for NEX-GDDP dataset. The RMSE was defined as below where O_i represents the observations at station i, D_i is the values from climatic dataset in correspond to station i and N is the number of stations.

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}\left(\frac{D_i - O_i}{\sigma_i}\right)^2} \tag{4.1}$$

Landscape dataset

The landscape conditions were represented by land cover and surface features that influence elephant presence as identified in Chapter 3 (Kitratporn and Takeuchi, 2019) and previous studies (Chen et al., 2016; Estes et al., 2012; Naha et al., 2020; Wato et al., 2016; Wilson et al., 2015). Table 4.4 listed the data used in this study.

The 2015 baseline land cover was classified from remotely-sensed satellite imagery available during 2014-2016. The combination of spectral refletance and indices from the following products were used: MOD09A1 Version 6 product from the Moderate REsolution Imaging Spectroradiometer (MODIS) sensor onboard NASA's Terra satellite (Vermote, Kotchenova, and Ray, 2011), yearly composite from the Phased Array L-band Synthetic Aperture Radar (PALSAR) on board the Advanced Land Observing Satellite (ALOS) (Shimada et al., 2014), and digital elevation dataset from the Shuttle Radar Topography Mission (SRTM) (USGS, 2004).

The topographic features were represented by terrain roughness index (TRI) calculated from SRTM product. For water availability, HydroSHED (Grill et al., 2019) and European Commission Joint Research Centre (JRC) yearly water classification version 1.2 derived from Landsat 5,7, and 8 (Pekel et al., 2016) were used to identify rivers and water points respectively. The pixel locations where seasonal and permanent water classes from JRC product occurred every year during the selected period were identified. Euclidean distance from river locations and water points were then calculated. Anthropogenic disturbances were represented by transport features from GRIP4 road network (Meijer et al., 2018) and Thai Railway dataset. Euclidean distance from these transport

Table 4.4: The landscape dataset used in this study was obtained or calculated from various remotely-sensed satellite products and spatial ancillary data

Dataset	Description	Spatial resolution	Temporal period
Baseline			
Land cover	MOD09A1	500m	2014-2016
	PALSAR yearly mosaic	25m	2015
	SRTM	90m	2000
Transport			
- Roads	GRIP4	Vector	multi-source
- Railways	Thai railway	Vector	2000
Water			
- Rivers	HydroSHED	Vector	2000
- Water bodies	JRC yearly water	30m	2014-2016
Terrain roughness index (TRI)	SRTM	90m	2000
Future			
Land cover	Simulated based on projected future land demand and location suitability	500m	2045
Transport / Water / TRI	Assumed static and the same 2015 baseline was used	500m	baseline

locations were calculated and used. All the data was re-projected to the WGS84 and resampled to a 500m resolution using bilinear interpolation.

For future dataset, the land cover was simulated based on the changes in underlying drivers from RCP-SSP scenarios. Other variables, namely topographic conditions, rivers and water points, and anthropogenic disturbances, were assumed static and the same dataset from the baseline scenario were used. The land cover classification and projections are discussed in more detail under section 4.2.5.

4.2.5 Data pre-processing

Bioclimatic variables and drought indicators

Bioclimatic variables are commonly used in species distribution modeling and many ecological modeling (Hijmans et al., 2005). They are generated from monthly temperature and precipitation values to create biologically meaningful variables (Hijmans et al., 2005;

O'Donnell and Ignizio, 2012). Previous studies identified significant contributions of certain bioclimatic variables in determining elephant presence (Deb et al., 2019; Silva et al., 2020; Li et al., 2019). These variables included annual mean temperature (bio1), diurnal range (bio2), isothermality (bio3), temperature seasonality (bio4), annual precipitation (bio12), and precipitation seasonality (bio15). To prevent multicollinearity, Variance Inflation Factor (VIF) was calculated and variable with VIF>10 was removed. Each remaining variable was defined below where T_{max}, T_{min}, and Pr_{annual} refers to maximum temperature, minimum temperature, and annual precipitation respectively.

$$bio1 = T_{mean} \tag{4.2}$$

$$bio2 = \frac{\Sigma_{i=1}^{i=12}(T_{max\,i} - T_{min\,i})}{12} \tag{4.3}$$

$$bio3 = \frac{bio2}{\max(T_{max1..12}) - \min(T_{min1..12})} \tag{4.4}$$

$$bio14 = \frac{SD(T_{mean1..12})}{T_{mean}} \times 100 \tag{4.5}$$

$$bio12 = Pr_{annual} \tag{4.6}$$

$$bio15 = \frac{SD(Pr_{1..12})}{Pr_{annual} \div 12} \times 100 \tag{4.7}$$

From Chapter 3, drought was suggested to influence the presence of elephant through the alteration of available food resources. In this study, Keetch-Byram Drought Index (KBDI) was used. KBDI reflects the net effect of evapotranspiration and precipitation in producing cumulative moisture deficiency in deep duff and upper soil layers. The index ranges from zero, the point of no moisture deficiency, to 800, the maximum drought that is possible. KBDI was calculated following Keetch and Byram (1968) and Alexander (1990) using daily climatic data introduced in the previous section.

$$KBDI = KBDI^{t-1} + \frac{[800 - KBDI^{t-1}][0.968e^{(0.0486\times T_{max})} - 8.3] \times 10^{-3}}{1 + 10.88e^{(-0.0441\times Pr_{annual})}} - (100 \times Pr) \tag{4.8}$$

where $KBDI^{t-1}$ is previous day KBDI, T_{max} is daily maximum temperature, Pr is daily precipitation and Pr_{annual} is the average annual precipitation. Drought day (D_{day}) was then identified when standard anomaly of KBDI is over 1.5, while drought event (D_{event}) was defined as when at least seven consecutive D_{day} was measured. Drought intensity and frequency for baseline and future period were then calculated where $KBDI_{Dday}$ and day_{Dday}

refer to the value of KBDI and number of day identified as D_{day}.KBDI was then used to calculated drought indicators which include $Drought\ intensidy$ and $Drought\ frequency$. Prior to the calculation of these two drought indicators, drought days (D_{day}) and drought events (D_{event}) must first be identified. D_{day} was defined as the day with the standard anomaly of KBDI over 1.5, while D_{event} is defined as when at least seven consecutive D_{day} was measured. The standard anomaly of KBDI, drought intensity and drought frequency are define as below:-

$$KBDI_{std.anomaly} = \frac{(KBDI_{i,d} - \mu)}{\sigma} \tag{4.9}$$

$$Drought\ Intensity = \frac{\sum KBDI_{Dday}}{\sum day_{Dday}} \tag{4.10}$$

$$Drought\ Frequency = \sum D_{event} \tag{4.11}$$

Comparison between KBDI calculated in this study and that derived from satellite data (Takeuchi et al., 2015) were performed to evaluate the agreement and general performance. Agreement between KBDI-based drought defined in this study and the Palmer Drought Severity Index (PDSI, Palmer 1965) provided by TerraClim dataset (Abatzoglou et al., 2018) was also assessed.

Land cover supervised classification

The flow for supervised classification of baseline land cover is shown in Figure 4.5. Five land cover classes were selected, namely *Abandoned*, *Crops*, *Plantations*, *Forest*, *Built-up*, and *Water*. The description of each land cover class was adapted from Thailand Land Development Department (LDD, 2016). Abandoned land comprised of all abandoned parcels, such as abandoned field crops, abandoned rice field, abandoned perennial crops, and abandoned orchards. Agriculture land were represented by two classes, crops and plantations. Crop land cover class included paddy rice, field crop, and shifting cultivation. Plantations referred to perennial crops and orchards. Forest comprised of both intact and disturbed evergreen, deciduous, mangrove and swamp forest, as well as ago-forestry. Built-up represented city and industrial land, while water included both artificial and natural water bodies.

Prior to performing the classification, satellite dataset were pre-processed to obtain accurate surface information. MOD09A1 product was masked using quality band, 'StateQA', to remove pixel with cloud, shadow, cirrus, and aerosol. All masked images available during 2014-2016 were median-composited based on wet months (May-October) and dry months (December-February). Using temporal profile can support the classifier

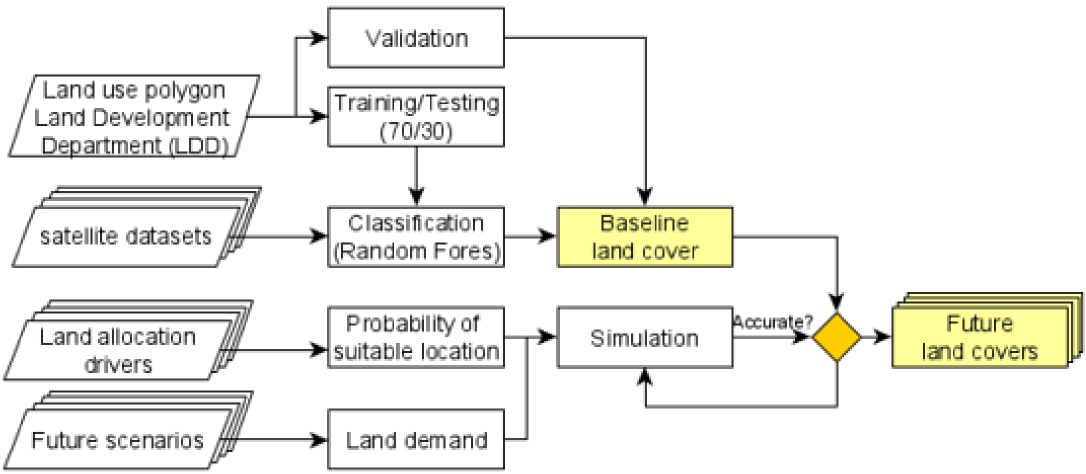


Figure 4.5: Overview of the flow to perform supervised classification of the land cover map at baseline and to simulation land cover for four future scenarios

in distinguish crops (Kuenzer et al., 2014). The following spectral indices were then calculated, Enhanced Vegetation Index (EVI, Huete 1997), Normalized Different Water Index (NDWI, Gao 1996), Normalized Built-up Index (NDBI, Zha, Gao, and Ni 2010). For PALSAR dataset, Lee filter (Lee, 1980) was applied and digital numbers were converted to sigma-naught values (Rosenqvist et al., 2007).

All pre-processed spectral bands and indices from MOD09A1, PALSAR, and SRTM were used with supervised classification using Random Forest classifier. The training (136,765 pixels), testing (58,485 pixels) and independent validation (20,817 pixels) samples were obtained from 2015/2016 land use polygon provided by LDD. The results were evaluated using producer and user accuracy for each land cover class, as well as the over all accuracy and Kappa value.

Simulation of future land demand

To simulate future land cover, two inputs are necessary, namely land demand and land allocation (Figure 4.5). The simulation of future land demand was based on the assumptions as follows:-

Water: Water areas were assumed to be constant from 2015 baseline into the future.

Built-up: Built-up areas were based on projections by Gao and O'Neill (2020). Gao and O'Neill (2020) provided country-level quantification of future built-up land at 10-year interval under different SSPs (Figure 4.6a). The built-up cover for the year 2040 from SSP2 and SSP5 were obtained for this study.

Forest: Forest areas were assumed to increase in the future based on the recent trend (2010-2019) of increasing protected areas in Thailand (World Bank, 2020b) and Thailand National Forestry Strategy which aimed to reach 40% of forest cover by 2036 (RFD, 2017). Across all future scenarios, the same amount of forest areas was assumed. Forestry industry is not explicitly considered. To simulate future forested area, the coefficient (β_{F0}) from a linear trend model of the recent forested area under protection was used to extrapolate for forest land demand in the future (Figure 4.6b).

$$Protected\ areas(km^2) = \beta_{F0} + \beta_{F1}(Year) \tag{4.12}$$

Agriculture (Crops/Plantations): The same assumption and simulation techniques were applied for crop land cover class and plantation land cover class. Based on existing studies, land under agriculture activities were assumed as a function of production demand and yield (Alexandratos and Bruinsma, 2012; Stehfest et al., 2019). Historical data of the top ten highest production agriculture products of Thailand were selected. Sugar cane, sugar crop, cereal, rice, roots and tubers, and cassava were selected to represent crops. For plantation, palm oil, palm oil fruit, fruits, rubber natural were used. Historical agricultural data (production quantity and harvested areas) (FAO, 2020) and economic data (GDP, % agriculture contribution to GDP, and rural population) (World Bank, 2020b) were used to fit historical production demand and yield.

Firstly, historical production demand was fitted using GDP, % agriculture distribution to GDP ($Agri\%$), and rural population (*Rural.pop*) . For both crops and plantation, the production regression model achieved $R^2 > 0.9$. A model for historical yield was calculated using GDP which showed good fit ($R^2 > 0.7$). For future simulation, GDP and rural population for future scenarios under SSP2 and SSP5 were obtained from IIASA database, https://tntcat.iiasa.ac.at/SspDb/ (Riahi et al., 2017), while $Agri\%$ was calculated based on historical linear trend. For the future yield, it was assumed based on SSP narrative that higher agriculture productivity is expected for RCP8.5-SSP5. Hence, yield was simulated for RCP8.5-SSP5 first and then only two-third of that yield was assumed to be achieved under RCP4.5-SSP2. The simulated results are shown in Figure 4.6c.

$$Production\ (tonnes) = \beta_{P0} + \beta_{P1}(Agri\%) + \beta_{P2}(GDP) + \beta_{P3}(Rural.pop) \tag{4.13}$$

$$Yield_{RCP8.5-SSP5}\ (tonnes/km^2) = \beta_{Y0} + \beta_{Y1}(GDP) \tag{4.14}$$

$$Yield_{RCP4.5-SSP2}\ (tonnes/km^2) = \frac{2}{3} Yield_{RCP8.5-SSP5} \tag{4.15}$$

Abandoned: Abandoned land cover was assumed to be fulfilled only after other land demands are met.

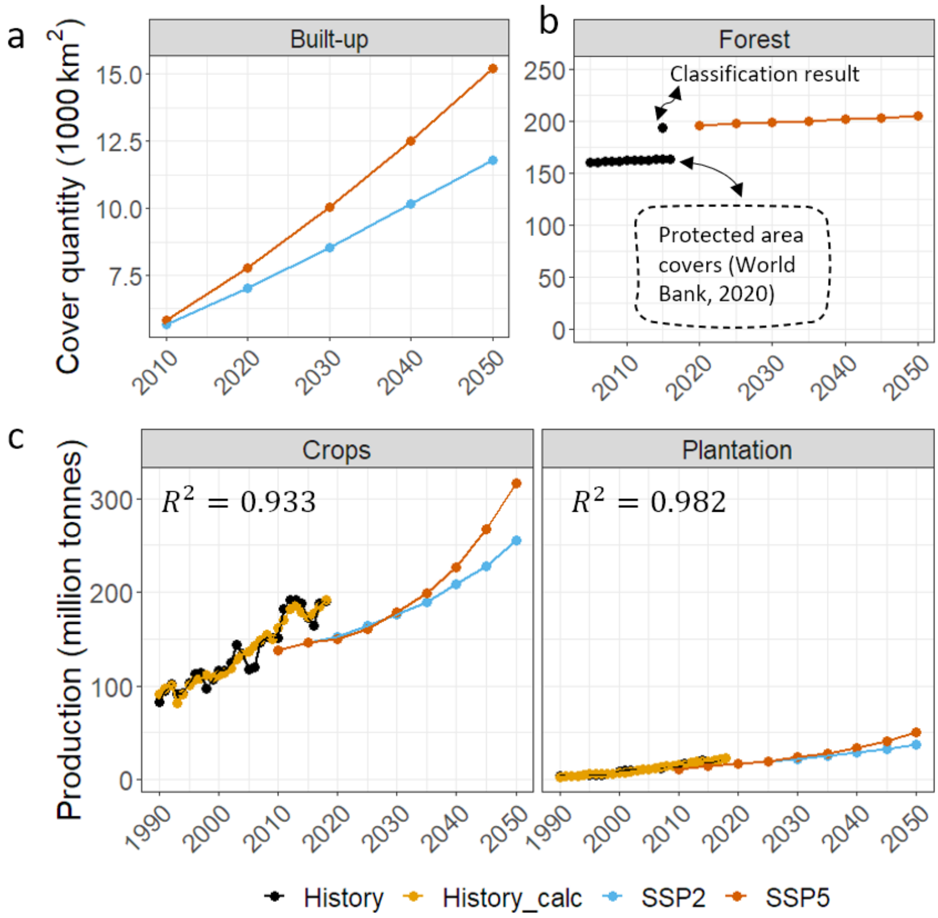


Figure 4.6: Built-up areas projected by Gao, and O' Neill (2020) (a), forest areas projected from recent historical trend (b), and historical trend (*History*), simulated historical trend (*History_calc*), and projection result under SSP2 and SSP5 for crops and plantations land cover (c)

Spatial allocation of future land cover

The CLUE-S model (Conversion of Land Use and its Effects Modeling Framework) Verburg et al., 1999; Verburg et al., 2002 was employed to perform spatially explicit allocation of land cover under future scenarios. The CLUE method was applied in various studies, including those in Thailand Reidsma et al., 2006; Trisurat, Alkemade, and Verburg, 2010; Waiyasusri, Yumuang, and Chotpantarat, 2016. The model also allowed multiple interacting variables and the simulation of spatial policy, such as exclusion areas and restriction areas Verburg et al., 2002.

To use the CLUE model, four inputs are necessary, namely (i) future land demand (simulated as discuss in main text), (ii) baseline land cover (satellite image classification as discussed in main text), (iii) conversion rules, (iv) spatial restriction, and (v) location characteristics.

Conversion rules comprised of conversion elasticity and sequence. The relative elasticity values range from 0 to 1 (easy conversion to irreversible change) must be defined in which a general assumption based on cost for investment was considered. For example, built-up areas are not likely converted due to permanent features, but crops are easily convertible. Here, we set abandoned class with easiest conversion, followed by crops, plantations, and forest. Water and built-up classes were assumed to not be convertible once gained. Neighborhood effect was specifically set for built-up class in which conversion to built-up is more likely when surrounded pixels are already under built-up. Conversion sequence covers temporal characteristics, but was not considered in this study. For spatial restriction, the existing protected areas were defined as exclusion areas in which no changes were allowed. This spatial restriction settings allow buffer zone scenarios to be incorporated. For scenario under 12-km buffer zone, further expansion of exclusion areas were applied with 12-km buffer from protected areas with known elephant population.

To determine the suitable location for each land cover class, logistic regression was used. The logistic regression identifies the relationship between land cover type (dependent variable) and a set of possible drivers (independent variables).

$$\ln \frac{P_i}{(1-P_i)} = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_n X_{ni} \tag{4.16}$$

where P_i represents the probability of occurrence of a particular land cover class, X_i are the independent variables, and β is the estimated coefficient. Independent variables that potentially influenced land use occurrence are anthropocentric drivers (travel time to cities: Weiss et al., 2018, distance to roads: Meijer et al., 2018, human population count: LandScan, GDP: World Bank, 2020b), topographic drivers (elevation and slope), climatic drivers (temperature and precipitation), distance to rivers, soil characteristics including nutrient level, oxygen level, and rooting conditions FAO/IIASA, 2012. Soil characteristics are particularly important to determine different type of vegetation land cover. For example, soil with low oxygen and rooting level is likely to be unsuitable for agriculture.

Soil data is categorical. Thus, dummy coding was applied. Multicollinearity between independent variables was performed. In addition, the total number of independent variables was limited to seven, reducing potential over-fitting of the model. The list of driving factors (independent variables) and the regression coefficient of different land cover types are shown in Table 4.8. Each land cover typed showed different characteristic. The performance of land cover simulation was assessed by comparing the simulated land cover map in 2015 to land cover classification result.

4.2.6 Hazard modeling and projection

The modeling of hazard is comprised of three main sub-indicators, namely climatic suitability for elephant, landscape suitability for elephant, and dispersal probability of elephants. In total, 20 future projects were obtained under hazard, 5 GCMs under each future with different climate scenarios (RCP-SSP) and buffer zone combination.

Suitability of climate and landscape for elephants

The methodology for habitat suitability followed the SDM techniques in which location of known species presence are used to identify relationships with ecologically relevant environmental variables, resulting in probability ranging from 0 (no chance of presence) to 1 (high presence probability).

Climatic and landscape suitability were separately modeled because climatic acts on a larger scale in compare to landscape variables, thus they should be separately modeled (Mateo et al., 2019; Fournier et al., 2017). Specifically, climatic suitability reflects species built-in physical tolerance to factors such as thermal regulation. The suitable climatic range should capture the whole spectrum of species tolerance regardless of their location. Hence, regional coverage was considered when modeling climatic suitability (incorporate all 13 range countries), while landscape suitability modeling considered areas within Thailand.

Environmental factors under climatic suitability models include six bioclimatic and three drought variables: bio1, bio2, bio3, bio12, bio14, bio15, drought intensity, drought frequency, and KBDI in dry quarter. Nine factors were considered for landscape models, namely forest cover within 6km, percent food cover (forest and crop land cover) within 6km, distance to crop, distance to forest, distance to plantation, distance to transport, distance to urban, distance to water, and TRI. Environmental variables from the baseline scenario are shown in Figure 4.7 and 4.8 for climate and landscape suitability respectively.

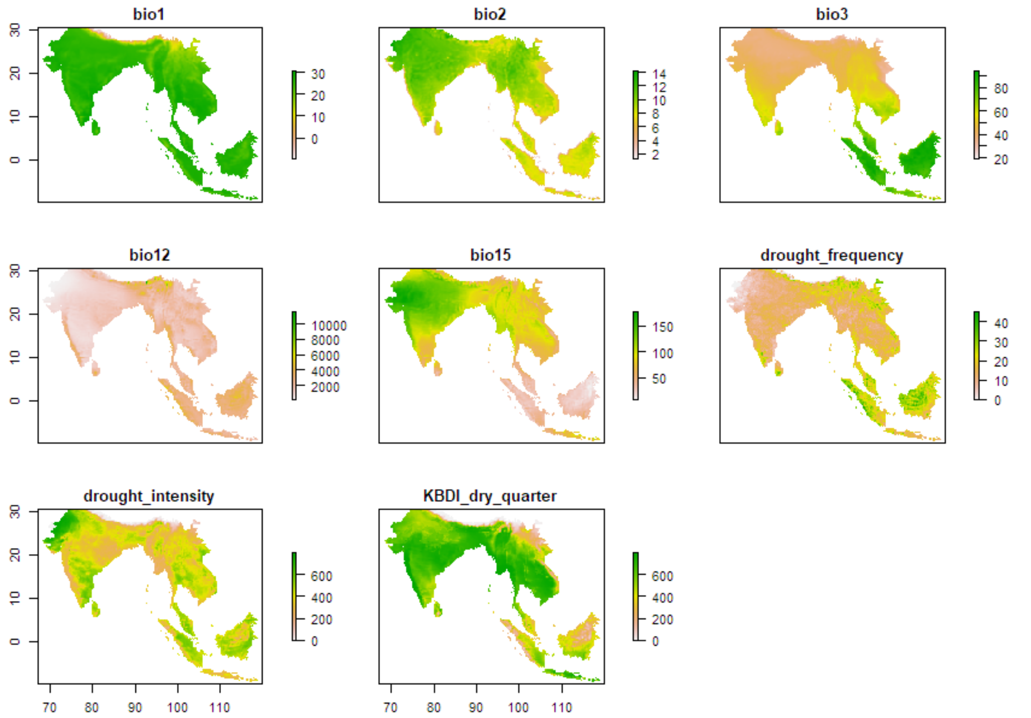


Figure 4.7: Environmental variables used for climatic suitability modeling.

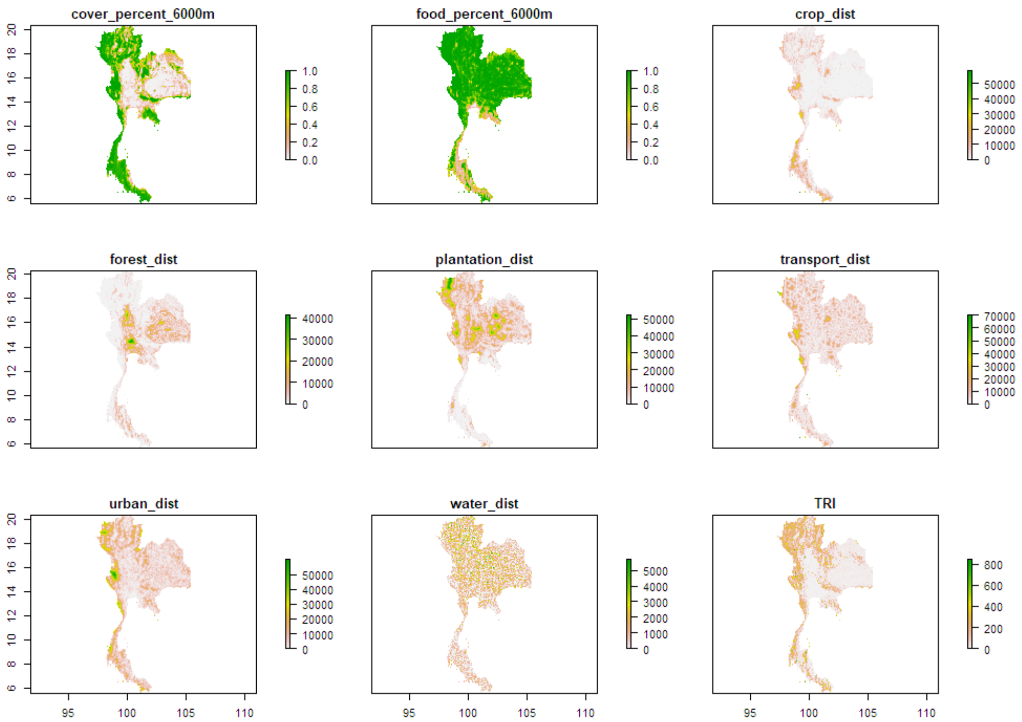
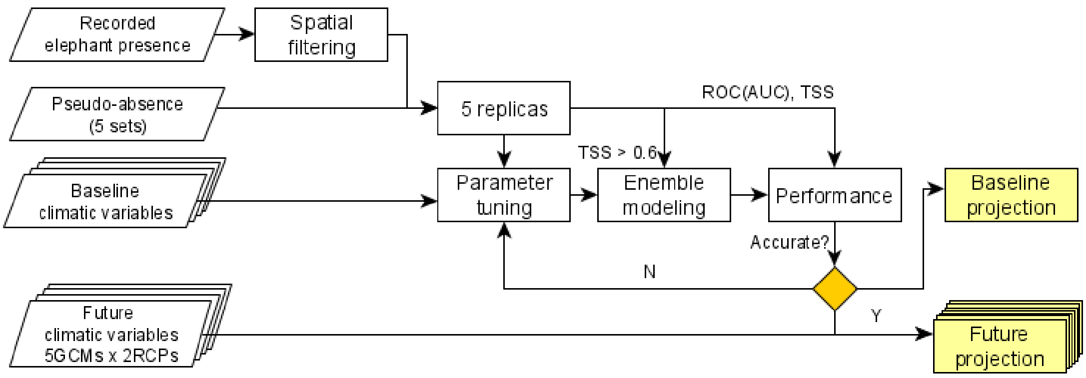
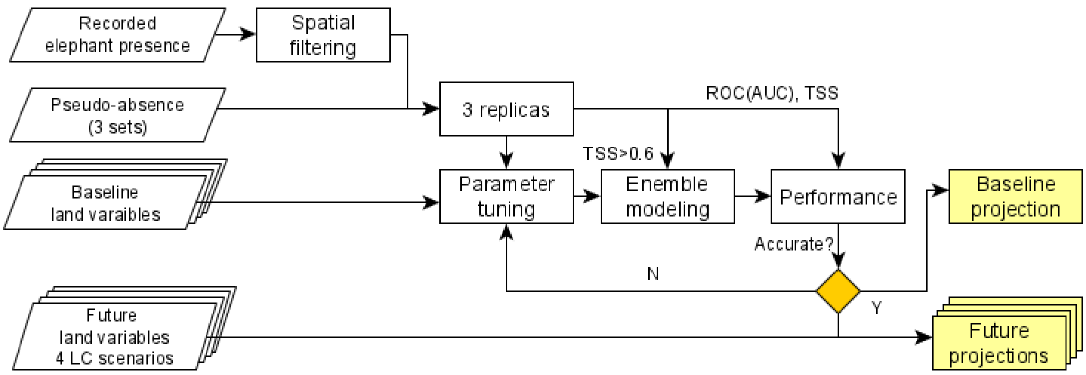


Figure 4.8: Environmental variables used for landscape suitability modeling.

The overall procedures are similar for both climatic and landscape suitability model, but the presence dataset and environmental variables were differed. Figure 4.9a and 4.9b illustrated the overall methodology employed for climatic suitability and landscape suitability modeling respectively. In this study, the ensemble modeling approach was employed using BIOMOD2 package (Thuiller et al., 2020) with R version 4.0.2 (Team, 2020).



(a)



(b)

Figure 4.9: The overview of methodology used for climatic (a) and landscape (b) suitability modeling to estimate the probability of elephant presence.

For climatic suitability, the elephant presences (Figure 4.10a) were obtained from GBIF database (http://gbif.org) and previous literature (Bi et al., 2016; Sampson et al., 2019; Naha et al., 2019). Spatial filtering was applied to reduce potential autocorrelation among presence points (Fourcade et al., 2014). Only one occurrence was considered within 25km (1 pixel). After spatial filtering, 328 presences were left for further modeling. Absence locations of elephant are required for modeling, but not available. Therefore, five sets of 5,000 random pseudo-absence points were generated instead. The data was

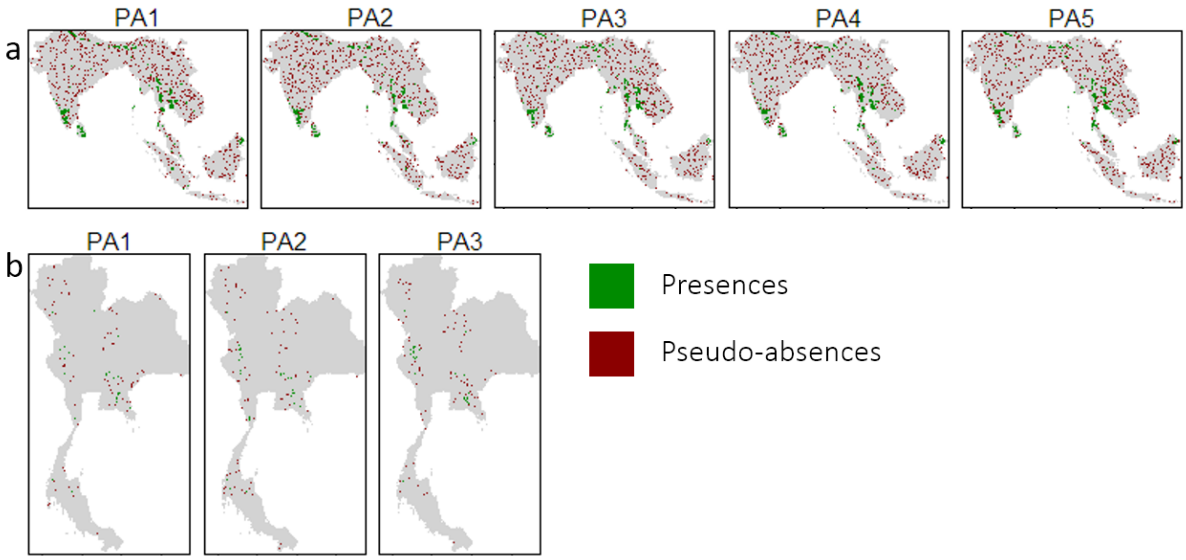


Figure 4.10: The elephant occurrences as well as the pseudo-absences (PA) for climatic (a) and landscape (b) suitability model. Five and three replicas were generated for climate and landscape.

then split into 70%/30% for training/testing with 5 replicas. For parameter tuning, first multicollinearity was checked in which variable with $r < |0.75|$ and $VIF > 10$ were removed.

For landscape suitability, the elephant presences (Figure 4.10b) were digitized from the Department of Thailand National Parks, Wildlife and Plant Conservation (DNP n.d.). Similar procedures to climatic suitability modeling was employed. First, spatial filtering was applied which only allowed one presence point within 2 km radius resulting in 3,018 presences. Random pseudo-absences were generated with spatial restriction in which only areas within 30-km buffer from protected areas and not within 1km from known presence location were allowed. This is to ensure representative of true absence points. Three sets of 20,000 pseudo-absence points were generated. Multicollinearity was also applied using the same criteria with that of climatic suitability modeling.

The model performance was evaluated using two index, True Skill Statistic (TSS, Allouche, Tsoar, and Kadmon 2006) and area under the curve (AUC) of the receiver operating characteristic (ROC). TSS takes into account both omission and commission errors and ranges also from -1 to 1. For TSS, the values from 0.2 to 0.5 were poor, from 0.6 to 0.8 were useful, and values larger than 0.8 were good to excellent. For AUC, the prediction accuracy is considered to be no better than random for AUC values of <0.5, poor between 0.5-0.7, and useful in the range 0.7-0.9. AUC values that are greater than

0.9 are considered to be excellent. Generalized Linear Modeling (GLM, McCullagh 1984), Generalized Additive Modeling (GAM, Trotter 1986), Generalized Boosted Modeling (GBM, Ridgeway 1999), Multivariate Adaptive Regression Spline (MARS, Kariya 1991), Random Forest (RF, Pavlov 2019), Maximum Entropy (MaxEnt, Phillips, Anderson, and Schapire 2006 were chosen for model training based on previous literature (Kanagaraj et al., 2019). Then, only model with $TSS \geq 0.6$ were considered for ensemble calculation with weighted average.

Area reachable by wild elephants

Dispersal probability is also important to be considered. The closer to elephant habitat, the more likelihood for communities to face with HEC which was demonstrated in Chapter 3. Euclidean distance from the boundary of protected areas with known elephant presence was calculated. The inverse function was then applied to place a higher value on the areas with closer proximity to the boundary of elephant habitats. In addition, the distance was restricted to 50km in which beyond this threshold likelihood became 0. This is to reflect that elephants are not able to travel beyond this distance considering the landscape condition in Thailand.

4.2.7 Exposure modeling and projection

Exposure was represented by number of rural population. The projected maps provided by Gao (2020) under SSP2 and SSP5 were at 10-year interval from 2010 to 2100. For this study, the data at the year 2040 were used for calculation. Since the population count is commonly skewed, natural log was applied to the data before further processing was performed. In total, two exposure future projections were obtained which represent climate change scenarios (RCP-SSP) without the influences from buffer zone policy.

4.2.8 Vulnerability modeling and projection

Vulnerability was comprised of human capital and drought probability. Total of ten future projections were obtained with 5 GCMs under each climate change scenario (RCP-SSP) without the influences of buffer zones. The detail of each variable was discussed below.

Human capital

Human capital reflects level of susceptibility to the exposed hazard. In this study, technology, education, and income level were represented by percentage of household with internet access (*%Internet*), percentage of workforce with higher secondary (*%Edu*), and the average household monthly income (*Income*). Accessibility to information sharing and technology were suggested reduce crop damage and strengthen HEC-affected community (Nyirenda et al., 2018). Additionally, previous research showed that education level allowed possible access to alternative sources of income and indicated the ability to implement more effective crop protection measures (Nyirenda et al., 2018). Low income limited household's ability to mitigate conflict and more likely to suffer greater impacts from wildlife-induced loss (Inskip and Zimmermann, 2009). The three sub-indicators were obtained from Thailand National Statistical Office (NSO, 2020) at province-level, the finest level of available data from the year as close to 2015 as possible. The data was from 2015, 2019, and 2015 for *%Internet*, *%Edu*, and *Income* respectively.

Drought probability

Drought was chosen as it historically disrupted Thailand agricultural sector (Prabnakorn et al., 2019) and expected to cause large yield reduction in the future (Leng and Hall, 2019). Drought probability was calculated to represent added pressure to communities exposed to HEC.

$$Drought\ Probability = \frac{\sum D_{event\ 20\ years}}{N} \tag{4.17}$$

where $D_{event\ 20\ year}$ refers to the number of drought events, on when drought are measured at least seven consecutive drought days, over the 20-year period. Drought probability then measures the number of drought event during 20-year period over the maximum number of drought detected in the region (N).

4.2.9 Risk index aggregation and projection

To generate composite index, I followed the guideline as provided by United Nations (2019a). Each sub-indicators under each component were first check for multicollinearity. All sub-indicators must then be normalized. In this study, min-max normalization was applied. In addition, weighting can be incorporated when aggregate sub-indicators. However, the level of influence from each sub-indicators was not cleared and uncertain to determine. Therefore, equal weighting was used. The aggregation followed geometric mean method. Similar normalization, equal-weighting, and aggregation approach were also applied for well-known index, such as Human Development Index (HDI, United

Nations Development Program 2020). The normalization and geometric mean are represented as follows:-

$$I_i^{'} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{4.18}$$

$$\left(\prod_{i=1}^{n} I'^{w_i}{}_i\right)^{\frac{1}{\sum_{i=1}^{n} w_i}} = \sqrt[n]{I_1'^{w_1} I_2'^{w_2} \cdots I_n'^{w_n}} \tag{4.19}$$

where X_i is the value of indicator i, while X_{min} and X_{max} represents minimum and maximum value within the range of indicator i respectively. $I_i^{'}$ refers to normalized sub-indicator i and w_i represents weighting power, which is equally set in this study. The score of risk and its underlying components ranges from 0 to 1. A 5-class equal interval classification was applied from *Very Low* to *Very High*.

4.2.10 Validation

Validation of HEC risk require long-term historical data of HEC events and related information (e.g. loss quantity, compensation records, etc.), but this information has not been tracked systematically for Thailand. Alternatively, we performed validation using only location of HEC events from Khaoyai-Dong Phayayen FC(2) together with 60 sets of randomized HEC pseudo-absences (200 $\leq$n$\leq$2,400) as shown in Figure 4.11. This independent HEC records were collected with GPS coordinates by DNP (DNP, 2019) and WongramWongram and Salee, 2017 in 2019 and 2012 to 2017 respectively. 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).

4.3 Results and discussion

4.3.1 Climatic variables evaluation

Accuracy of ERA5 and NEX-GDDP climate data

The Root Mean Square Error (RMSE) is calculated as in Table 4.5, while the overall range of each dataset is shown in Figure 4.12. The results showed similar performance with studies from other regions. The RMSE of minimum and maximum temperature ranged between 1.6 to 3.5 depending on the dataset. The RMSE of ERA5 were at the lowest error among the chosen dataset. The results were similar to a previous study in China (Wang et al., 2020) and with lower RMSE than that in Asia (Mahto and Mishra,

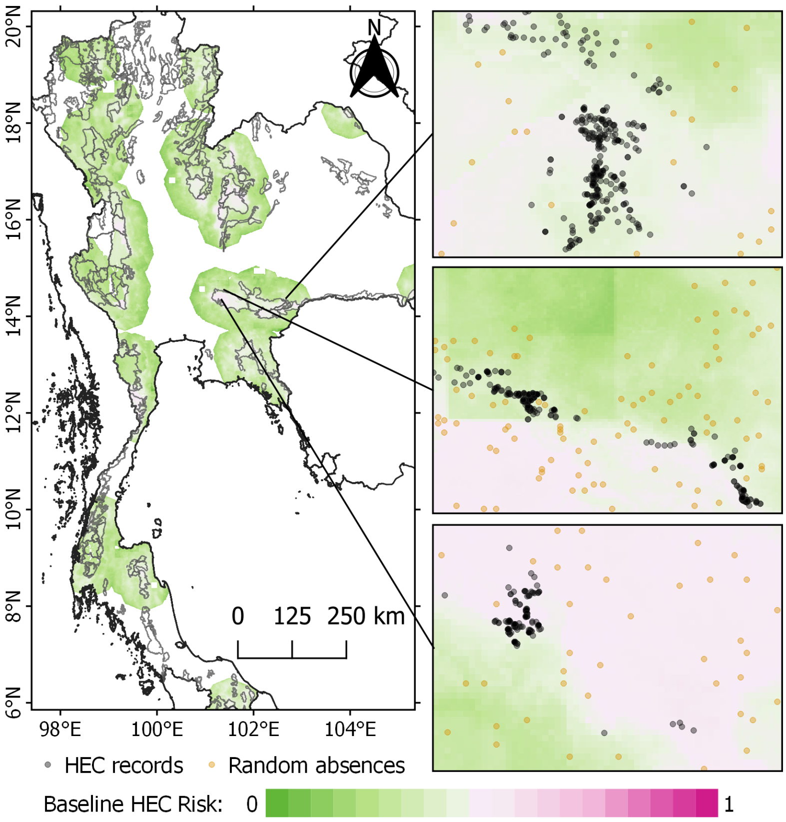


Figure 4.11: HEC presences (n=803) from Khaoyai-Dong Phayayen forest complex as collected by a previous study (Wongram and Salee, 2017) and the Department of National Park, Wildlife and Plant Conservation (DNP, 2019) and an example of randomized HEC absences.

2019). The error of precipitation were relatively high across the dataset, ranging between 10.5 to 15.5 mm.day^{-1}. A study in China identified higher RMSE of ERA5 precipitation at the lower attitude, up to approx. 9 mm.day^{-1}(Wang et al., 2020). The average daily precipitation were lower for all models compared to the observations. Close inspection showed that both ERA5 and NEX-GDDP dataset contain higher number of days without rain.

Evaluation of simulated KBDI and drought indicator

The evaluation of calculated KBDI based on the chosen climatic dataset with those calculated from satellite-derived data showed overestimation (Figure 4.13a). The comparison indicated that overestimation of ERA5-derived KBDI were more likely to happen at the lower KBDI level. Figure 4.13b compared the temporal pattern of ERA5-derived KBDI

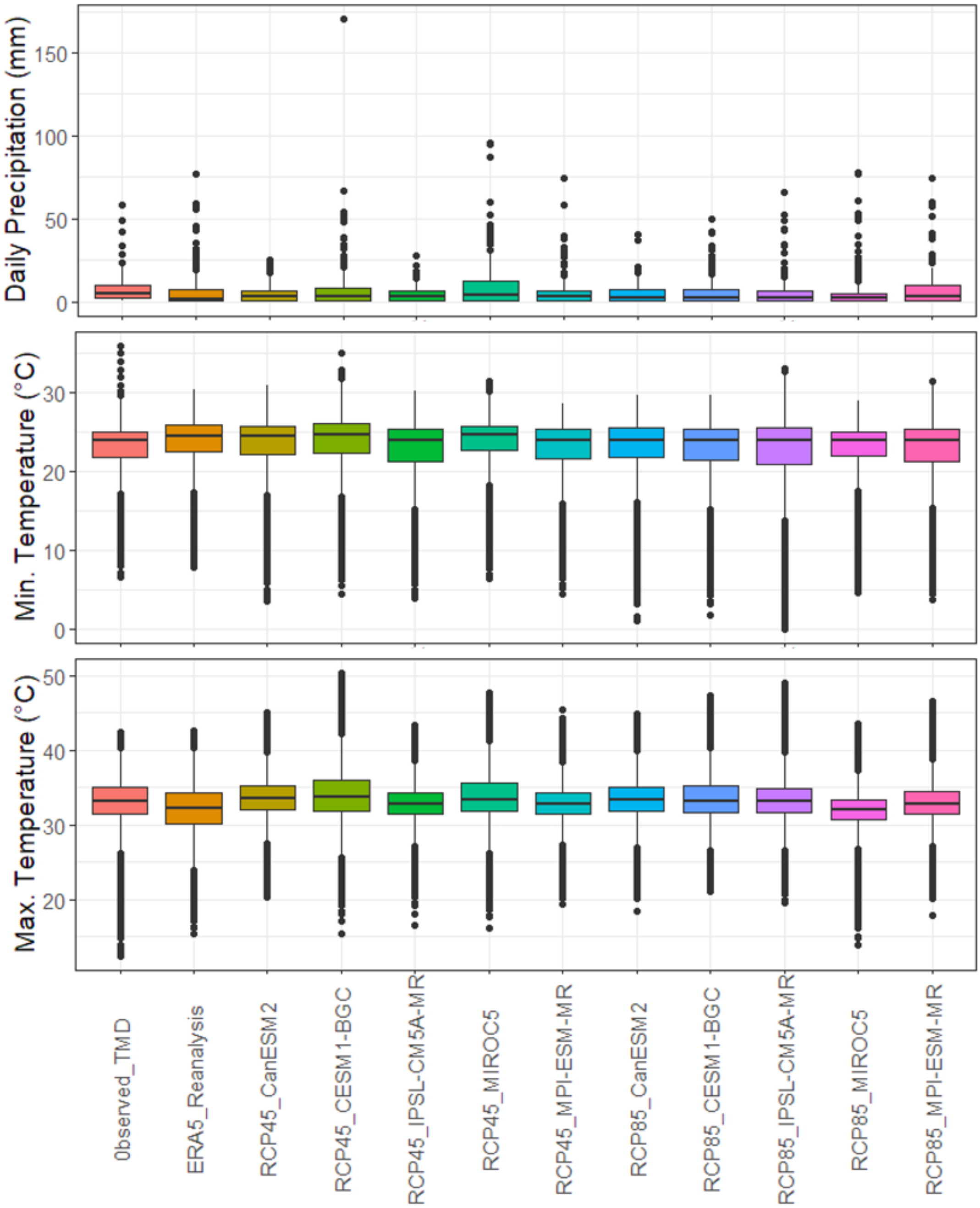


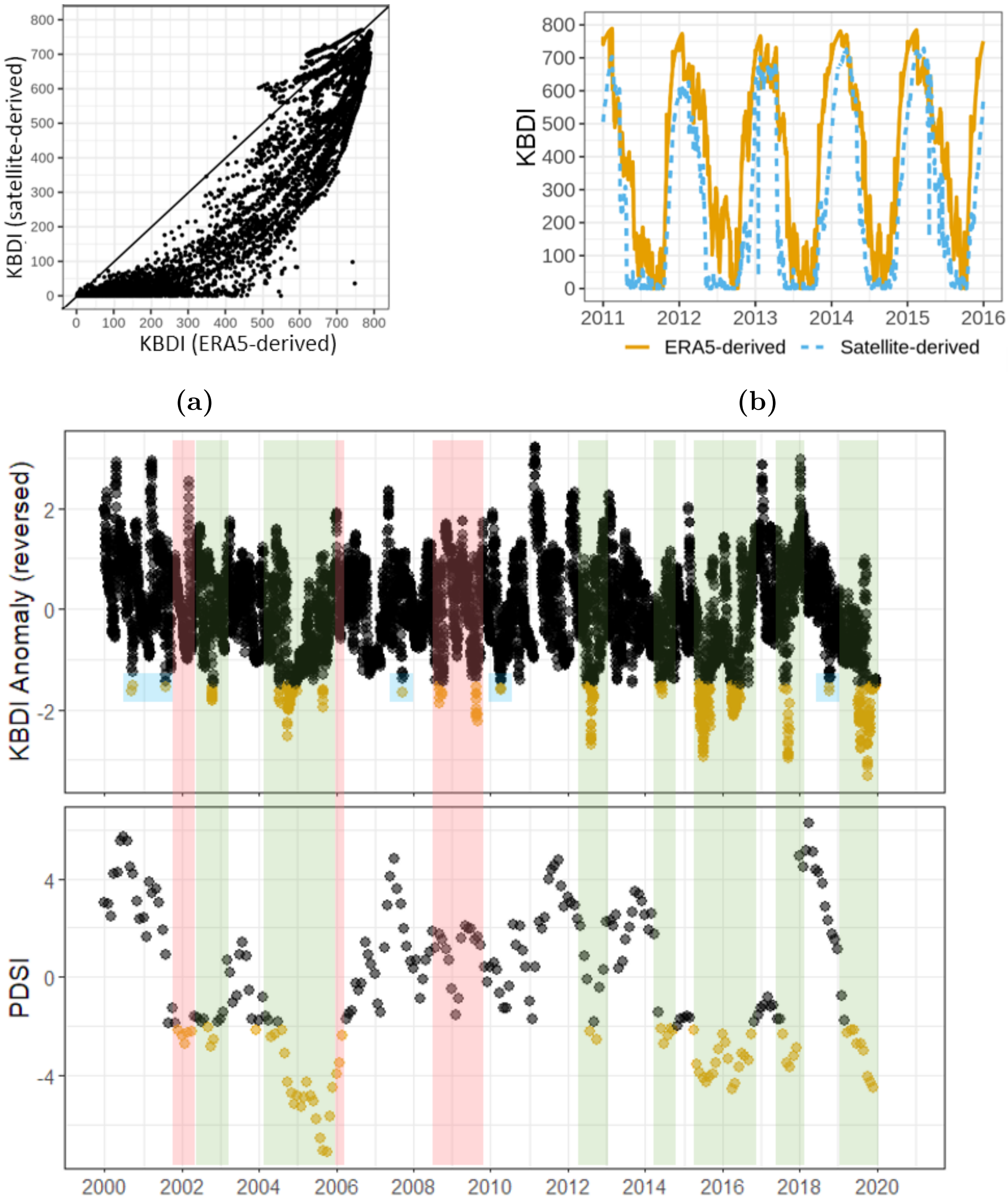
Figure 4.12: Comparison of observed climatic values from weather station (n=124) to ERA5 and 5 General Climatic Models (GCMs) from GDDP-NEX dataset under RCP4.5 and RCP8.5 scenarios over Thailand during 2015.

Table 4.5: The Root Mean Square Error (RMSE) between observed climatic values from weather stations (n=124) and different climatic dataset chosen for this study, namely ERA5 and 5GCMs under RCP4.5 and RCP8.5 from NEX-GDDP

		RMSE		
	Variables	**Pr**	**Tmax**	**Tmin**
Baseline	ERA5	10.58	2.18	1.60
RCP4.5 (A1/B1)	CESM1-BGC	15.58	3.51	2.49
	MPI-ESM-MR	12.92	2.75	2.27
	MIROC5	14.31	3.32	2.48
	IPSL-CM5A-MR	12.79	2.78	2.50
	CanESM2	12.53	2.96	2.32
RCP8.5 (A2/B2)	CESM1-BGC	13.43	3.03	2.58
	MPI-ESM-MR	13.53	2.75	2.30
	MIROC5	14.13	3.15	2.12
	IPSL-CM5A-MR	12.52	2.92	2.79
	CanESM2	12.53	2.84	2.45

and Satellite-derived KBDI which also showed overestimated from ERA5 at lower KBDI. This was likely influenced by the high RMSE and lower daily average discussed in the previous section. Moreover, the satellite-derived KBDI are at smaller spatial resolution (4km) which also likely causes this discrepancy. Nevertheless, the general temporal pattern between both data remain relatively similar.

The identification of drought was also evaluated as shown in Figure 4.13c. Overall, the calculated KBDI in this study agreed with majority of the drought identified from PDSI result. Since PDSI was measured in monthly unit, most of the missed identification of drought from KBDI consisted of short drought days as highlighted in blue and likely were not detected in PDSI. In 2009-2010, severe drought was reported in Thailand (NOAA/National Weather Service, 2019) which was detected by KBDI, but not PDSI. Hence, the drought derived from KBDI in this study deems to have acceptable performance.



(a) (b)

(c)

Figure 4.13: Comparison of KBDI value (a) and temporal pattern (b) calculated from ERA5 and satellite-based climatic dataset and (c) comparison of KBDI from ERA5 and PDSI which is a commonly used drought indicator

4.3.2 Landscape variables evaluation

Baseline land cover classification map

The accuracy of the baseline land cover was shown in Table 4.6. Overall accuracy was 0.89 with Kappa of 0.83 which indicates highly accurate result. Most land cover class showed moderate to high producer and user accuracy. Only abandoned land cover yield lower user accuracy at 0.17. Based on LDD definition, the training samples for abandoned include mixed of various abandoned land, such as abandoned croplands, plantations, and aquaculture ponds. Therefore, the low accuracy was likely due to the lack of unique spectral signatures of such land cover class. The map of baseline land cover was shown in Figure 4.14. Majority of the areas were covered by crops land cover class ($> 250,000$ km^2), followed by forest, plantation, water, built-up, and abandoned respectively. Additionally, the classified map showed that most of the protected areas were surrounded by agriculture land, mostly crops cover type. The eastern and southern areas were distinct in which plantations and orchards were the dominant land cover surrounding forested areas.

Table 4.6: The accuracy of the baseline land cover from the supervised classification was measured by producer accuracy, user accuracy, overall accuracy, and Kappa.

Variables	Producer Accuracy	User Accuracy	
Abandoned	0.75	0.17	**Overall**
Crops	0.85	0.94	**Accuracy**
Plantations	0.86	0.73	0.89
Forest	0.92	0.95	
Built-up	0.89	0.60	**KAPPA**
Water	0.87	0.83	0.83

Simulated results of the future land demands

The projection of land cover demand is listed in Table 4.7, while the proportion of each class is shown in Figure 4.15. The demand for agriculture lands was reduced due to an increase in yield production. The RCP8.5-SSP5 scenario showed large increase in abandoned land compare to RCP4.5-SSP2.

Simulated result of the future land cover spatial allocation

Prior to fitting logistic regression to determine suitable probability for each cover type, multicollinearity was performed in which elevation and temperature were found to have

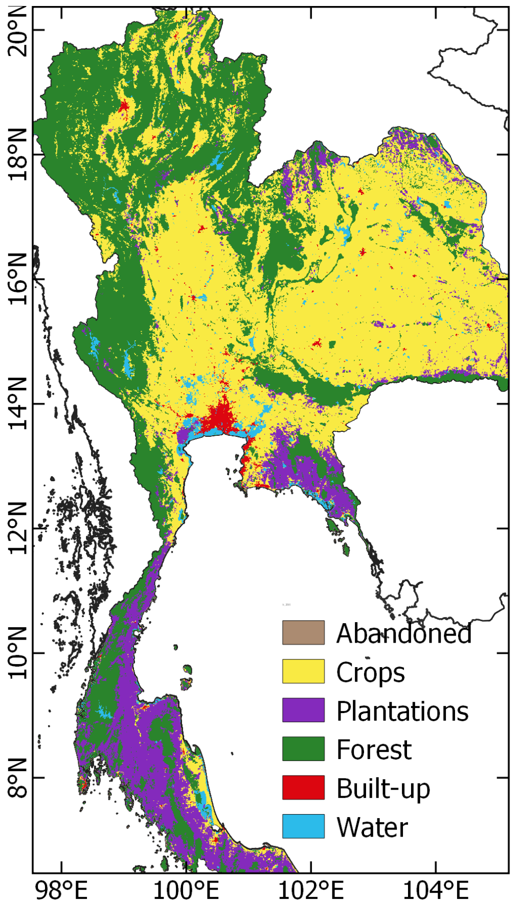


Figure 4.14: The baseline land cover map for Thailand which was generated by supervised classification of satellite data.

high correlation ($r^2 > 0.85$). Therefore, elevation and temperature are not included in the same regression model. The list of driving factors (independent variables) and the regression coefficient of different land cover types are shown in Table 4.8. For each land cover type, not all driving variables are significant. Each land cover typed showed different characteristic.

The maps of land cover projection for the year 2045 under four different scenarios are shown in Figure 4.16. Large expansion of abandoned land were projected under RCP8.5-SSP5 (A2/B2) scenario , especially at the northeastern part of Thailand near the country border. Built-up areas under RCP8.5-SSP5 (A2/B2) increased in the east of Bangkok and the southern region of the country. On the other hand, RCP4.5-SSP2 (A1/B1) projected that built-up areas were likely expanded in the eastern region of Thailand.

The restriction posed on the buffer zone resulted in the stable areas of agriculture lands near the protected areas, while conversion to abandoned lands were projected in

Table 4.7: The land demand in km^2 for baseline scenario were obtained from 2015 land cover classification map and that for future scenarios at year 2045 were simulated under RCP4.5-SSP2 (A1/B1) and RCP8.5-SSP5 (A2/B2).

Land cover	2015	2045	
		RCP4.5-SSP2 (A1/B1)	RCP8.5-SSP5 (A2/B2)
Abandoned	1,559.25	14,742.13	72,044.37
Crops-Rice	257,860.75	237,798.63	185,831.92
Plantations-Orchards	63,202.75	55,118.22	46,912.84
Forest	193,837.75	203,951.28	203,951.28
Built-up	6,120.25	10,970.50	13,840.35
Water	11,574.00	11,574.00	11,574.00

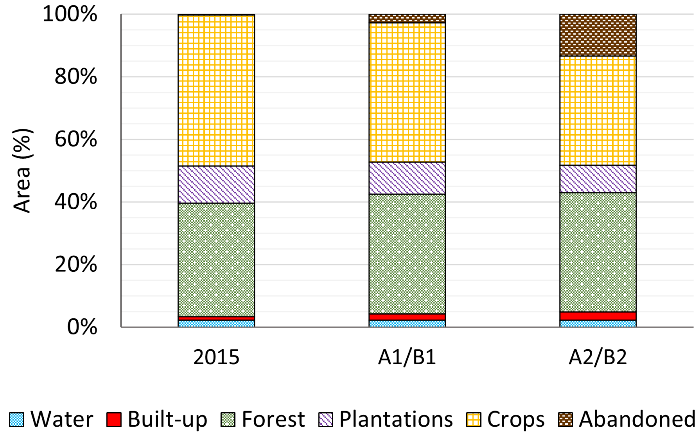


Figure 4.15: The proportion of land demand for baseline obtained from land cover classification and future simulated under RCP4.5-SSP2 (A1/B1) and RCP8.5-SSP5 (A2/B2).

the same areas when no restriction was placed. Abandoned land cover types were usually projected near existing forested cover.

4.3.3 Hazard index

Performance of suitability model

The model performance was measured from TSS and ROC values. The result are shown in Figure 4.17a and 4.17b for climate and landscape suitability respectively. Three models under climatic suitability (GBM, GAM, and RF) had TSS ≥ 0.6 and were selected for ensemble, while two models (GBM and RF) under landscape suitability met this criteria.

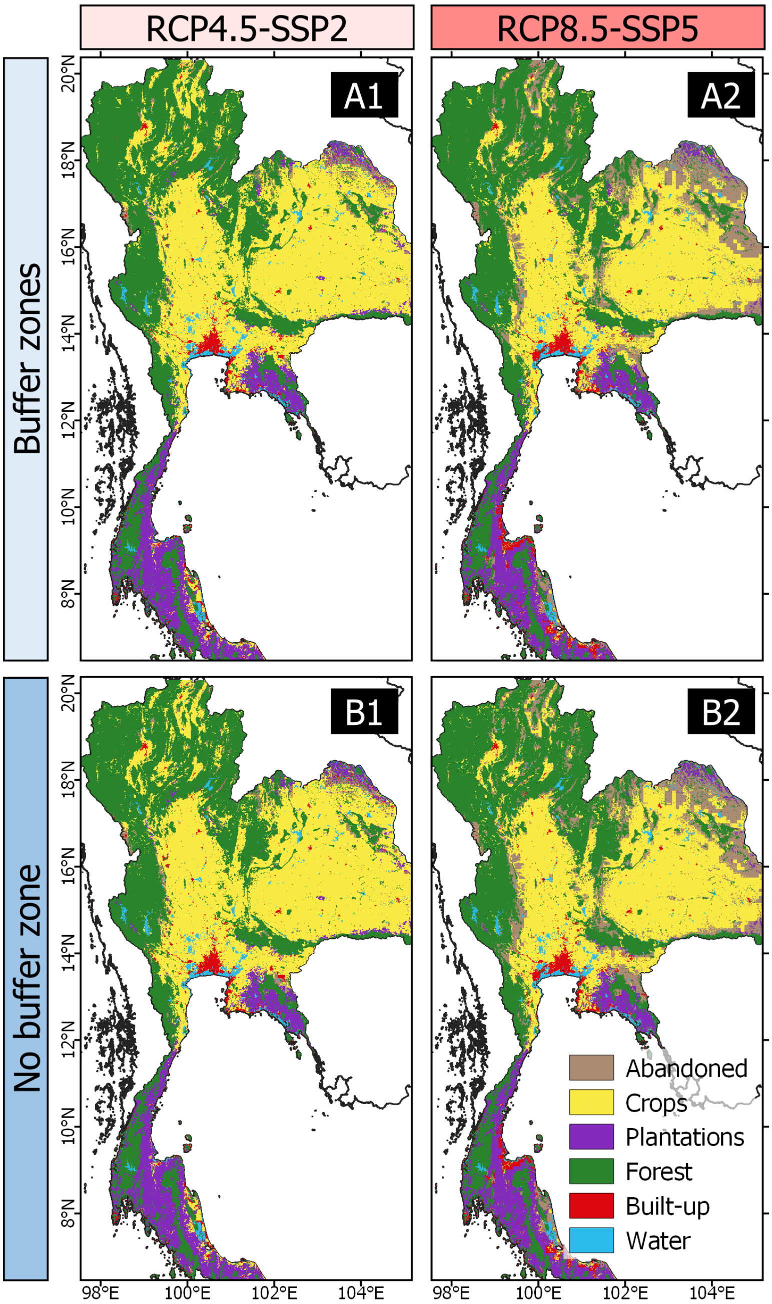


Figure 4.16: Future land cover map projected under four scenarios A1: RCP4.5-SSP2-BZ, A2: RCP8.5-SSP5-BZ, B1: RCP4.5-SSP2-no BZ, and B2: RCP8.5-SSP5-no BZ. RCP-Representative Concentration Pathways, SSP-Shared Socioeconomic Pathways, and BZ-Buffer zones.

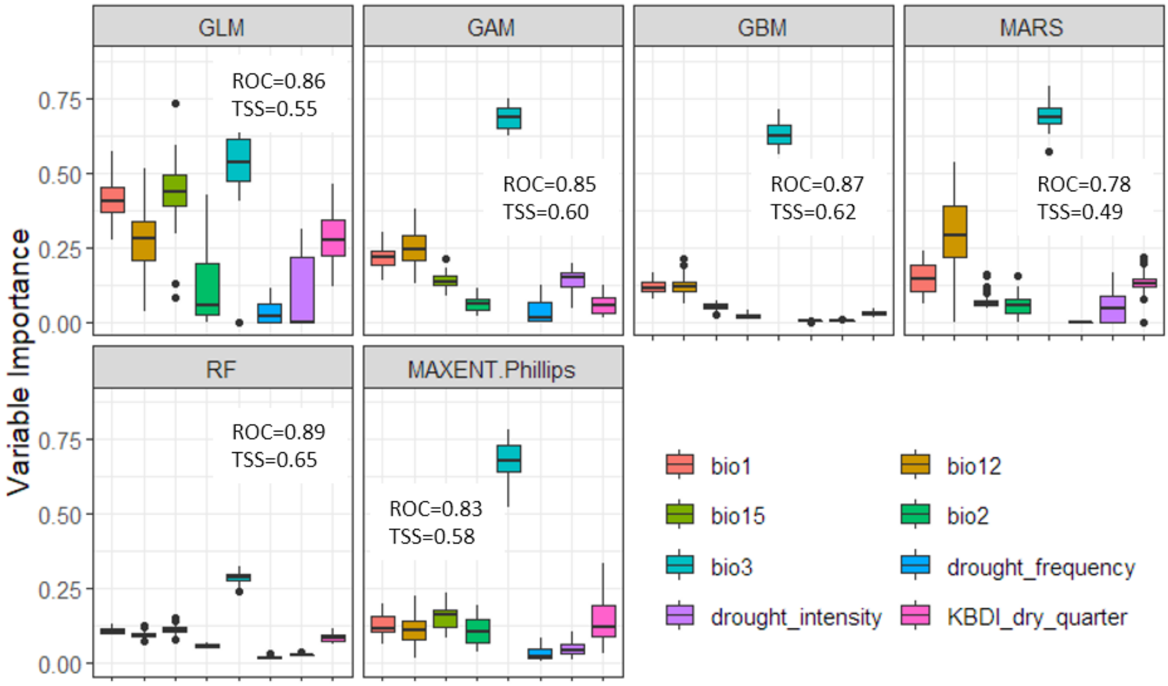
Table 4.8: Driving factors for location suitability with associated coefficient (β) of significant factors, and AUC for each land cover type.

Variables	**Abandoned**	**Crops**	**Plantations**	**Forest**	**Built-up**	**Water**
constant	-7.2077	-9.1528	-2.6194	-2.8961	-25.0439	-0.6300
access_cities	-	-	-	-	-0.0732	0.0039
access_rivers	0.0003	-	-	-	-	-0.0005
access_roads	-	-0.0004	-0.0001	0.0002	-0.0001	-
GDP	-	-	0.0000	0.0000	0.0000	-
population	-	-	0.0004	-	0.0069	-
temperature	-0.0023	0.4391	-	-	0.8871	-
precipitation	0.0016	-0.0021	0.0018	0.0002	-0.0019	-
elevation	-	-	-0.0088	0.0034	-	-0.0099
slope	-	-	-	0.4706	-	-
soil_nutrient_high	-	-	-1.3959	-	-	-
soil_nutrient_med.	-	-	-1.469	-	-	-
soil_oxygen_high	-2.7516	-0.3724	-	-	-	-1.3520
soil_oxygen_med.	-2.4622	0.7534	-	-	-	-0.6208
soil_rooting_high	-	1.3128	-	-1.0578	-	-1.0887
soil_rooting_med.	-	0.9200	-	-0.4572	-	-0.7068
AUC	0.937	0.931	0.904	0.971	0.979	0.843

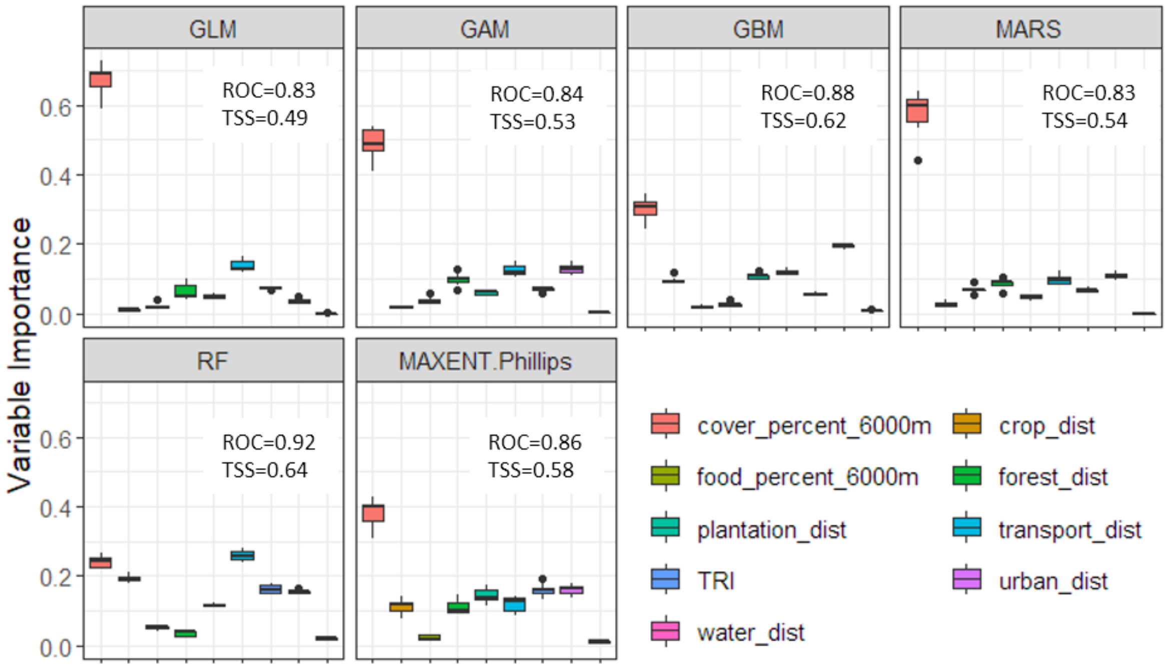
These models, thus, were used for ensemble modeling with weighted average. The coefficient of variation computed for the ensembled results under both climate and landscape suitability showed high agreement among the models, 0.05 and 0.3. Variations were larger at central and northeastern areas. The ensembled models were used for projection.

Comparison of future habitat suitability between climate and landscape conditions

Overall, Thailand became less suitable under both future climatic and landscape consideration (Figure 4.18). However, more reductions were likely the result of changes in climatic conditions. All GCMs showed an overall reduction in suitability, except for MIROC5 under RCP8.5-SSP5 (A2/B2) in which a stable condition with a slight increase was projected. The country's median climatic suitability at the baseline was 0.45 and decreased by 0.01-0.28 depending on GCMs. Among different GCMs, CanESM2 showed the largest reduction. The maximum suitability reduced from 0.90 at baseline scenario to an average of 0.76 and 0.75 under RCP4.5-SSP2 (A1/B1) and RCP8.5-SSP5 (A2/B2)



(a)



(b)

Figure 4.17: True Skill Statistics (TSS) and area under the curve of the receiver operating characteristic (ROC) of climatic suitability (a) and landscape suitability (b) model

respectively. Comparison of the same GCM under A1/B1 and A2/B2 scenarios showed that all models predicted slightly lower suitability under A1/B1 except for MIROC5. For further analysis, an average of 5 GCMs within the same scenario was used resulted in similar suitability of 0.34 and 0.32 for A1/B1 and A2/B2 respectively.

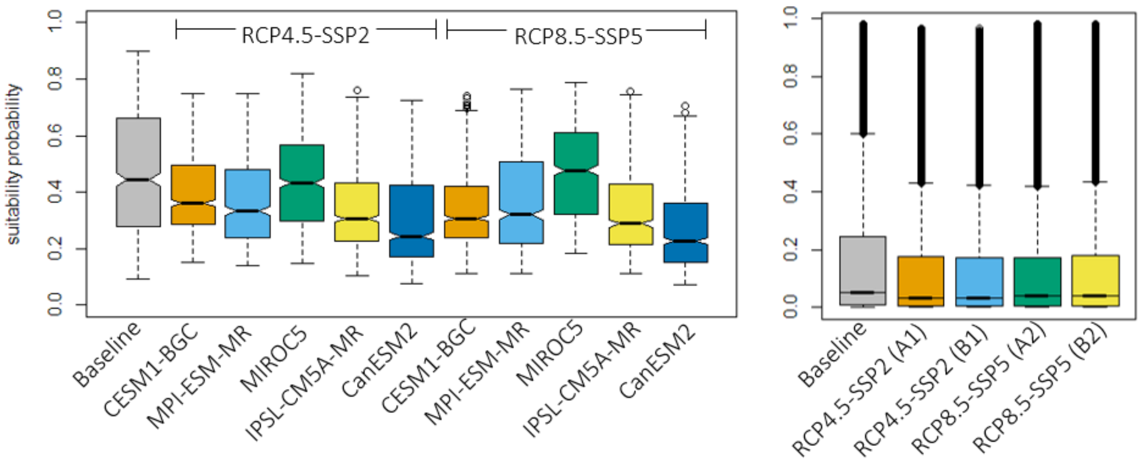


Figure 4.18: Boxplot of suitability probability, indicating likelihood of elephant presences, for baseline period and future scenarios under climatic (with five GCMs) and landscape models.

For landscape suitability results, the baseline was projected with an average suitability of 0.05 across the whole country. The median values were low because high suitable areas were mostly clustered and concentrated near protected areas. Under future scenarios, the suitability decreased around 0.01-0.02 depending on the scenarios. RCP4.5-SSP2 (A1/B1) had a slightly larger decrease compared to RCP8.5-SSP5 (A2/B2). The maximum suitability under baseline was 0.98 which reduced slightly to 0.96 under A1/B1, but remained the same under A2/B2. The impacts from buffer zones implementation was not evident which likely due to their small spatial coverage compared tot he whole study area.

Although the spatial pattern showed an overall reduction in most of the areas, northwestern shift in climatic suitability was observed, especially near FC5, 8, and 9 (Figure 4.19a). More localized geographical changes were projected under landscape suitability, especially as a result of HEC buffer zones as visible under A1 and A2 scenarios (Figure 4.19b). Under landscape suitability, abandoned land cover class which were projected to occur between forest area and agriculture land has potential for conservation planning, but its applicability is beyond the scope of the current study.

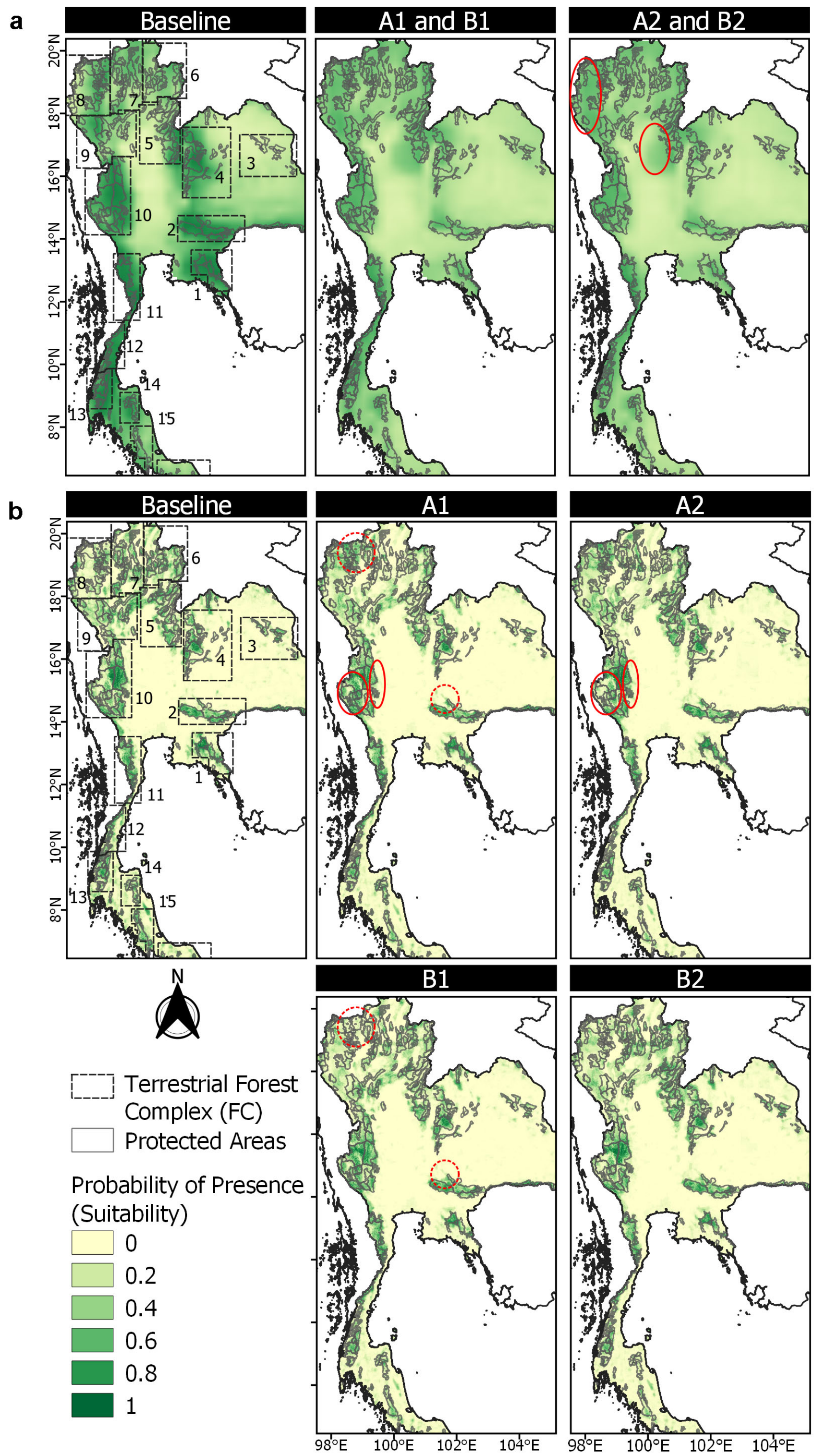


Figure 4.19: Relative probability of elephant presences (habitat suitability). a. Climatic suitability and b. landscape suitability were projected under baseline and future scenarios, A1: RCP4.5-SSP2-BZ, A2: RCP8.5-SSP5-BZ, B1: RCP4.5-SSP2-noBZ, and B2: RCP8.5-SSP5-noBZ. Solid circle indicated climate-induced changes, while dashed circle highlighted effects of buffer zones.

Composite hazard component

The high level of baseline hazard (>0.8) was concentrated close to protected areas, especially near 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) (Figure 4.20), which corresponded to current areas estimated to host large number of elephant population (Figure 4.1). However, these locations were projected with an overall decreasing hazard level across future scenarios (Figure 4.20). On the other hand, increasing future hazard level was estimated for some areas, specifically in Lamnampai-Salawin FC(8), west of Mae Pin-Omgoi FC(9), west of Western FC10, Phumieng-Phuthon FC(5), and north of FC2. Since dispersal probability remained constant under future scenarios, changes in suitability sub-indicators were the main cause of variations in future hazard.

The overall changes were similar across the four future scenarios with localized different in level of changes as shown in Figure 4.20 under S1-S3 highlighted areas. In S1 highlighted areas, west of FC8 and FC9 were projected with an increase in hazard under scenarios with buffer zones (A1/A2, >100% change in hazard level in some locations) compared to B1/B2. For S2 highlighted area in FC10, larger increase in hazard under A1 and B1 (RCP4.5-SSP2) was projected on the west side, but on the east side A2 and B2 scenarios projected with higher hazard. In S3 highlighted areas, opposite from situation in S1, the buffer zone policy (A1/A2) was projected to cause a reduction in hazard level.

4.3.4 Exposure component

The exposure levels were calculated with min-max normalization of natural-log transformed rural population based on Gao (2020) results. The exposure map at baseline, RCP4.5-SSP2 (A1/B1) and RCP8.5-SSP5 (A2/B2) are shown in Figure 4.21. Reduction in exposure level was projected in most areas of Thailand due to the combination of urban expansion and lower rural population in the future. Large reduction was projected in three locations: peripheral of Bangkok, northeastern plain, and southern region. Most areas adjacent to protected areas were projected with rather stable exposure level (within ±5-6% increase). The overall greater reduction in the number of exposed persons under RCP8.5-SSP5 (A1 and B1), -38%, compared to RCP4.5-SSP2 (A2 and B2), -21% (Table 4.9). This larger reduction in exposed population under RCP8.5-SSP5 corresponded with the demographic trajectory of SSP5 in which relatively low population growth and fertility with high migration and urbanization (O'Neill et al., 2017).

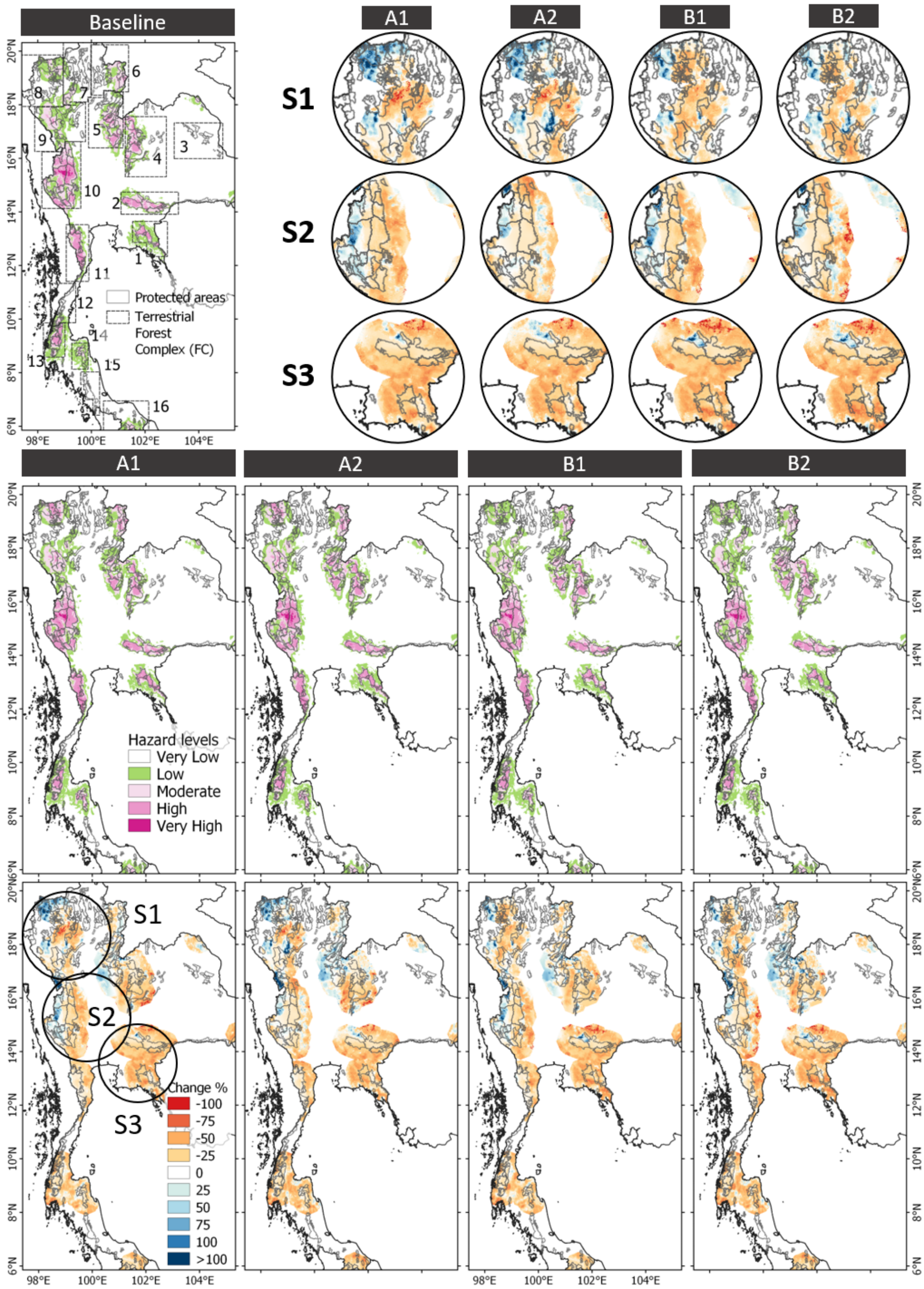


Figure 4.20: The hazard level aggregated from all sub-indicators for baseline and future scenarios (A1: RCP4.5-SSP2-BZ, A2: RCP8.5-SSP5-BZ, B1: RCP4.5-SSP2-noBZ, and B2: RCP8.5-SSP5-noBZ), as well as the average percentage change from baseline are shown. Selected areas with large increase or decrease are highlighted in S1-3.

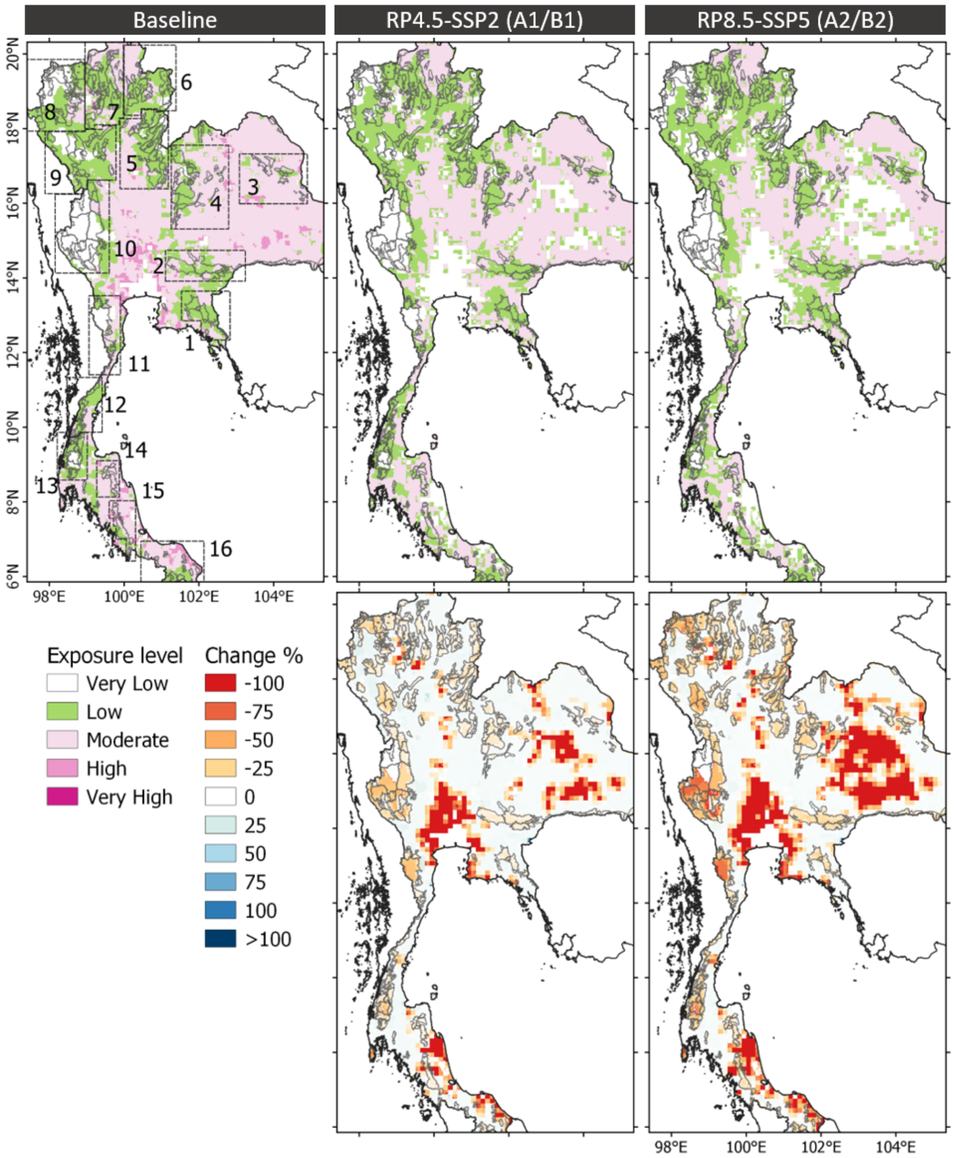


Figure 4.21: The exposure level calculated with min-max normalization of natural-log transformed rural population at the baseline, RCP4.5-SSP2 (A1/B1), and RCP8.5-SSP5 (A2/B2) scenario showed from left to right. The average change in percentage under future scenarios was also computed.

4.3.5 Vulnerability component

Static socioeconomic sub-indicators

Vulnerability scores for socioeconomic sub-indicators are shown in Figure 4.22, which included household access to Internet (a), workforce with at least higher secondary education (b), and household average monthly income (c). These sub-indicators were assumed static and remained constant for across future scenarios. For all sub-indicators, the northern region was consistently one of the highest vulnerable areas. Northeastern regions and the south most areas of Thailand were closely followed with high vulnerability, especially under income sub-indicator.

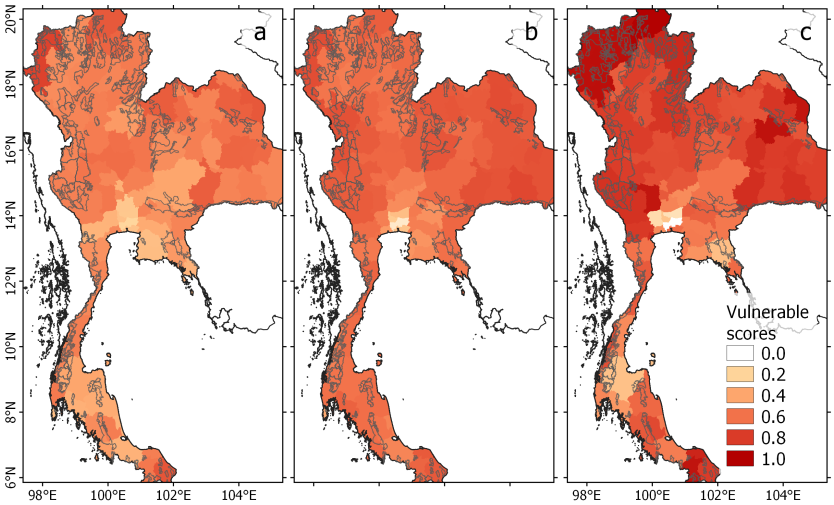


Figure 4.22: The vulnerability scores for socioeconomic sub-indicators under baseline including (a) household access to Internet, (b) workforce with at least higher secondary education, (c) and household average monthly income.

Drought probability sub-indicator

The results of future drought probability showed an increase across all GCMs and scenarios 4.23. Similar projection with the overall increasing drought was also previously identified for Thailand (Seeboonruang, 2016). CESM1-BGC showed the highest increase, while CanESM2 had the smallest increase. Although all five General Circulation Models (GCM) under RCP8.5-SSP5 (A2/B2) had slightly higher drought probability compared to RCP4.5-SSP2 (A1/B1), they were very close without clear differences in spatial distribution. Similar projections of future drought in southeast Asia was identified with an average increase and relatively low spatial differences among RCPs Lu, Carbone, and

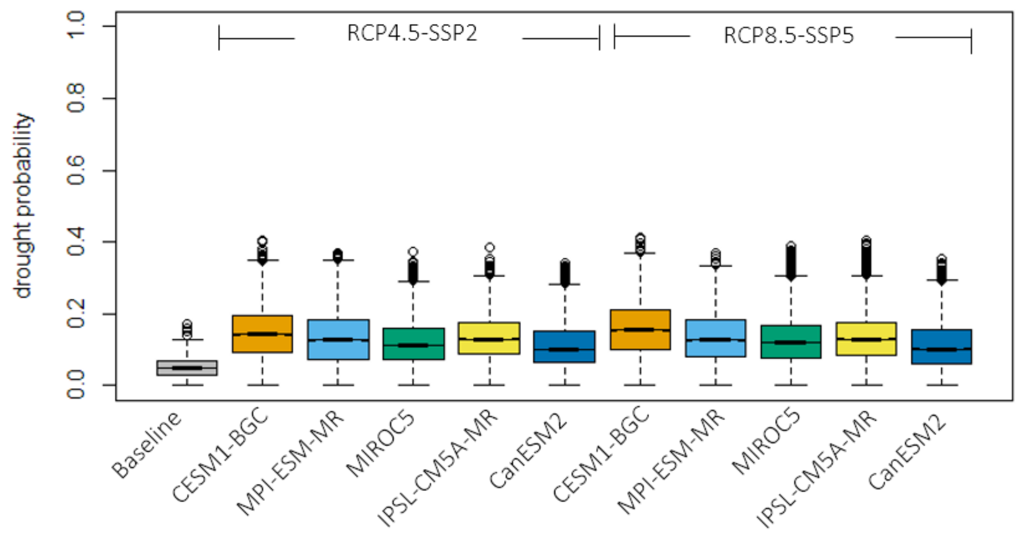


Figure 4.23: Comparison between drought probability from five selected GCMs at baseline period and the future scenarios under RCP4.5-SSP2 (A1/B1) and RCP8.5-SSP5 (A2/B2) showed an increase across all models.

Grego, 2019. The largest increase was projected in northern region near FC8 and FC9. Within this region, some areas had low to no drought likelihood in baseline, but were projected to increase 60% to >100%. Despite increasing in lower magnitude, the FC10, FC4, FC2, and FC1 also showed higher in drought probability of around 20% to 50% increase depending on the areas.

Composite vulnerability component

With a static vulnerability scores from socioeconomic sub-indicators, the future aggregated vulnerability level were projected to increase due solely to the higher drought probability. At the baseline period, moderate vulnerability was mainly projected at northeastern region and sparsely clustered in northern and southern areas of Thailand (Figure 4.25). Across all future scenarios, RCP4.5-SSP2 (A1/B1) and RCP8.5-SSP5 (A2/B2), vulnerability increased at almost all areas in north, northeastern, and central region of Thailand. The largest increased was projected near FC8, followed by FC9, FC10, Srilanna-Khuntan FC (7). Other areas that also projected with an increase, but at a lower level, FC4 and FC11. Overall higher vulnerability level was expected.

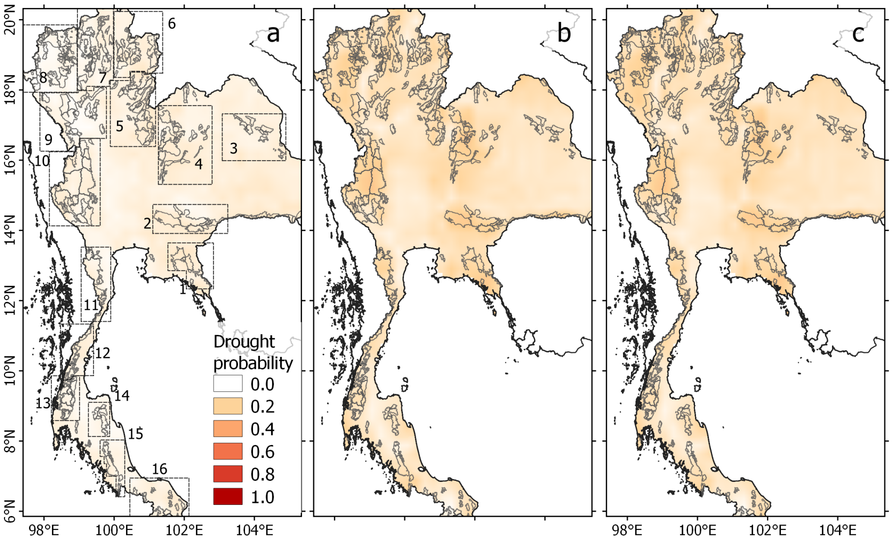


Figure 4.24: Spatial distribution of drought probability at baseline period and the future scenarios under RCP4.5-SSP2 (A1/B1) and RCP8.5-SSP5 (A2/B2) averaged across five GCMs.

4.3.6 Composite HEC risk

Validation of baseline projection

Due to inadequate information from HEC incidents, validation was only performed for baseline HEC risk from FC2. Validation data with HEC presences and 60 sets of randomized HEC absences were used. The results showed an average area under the receiver operating characteristics curve (AUC) of 0.71 with 0.01 standard deviation (Figure 4.26).

HEC Risk under baseline and future scenarios

The baseline HEC risk in Thailand was under *Very Low* to *Low* (0.0-0.4) in most locations and increased to *Moderate* and *High* (0.4-0.8) closer to protected areas (Figure 4.27). Five FCs with the highest average baseline HEC risk were FC1, FC2, FC14, FC11, and FC13 respectively. These FCs remained at the top five under future scenarios, but FC1 was projected to replace FC2 as an area with the highest HEC risk. Under future scenarios, areas that were projected to face with increasing HEC risk included FC8, FC9, west of FC10, surrounding areas of FC5, north of FC2. Ares that showed the largest reduction in HEC risk level were at the southern region close to FC14 and west of FC2. In both locations, urban expansion was expected to reduce exposure and hazard

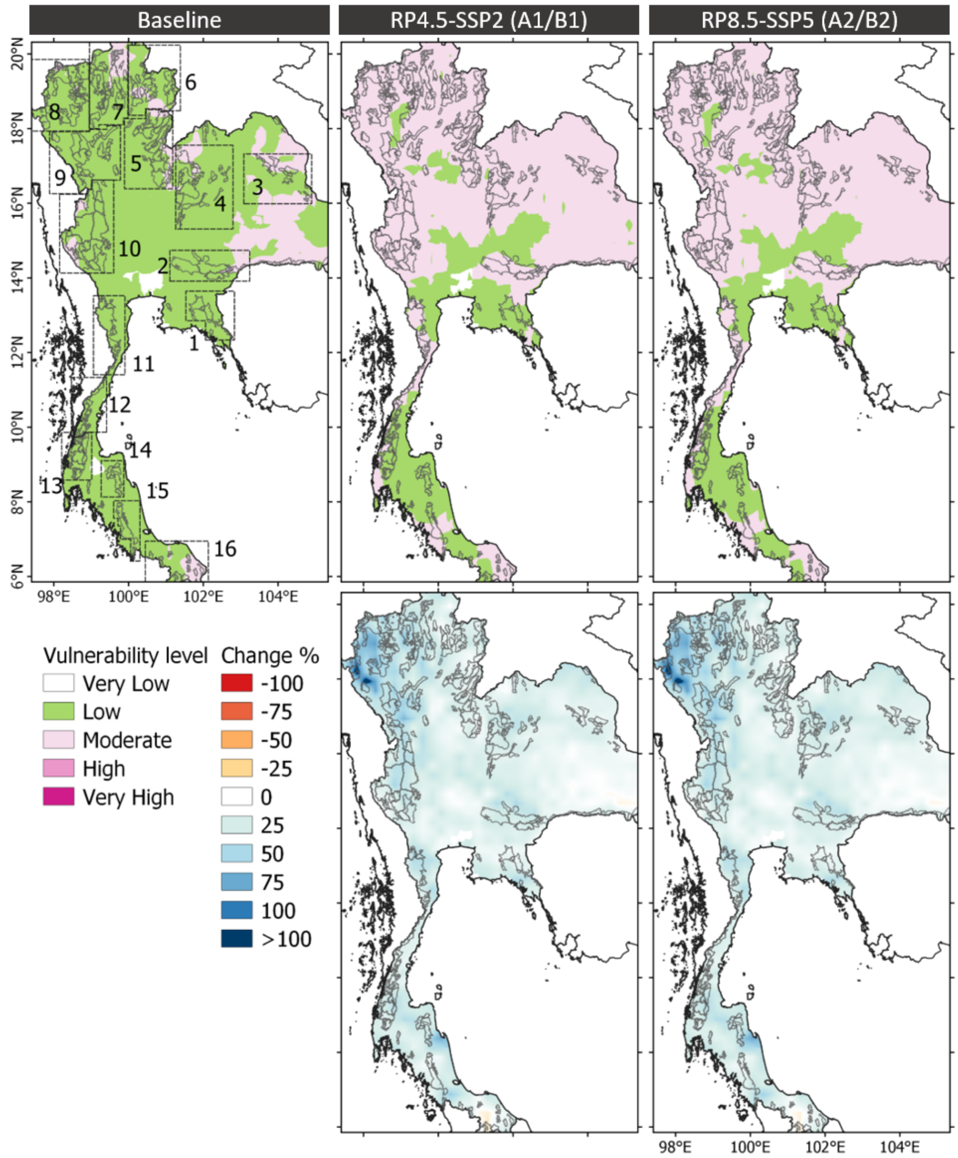


Figure 4.25: The vulnerability level aggregated from all sub-indicators for the baseline, RCP4.5-SSP2 (A1/B1), and RCP8.5-SSP5 (A2/B2) as well as the average percentage change.

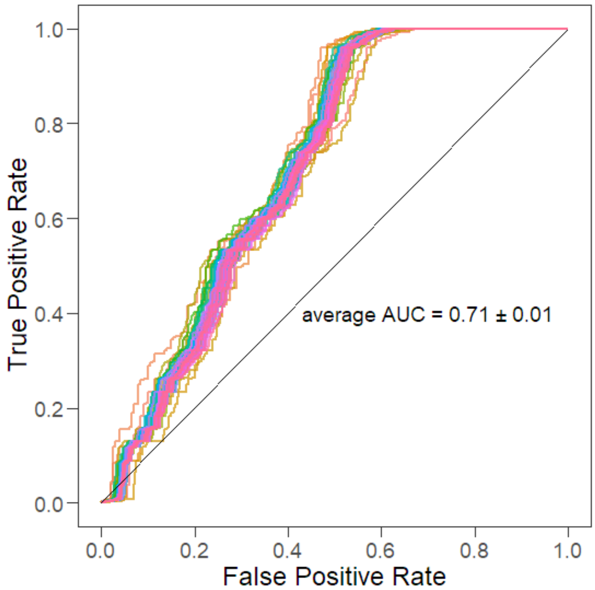


Figure 4.26: Receiver operating characteristic (ROC) curves for 60 run of HEC validation data was calculated with an average area under the curve (AUC) and its standard deviation.

level through decreasing in rural exposed human population and habitat suitability respectively. Although overall similar spatial pattern was projected for all four scenarios, variations in some locations can be identified. Under A1/B1 (RCP4.5-SSP2) compared to A2/B2 (RCP8.5-SSP5), larger spatial coverage of increasing and decreasing HEC risk was projected on the east and west of FC10 respectively (Figure 4.27, S2). In S1 and S3 area (Figure 4.27), impacts from buffer zones were identified where increase and decrease in HEC risk were estimated under A1/A2 (buffer zone) scenarios.

The number of population under exposed hazard at different vulnerable level varied in the future as shown in Table 4.9. Overall reduction under all hazard level was projected across four future scenarios, but higher level of vulnerability was estimated within each hazard level. This pattern is due to the increase in drought probability and subsequent vulnerability level. Under *Very High Hazard*, approximately 332,000 exposed persons were projected at baseline period, but decreased to around 19,000, 11,000, 15,000, and 11,000 at A1, A2, B1, and B2 scenario respectively. Total of approximately 1.4 million persons were estimated to be exposed to *High Hazard* at baseline period which then decreased 2-3 times in future scenarios. Similar pattern of exposed population also projected under *Moderate Hazard* and *Low Hazard* with less reduction (<0.25 time decreased from baseline), despite an over increase in exposed area under some scenario, A1 and A2.

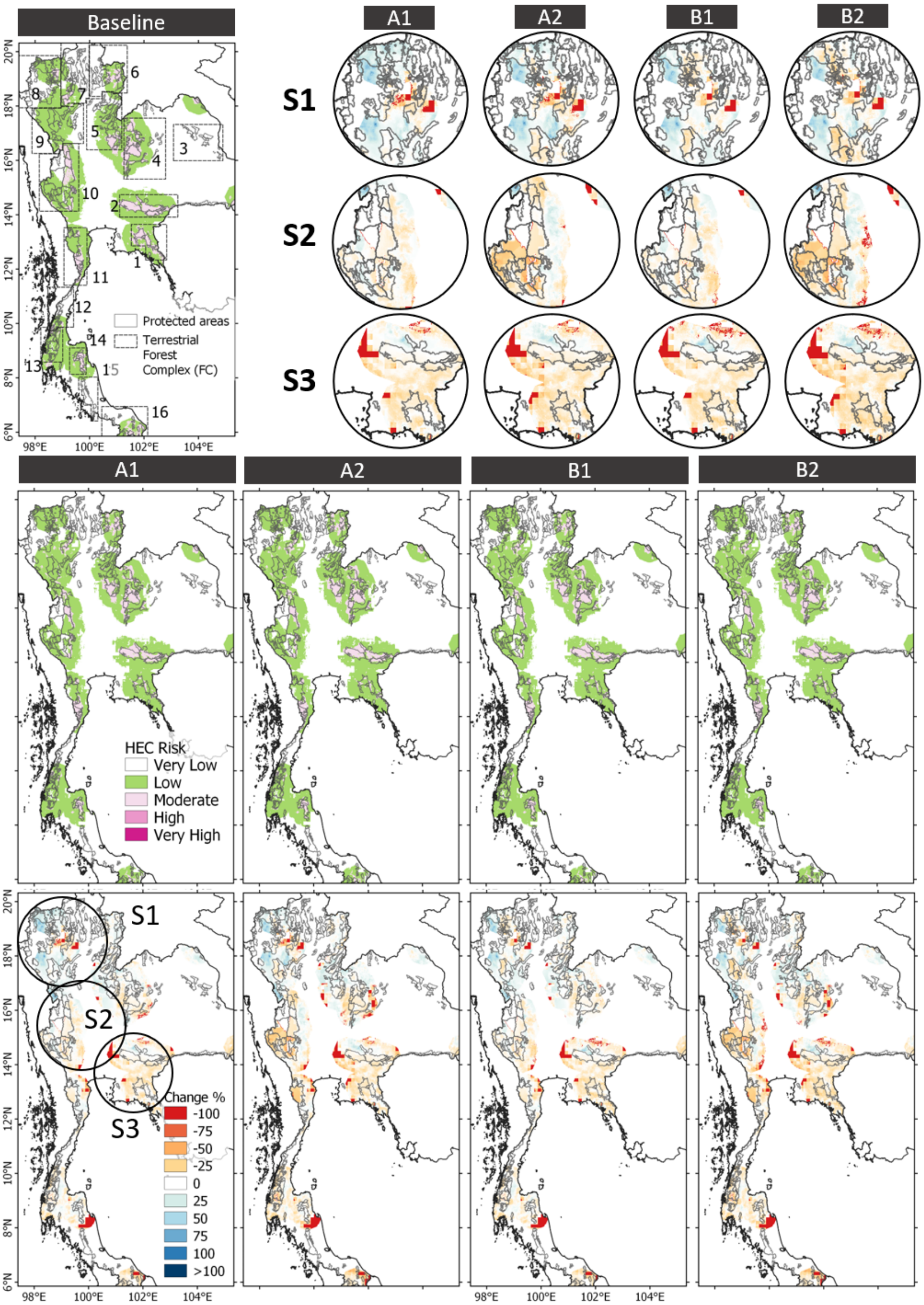


Figure 4.27: The HEC risk aggregated from hazard, exposure, and vulnerability components for baseline and future scenarios (A1: RCP4.5-SSP2-BZ, A2: RCP8.5-SSP5-BZ, B1: RCP4.5-SSP2-noBZ, and B2: RCP8.5-SSP5-noBZ), as well as the average percentage changes from baseline are shown. Selected areas are highlighted in S1-3.

Table 4.9: The number of population (shown in 1,000 persons) with different level of vulnerability that were exposed to varying levels of hazard under baseline, A1 (RCP4.5-SSP2-BZ), A2 (RCP8.5-SSP5-BZ), B1 (RCP4.5-SSP2-noBZ), and B2 (RCP8.5-SSP5-noBZ) scenario.

		Exposed population (1,000 person)				
Hazard	**Vulnerability**	**Baseline**	**A1**	**B1**	**A2**	**B2**
Very High	Moderate	9	18	14	10	11
	Low	323	1	1	0	0
	Very Low					
Total very high hazard		332	19	15	11	11
High	Moderate	115	613	613	468	480
	Low	1,286	176	204	86	117
	Very Low	0				
Total high hazard		1,401	789	817	554	597
Moderate	Moderate	213	1,290	1,228	1,296	1,121
	Low	1,963	468	498	334	395
	Very Low	25				
Total moderate hazard		2,201	1,758	1,727	1,630	1,516
Low	Moderate	537	2,280	2,057	1,992	1,881
	Low	3,553	1,421	1,399	1,332	1,270
	Very Low	66				
Total low hazard		4,156	3,701	3,457	3,314	3,151
Very Low	Moderate	7,029	19,605	19,894	15,103	15,377
	Low	24,146	5,362	5,325	3,790	3,749
	Very Low	374	42	42	36	36
Total very low hazard		31,549	25,010	25,261	18,928	19,161
Total exposed population		39,638	31,276	31,276	24,436	24,436

4.4 Discussion

4.4.1 Policy implications

Our projections suggested a northward shift in HEC risk which resulted in an average of 1.7% to 7.4% increase within four FCs in northern region. On the other hand, FCs in lower latitude showed decreasing future HEC risk of -3.1% to -57.9% on average.

Higher hazard and vulnerability levels due to more favorable habitat conditions and increase in drought probability were projected to cause an increase in HEC risk for FCs in northern regions of Thailand. This shift in suitable ranges of various species to higher latitude or elevation were observed and projected in various species Scheffers et al., 2016. Although these areas currently host relatively low wild elephant population and face *Very Low* level of HEC risk (Figure 4.27), climate change impacts through drought was expected to reduce the capacity of exposed population to bare damages from HEC in the future. Local observations already identified changing in weather patterns which caused decrease in crop yield, intensified extreme events, and escalated resource competitions (Savo et al., 2016). 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 (Eeden et al., 2018). Additionally, since these areas are still not fully developed, land use planning to selectively limit access to potential habitats can also be applied.

On the other hand, varying level of risk reduction was estimated for most FCs in southern, eastern, and lower western regions of Thailand. Many of FCs in these regions currently host large elephant populations, but existing favorable habitat conditions were expected to decline (Figure 4.27). Since population responses usually lag behind disturbances (Kuussaari et al., 2009), the reduction in habitat suitability would not immediately lead to decrease in population and subsequent HEC hazard. Consequently, those FCs with less favorable habitat conditions may retain high number of elephant for a period of time, but its long-term survival are likely hammered with increasing localized extinction (Figueiredo et al., 2019). Human-dominated land cover around these protected areas will further restrict elephants' dispersal to more suitable habitats. Therefore, management actions must be identified to buffer the future impacts which may include establishment of protected area networks (Maron et al., 2015), increasing existing carrying capacity through habitat improvements (Bonebrake et al., 2018), and translocation of population to more suitable locations (Bonebrake et al., 2018).

This study also evaluated the impacts of HEC buffer zones within which no additional land conversion was allowed under future scenarios. However, it was identified that buffer zones with this simple restriction can cause both negative and positive impact on HEC risk. Further analysis with more specific restriction is, hence, necessary to evaluate appropriate buffer zones.

4.4.2 Caveats and limitations

First, although multiple GCMs was employed to cover ranges of plausible climate, results of future projection still contained possible uncertainty (Sanderson, Knutti, and Caldwell, 2015). Second, bias could also be present in the elephant presence-only data used for suitability modeling. Although the official database and creditable materials were used to obtain presence-only data, the species may have broader niche. Third, simplified land cover classes and straightforward assumptions were made to project future land cover. Here, I did not specify the usage and potential impacts of abandoned land cover. Large agricultural areas in this study were projected to convert into abandoned lands which has potential to support conservation causes as well as bioenergy demand. Each will cause opposite impacts on the distribution of elephants and the subsequent HEC risk. Fourth, when apply to different species, care must be taken to ensure ecologically relevant underlying variables and sub-indicators are chosen. Additionally, potential improvements of the proposed framework was also identified. Since human perception and tolerance are an informative determinant of human-wildlife coexistence (Nyhus, 2016; Dickman, 2010; Struebig et al., 2018), more exhaustive list of vulnerability sub-indicators should be incorporated. Sensitivity analysis and further evaluation of contribution from each components can also be performed. More realistic dispersal probability can also be evaluated. Lastly, since our findings suggested that buffer zones can alter spatial locations of HEC risk, more comprehensive spatial policy can be evaluated.

4.5 Conclusion

In this chapter, I adopted risk assessment framework from IPCC (IPCC, 2012) and UNSDRR (UNISDR, 2015) with plausible future scenarios from RCP-SSP climate change projections and buffer zone (BZ) policy to evaluate the spatial distribution of HEC risk. To demonstrate its application, I applied the framework to evaluate HEC risk in Thailand during the baseline (2000-2019) and near future (2025-2044) by considering four future scenarios which included A1 (RCP4.5-SSP2-BZ), A2 (RCP8.5-SSP5-BZ), B1 (RCP4.5-SSP2-noBZ), and B2 (RCP8.5-SSP5-noBZ). The specific objectives were to (i) assess the change in hazard components between baseline and future scenarios, (ii) assess the change in exposure components between baseline and future scenarios, (iii) assess the change in vulnerability components between baseline and future scenarios, and (iv) compare baseline HEC risk and quantify relative changes in the future.

For the first objective, majority of the FCs in Thailand, especially those located in eastern, lower western, and southern region, were projected with reduction in hazard level across all future scenarios. On the other hand, some locations with increasing hazard are situated at the northern region, including FC5, FC8, FC9, and west of FC10. Inspecting the contributions between climate and landscape suitability, I identified prominent and uniform reduction as a result of changes in future climate conditions. In most locations, only small differences between RCP4.5-SSP2 (A1/B1) and RCP8.5-SSP5 (A2/B2) was observed, except on the east of FC10 where A2/B2 scenarios were projected with an increasing hazard. The implementation of buffer zones caused both negative and positive impacts causing varying changes in hazard level depending on locations.

As for the second objective, exposure were projected to reduce in large areas due to the expected decrease in rural population and urbanization, especially at the peripheral of Bangkok, northeastern high plain, and the southern region of the country. Smaller magnitude of reduction was also projected with forest areas. However, areas adjacent to many FCs were projected with rather stable exposure level.

The third objective was addressed in which higher HEC vulnerability level was projected due to an increase in drought probability in many areas of Thailand. Even though there were slight differences among GCMs, similar drought probability and spatial distribution were estimated from all future scenarios. The highest increase was projected at the northern region of the country, specifically near FC8 and FC9. The other areas located close to protected areas also expected to experience an increase in vulnerability, though, less severe. These areas include north of FC2, northwest of FC4, FC7, west of FC10, FC11, and south of FC14.

For the fourth objective, low to moderate HEC risk level was projected close to protected areas under baseline scenario. The future risk level is estimated to reduce for most FCs at lower latitude with an average HEC risk reduction of -3.1% to -57.9% at FC level. This reduction in HEC risk was a result of decreasing in hazard and exposure from lessen habitat conditions and urbanization respectively. These FCs, however, were already shown moderate level of risk and high elephant populations at baseline period.

Improvement in habitat quality is, thus, importance to buffer these impacts. On the other hand, the increase of HEC risk were projected for some FCs which include FC5, FC8, FC9, west of FC10, and north of FC2. Specifically for these locations, the combination of increasing hazard and vulnerability from more favorable habitat condition and higher drought probability largely altered HEC risk. Among the FCs with projected increase in HEC risk, FC5, FC8 and FC9 in the north of Thailand were estimated with very low to low HEC at baseline period which implied that the exposed population would be likely unfamiliar with HEC. Hence, adaptive capacity and limiting access to futures habitat can be considered.

Based from the results, it was demonstrated that climate-induced changes were expected to cause high impact on HEC situation in the country. The HEC risk is expected to shift north and west-ward as a result of changing habitat suitability (hazard) and drought probability (vulnerability). Urbanization dominantly causes exposure and risk reduction for FCs in southern region. Changes in land cover created localized increase and decrease in HEC risk for many areas, specifically the conversion of existing land cover to abandoned land cover type. Although the usage and impacts of abandoned land cover were not specified in the current study, such areas can potentially be used for conservation and habitat restoration. Buffer zone both negatively and positively affect risk; hence, more specific spatial restrictions within buffer zone should also be investigated.

This chapter demonstrated the possibility of applying risk assessment framework on HEC. The results identified specific risk components that should be focused by management for different forest complexes. In addition, it also highlighted the ability to utilize RCPs and SSPs projections at the national level, while also allow user-define spatial policy to be implemented. This proposed framework is flexible and can be applied on different locations and targeted species. However, care must be taken to selected ecologically relevant underlying variables and sub-indicators when apply this framework on different species. Lastly, I also recognized that the evaluation remain preliminary and limitations existed which can be further improved as highlighted under discussion section.

Chapter 5

Conclusions

Considering the increasing frequency and magnitude of conflicts between humans and wild Asian elephants, national strategies to prevent future HEC and mitigate existing conflicts are critical. Appropriate actions to manage HEC will also likely boost the support for Asian elephant conservation from local communities. Nevertheless, the lack of holistic landscape-scale assessment impedes the ability of government and relevant stakeholders to have evident-based discussion and plan for long-term resolutions.

This dissertation contributes to the scientific community and wildlife conservation managers by proposing the assessment methods that enables large spatial coverage, allows multi-dimensional analysis, and considers climate change scenarios. The HEC risk assessment framework proposed in this study is flexible and can be extended to consider ranges of relevant factors, diverse spatial policies as well as apply on different locations and species. More generally, this dissertation also attests and demonstrates the importance of climate change consideration in wildlife conflict planning. In addition, the findings from this study also support the prioritization of areas that required management attention.

To construct HEC risk assessment framework, three sets of research questions were raised in Chapter 1 which include the followings:-

1. What are the main priority for Asian elephant conservation in each range country considering long-term historical changes in elephant population and key driving factors within elephant home ranges?, and which country is the most concern for HEC? (Chapter 2)

2. Within the country of most concern, how did HEC distribution change over time? and what are the important environmental variables influencing changes in HEC? (Chapter 3)

3. Within the country of most concern, how HEC will change in the future, and which location should be given priority? (Chapter 4)

Through this dissertation, each of the questions was addressed in separate chapters. Here I first discussed the implications and significance of the findings, followed by recommendations, limitations of current study, and future works. Finally, I provided concluding remarks.

5.1 Summary of findings and key recommendations

In Chapter 2, to addresses the first set of research question, I performed cross-country assessment based on the Asian elephant population dynamic and associated socio-environmental factors from three time periods (1990, 2003, and 2015). The results suggested that substantial Asian elephant population can persist in highly diverse landscape along side human population when a large forest area with less fragmentation were maintained. Range countries were also classified into four groups. First, a decrease in elephants with high forest loss and fragmentation were found in Cambodia, Laos, and Vietnam, implying key habitat loss. Second, Indonesia and Myanmar had a decrease in elephants even with remaining large forest patch which was likely a result of illegal forest encroachment and poaching respectively. Third, effective protection in key forest habitat was identified in Bhutan, India, and Nepal which should be expanded across the countries. Fourth, a stable or increasing elephant population even with human disturbance and habitat loss was identified in Bangladesh, China, Malaysia, Thailand, Sri Lanka, implying the likelihood of overlapping resource usage and HEC. This result highlighted different management focus for each country. In particular, Thailand was discussed to possess an interesting position in which other range countries may follow. Hence, HEC situation in Thailand was further analyzed and discussed in Chapter 3 and 4.

In chapter 3, I addressed the second research question. The results highlighted the expansion of HEC hotspot over the 10-year period. In 2018, overall area of HEC under high category in the wet and dry season was approximately triple and double that in 2009. Chantaburi province, particularly near Khao Chamao-Khao Wong and Ang Ruenai Wildlife Sanctuary, was identified with the largest area of HEC. Nakhon Ratchasima province was also estimated with large HEC areas, followed by Prachinburi, Rayong, and Sa Kaeo. Looking at the changes over time, the results indicated a gradual increasing trend of direct human pressure but more erratic patterns of resource suitability. In particular, a large reduction of high suitable resources was observed during drought year.

Key drivers governing HEC distribution were also identified from namely, forest coverage, drought conditions, distance to forest, distance to protected habitat, human density, and distance to transport network. These drivers were considered for further modeling in Chapter 4.

To address the third set of research questions, I proposed HEC risk assessment framework and demonstrated its application by analysis spatial distribution of HEC in Thailand under current and future scenarios in Chapter 4. This chapter illustrates the utilization of well-established projections under RCPs and SSPs at national scale. The results suggested that HEC risk were likely decrease in the future at lower latitude, particularly in southern, central, and eastern region of Thailand. Specific areas that were projected with higher HEC risk where mostly located toward the north of Thailand which include Lamnampai-Salawin Forest Complex (FC), Mae Pin-Omgoi FC, Phumieng-Phuthon FC, and west of Western FC. Despite its location at lower latitude, areas north of FC2 is also expected with higher risk. Climate-induced changes were estimated to prominently impact the change in HEC risk by reducing habitat suitability and increasing drought probability which influenced hazard and vulnerability components. Urbanization and reduction of rural population are expected to decrease number of exposed population and the subsequent future exposure level. Although land cover changes had overall lower effect on HEC risk, it caused localized added impact on top of climate, especially from the conversion to abandoned land cover class.

Based on the findings of this dissertation, a number of key statements and policy implication can be highlighted which cloud support conservation strategies.

1. Climate, especially changes in drought, prominently impacted historical pattern of HEC and its future risk; hence should be incorporated in all future conservation and human-wildlife conflict related policy.

2. Map of HEC risk distribution in Thailand suggested that conservation strategies to buffer climate volatility is necessary, especially in areas currently host high elephant population but lower future habitat suitability. Such locations include (i) Eastern FC, (ii) Khao Yai-Dong Phayayen FC, (iii) Phukeio-Namnow FC, (iv) eastern areas within Western FC, (v) Khaengkrachan FC, (vi) Klong Saeng-Khaosok FC, and (vii) Khao Laung FC. Improvement of habitat quality (e.g. protected area network, and improve carrying capacity) within these groups of FCs may reduce climate impacts as well as prevent crop-raiding due to lack of available natural forages.

3. Map of HEC risk distribution in Thailand also suggested areas with existing low human population but high future HEC risk: (i) west of Lumnampai-Salawin FC, (ii) west of Mae Pin-Omgui FC, (iii) west of Western FC, (iv) and adjacent areas around Phumeing-Phuthon FC. Building adaptive capacity and limited human access in potential future habitats may be considered.

4. Evaluation at regional scale implied country specific conservation priority for range states. Halting habitat conversion and deforestation are recommended priority for Cambodia, Laos, and Vietnam. Strengthening of conservation laws and better their execution are recommended for Myanmar and Indonesia. For most countries including Bangladesh, China, India, Malaysia, Nepal, Sri Lanka, and Thailand, further focus on HEC investigation and mitigation are crucial. Lastly, Bhutan, India, and Nepal likely possess effective protection of key habitats, hence how to further expand the effort to other locations within the country should be priority.

5. Specifically for Eastern Thailand, HEC-zone dependent management can be planned after further investigation. These HEC-zone included:-
   - High HEC: directly adjacent to protected area boundaries in the south of Khao Angruenai, surrounding areas of Khao Chamao-Khao Wong, and north of Khao Yai.
   - Likely HEC: approximately 6-12km from protected area boundaries mainly present in wet season.
   - Low HEC: approximately over 12km from protected area boundaries mainly present in dry season.
   - Rare HEC: scattered around main roads with most clustered predicted in Chachoengsao, Chonburi, and Chantaburi provinces, implying necessary prevention of vehicle-elephant collision.

6. The proposed framework should be applicable to different locations and targeted species. However, when applying the proposed risk framework to different species, care must be taken to ensure ecologically relevant underlying variables and sub-indicators are chosen.

5.2 Limitations of this research

Despite the promising outcome of the proposed framework, some limitations existed and should be addressed:

- Home range of Asian elephants are fragmented and sparsely distributed even within the same country. Countries with large geospatial areas, such as India and Indonesia, may have drastically different characteristics among regions. However, the lack of long-term baseline data on Asian elephant population at home range level restricted a finer-scale assessment. The current results are useful, but general.

- Presence-only elephant presences and HEC incidents most likely represent realized niche of the species, but not the fundamental niches. Therefore, there remain potential bias which may be enhanced by the improvement of on-the-ground data.

- Socioeconomic factors are critical in governing human tolerance and vulnerability. In this study, economic and human development indicators, such as average monthly income, education level, and access to technology were used to represent these complex aspects. Due to the coarse temporal (1-5 years collection) and spatial (province-level) measurement of these indicators, conversion of such statistical parameters to geospatial data will not capture finer variations.

- Related with the aforementioned limitation and the literature discussed in 1, more exhaustive social factors, such as culture, religions, and trust toward institutions have yet to be incorporated.

- Validation of baseline risk is critical and required large-scale past records of disaster events. Nevertheless, country-wide historical data on HEC is limited or non-existed in Thailand. Data on damages by elephants in Thailand are not regularly and systematically recorded due to the lack of compensation schemes. Hence, no incentive to do report. Only in mid-2019 that the compensation for damages on rice (other crops are not covered) started in some locations. With this limitation, the validation data was obtained from one FC in northeastern region which may or may not represent the nature of conflict other regions.

- Future projection relied on various empirical modeling results (e.g. GCMs, land cover, etc.), all of which inherited errors and uncertainties. Hence, the aggregation of these dataset may cause propagation of uncertainty into model results. Since projection is not prediction and uncertainties are expected, care must be taken when interpreting the results.

5.3 Future works

Even though I have been able to demonstrate the applicability and discuss the assessment of long-term Asian elephant habitats and the current and future HEC distribution, further study remains. The variability in land surface phenology and human activities at higher temporal (seasonally) and spatial (farm-level) resolutions remain unclear. Satellite-derived vegetation productivity are now available at finer resolution (e.g 10m at 5-day revisit), while elephant movement from GPS collars are also being collected in many areas. Therefore, the utilization of such finer resolution dataset will allow the assessment of crop types and cropping pattern at finer spatial scale. With more elephant data being collected, the implementation of centralize and systematic sharing of baseline data on Asian elephant population and HEC incidents should be considered. Accessibility to nation-wide baseline data would advance conservation research and improve decision making. Since the perception of communities greatly influence elephant tolerance and conservation support, indicators that reflect these human dimension should be further evaluated under vulnerability component which would improve the accuracy of HEC risk projection. In addition, social and economic inequality exist in many countries including Thailand which likely impacts exposed human population and subsequent distribution of HEC risk. Therefore, further study should also incorporate inequality. Most importantly, collaboration with stakeholders must be implemented, so that feedback can be obtained to certain the applicability of this proposed framework.

5.4 Conclusion

Human-elephant conflict in Asia is a “wicked problem” (Game et al., 2014) and one of the greatest challenges facing the species long-term conservation. For Asian elephant conservation to be successful, conflicts between the species and humans must be appropriately measured and managed. The key contribution of this dissertation is through the improvement of assessment framework that allows large spatial coverage, multi-dimensional analysis, and climate change considerations. Although the current study focuses on conflicts between wild Asian elephants and humans, the proposed framework should also be applicable to other targeted species. More generally, the findings attest the importance in climate change consideration in wildlife conflict management. Additionally, various analysis in this study highlight the possibility of large-scale assessment that integrated the knowledge and techniques from remote sensing, geographical information system, ecology, and climate change. The knowledge and outcomes gained in this research, which include the country conservation priority, the hotspot of HEC conflict in Eastern Thailand, the changes in countrywide distribution of HEC risk under future scenarios, can support the prioritization of locations in need for management attention and guide further scientific studies on this issue. Engagement from stakeholders is necessary to advance the understanding of HEC. Extending the implications of this proposed framework to local communities is, hence, a necessary next step to certain the future of Asian elephants.

Bibliography

Abatzoglou, John T et al. (2018). “TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015”. In: *Scientific Data* 5, pp. 1–12. ISSN: 20524463. DOI: 10.1038/sdata.2017.191.

Aini, Suhaida et al. (2017). “A GIS Based Multi-Criteria Evaluation Approach to Develop an Asian Elephant Habitat Suitability Model in Peninsular Malaysia”. In: 47, pp. 10–17.

Alabia, Irene D et al. (2016). “Seasonal habitat patterns of Japanese common squid (Todarodes pacificus) inferred from satellite-based species distribution models”. In: *Remote Sensing* 8.11. ISSN: 20724292. DOI: 10.3390/rs8110921.

Albergel, Clement et al. (2018). “ERA-5 and ERA-Interim driven ISBA land surface model simulations: Which one performs better?” In: *Hydrology and Earth System Sciences Discussions*, pp. 1–37. ISSN: 1027-5606. DOI: 10.5194/hess-2018-117.

Alexander, Martin E (1990). “Computer Calculation of the Keetch-Byram Drought Index-Programmers Beware!” In: *Fire Management Notes* 51.4, pp. 23–25.

Alexandratos, Nikos and Jelle Bruinsma (2012). “WORLD AGRICULTURE TOWARDS 2030 / 2050”.

Allouche, Omri, Asaf Tsoar, and Ronen Kadmon (2006). “Assessing the accuracy of species distribution models: Prevalence, kappa and the true skill statistic (TSS)”. In: *Journal of Applied Ecology* 43.6, pp. 1223–1232. ISSN: 00218901. DOI: 10.1111/j.1365-2664.2006.01214.x.

Anand, Shaurabh and Sindhu Radhakrishna (2017). “Investigating trends in human-wildlife conflict: is conflict escalation real or imagined?” In: *Journal of Asia-Pacific Biodiversity* 10.2, pp. 154–161. ISSN: 22879544. DOI: 10.1016/j.japb.2017.02.003.

Artelle, Kyle A et al. (2016). “Ecology of conflict: Marine food supply affects human-wildlife interactions on land”. In: *Scientific Reports* 6.October 2015, pp. 1–9. ISSN: 20452322. DOI: 10.1038/srep25936.

Athreya, Vidya et al. (2013). “Big Cats in Our Backyards: Persistence of Large Carnivores in a Human Dominated Landscape in India”. In: *PLoS ONE* 8.3, pp. 2–9. ISSN: 19326203. DOI: 10.1371/journal.pone.0057872.

Bai, Xuemei et al. (2016). "Plausible and desirable futures in the Anthropocene: A new research agenda". In: *Global Environmental Change* 39, pp. 351–362. ISSN: 09593780. DOI: 10.1016/j.gloenvcha.2015.09.017. URL: http://dx.doi.org/10.1016/j.gloenvcha.2015.09.017.

Bandara, Ranjith and Clem Tisdell (2003). "Comparison of rural and urban attitudes to the conservation of Asian elephants in Sri Lanka: Empirical evidence". In: *Biological Conservation* 110.3, pp. 327–342. ISSN: 00063207. DOI: 10.1016/S0006-3207(02)00241-0.

Barnes, Megan D et al. (2016). "Wildlife population trends in protected areas predicted by national socio-economic metrics and body size". In: *Nature Communications* 7, pp. 1–9. ISSN: 20411723. DOI: 10.1038/ncomms12747.

Barua, Maan, Shonil A. Bhagwat, and Sushrut Jadhav (2013). "The hidden dimensions of human-wildlife conflict: Health impacts, opportunity and transaction costs". In: *Biological Conservation* 157, pp. 309–316. ISSN: 0006-3207. DOI: 10.1016/J.BIOCON.2012.07.014. URL: https://www.sciencedirect.com/science/article/pii/S0006320712003345?via{\%}3Dihub{\#}b0245.

Barua, Maan, Jatin Tamuly, and Riyaz Akhtar Ahmed (2010). "Mutiny or clear sailing? Examining the role of the asian elephant as a flagship species". In: *Human Dimensions of Wildlife* 15.2, pp. 145–160. ISSN: 10871209. DOI: 10.1080/10871200903536176.

Bedia, Joaquín, Sixto Herrera, and José Manuel Gutiérrez (2013). "Dangers of using global bioclimatic datasets for ecological niche modeling. Limitations for future climate projections". In: *Global and Planetary Change* 107, pp. 1–12. ISSN: 09218181. DOI: 10.1016/j.gloplacha.2013.04.005. URL: https://linkinghub.elsevier.com/retrieve/pii/S0921818113000957.

Berzaghi, Fabio et al. (2019). "Carbon stocks in central African forests enhanced by elephant disturbance". In: *Nature Geoscience* 12.9, pp. 725–729. ISSN: 17520908. DOI: 10.1038/s41561-019-0395-6.

Beyer, Robert M and Andrea Manica (2020). "Historical and projected future range sizes of the world's mammals, birds, and amphibians". In: *Nature Communications* 11.1, pp. 1–8. ISSN: 20411723. DOI: 10.1038/s41467-020-19455-9. URL: http://dx.doi.org/10.1038/s41467-020-19455-9.

Bhagwat, Tejas et al. (2017). "Losing a jewel-Rapid declines in Myanmar's intact forests from 2002-2014". In: *PLoS ONE* 12.5, pp. 1–22. ISSN: 19326203. DOI: 10.1371/journal.pone.0176364.

Bi, Yingfeng et al. (2016). "Kamala tree as an indicator of the presence of Asian elephants during the dry season in the Shivalik landscape of northwestern India". In: *Ecological Indicators* 71, pp. 239–247. ISSN: 1470160X. DOI: 10.1016/j.ecolind.2016.07.011. URL: http://dx.doi.org/10.1016/j.ecolind.2016.07.011.

Birkmann, Joern and Torsten Welle (2015). "Assessing the risk of loss and damage: Exposure, vulnerability and risk to climate-related hazards for different country classifications". In: *International Journal of Global Warming* 8.2, pp. 191–212. ISSN: 17582091. DOI: 10.1504/IJGW.2015.071963.

Blake, Stephen and Simon Hedges (2004). "Sinking the flagship: The case of forest elephants in Asia and Africa". In: *Conservation Biology* 18.5, pp. 1191–1202. ISSN: 08888892. DOI: 10.1111/j.1523-1739.2004.01860.x.

Blake, Stephen and Clement Inkamba-Nkulu (2004). "Fruit, minerals, and forest elephant trails: Do all roads lead to Rome?" In: *Biotropica* 36.3, pp. 392–401. ISSN: 00063606. DOI: 10.1111/j.1744-7429.2004.tb00332.x.

Bleyhl, Benjamin et al. (2015). "Mapping seasonal European bison habitat in the Caucasus Mountains to identify potential reintroduction sites". In: *Biological Conservation* 191, pp. 83–92. ISSN: 00063207. DOI: 10.1016/j.biocon.2015.06.011. URL: http://dx.doi.org/10.1016/j.biocon.2015.06.011https://linkinghub.elsevier.com/retrieve/pii/S0006320715002347.

Bohrer, Gil et al. (2014). "Elephant movement closely tracks precipitation-driven vegetation dynamics in a Kenyan forest-savanna landscape." In: *Movement ecology* 2.1, p. 2. ISSN: 2051-3933. DOI: 10.1186/2051-3933-2-2. URL: http://www.ncbi.nlm.nih.gov/pubmed/25520813http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4267703.

Bonebrake, Timothy C. et al. (2018). "Managing consequences of climate-driven species redistribution requires integration of ecology, conservation and social science". In: *Biological Reviews* 93.1, pp. 284–305. ISSN: 14647931. DOI: 10.1111/brv.12344. URL: http://doi.wiley.com/10.1111/brv.12344.

Borowik, Tomasz et al. (2013). "Normalized difference vegetation index (NDVI) as a predictor of forage availability for ungulates in forest and field habitats". In: *European Journal of Wildlife Research* 59.5, pp. 675–682. ISSN: 16124642. DOI: 10.1007/s10344-013-0720-0.

Bottrill, Madeleine C. et al. (2008). "Is conservation triage just smart decision making?" In: *Trends in Ecology & Evolution* 23.12, pp. 649–654. ISSN: 01695347. DOI: 10.1016/

j.tree.2008.07.007. URL: https://linkinghub.elsevier.com/retrieve/pii/S0169534708002814.

Boult, Victoria L et al. (2019a). “Human-driven habitat conversion is a more immediate threat to Amboseli elephants than climate change”. In: *Conservation Science and Practice* 1.9, pp. 1–10. ISSN: 2578-4854. DOI: 10.1111/csp2.87.

Boult, Victoria L et al. (2019b). “Modelling large herbivore movement decisions: Beyond food availability as a predictor of ranging patterns”. In: *African Journal of Ecology* 57.1, pp. 10–19. ISSN: 13652028. DOI: 10.1111/aje.12553.

Brambilla, Mattia et al. (2016). “Climate change will increase the potential conflict between skiing and high-elevation bird species in the Alps”. In: *Journal of Biogeography* 43.11, pp. 2299–2309. ISSN: 13652699. DOI: 10.1111/jbi.12796.

Branco, Paola S et al. (2019). “Determinants of elephant foraging behaviour in a coupled natural system : Is brown the new green ?” In: *Jouranl of Animal Ecology* 88, pp. 780–792. DOI: 10.1111/1365-2656.12971.

Branton, Margaret and John S Richardson (2011). “Evaluación del Valor del Concepto de Especie Sombrilla para la Planificación de la Conservación Mediante Meta-Análisis”. In: *Conservation Biology* 25.1, pp. 9–20. ISSN: 08888892. DOI: 10.1111/j.1523-1739.2010.01606.x.

Bruskotter, Jeremy T and Robyn S Wilson (2014). “Determining where the wild things will be: Using psychological theory to find tolerance for large carnivores”. In: *Conservation Letters* 7.3, pp. 158–165. ISSN: 1755263X. DOI: 10.1111/conl.12072.

Bütikofer, Luca et al. (2020). “The problem of scale in predicting biological responses to climate”. In: *Global Change Biology* August, pp. 6657–6666. ISSN: 13652486. DOI: 10.1111/gcb.15358.

Calabrese, A et al. (2017). “Conservation status of Asian elephants: the influence of habitat and governance”. In: *Biodiversity and Conservation* 26.9, pp. 2067–2081. ISSN: 15729710. DOI: 10.1007/s10531-017-1345-5.

Campos-Arceiz, Ahimsa and Steve Blake (2011). “Megagardeners of the forest - the role of elephants in seed dispersal”. In: *Acta Oecologica* 37.6, pp. 542–553. ISSN: 1146609X. DOI: 10.1016/j.actao.2011.01.014. URL: http://dx.doi.org/10.1016/j.actao.2011.01.014.

Cardinale, Bradley J et al. (2012). “Biodiversity loss and its impact on humanity”. In: *Nature* 486.7401, pp. 59–67. ISSN: 00280836. DOI: 10.1038/nature11148.

Carter, Neil H and John D C Linnell (2016). “Co-Adaptation Is Key to Coexisting with Large Carnivores”. In: *Trends in Ecology and Evolution* 31.8, pp. 575–578. ISSN:

01695347. DOI: 10.1016/j.tree.2016.05.006. URL: http://dx.doi.org/10.1016/j.tree.2016.05.006.

Carter, Neil H et al. (2012). "Coexistence between wildlife and humans at fine spatial scales". In: *Proceedings of the National Academy of Sciences of the United States of America* 109.38, pp. 15360–15365. ISSN: 00278424. DOI: 10.1073/pnas.1210490109.

Carter, Neil H et al. (2014). "Coupled human and natural systems approach to wildlife research and conservation". In: *Ecology and Society* 19.3. ISSN: 1708-3087. DOI: 10.5751/es-06881-190343.

Ceballos, Gerardo, Paul R Ehrlich, and Rodolfo Dirzo (2017). "Biological annihilation via the ongoing sixth mass extinction signaled by vertebrate population losses and declines". In: *Proceedings of the National Academy of Sciences of the United States of America* 114.30, E6089–E6096. ISSN: 10916490. DOI: 10.1073/pnas.1704949114.

Chamaillé-Jammes, Simon et al. (2013). "African Elephants Adjust Speed in Response to Surface-Water Constraint on Foraging during the Dry-Season". In: *PLoS ONE* 8.3. ISSN: 19326203. DOI: 10.1371/journal.pone.0059164.

Chapin, F Stuart et al. (2000). "Consequences of changing biodiversity". In: *Nature* 405.6783, pp. 234–242. ISSN: 00280836. DOI: 10.1038/35012241.

Chapron, Guillaume et al. (2014). "Recovery of large carnivores in Europe's modern human-dominated landscapes". In: *Science* 346.6216, pp. 1517–1519. ISSN: 0036-8075. DOI: 10.1126/science.1257553. URL: https://www.sciencemag.org/lookup/doi/10.1126/science.1257553.

Chen, Shu et al. (2013). "Developing a spatially-explicit, sustainable and risk-based insurance scheme to mitigate human-wildlife conflict". In: *Biological Conservation* 168, pp. 31–39. ISSN: 00063207. DOI: 10.1016/j.biocon.2013.09.017. URL: https://linkinghub.elsevier.com/retrieve/pii/S0006320713003340.

Chen, Ying et al. (2016). "Predicting Hotspots of Human-Elephant Conflict to Inform Mitigation Strategies in Xishuangbanna, Southwest China". In: *PLOS ONE* 11.9. Ed. by Elissa Z. Cameron, e0162035. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0162035. URL: https://dx.plos.org/10.1371/journal.pone.0162035.

Choudhury, A et al. (2008). "Elephas maximus. The IUCN Red List of Threatened Species 2008". In: *The IUCN Red List of Threatened Species 2008* 8235, p. 16. DOI: http://dx.doi.org/10.2305/IUCN.UK.2008.RLTS.T7140A12828813.en.

Crist, Eileen, Camilo Mora, and Robert Engelman (2017). "and Biodiversity Protection". In: *Science* 264.April, pp. 260–264. ISSN: 0036-8075.

Cuba, Nicholas (2015). “Research note: Sankey diagrams for visualizing land cover dynamics”. In: *Landscape and Urban Planning* 139, pp. 163–167. ISSN: 01692046. DOI: 10.1016/j.landurbplan.2015.03.010. URL: http://dx.doi.org/10.1016/j.landurbplan.2015.03.010.

Czech, Brian (2000). “Economic growth as the limiting factor for wildlife conservation”. In: *Wildlife Society Bullentin* 28(1), pp. 4–14. URL: https://mpra.ub.uni-muenchen.de/9038/.

De Angelo, Carlos et al. (2013). “Understanding species persistence for defining conservation actions: A management landscape for jaguars in the Atlantic Forest”. In: *Biological Conservation* 159, pp. 422–433. ISSN: 00063207. DOI: 10.1016/j.biocon.2012.12.021. URL: http://dx.doi.org/10.1016/j.biocon.2012.12.021.

De Boer, Willem F et al. (2013). “Understanding spatial differences in African elephant densities and occurrence, A continent-wide analysis”. In: *Biological Conservation* 159, pp. 468–476. ISSN: 00063207. DOI: 10.1016/j.biocon.2012.10.015. URL: http://dx.doi.org/10.1016/j.biocon.2012.10.015.

Deb, Jiban Chandra et al. (2019). “Adaptive management and planning for the conservation of four threatened large Asian mammals in a changing climate”. In: *Mitigation and Adaptation Strategies for Global Change* 24.2, pp. 259–280. ISSN: 15731596. DOI: 10.1007/s11027-018-9810-3.

DeFries, Ruth et al. (2007). “Land use change around protected areas: Management to balance human needs and ecological function”. In: *Ecological Applications* 17.4, pp. 1031–1038. ISSN: 10510761. DOI: 10.1890/05-1111.

DeMotts, Rachel and Parakh Hoon (2012). “Whose Elephants? Conserving, Compensating, and Competing in Northern Botswana”. In: *Society and Natural Resources* 25.9, pp. 837–851. ISSN: 08941920. DOI: 10.1080/08941920.2011.638362.

Desai, Ajay A and Heidi S Riddle (2015). *Human-Elephant Conflict in Asia*. Tech. rep. June. U.S. Fish and Wildlife Service Asian Elephant Support, p. 92.

Diana Vollmerhausen (2014). *Elephants in the Dust | The Independent*. ISBN: 9788277011110. URL: http://www.independent.co.uk/voices/comment/elephants-in-the-dust-9114448.html.

Dickman, A J (2010). “Complexities of conflict: The importance of considering social factors for effectively resolving human-wildlife conflict”. In: *Animal Conservation* 13.5, pp. 458–466. ISSN: 13679430. DOI: 10.1111/j.1469-1795.2010.00368.x.

Dickman, Amy, Silvio Marchini, and Michael Manfredo (2013). “The human dimension in addressing conflict with large carnivores”. In: *Key Topics in Conservation Biology*

2. Oxford: John Wiley & Sons, pp. 110–126. DOI: 10.1002/9781118520178.ch7. URL: http://doi.wiley.com/10.1002/9781118520178.ch7.

Distefano, E (2005). *Human-wildlife conflict worldwide: a collection of case studies, analysis of management strategies and good practices*. Tech. rep. ood, Agricultural Organization of the United Nations (FAO), Sustainable Agriculture, and Rural Development (SARD). URL: http://www.fao.org/documents/card/en/c/e21b6162-b3ad-4661-8c52-710f95ebeaf7/.

DNP (n.d.). *Survey of elephant sighting location from Thailand protected areas (in Thai)*. Tech. rep. Department of National Parks, Wildlife, and Plant Conservations, pp. 1–17.

— (2019). *Elephant sighting outside of Khao Yai National Park*. Nakhon Ratchsima, Thailand.

Dorji, Sangay, Rajanathan Rajaratnam, and Karl Vernes (2019). “Mammal richness and diversity in a Himalayan hotspot: the role of protected areas in conserving Bhutan’s mammals”. In: *Biodiversity and Conservation* 28.12, pp. 3277–3297. ISSN: 15729710. DOI: 10.1007/s10531-019-01821-9. URL: https://doi.org/10.1007/s10531-019-01821-9.

Dorji, Sangay et al. (2018). “Identifying conservation priorities for threatened Eastern Himalayan mammals”. In: *Conservation Biology* 32.5, pp. 1162–1173. ISSN: 15231739. DOI: 10.1111/cobi.13115.

Doyle, Sarah et al. (2010). “Human-elephant conflict- what can we learn from the news?” In: *Gajah* 32, pp. 14–20.

Dublin, Holly T. and Richard E. Hoare (2004). “Searching for solutions: The evolution of an integrated approach to understanding and mitigating human-elephant conflict in africa”. In: *Human Dimensions of Wildlife* 9.4, pp. 271–278. ISSN: 1533158X. DOI: 10.1080/10871200490505701.

Duffy, James P and Nathalie Pettorelli (2012). “Exploring the relationship between NDVI and African elephant population density in protected areas”. In: *African Journal of Ecology* 50.4, pp. 455–463. ISSN: 01416707. DOI: 10.1111/j.1365-2028.2012.01340.x. URL: http://doi.wiley.com/10.1111/j.1365-2028.2012.01340.x.

Eeden, Lily M. van et al. (2018). “Managing conflict between large carnivores and livestock”. In: *Conservation Biology* 32.1, pp. 26–34. ISSN: 08888892. DOI: 10.1111/cobi.12959. URL: http://doi.wiley.com/10.1111/cobi.12959.

Elith, Jane and Catherine H. Graham (2009). “Do they? How do they? WHY do they differ? On finding reasons for differing performances of species distribution models”.

In: *Ecography* 32.1, pp. 66–77. ISSN: 1600-0587. DOI: 10.1111/j.1600-0587.2008.05505.x.

Elith, Jane, Michael Kearney, and Steven Phillips (2010). “The art of modelling range-shifting species”. In: *Methods in Ecology and Evolution* 1.4, pp. 330–342. ISSN: 2041210X. DOI: 10.1111/j.2041-210X.2010.00036.x. URL: http://doi.wiley.com/10.1111/j.2041-210X.2010.00036.x.

Elith, Jane et al. (2011). “A statistical explanation of MaxEnt for ecologists”. In: *Diversity and Distributions* 17.1, pp. 43–57. ISSN: 13669516. DOI: 10.1111/j.1472-4642.2010.00725.x. URL: http://doi.wiley.com/10.1111/j.1472-4642.2010.00725.x.

Elvidge, Christopher D. et al. (2014). “National trends in satellite-observed lighting 1992-2012”. In: *Global Urban Monitoring and Assessment through Earth Observation*. Ed. by Qihao Weng. Boca Raton, FL: CRC Press, pp. 97–119.

Epps, Clinton W et al. (2011). “An empirical evaluation of the African elephant as a focal species for connectivity planning in East Africa”. In: *Diversity and Distributions* 17.4, pp. 603–612. ISSN: 13669516. DOI: 10.1111/j.1472-4642.2011.00773.x.

Estes, Jason G et al. (2012). “Quantity and Configuration of Available Elephant Habitat and Related Conservation Concerns in the Lower Kinabatangan Floodplain of Sabah, Malaysia”. In: *PLoS ONE* 7.10. ISSN: 19326203. DOI: 10.1371/journal.pone.0044601.

Evans, Luke J., Gregory P. Asner, and Benoit Goossens (2018). “Protected area management priorities crucial for the future of Bornean elephants”. In: *Biological Conservation* 221, pp. 365–373. ISSN: 0006-3207. DOI: 10.1016/J.BIOCON.2018.03.015. URL: https://www.sciencedirect.com/science/article/pii/S0006320717318141.

FAO (2016). *Agricultural land (% of land area)*. URL: https://data.worldbank.org/indicator/AG.LND.AGRI.ZS (visited on 04/01/2020).

— (2020). *FAOSTAT*. URL: http://www.fao.org/faostat/en/{\#}data/QC (visited on 09/20/2020).

FAO and UNEP (2020). *The State of the World’s Forests 2020*. Tech. rep. URL: https://doi.org/10.4060/ca8642en.

FAO/IIASA (2012). *FAO/IIASA/ISRIC/ISSCAS/JRC, 2012. Harmonized World Soil Database (version 1.2).* Rome, Italy (FAO) and Laxenburg, Austria (IIASA).

Fay, Michael P and Michael A Proschan (2010). “Wilcoxon-Mann-Whitney or t-test? On assumptions for hypothesis tests and multiple interpretations of decision rules.” In: *Statistics surveys* 4, pp. 1–39. ISSN: 1935-7516. DOI: 10.1214/09-SS051. URL:

http://www.ncbi.nlm.nih.gov/pubmed/20414472http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC2857732.

Fernando, Prithiviraj. and Peter. Leimgruber (2011). “Asian elephants and seasonally dry forests”. In: *The ecology and conservation of seasonally dry forests in Asia*, pp. 151–163.

Fernando, Prithiviraj and Jennifer Pastorini (2011). “Range-wide Status of Asian Elephants”. In: *Gajah* 35, pp. 15–20. DOI: 10.5167/uzh-59036.

Fernando, Prithiviraj et al. (2005). “Perceptions and Patterns of Human-elephant Conflict in Old and New Settlements in Sri Lanka: Insights for Mitigation and Management”. In: *Biodiversity and Conservation* 14.10, pp. 2465–2481. ISSN: 0960-3115. DOI: 10.1007/s10531-004-0216-z. URL: http://link.springer.com/10.1007/s10531-004-0216-z.

Fernando, Prithiviraj et al. (2012). “Problem-Elephant Translocation: Translocating the Problem and the Elephant?” In: *PLoS ONE* 7.12. ISSN: 19326203. DOI: 10.1371/journal.pone.0050917.

Figueiredo, Ludmilla et al. (2019). “Understanding extinction debts: spatio-temporal scales, mechanisms and a roadmap for future research”. In: *Ecography* 42.12, pp. 1973–1990. ISSN: 0906-7590. DOI: 10.1111/ecog.04740. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/ecog.04740.

Foden, Wendy B et al. (2019). “Climate change vulnerability assessment of species”. In: *Wiley Interdisciplinary Reviews: Climate Change* 10.1, pp. 1–36. ISSN: 17577799. DOI: 10.1002/wcc.551.

Foley, Charles, Nathalie Pettorelli, and Lara Foley (2008). “Severe drought and calf survival in elephants”. In: *Biology Letters* 4.5, pp. 541–544. ISSN: 1744-9561. DOI: 10.1098/rsbl.2008.0370. URL: http://www.royalsocietypublishing.org/doi/10.1098/rsbl.2008.0370.

Fourcade, Yoan et al. (2014). “Mapping Species Distributions with MAXENT Using a Geographically Biased Sample of Presence Data: A Performance Assessment of Methods for Correcting Sampling Bias”. In: *PLoS ONE* 9.5. Ed. by John F Valentine, e97122. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0097122. URL: https://dx.plos.org/10.1371/journal.pone.0097122.

Fournier, Alice et al. (2017). “Predicting species distribution combining multi-scale drivers”. In: *Global Ecology and Conservation* 12, pp. 215–226. ISSN: 23519894. DOI: 10.1016/j.gecco.2017.11.002. URL: https://linkinghub.elsevier.com/retrieve/pii/S2351989417302020.

Freire, Sergio et al. (2016). "Development of new open and free multi-temporal global population grids at 250 m resolution". In: *Agile*. June. Helsinki: the Association of Geographic Information Laboratories in Europe, p. 6. ISBN: 978-90-816960-6-7. URL: https://agile-online.org/conference_paper/cds/agile_2016/shortpapers/152_Paper_in_PDF.pdf.

Gaillard, J C et al. (2019). "Wildlife hazards and disaster risk reduction". In: *International Journal of Disaster Risk Reduction* 33.August 2018, pp. 55–63. ISSN: 22124209. DOI: 10.1016/j.ijdrr.2018.09.009. URL: https://doi.org/10.1016/j.ijdrr.2018.09.009.

Galetti, Mauro et al. (2018). "Ecological and evolutionary legacy of megafauna extinctions". In: *Biological Reviews* 93.2, pp. 845–862. ISSN: 1469185X. DOI: 10.1111/brv.12374.

Game, Edward T. et al. (2014). "Conservation in a Wicked Complex World; Challenges and Solutions". In: *Conservation Letters* 7.3, pp. 271–277. ISSN: 1755263X. DOI: 10.1111/conl.12050. URL: http://doi.wiley.com/10.1111/conl.12050.

Gao, Bo-cai (1996). "NDWI A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water From Space". In: *Remote Sensing of Environment* 266.April 1995, pp. 257–266.

Gao, J (2020). *Global 1-km Downscaled Population Base Year and Projection Grids Based on the Shared Socioeconomic Pathways*. New York. URL: https://sedac.ciesin.columbia.edu/data/set/popdynamics-1-km-downscaled-pop-base-year-projection-ssp-2000-2100-rev01.

Gao, Jing and Brian C O'Neill (2020). "Mapping global urban land for the 21st century with data-driven simulations and Shared Socioeconomic Pathways". In: *Nature Communications* 11.1, pp. 1–12. ISSN: 20411723. DOI: 10.1038/s41467-020-15788-7. URL: http://dx.doi.org/10.1038/s41467-020-15788-7.

Gaucherel, C et al. (2010). "At which scales does landscape structure influence the spatial distribution of elephants in the Western Ghats (India)?" In: *Journal of Zoology* 280.2, pp. 185–194. ISSN: 09528369. DOI: 10.1111/j.1469-7998.2009.00652.x.

Gautam, Hansraj, Evangeline Arulmalar, and Mihir R Kulkarni (2019). "NDVI is not reliable as a surrogate of forage abundance for a large herbivore in tropical forest habitat". In: *Biotropica* 51, pp. 443–456. DOI: 10.1111/btp.12651.

Goossens, Benoit et al. (2016). "Habitat fragmentation and genetic diversity in natural populations of the Bornean elephant: Implications for conservation". In: *Biological*

Conservation 196, pp. 80–92. ISSN: 00063207. DOI: 10.1016/j.biocon.2016.02.008. URL: http://dx.doi.org/10.1016/j.biocon.2016.02.008.

Gorelick, Noel et al. (2017). "Google Earth Engine: Planetary-scale geospatial analysis for everyone". In: *Remote Sensing of Environment* 202, pp. 18–27. ISSN: 00344257. DOI: 10.1016/j.rse.2017.06.031. URL: https://linkinghub.elsevier.com/retrieve/pii/S0034425717302900.

Goswami, Varun R. and Divya Vasudev (2017). "Triage of Conservation Needs: The Juxtaposition of Conflict Mitigation and Connectivity Considerations in Heterogeneous, Human-Dominated Landscapes". In: *Frontiers in Ecology and Evolution* 4. ISSN: 2296-701X. DOI: 10.3389/fevo.2016.00144. URL: http://journal.frontiersin.org/article/10.3389/fevo.2016.00144/full.

Goswami, Varun R. et al. (2015). "Mechanistic understanding of human-wildlife conflict through a novel application of dynamic occupancy models". In: *Conservation Biology* 29.4, pp. 1100–1110. ISSN: 08888892. DOI: 10.1111/cobi.12475. URL: http://doi.wiley.com/10.1111/cobi.12475.

Graham, Maximilian D. et al. (2010). "Patterns of crop-raiding by elephants, Loxodonta africana, in Laikipia, Kenya, and the management of human-elephant conflict". In: *Systematics and Biodiversity* 8.4, pp. 435–445. ISSN: 14772000. DOI: 10.1080/14772000.2010.533716.

Grainger, Alan (2004). "Societal change and the control of deforestation in Thailand". In: *International Journal of Sustainable Development and World Ecology* 11.4, pp. 364–379. ISSN: 17452627. DOI: 10.1080/13504500409469840.

Grill, G et al. (2019). "Mapping the world's free-flowing rivers". In: *Nature* 569.7755, pp. 215–221. ISSN: 14764687. DOI: 10.1038/s41586-019-1111-9.

Gubbi, Sanjay et al. (2014). "An elephantine challenge: human-elephant conflict distribution in the largest Asian elephant population, southern India". In: *Biodiversity and Conservation* 23.3, pp. 633–647. ISSN: 0960-3115. DOI: 10.1007/s10531-014-0621-x. URL: http://link.springer.com/10.1007/s10531-014-0621-x.

Haralick, Robert M., K. Shanmugam, and Its'Hak Dinstein (1973). "Textural Features for Image Classification". In: *IEEE Transactions on Systems, Man, and Cybernetics* SMC-3.6, pp. 610–621. ISSN: 0018-9472. DOI: 10.1109/TSMC.1973.4309314. URL: http://ieeexplore.ieee.org/document/4309314/.

Harich, Franziska K et al. (2016). "Seed dispersal potential of Asian elephants". In: *Acta Oecologica* 77, pp. 144–151. ISSN: 1146609X. DOI: 10.1016/j.actao.2016.10.005. URL: http://dx.doi.org/10.1016/j.actao.2016.10.005.

Hawthorne, William D and Marc P E Parren (2000). “How Important Are Forest Elephants to the Survival of Woody Plant Species in Upper Guinean Forests ?” In: *Journal of Tropical Ecology* 16.1, pp. 133–150.

He, Kate S et al. (2015). “Will remote sensing shape the next generation of species distribution models?” In: *Remote Sensing in Ecology and Conservation* 1.1. Ed. by Harini Nagendra and Ned Horning, pp. 4–18. ISSN: 20563485. DOI: 10.1002/rse2.7. URL: http://doi.wiley.com/10.1002/rse2.7.

Hesselbarth, Maximilian H K et al. (2019). “landscapemetrics: an open-source R tool to calculate landscape metrics”. In: *Ecography* 42.10, pp. 1648–1657. ISSN: 16000587. DOI: 10.1111/ecog.04617.

Hijmans, Robert J et al. (2005). “Very high resolution interpolated climate surfaces for global land areas”. In: *International Journal of Climatology* 25.15, pp. 1965–1978. ISSN: 08998418. DOI: 10.1002/joc.1276.

Hijmans, Robert J et al. (2017). *Package ’dismo’ Type Package Title Species Distribution Modeling*. Tech. rep. URL: https://cran.r-project.org/web/packages/dismo/dismo.pdf.

Hill, Catherine M (2004). “Farmers’ perspectives of conflict at the wildlife-agriculture boundary: Some lessons learned from african subsistence farmers”. In: *Human Dimensions of Wildlife* 9.4, pp. 279–286. ISSN: 1533158X. DOI: 10.1080/10871200490505710.

Hirsch, Philip (1990). “Forests , Forest Reserve , and Forest Land in Thailand”. In: *The Geographical Journal* 156.2, pp. 166–174.

Hoare, Richard E. (1999). “Determinants of human-elephant conflict in a land-use mosaic”. In: *Journal of Applied Ecology* 36.5, pp. 689–700. ISSN: 0021-8901.

— (2015). “Lessons From 20 Years of Human-Elephant Conflict Mitigation in Africa”. In: *Human Dimensions of Wildlife* 20.4, pp. 289–295. ISSN: 1533158X. DOI: 10.1080/10871209.2015.1005855. URL: http://dx.doi.org/10.1080/10871209.2015.1005855.

Hoare, Richard E and Johan T Du Toit (1999). “Coexistence between people and elephants in African savannas”. In: *Conservation Biology* 13.3, pp. 633–639. ISSN: 08888892. DOI: 10.1046/j.1523-1739.1999.98035.x.

Huang, Cheng et al. (2019). “Habitat suitability and connectivity inform a co-management policy of protected area network for asian elephants in China”. In: *PeerJ* 2019.4, pp. 1–16. ISSN: 21678359. DOI: 10.7717/peerj.6791.

Huete, A (1997). “A comparison of vegetation indices over a global set of TM images for EOS-MODIS”. In: *Remote Sensing of Environment* 59.3, pp. 440–451. ISSN: 00344257.

DOI: 10.1016/S0034-4257(96)00112-5. URL: https://linkinghub.elsevier.com/retrieve/pii/S0034425796001125.

ICEM (2003). *Thailand National Report on Protected Areas and Development. Review of Protected Areas and Development in the Lower Mekong River Region*. Tech. rep. Queensland, Australia: International Centre for Environmental Management, p. 131.

Ingalls, Micah L et al. (2018). "The transboundary displacement of deforestation under REDD+: Problematic intersections between the trade of forest-risk commodities and land grabbing in the Mekong region". In: *Global Environmental Change* 50.November 2017, pp. 255–267. ISSN: 09593780. DOI: 10.1016/j.gloenvcha.2018.04.003. URL: https://doi.org/10.1016/j.gloenvcha.2018.04.003.

Inskip, Chloe and Alexandra Zimmermann (2009). "Human-felid conflict: A review of patterns and priorities worldwide". In: *Oryx* 43.1, pp. 18–34. ISSN: 00306053. DOI: 10.1017/S003060530899030X.

IPBES (2019). *Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*. Ed. by E. S. Brondizio et al. Bonn, Germany: IPBES secretariat.

IPCC (2012). *National systems for managing the risks from climate extremes and disasters*. Ed. by C B Field et al. Vol. 9781107025. Cambridge, UK, and New York, NY, USA: Cambridge University Press, pp. 339–392. ISBN: 9781139177245. DOI: 10.1017/CBO9781139177245.009.

— (2014). "Summary for Policymakers". In: *Climate Change 2014: Impacts, Adaptation and Vulnerability - Contributions of the Working Group II to the Fifth Assessment Report*. Ed. by C B Field et al. ambridge, United Kingdom and NewYork, NY, USA: Cambridge University Press, chap. Summary fo, pp. 1–32. ISBN: 9781139177245. DOI: 10.1016/j.renene.2009.11.012. arXiv: arXiv:1011.1669v3.

IUCN (2015). *Benefits beyond boundaries: proceedings of the Vth IUCN World Parks Congress*. Tech. rep., p. 306. URL: https://www.iucn.org/content/benefits-beyond-boundaries-proceedings-vth-iucn-world-parks-congress.

IUCN/SSC Asian Elephant Special ist Group (2017). *Asian Elephant Range States Meeting: Final Report*. Tech. rep. Jakarta, Indonesia, pp. 1–68.

IUCN/SSC Human Wildlife Conflict Taskforce (2020). *Human-Wildlife Conflict*. URL: http://www.hwctf.org/about (visited on 10/20/2020).

Jadhav, Sushrut and Maan Barua (2012). "The Elephant Vanishes: impact of human-elephant conflict on people's wellbeing." In: *Health & place* 18.6, pp. 1356–1365. ISSN:

18732054. DOI: 10.1016/j.healthplace.2012.06.019. URL: http://dx.doi.org/10.1016/j.healthplace.2012.06.019.

Jain, Shipra et al. (2019). "Advantage of NEX-GDDP over CMIP5 and CORDEX Data: Indian Summer Monsoon". In: *Atmospheric Research* 228.October 2018, pp. 152–160. ISSN: 01698095. DOI: 10.1016/j.atmosres.2019.05.026. URL: https://doi.org/10.1016/j.atmosres.2019.05.026.

Jarungrattanapong, R, N Olewiler, and O Nabangchang (2017). "A payment for ecosystem services program to support elephant conservation and reduce humna-elephant conflict in Thailand". In: *Co-investment in ecosystem services: global lessons from payment and incentive schemes.* Ed. by S Namirembe et al. Nairobi: World Agroforestry Centre (ICRAF). Chap. 10, pp. 1–13. URL: https://www.worldagroforestry.org/sites/default/files/Ch10HumanElephantConflict_ebookB-DONE.pdf.

Jathanna, Devcharan et al. (2015). "Patterns and Determinants of Habitat Occupancy by the Asian Elephant in the Western Ghats of Karnataka, India". In: *PLOS ONE* 10.7. Ed. by Sadie Jane Ryan, e0133233. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0133233. URL: https://dx.plos.org/10.1371/journal.pone.0133233.

Jenks, Kate E et al. (2013). "Community Attitudes toward Protected Areas in Thailand". In: *Natural History Bulletin of the Siam Society* 59.2, pp. 65–76. ISSN: 00809462.

Jia, Kang and Han Wei (2020). *Human-elephant conflict escalates in China's Xishuangbanna.* Xishuangbanna. URL: https://asia.nikkei.com/Spotlight/Caixin/Human-elephant-conflict-escalates-in-China-s-Xishuangbanna.

Kanagaraj, Rajapandian et al. (2019). "Predicting range shifts of Asian elephants under global change". In: *Diversity and Distributions* 25.5. Ed. by Wilfried Thuiller, pp. 822–838. ISSN: 1366-9516. DOI: 10.1111/ddi.12898. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/ddi.12898.

Kansky, Ruth, Martin Kidd, and Andrew T Knight (2014). "Meta-analysis of attitudes toward damage-causing mammalian wildlife". In: *Conservation Biology* 28.4, pp. 924–938. ISSN: 15231739. DOI: 10.1111/cobi.12275.

— (2016). "A wildlife tolerance model and case study for understanding human wildlife conflicts". In: *Biological Conservation* 201, pp. 137–145. ISSN: 00063207. DOI: 10.1016/j.biocon.2016.07.002. URL: http://dx.doi.org/10.1016/j.biocon.2016.07.002.

Kansky, Ruth and Andrew T Knight (2014). "Key factors driving attitudes towards large mammals in conflict with humans". In: *Biological Conservation* 179, pp. 93–105. ISSN:

00063207. DOI: 10.1016/j.biocon.2014.09.008. URL: http://dx.doi.org/10.1016/j.biocon.2014.09.008.

Kariya, Takeaki (1991). "Multivariate Adaptive Regression Spline". In: *Annals of Statistics* 19.3, pp. 1403–1433.

Kebede, Abiy S et al. (2018). "Applying the global RCP-SSP-SPA scenario framework at sub-national scale: A multi-scale and participatory scenario approach". In: *Science of the Total Environment* 635.April 2018, pp. 659–672. ISSN: 18791026. DOI: 10.1016/j.scitotenv.2018.03.368. URL: https://doi.org/10.1016/j.scitotenv.2018.03.368.

Keetch, John J and George M Byram (1968). "A Drought Index for Forest Fire Control". In: *Research Paper* E-38. Ashe, p. 35. ISSN: 01681923. URL: http://www.treesearch.fs.fed.us/pubs/40.

Kitratporn, Nuntikorn and Wataru Takeuchi (2019). "Spatiotemporal Distribution of Human-Elephant Conflict in Eastern Thailand: A Model-Based Assessment using News Reports and Remotely Sensed Data". In: *Remote Sensing* 12.1, p. 90. ISSN: 2072-4292. DOI: 10.3390/rs12010090. URL: https://www.mdpi.com/2072-4292/12/1/90.

Kramer-Schadt, Stephanie et al. (2013). "The importance of correcting for sampling bias in MaxEnt species distribution models". In: *Diversity and Distributions* 19.11. Ed. by Mark Robertson, pp. 1366–1379. ISSN: 13669516. DOI: 10.1111/ddi.12096. URL: http://doi.wiley.com/10.1111/ddi.12096.

Krishnan, Vinod et al. (2019). "Distribution and Habitat Use by Asian Elephants (Elephas maximus) in a Coffee-Dominated Landscape of Southern India". In: *Tropical Conservation Science* 12. ISSN: 19400829. DOI: 10.1177/1940082918822599.

Kuenzer, Claudia et al. (2014). "Earth observation satellite sensors for biodiversity monitoring: potentials and bottlenecks". In: *International Journal of Remote Sensing* 35.18, pp. 6599–6647. ISSN: 13665901. DOI: 10.1080/01431161.2014.964349. URL: http://dx.doi.org/10.1080/01431161.2014.964349.

Kumar, M. Ananda, Divya Mudappa, and T. R. Shankar Raman (2010). "Asian Elephant <i>Elephas Maximus</i> Habitat Use and Ranging in Fragmented Rainforest and Plantations in the Anamalai Hills, India". In: *Tropical Conservation Science* 3.2, pp. 143–158. ISSN: 1940-0829. DOI: 10.1177/194008291000300203. URL: http://journals.sagepub.com/doi/10.1177/194008291000300203.

Kuussaari, Mikko et al. (2009). "Extinction debt: a challenge for biodiversity conservation". In: *Trends in Ecology & Evolution* 24.10, pp. 564–571. ISSN: 01695347. DOI:

10.1016/j.tree.2009.04.011. URL: https://linkinghub.elsevier.com/retrieve/pii/S0169534709001918.

Lakshminarayanan, N. et al. (2016). “Determinants of dry season habitat use by Asian elephants in the Western Ghats of India”. In: *Journal of Zoology* 298.3, pp. 169–177. ISSN: 09528369. DOI: 10.1111/jzo.12298. URL: http://doi.wiley.com/10.1111/jzo.12298.

Lamichhane, Babu Ram et al. (2019). “Contribution of Buffer Zone Programs to Reduce Human-Wildlife Impacts: the Case of the Chitwan National Park, Nepal”. In: *Human Ecology* 47.1, pp. 95–110. ISSN: 15729915. DOI: 10.1007/s10745-019-0054-y.

Laohachaiboon, Suphawat (2010). “Conservation for whom? Elephant conservation and elephant conservationists in Thailand”. In: *Southeast Asian Studies* 48.1, pp. 74–95. ISSN: 05638682.

LDD (2016). *2015/2016 Land Use Data*. Bangkok, Thailand.

Lee, Jong-sen (1980). “by Use of Local Statistics”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* PAMI-2.2, pp. 165–168.

Leimgruber, P et al. (2011). “Current Status of Asian Elephants in Myanmar”. In: *Gajah* 35, pp. 76–86. DOI: 10.5167/uzh-59037.

Leimgruber, Peter et al. (2003). “Fragmentation of Asia’s remaining wildlands: Implications for Asian elephant conservation”. In: *Animal Conservation* 6.4, pp. 347–359. ISSN: 13679430. DOI: 10.1017/S1367943003003421.

Leng, Guoyong and Jim Hall (2019). “Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future”. In: *Science of the Total Environment* 654, pp. 811–821. ISSN: 18791026. DOI: 10.1016/j.scitotenv.2018.10.434. URL: https://doi.org/10.1016/j.scitotenv.2018.10.434.

Li, Wenwen et al. (2018). “Human-elephant conflict in Xishuangbanna Prefecture, China: Distribution, diffusion, and mitigation”. In: *Global Ecology and Conservation* 16, e00462. ISSN: 2351-9894. DOI: 10.1016/J.GECCO.2018.E00462. URL: https://www.sciencedirect.com/science/article/pii/S2351989418303548.

Li, Wenwen et al. (2019). “Identifying climate refugia and its potential impact on small population of Asian elephant (Elephas maximus)in China”. In: *Global Ecology and Conservation* 19. ISSN: 23519894. DOI: 10.1016/j.gecco.2019.e00664.

Li, Xi et al. (2017). “Intercalibration between DMSP/OLS and VIIRS night-time light images to evaluate city light dynamics of Syria’s major human settlement during Syrian Civil War”. In: *International Journal of Remote Sensing* 38.21, pp. 5934–5951.

ISSN: 0143-1161. DOI: 10.1080/01431161.2017.1331476. URL: https://www.tandfonline.com/doi/full/10.1080/01431161.2017.1331476.

Lischka, Stacy A et al. (2018). "A conceptual model for the integration of social and ecological information to understand human-wildlife interactions". In: *Biological Conservation* 225.May, pp. 80–87. ISSN: 00063207. DOI: 10.1016/j.biocon.2018.06.020. URL: https://doi.org/10.1016/j.biocon.2018.06.020.

Liu, Canran, Graeme Newell, and Matt White (2016). "On the selection of thresholds for predicting species occurrence with presence-only data". In: *Ecology and Evolution* 6.1, pp. 337–348. ISSN: 20457758. DOI: 10.1002/ece3.1878. URL: http://doi.wiley.com/10.1002/ece3.1878.

Liu, Canran, Matt White, and Graeme Newell (2013). "Selecting thresholds for the prediction of species occurrence with presence-only data". In: *Journal of Biogeography* 40, pp. 778–789. DOI: 10.1111/jbi.12058.

Liu, Hui Qing and Alfredo Huete (1995). "Feedback based modification of the NDVI to minimize canopy background and atmospheric noise". In: *IEEE Transactions on Geoscience and Remote Sensing* 33.2, pp. 457–465. ISSN: 01962892. DOI: 10.1109/36.377946.

Liu, Jianguo et al. (2007). "Complexity of coupled human and natural systems". In: *Science* 317.5844, pp. 1513–1516. ISSN: 00368075. DOI: 10.1126/science.1144004.

Liu, Peng et al. (2016). "Habitat evaluation for Asian elephants (Elephas maximus) in Lincang: Conservation planning for an extremely small population of elephants in China". In: *Biological Conservation* 198, pp. 113–121. ISSN: 00063207. DOI: 10.1016/j.biocon.2016.04.005. URL: http://dx.doi.org/10.1016/j.biocon.2016.04.005.

Liu, Peng et al. (2017). "Conflict between conservation and development: Cash forest encroachment in Asian elephant distributions". In: *Scientific Reports* 7.1, pp. 1–10. ISSN: 20452322. DOI: 10.1038/s41598-017-06751-6.

Lu, Junyu, Gregory J. Carbone, and John M. Grego (2019). "Uncertainty and hotspots in 21st century projections of agricultural drought from CMIP5 models". In: *Scientific Reports* 9.1, p. 4922. ISSN: 2045-2322. DOI: 10.1038/s41598-019-41196-z. URL: http://www.nature.com/articles/s41598-019-41196-z.

Madhusudan, M D et al. (2015). "Distribution, relative abundance, and conservation status of Asian elephants in Karnataka, southern India". In: *Biological Conservation* 187, pp. 34–40. ISSN: 00063207. DOI: 10.1016/j.biocon.2015.04.003. URL: http://dx.doi.org/10.1016/j.biocon.2015.04.003.

Mahmoud, Mohammed et al. (2009). "A formal framework for scenario development in support of environmental decision-making". In: *Environmental Modelling and Software* 24.7, pp. 798–808. ISSN: 13648152. DOI: 10.1016/j.envsoft.2008.11.010. URL: http://dx.doi.org/10.1016/j.envsoft.2008.11.010.

Mahto, Shanti Shwarup and Vimal Mishra (2019). "Does ERA-5 Outperform Other Reanalysis Products for Hydrologic Applications in India?" In: *Journal of Geophysical Research: Atmospheres* 124.16, pp. 9423–9441. ISSN: 21698996. DOI: 10.1029/2019JD031155.

Malhi, Yadvinder et al. (2016). "Megafauna and ecosystem function from the Pleistocene to the Anthropocene". In: *Proceedings of the National Academy of Sciences of the United States of America* 113.4, pp. 838–846. ISSN: 10916490. DOI: 10.1073/pnas.1502540113.

Maron, Martine et al. (2015). "Climate-induced resource bottlenecks exacerbate species vulnerability: a review". In: *Diversity and Distributions* 21.7. Ed. by Alan Andersen, pp. 731–743. ISSN: 13669516. DOI: 10.1111/ddi.12339. URL: http://doi.wiley.com/10.1111/ddi.12339.

Mateo, Rubén G. et al. (2019). "Hierarchical species distribution models in support of vegetation conservation at the landscape scale". In: *Journal of Vegetation Science* 30.2. Ed. by Sebastian Schmidtlein, pp. 386–396. ISSN: 1100-9233. DOI: 10.1111/jvs.12726. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jvs.12726.

Mateo-Tomás, Patricia et al. (2012). "Alleviating human-wildlife conflicts: Identifying the causes and mapping the risk of illegal poisoning of wild fauna". In: *Journal of Applied Ecology* 49.2, pp. 376–385. ISSN: 00218901. DOI: 10.1111/j.1365-2664.2012.02119.x.

McCullagh, Peter (1984). "Generalized linear models". In: *European Journal of Operational Research* 16.3, pp. 285–292. ISSN: 03772217. DOI: 10.1016/0377-2217(84)90282-0.

Meijaard, Erik et al. (2018). *Oil palm and biodiversity: a situation analysis by the IUCN Oil Palm Task Force.* June. ISBN: 9782831719108. DOI: 10.2305/iucn.ch.2018.11.en.

Meijer, Johan R et al. (2018). "Global patterns of current and future road infrastructure". In: *Environmental Research Letters* 13.6. ISSN: 17489326. DOI: 10.1088/1748-9326/aabd42.

Menon, V and S K R Tiwari (2019). "Population status of Asian elephants Elephas maximus and key threats". In: *International Zoo Yearbook* 53.1, pp. 17–30. ISSN: 17481090. DOI: 10.1111/izy.12247.

Merow, Cory, Matthew J Smith, and John A Silander (2013). "A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter". In: *Ecography* 36.10, pp. 1058–1069. ISSN: 09067590. DOI: 10.1111/j.1600-0587.2013.07872.x. URL: http://doi.wiley.com/10.1111/j.1600-0587.2013.07872.x.

Meyfroidt, Patrick and Eric F Lambin (2009). "Forest transition in Vietnam and displacement of deforestation abroad". In: *Proceedings of the National Academy of Sciences of the United States of America* 106.38, pp. 16139–16144. ISSN: 00278424. DOI: 10.1073/pnas.0904942106.

Morzillo, Anita T, Kirsten M de Beurs, and Chelsea J Martin-Mikle (2014). "A conceptual framework to evaluate human-wildlife interactions within coupled human and natural systems". In: *Ecology and Society* 19.3. ISSN: 17083087. DOI: 10.5751/ES-06883-190344.

Morzillo, Anita T, Kirsten M De Beurs, and Chelsea J Martin-mikle (2019). "and natural systems A conceptual framework to evaluate human-wildlife interactions within coupled human and natural systems". In: *Ecology and Society* 19.3.

Moss, Richard H et al. (2010). "The next generation of scenarios for climate change research and assessment". In: *Nature* 463.7282, pp. 747–756. ISSN: 00280836. DOI: 10.1038/nature08823.

Mumby, Hannah S. and Joshua M. Plotnik (2018). "Taking the Elephants' Perspective: Remembering Elephant Behavior, Cognition and Ecology in Human-Elephant Conflict Mitigation". In: *Frontiers in Ecology and Evolution* 6. ISSN: 2296-701X. DOI: 10.3389/fevo.2018.00122. URL: https://www.frontiersin.org/article/10.3389/fevo.2018.00122/full.

Murwira, Amon and Andrew K Skidmore (2005). "The response of elephants to the spatial heterogeneity of vegetation in a Southern African agricultural landscape". In: *Landscape Ecology* 20.2, pp. 217–234. ISSN: 09212973. DOI: 10.1007/s10980-004-3159-6.

Muscarella, Robert et al. (2014). *ENMeval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models*. Ed. by Jana McPherson. DOI: 10.1111/2041-210X.12261. URL: http://doi.wiley.com/10.1111/2041-210X.12261.

Naha, Dipanjan et al. (2019). "Assessment and prediction of spatial patterns of human-elephant conflicts in changing land cover scenarios of a human-dominated landscape in North Bengal". In: *PLoS ONE* 14.2, pp. 1–19. ISSN: 19326203. DOI: 10.1371/journal.pone.0210580.

Naha, Dipanjan et al. (2020). "Elephants in the neighborhood: Patterns of crop-raiding by Asian elephants within a fragmented landscape of Eastern India". In: *PeerJ* 2020.7. ISSN: 21678359. DOI: 10.7717/peerj.9399.

Naves, Javier et al. (2003). "Endangered Species Constrained by Natural and Human Factors: the Case of Brown Bears in Northern Spain". In: *Conservation Biology* 17.5, pp. 1276–1289. ISSN: 0888-8892. DOI: 10.1046/j.1523-1739.2003.02144.x. URL: http://doi.wiley.com/10.1046/j.1523-1739.2003.02144.x.

Neupane, Dinesh, Ronald L. Johnson, and Thomas S. Risch (2017). "How do land-use practices affect human–elephant conflict in nepal?" In: *Wildlife Biology* 2017.1, wlb.00313. ISSN: 0909-6396. DOI: 10.2981/wlb.00313. URL: http://www.bioone.org/doi/10.2981/wlb.00313.

Neupane, Dinesh et al. (2019). "Habitat use by Asian elephants: Context matters". In: *Global Ecology and Conservation* 17, e00570. ISSN: 23519894. DOI: 10.1016/j.gecco.2019.e00570. URL: https://doi.org/10.1016/j.gecco.2019.e00570.

NOAA/National Weather Service (2019). *Historical El Nino / La Nina episodes (1950-present).* URL: https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php (visited on 08/17/2019).

Noonto, B (2009). "MANAGING HUMAN-ELEPHANT CONFLICT (HEC) BASED ON ELEPHANT AND HUMAN BEHAVIORS : A CASE STUDY AT THONG PHA PHUM NATIONAL PARK , KANCHANABURI , THAILAND BHICHET NOONTO A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER O". PhD thesis.

Nounmusig, Wonlee (2018). "Analysis of rainfall in the eastern Thailand". In: *International Journal of GEOMATE* 14.46, pp. 150–155. ISSN: 21862982. DOI: 10.21660/2018.46.7282.

NSO (2020). *Key Statistical Data.* URL: http://statbbi.nso.go.th/staticreport/page/sector/en/index.aspx (visited on 09/10/2020).

Nsonsi, Félicien et al. (2017). "Attitudes Towards Forest Elephant Conservation Around a Protected Area in Northern Congo". In: *Conservation and Society* 15.1, pp. 59–73. ISSN: 09753133. DOI: 10.4103/0972-4923.201394.

Nuntatripob, Narakorn (2019). "Management Solution for Conflict between Human and Wild Elephant". In: *Legislative Institutional Repository of Thailand (LIRT)*, pp. 1–9. URL: https://library2.parliament.go.th/ebook/content-issue/2562/hi2562-049.pdf.

NYDF Progress Assessment (2019). "Protecting and Restoring Forests A Story of Large Commitments". In: September, p. 99. URL: forestdeclaration.org.

Nyhus, Philip J (2016). "Human-Wildlife Conflict and Coexistence". In: *Annual Review of Environment and Resources* 41.1, pp. 143–171. ISSN: 1543-5938. DOI: 10.1146/annurev-environ-110615-085634.

Nyirenda, Vincent R et al. (2018). "Elephant crop damage: Subsistence farmers' social vulnerability, livelihood sustainability and elephant conservation". In: *Sustainability (Switzerland)* 10.10. ISSN: 20711050. DOI: 10.3390/su10103572.

O'Donnell, Michael S and Drew A Ignizio (2012). "Bioclimatic Predictors for Supporting Ecological Applications in the Conterminous United States". In: *U.S Geological Survey Data Series 691*, p. 10. ISSN: 09505849.

O'Neill, Brian C et al. (2016). "The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6". In: *Geoscientific Model Development* 9.9, pp. 3461–3482. ISSN: 19919603. DOI: 10.5194/gmd-9-3461-2016.

O'Neill, Brian C et al. (2017). "The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century". In: *Global Environmental Change* 42, pp. 169–180. ISSN: 09593780. DOI: 10.1016/j.gloenvcha.2015.01.004. URL: http://dx.doi.org/10.1016/j.gloenvcha.2015.01.004.

O'Neill, Brian C. et al. (2020). "The effect of education on determinants of climate change risks". In: *Nature Sustainability* 3.7, pp. 520–528. ISSN: 2398-9629. DOI: 10.1038/s41893-020-0512-y. URL: http://www.nature.com/articles/s41893-020-0512-y.

O'Neill, R V et al. (1988). "Indices of landscape pattern". In: *Landscape Ecology* 1.3, pp. 153–162. ISSN: 09212973. DOI: 10.1007/BF00162741.

Osipova, Liudmila et al. (2018). "Fencing solves human-wildlife conflict locally but shifts problems elsewhere: A case study using functional connectivity modelling of the African elephant". In: *Journal of Applied Ecology* 55.6, pp. 2673–2684. ISSN: 13652664. DOI: 10.1111/1365-2664.13246.

Ostrom, Elinor (2009). "Special Section : Special Section :" in: *Science* 325.July, pp. 419–422.

Palmer, Wayne C (1965). *Meteorological Drought*. URL: `https://www.ncdc.noaa.gov/temp-and-precip/drought/docs/palmer.pdf`.

Palomo, Ignacio et al. (2014). "Incorporating the social-ecological approach in protected areas in the anthropocene". In: *BioScience* 64.3, pp. 181–191. ISSN: 15253244. DOI: `10.1093/biosci/bit033`.

Parr, John W K et al. (2008). "Exploratory co-management interventions in Kuiburi National Park, Central Thailand, including human-elephant conflict mitigation". In: *International Journal of Environment and Sustainable Development* 7.3, pp. 293–310. ISSN: 14746778. DOI: `10.1504/IJESD.2008.021901`.

Pavlov, Yu L (2019). "Random forests". In: *Random Forests*, pp. 1–122. DOI: `10.1201/9780429469275-8`.

Pekel, Jean François et al. (2016). "High-resolution mapping of global surface water and its long-term changes". In: *Nature* 540.7633, pp. 418–422. ISSN: 14764687. DOI: `10.1038/nature20584`.

Perz, Stephen G (2007). "Reformulating modernization-based environmental social theories: Challenges on the road to an interdisciplinary environmental science". In: *Society and Natural Resources* 20.5, pp. 415–430. ISSN: 08941920. DOI: `10.1080/08941920701211777`.

Peterson, Garry D, Graeme S Cumming, and Stephen R Carpenter (2003). "Scenario planning: A tool for conservation in an uncertain world". In: *Conservation Biology* 17.2, pp. 358–366. ISSN: 08888892. DOI: `10.1046/j.1523-1739.2003.01491.x`.

Pettorelli, Nathalie et al. (2005). "Using the satellite-derived NDVI to assess ecological responses to environmental change". In: *Trends in Ecology & Evolution* 20.9, pp. 503–510. ISSN: 0169-5347. DOI: `10.1016/J.TREE.2005.05.011`. URL: `https://www.sciencedirect.com/science/article/pii/S016953470500162X`.

Phillips, Steven J., Robert P. Anderson, and Robert E. Schapire (2006). "Maximum entropy modeling of species geographic distributions". In: *Ecological Modelling* 190.3-4, pp. 231–259. ISSN: 03043800. DOI: `10.1016/j.ecolmodel.2005.03.026`. arXiv: `arXiv:1011.1669v3`.

Phillips, Steven J. et al. (2009). "Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data". In: *Ecological Applications* 19.1, pp. 181–197. ISSN: 1051-0761. DOI: `10.1890/07-2153.1`. URL: `http://doi.wiley.com/10.1890/07-2153.1`.

Pimm, S L et al. (2014). "The biodiversity of species and their rates of extinction, distribution, and protection". In: *Science* 344.6187. ISSN: 10959203. DOI: 10.1126/science.1246752.

Pokharel, S S et al. (2019). "Lower levels of glucocorticoids in crop-raiders: diet quality as a potential 'pacifier' against stress in free-ranging Asian elephants in a human-production habitat". In: *Animal Conservation* 22.2, pp. 177–188. ISSN: 1367-9430. DOI: 10.1111/acv.12450. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/acv.12450.

Pooley, S et al. (2017). "An interdisciplinary review of current and future approaches to improving human-predator relations". In: *Conservation Biology* 31.3, pp. 513–523. ISSN: 15231739. DOI: 10.1111/cobi.12859.

Powers, Ryan P and Walter Jetz (2019). "Global habitat loss and extinction risk of terrestrial vertebrates under future land-use-change scenarios". In: *Nature Climate Change* 9.4, pp. 323–329. ISSN: 17586798. DOI: 10.1038/s41558-019-0406-z. URL: http://dx.doi.org/10.1038/s41558-019-0406-z.

Prabnakorn, Saowanit et al. (2019). "Assessment of drought hazard, exposure, vulnerability, and risk for rice cultivation in the Mun River Basin in Thailand". In: *Natural Hazards* 97.2, pp. 891–911. ISSN: 15730840. DOI: 10.1007/s11069-019-03681-6. URL: https://doi.org/10.1007/s11069-019-03681-6.

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. Vienna, Austria. URL: https://www.r-project.org/.

Radeloff, V C et al. (2019). "The Dynamic Habitat Indices (DHIs) from MODIS and global biodiversity". In: *Remote Sensing of Environment* 222.February 2018, pp. 204–214. ISSN: 00344257. DOI: 10.1016/j.rse.2018.12.009. URL: https://doi.org/10.1016/j.rse.2018.12.009.

Radosavljevic, Aleksandar and Robert P. Anderson (2014). "Making better MaxEnt models of species distributions: complexity, overfitting and evaluation". In: *Journal of Biogeography* 41.4. Ed. by Miguel Araújo, pp. 629–643. ISSN: 03050270. DOI: 10.1111/jbi.12227. URL: http://doi.wiley.com/10.1111/jbi.12227.

Raghavan, Srivatsan V, Jina Hur, and Shie Yui Liong (2018). "Evaluations of NASA NEX-GDDP data over Southeast Asia: present and future climates". In: *Climatic Change* 148.4, pp. 503–518. ISSN: 15731480. DOI: 10.1007/s10584-018-2213-3.

Ramesh, Gowtham et al. (2017). "An automated vision-based method to detect elephants for mitigation of human-elephant conflicts". In: *2017 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2017* 2017-Janua, pp. 2284–2288. DOI: 10.1109/ICACCI.2017.8126187.

Randin, Christophe F et al. (2020). "Monitoring biodiversity in the Anthropocene using remote sensing in species distribution models". In: *Remote Sensing of Environment* 239.December 2018, p. 111626. ISSN: 00344257. DOI: 10.1016/j.rse.2019.111626. URL: https://doi.org/10.1016/j.rse.2019.111626.

Rangarajan, Mahesh et al. (2010). *Gajah: Securing the Future for Elephants in India.* Tech. rep. New Delhi: The Report of the Elephant Task Force, Ministry of Environment and Forests, pp. 1–188.

Redman, Charles L, J Morgan Grove, and Lauren H Kuby (2004). "Integrating social science into the Long-Term Ecological Research (LTER) Network: Social dimensions of ecological change and ecological dimensions of social change". In: *Ecosystems* 7.2, pp. 161–171. ISSN: 14329840. DOI: 10.1007/s10021-003-0215-z.

Redpath, Stephen Mark, Saloni Bhatia, and Juliette Young (2015). "Tilting at wildlife: reconsidering human-wildlife conflict". In: *Oryx* 49.2, pp. 222–225. ISSN: 0030-6053. DOI: 10.1017/S0030605314000799.

Reed, James et al. (2016). "Integrated landscape approaches to managing social and environmental issues in the tropics: learning from the past to guide the future". In: *Global change biology* 22.7, pp. 2540–2554. ISSN: 13652486. DOI: 10.1111/gcb.13284.

Reidsma, Pytrik et al. (2006). "Impacts of land-use change on biodiversity: An assessment of agricultural biodiversity in the European Union". In: *Agriculture, Ecosystems and Environment* 114.1, pp. 86–102. ISSN: 01678809. DOI: 10.1016/j.agee.2005.11.026.

RFD (2017). *20-year National Forestry Strategy (2017-2036).* Tech. rep. Bangkok, Thailand: Royal Forestry Department, pp. 1–78.

Riahi, Keywan et al. (2017). "The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview". In: *Global Environmental Change* 42, pp. 153–168. ISSN: 09593780. DOI: 10.1016/j.gloenvcha.2016.05.009.

Ridgeway, Greg (1999). "The state of boosting". In: *Computing Science and Statistics* 31, pp. 172–181.

Ripple, William J. et al. (2015). "Collapse of the world's largest herbivores". In: *Science Advances* 1.4. ISSN: 23752548. DOI: 10.1126/sciadv.1400103. arXiv: 9605103 [cs].

Romero-Muñoz, Alfredo et al. (2019). “Habitat loss and overhunting synergistically drive the extirpation of jaguars from the Gran Chaco”. In: *Diversity and Distributions* 25.2, pp. 176–190. ISSN: 14724642. DOI: 10.1111/ddi.12843.

Rood, Ente, Abdullah A. Ganie, and Vincent Nijman (2010). “Using presence-only modelling to predict Asian elephant habitat use in a tropical forest landscape: Implications for conservation”. In: *Diversity and Distributions* 16.6, pp. 975–984. ISSN: 13669516. DOI: 10.1111/j.1472-4642.2010.00704.x.

Rosenqvist, Ake et al. (2007). “ALOS PALSAR : A Pathfinder Mission for Global-Scale Monitoring of the Environment”. In: *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING* 45.11, pp. 3307–3316.

Rowell, Zoe (2014). “Locomotion in captive Asian elephants (<i>Elephas maximus </i>)”. In: *Journal of Zoo and Aquarium Research* 2.4, pp. 130–135. DOI: https://doi.org/10.19227/jzar.v2i4.50.

Saif, Omar et al. (2019). “Costs of coexistence: understanding the drivers of tolerance towards Asian elephants Elephas maximus in rural Bangladesh”. In: *Oryx*, pp. 1–9. ISSN: 0030-6053. DOI: 10.1017/S0030605318001072.

Saito, Masayuki U et al. (2016). “Range-expanding wildlife: modelling the distribution of large mammals in Japan, with management implications”. In: *International Journal of Geographical Information Science* 30.1, pp. 20–35. ISSN: 13623087. DOI: 10.1080/13658816.2014.952301. URL: http://dx.doi.org/10.1080/13658816.2014.952301.

Salim, Sharon (2019). *Collaring Wild Elephants to Save Their Lives*. URL: https://blog.wwf.sg/forest/2019/02/asian-elephant-wild-eastern-thailand/ (visited on 06/20/2019).

Sampson, Christie (2013). “Conserving The Land of The Giants : Critical Threats To Asian Elephant Habitat in Sri Lankan Protected Areas”. In: p. 84.

Sampson, Christie et al. (2019). “Perception of Human‐Elephant Conflict and Conservation Attitudes of Affected Communities in Myanmar”. In: *Tropical Conservation Science* 12. ISSN: 19400829. DOI: 10.1177/1940082919831242.

Sanderson, Benjamin M, Reto Knutti, and Peter Caldwell (2015). “A representative democracy to reduce interdependency in a multimodel ensemble”. In: *Journal of Climate* 28.13, pp. 5171–5194. ISSN: 08948755. DOI: 10.1175/JCLI-D-14-00362.1.

Santiapillai, C (1997). “The Asian elephant conservation: A global strategy”. In: *Gajah* 18, pp. 21–39. URL: http://www.asesg.org/PDFfiles/Gajah/18-21-Santiapillai.pdf.

Santiapillai, Charles, M.R. Chambers, and N. Ishwaran (1984). "Aspects of the ecology of the Asian elephant Elephas maximus L. in the Ruhuna National Park, Sri Lanka". In: *Biological Conservation* 29.1, pp. 47–61. ISSN: 0006-3207. DOI: 10.1016/0006-3207(84)90013-2. URL: https://www.sciencedirect.com/science/article/pii/0006320784900132.

Santiapillai, Charles and Peter Jackson (1990). *The Asian Elephant - An Action Plan for its Conservation*, pp. 1–79. ISBN: 2-88032-997-3. URL: https://portals.iucn.org/library/node/6042.

Savo, V. et al. (2016). "Observations of climate change among subsistence-oriented communities around the world". In: *Nature Climate Change* 6.5, pp. 462–473. ISSN: 1758-678X. DOI: 10.1038/nclimate2958.

Scheffers, Brett R. et al. (2016). "The broad footprint of climate change from genes to biomes to people". In: *Science* 354.6313, aaf7671. ISSN: 0036-8075. DOI: 10.1126/science.aaf7671. URL: https://www.sciencemag.org/lookup/doi/10.1126/science.aaf7671.

Schmidt, Mario (2008). "The Sankey diagram in energy and material flow management: Part I: History". In: *Journal of Industrial Ecology* 12.1, pp. 82–94. ISSN: 10881980. DOI: 10.1111/j.1530-9290.2008.00004.x.

Schwartz, Charles C et al. (2012). "Impacts of rural development on Yellowstone wildlife: Linking grizzly bear Ursus arctos demographics with projected residential growth". In: *Wildlife Biology* 18.3, pp. 246–257. ISSN: 09096396. DOI: 10.2981/11-060.

Seeboonruang, Uma (2016). "Impact assessment of climate change on groundwater and vulnerability to drought of areas in Eastern Thailand". In: *Environmental Earth Sciences* 75.1, pp. 1–13. ISSN: 18666299. DOI: 10.1007/s12665-015-4896-3.

Seoraj-Pillai, Nimmi and Neville Pillay (2017). "A meta-analysis of human-wildlife conflict: South African and global perspectives". In: *Sustainability (Switzerland)* 9.1, pp. 1–21. ISSN: 20711050. DOI: 10.3390/su9010034.

Shaffer, L Jen et al. (2019). "Human-Elephant Conflict: A Review of Current Management Strategies and Future Directions". In: *Frontiers in Ecology and Evolution* 6, p. 235. ISSN: 2296-701X. DOI: 10.3389/fevo.2018.00235. URL: https://www.frontiersin.org/article/10.3389/fevo.2018.00235/full.

Sharma, Prashanti et al. (2020). "Mapping human wildlife conflict hotspots in a transboundary landscape, Eastern Himalaya". In: *Global Ecology and Conservation* 24, e01284. ISSN: 23519894. DOI: 10.1016/j.gecco.2020.e01284. URL: https://doi.org/10.1016/j.gecco.2020.e01284.

Shimada, Masanobu et al. (2014). "New global forest/non-forest maps from ALOS PALSAR data (2007-2010)". In: *Remote Sensing of Environment* 155, pp. 13–31. ISSN: 00344257. DOI: 10.1016/j.rse.2014.04.014. URL: http://dx.doi.org/10.1016/j.rse.2014.04.014.

Sieber, Anika et al. (2015). "Post-Soviet land-use change effects on large mammals' habitat in European Russia". In: *Biological Conservation* 191, pp. 567–576. ISSN: 00063207. DOI: 10.1016/j.biocon.2015.07.041. URL: https://linkinghub.elsevier.com/retrieve/pii/S0006320715300495.

Silva, Shermin de et al. (2020). "The Past, Present and Future of Elephant Landscapes in Asia". In: *bioRxiv*. URL: https://doi.org/10.1101/2020.04.28.066548.

Sirami, Clélia et al. (2017). "Impacts of global change on species distributions: obstacles and solutions to integrate climate and land use". In: *Global Ecology and Biogeography* 26.4, pp. 385–394. ISSN: 14668238. DOI: 10.1111/geb.12555.

Sitati, N W et al. (2003). "Predicting spatial aspects of human-elephant conflict". In: *Journal of Applied Ecology* 40.4, pp. 667–677. ISSN: 00218901. DOI: 10.1046/j.1365-2664.2003.00828.x.

Skidmore, Andrew K et al. (2015). "Environmental science: Agree on biodiversity metrics to track from space". In: *Nature* 523.7561, pp. 403–405. ISSN: 0028-0836. DOI: 10.1038/523403a. URL: http://www.nature.com/articles/523403a.

Smith, Robert J and Samuel M Kasiki (2000). *A Spatial Analysis of Human-Elephant Conflict in the Tsavo Ecosystem: A Report to the African Elephant Specialist Group, Human-Elephant Conflict Task Force*. Tech. rep. January. Switzerland: IUCN, pp. 1–82.

Sodhi, Navjot S et al. (2004). "Southeast Asian biodiversity: An impending disaster". In: *Trends in Ecology and Evolution* 19.12, pp. 654–660. ISSN: 01695347. DOI: 10.1016/j.tree.2004.09.006.

Stehfest, Elke et al. (2019). "Key determinants of global land-use projections". In: *Nature Communications* 10, pp. 1–10. ISSN: 2041-1723. DOI: 10.1038/s41467-019-09945-w. URL: http://dx.doi.org/10.1038/s41467-019-09945-w.

Stephens, D.W. and J.R. Krebs (1986). *Foraging Theory*. Princeton, New Jersey.: Princeton University Press.

Struebig, Matthew J. et al. (2018). "Addressing human-tiger conflict using socio-ecological information on tolerance and risk". In: *Nature Communications* 9.1, p. 3455. ISSN: 2041-1723. DOI: 10.1038/s41467-018-05983-y.

Suba, Rachmat B et al. (2017). "Rapid expansion of oil palm is leading to human-elephant conflicts in north Kalimantan province of Indonesia". In: *Tropical Conservation Science* 10. ISSN: 19400829. DOI: 10.1177/1940082917703508.

Sudmeier-Rieux, K et al. (2019). *Disasters and Ecosystems, Resilience in a Changing Climate - Source Book*. Tech. rep. Geneva: United Nations Environment Programme (UNEP), pp. 1–212. URL: https://postconflict.unep.ch/DRR/EcoDRR_Source_Book.pdf.

Sukmasuang, Ronglarp (2015). *Human-Elephant Conflict Status and Resolution in Thailand*. Tech. rep.

Suksavate, Warong, Prateep Duengkae, and Aingorn Chaiyes (2019). "Quantifying landscape connectivity for wild Asian elephant populations among fragmented habitats in Thailand". In: *Global Ecology and Conservation* 19. DOI: 10.1016/j.gecco.2019.e00685. URL: https://www.sciencedirect.com/science/article/pii/S2351989418303457.

Suksawang, By Songtam and Jeffrey A Mcneely (2015). *Parks for Life: Why We Love Thailand's National Parks*. Bangkok, Thailand: Department of National Parks, Wildlife, Plant Conservation, and the United Nations Development Programme, p. 204. ISBN: 9786163162564.

Suksawang, Songtam (2018). "Protected area complexes : a new approach to connectivity in Thailand". In: *Thai Forest Bullentin (Botany)* 46.1, pp. 25–33. DOI: https://doi.org/10.20531/tfb.2018.46.1.04.

Sukumar (1992). *The Asian Elephant: Ecology and Management*. Cambridge, UK: Cambridge University Press. ISBN: 052143758X.

Sukumar, R (1989). *The Asian elephant : ecology and management*. New York: Cambridge University Press. ISBN: 978-0521437585.

Sukumar, Raman (2003). *THE LIVING ELEPHANTS: EVOLUTIONARY ECOLOGY, BEHAVIOR, AND CONSERVATION*. New York: Oxford University Press, pp. 1–478. ISBN: 0-19-510778-0.

Takeuchi, W et al. (2015). "Near-Real Time Meteorological Drought Monitoring and Early Warning System for Croplands in Asia". In: *36th Asian Conference on Remote Sensing 2015 (ACRS 2015): Fostering Resilient Growth in Asia* 1.October, pp. 171–178. URL: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.741.9798&rep=rep1&type=pdf.

Team, R Core (2020). *R: A Language and Environment for Statistical Computing*. Vienna, Austria. URL: https://www.r-project.org.

Terborgh, J et al. (2016). “Megafaunal influences on tree recruitment in African equatorial forests”. In: *Ecography* 39.2, pp. 180–186. ISSN: 16000587. DOI: 10.1111/ecog.01641.

Thailand Meteorological Department (2015). *The Climate of Thailand (1981-2010)*. Tech. rep., pp. 1–7. URL: https://www.tmd.go.th/en/archive/thailand_climate.pdf.

Thomson, Allison M et al. (2011). “RCP4.5: A pathway for stabilization of radiative forcing by 2100”. In: *Climatic Change* 109.1, pp. 77–94. ISSN: 01650009. DOI: 10.1007/s10584-011-0151-4.

Thongjan, Nachatchaya et al. (2017). “Legal Measures for Managing Areas to Conserve Wild Elephants”. In: *CMU Journal of Law and Social Sciences* 10.1, pp. 115–132.

Thrasher, B et al. (2012). “Technical Note: Bias correcting climate model simulated daily temperature extremes with quantile mapping”. In: *Hydrology and Earth System Sciences* 16.9, pp. 3309–3314. ISSN: 10275606. DOI: 10.5194/hess-16-3309-2012.

Thuiller, Wilfried et al. (2020). *Ensemble Platform for Species Distribution Modeling: Package ‘biomod2’*.

Titeux, Nicolas et al. (2016). “Biodiversity scenarios neglect future land-use changes”. In: *Global change biology* 22.7, pp. 2505–2515. ISSN: 13652486. DOI: 10.1111/gcb.13272.

Treves, Adrian et al. (2006). “Co-Managing Human-Wildlife Conflicts: A Review”. In: *Human Dimensions of Wildlife* 11.6, pp. 383–396. ISSN: 1087-1209. DOI: 10.1080/10871200600984265. URL: http://www.tandfonline.com/doi/abs/10.1080/10871200600984265.

Trisurat, Yongyut, Rob Alkemade, and Peter H Verburg (2010). “Projecting land-use change and its consequences for biodiversity in northern thailand”. In: *Environmental Management* 45.3, pp. 626–639. ISSN: 0364152X. DOI: 10.1007/s00267-010-9438-x.

Trotter, H F (1986). “Generalized Additive Models”. In: *Statistical Science* 2.1, pp. 45–52. URL: https://projecteuclid.org/download/pdf_1/euclid.ss/1177013437.

Tsendbazar, N E, S de Bruin, and M Herold (2015). “Assessing global land cover reference datasets for different user communities”. In: *ISPRS Journal of Photogrammetry and Remote Sensing* 103, pp. 93–114. ISSN: 09242716. DOI: 10.1016/j.isprsjprs.2014.02.008. URL: http://dx.doi.org/10.1016/j.isprsjprs.2014.02.008.

Tsunoda, Hiroshi and Hiroto Enari (2020). “A strategy for wildlife management in depopulating rural areas of Japan”. In: *Conservation Biology* 34.4, pp. 819–828. ISSN: 15231739. DOI: 10.1111/cobi.13470.

Tuanmu, Mao Ning et al. (2011). “Temporal transferability of wildlife habitat models: Implications for habitat monitoring”. In: *Journal of Biogeography* 38.8, pp. 1510–1523. ISSN: 03050270. DOI: 10.1111/j.1365-2699.2011.02479.x.

Turkalo, Andrea K., Peter H. Wrege, and George Wittemyer (2018). "Demography of a forest elephant population". In: *PLoS ONE* 13.2, pp. 1–17. ISSN: 19326203. DOI: 10.1371/journal.pone.0192777.

Turner, B L et al. (2003). "Illustrating the coupled human-environment system for vulnerability analysis: Three case studies". In: *Proceedings of the National Academy of Sciences of the United States of America* 100.14, pp. 8080–8085. ISSN: 00278424. DOI: 10.1073/pnas.1231334100.

Turner, M G (1989). "Landscape ecology: the effect of pattern on process". In: *Annual review of ecology and systematics. Vol. 20*, pp. 171–197. ISSN: 0066-4162. DOI: 10.1146/annurev.es.20.110189.001131.

Turner, Monica G (2005). "Landscape ecology: What is the state of the science?" In: *Annual Review of Ecology, Evolution, and Systematics* 36, pp. 319–344. ISSN: 00664162. DOI: 10.1146/annurev.ecolsys.36.102003.152614.

UNDP (2010). *Disaster Risk Assessment.* URL: https://www.preventionweb.net/publications/view/51748 (visited on 09/10/2020).

UNISDR (2015). *Making Development Sustainable: The Future of Disaster Risk Management. Global Assessment Report on Disas-ter Risk Reduction.* Tech. rep. Geneva, Switzerland: United Nations Office for Disaster Risk Reduction (UNISDR). URL: https://www.preventionweb.net/english/hyogo/gar/2015/en/gar-pdf/GAR2015_EN.pdf.

United Nations (2019a). *Guidelines on Producing Leading, Composite and Sentiment Indicators.* Geneva, Switzerland: United Nations Publications, p. 135. ISBN: 9789211172195. DOI: 10.18356/3b565260-en.

— (2019b). *World Population Prospect 2019.* Tech. rep. 141, pp. 49–78. DOI: 10.3406/tiers.1983.4290. URL: http://www.ncbi.nlm.nih.gov/pubmed/12283219.

United Nations Development Program (2020). *Human Development Reports.* URL: http://hdr.undp.org/en/data (visited on 06/06/2020).

USGS (2004). *Shuttle Radar Topography Mission, 1 Arc Second scene SRTM.*

Van Hooidonk, Ruben et al. (2016). "Local-scale projections of coral reef futures and implications of the Paris Agreement". In: *Scientific Reports* 6.December, pp. 1–8. ISSN: 20452322. DOI: 10.1038/srep39666.

Veach, Victoria, Atte Moilanen, and Enrico Di Minin (2017). "Threats from urban expansion, agricultural transformation and forest loss on global conservation priority areas". In: *PLoS ONE* 12.11, pp. 1–14. ISSN: 19326203. DOI: 10.1371/journal.pone.0188397.

Venter, Oscar et al. (2016). "Global terrestrial Human Footprint maps for 1993 and 2009". In: *Scientific Data* 3, pp. 1–10. ISSN: 20524463. DOI: 10.1038/sdata.2016.67.

Verburg, P H et al. (1999). "A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use". In: *Ecological Modelling* 116.1, pp. 45–61. ISSN: 03043800. DOI: 10.1016/S0304-3800(98)00156-2.

Verburg, Peter H et al. (2002). "Modeling the spatial dynamics of regional land use: The CLUE-S model". In: *Environmental Management* 30.3, pp. 391–405. ISSN: 0364152X. DOI: 10.1007/s00267-002-2630-x. URL: http://link.springer.com/10.1007/s00267-002-2630-x.

Vermote, E. F., S. Y. Kotchenova, and J. P. Ray (2011). *MODIS Surface Reflectance User's Guide*. Tech. rep. NASA.

Vinitpornsawan, Supagit (2012). "Elephant-Proof Trench". In: *Wildlife Yearbook, Wildlife Research Division, Department of National Parks, Wildlife and Plant Conservation Thailand* 14, pp. 195–202.

Vinitpornsawan, Supagit et al. (2013). *Population Structure of Wild Elephant in Eastern Forest Complex*. Tech. rep., pp. 98–111.

Vinitpornsawan, Supakit and Thanawut Sirimanakul (2014). *Manual of Elephant Knowledge and Recommended Behaviors during Elephant Encounter (in Thai)*. Wildlife Research Division, Department of National Parks, Wildlife and Plant Conservation (DNP), pp. 1–50. URL: https://www.dnp.go.th/Wildlife/technique_document/elephant%20manual/elephant_manual.pdf.

Vuuren, Detlef P van et al. (2011). "The representative concentration pathways: An overview". In: *Climatic Change* 109.1, pp. 5–31. ISSN: 01650009. DOI: 10.1007/s10584-011-0148-z.

Vuuren, Detlef P van et al. (2014). "A new scenario framework for Climate Change Research: Scenario matrix architecture". In: *Climatic Change* 122.3, pp. 373–386. ISSN: 01650009. DOI: 10.1007/s10584-013-0906-1.

Wadey, Jamie et al. (2018). "Why did the elephant cross the road? The complex response of wild elephants to a major road in Peninsular Malaysia". In: *Biological Conservation* 218, pp. 91–98. ISSN: 0006-3207. DOI: 10.1016/J.BIOCON.2017.11.036. URL: https://www.sciencedirect.com/science/article/pii/S0006320717315501.

Waiyasusri, K, S Yumuang, and S Chotpantarat (2016). "Monitoring and predicting land use changes in the Huai Thap Salao Watershed area, Uthaithani Province, Thailand, using the CLUE-s model". In: *Environmental Earth Sciences* 75.6, pp. 1–16. ISSN: 18666299. DOI: 10.1007/s12665-016-5322-1.

Wang, Qiuling et al. (2020). "Evaluation of high-resolution crop model meteorological forcing datasets at regional scale: Air temperature and precipitation over major land areas of China". In: *Atmosphere* 11.9. ISSN: 20734433. DOI: 10.3390/atmos11091011.

Wannitikul, Gadsaraporn (2005). "DEFORESTATION IN NORTHEAST THAILAND , 1975-91 : Liu Institute for Global Issues , University of British Columbia ," in: *Methodology* 26.1, pp. 102–118.

Ward, Philip J et al. (2017). "A global framework for future costs and benefits of river-flood protection in urban areas". In: *Nature Climate Change* 7.9, pp. 642–646. ISSN: 17586798. DOI: 10.1038/nclimate3350.

Water, Antoinette van de and Kevin Matteson (2018). "Human-elephant conflict in western Thailand: Socio-economic drivers and potential mitigation strategies". In: *PLOS ONE* 13.6. Ed. by Bi-Song Yue, e0194736. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0194736. URL: https://dx.plos.org/10.1371/journal.pone.0194736.

Wato, Yussuf A. et al. (2016). "Prolonged drought results in starvation of African elephant (Loxodonta africana)". In: *Biological Conservation* 203, pp. 89–96. ISSN: 0006-3207. DOI: 10.1016/J.BIOCON.2016.09.007. URL: https://www.sciencedirect.com/science/article/pii/S0006320716303664?via{\%}3Dihub.

WCS Thailand (2007). *A Manual for Human-Elephant Conflict Mitigation*. Bangkok, Thailand: Saeng Muang Printing, pp. 1–56.

Wegge, Per, Shailendra Kumar Yadav, and Babu Ram Lamichhane (2018). "Are corridors good for tigers Panthera tigris but bad for people? An assessment of the Khata corridor in lowland Nepal". In: *Oryx* 52.1, pp. 35–45. ISSN: 13653008. DOI: 10.1017/S0030605316000661.

Weiss, D. J. et al. (2018). "A global map of travel time to cities to assess inequalities in accessibility in 2015". In: *Nature* 553.7688, pp. 333–336. ISSN: 0028-0836. DOI: 10.1038/nature25181. URL: http://www.nature.com/articles/nature25181.

Wilson, Scott et al. (2015). "Understanding spatial and temporal patterns of human-elephant conflict in Assam, India". In: *Oryx* 49.1, pp. 140–149. ISSN: 13653008. DOI: 10.1017/S0030605313000513.

Wisner, Ben and J C Gaillard (2009). "An introduction to neglected disasters". In: *Jàmbá: Journal of Disaster Risk Studies* 2.3, pp. 2002–2009. ISSN: 1996-1421. DOI: 10.4102/jamba.v2i3.23.

Wongram, Nattapon and Somkid Salee (2017). *An Analysis of Risky Area from Wild Elephants by Geo-information in Dong-Yai Wildlife Sanctuary, Buriram Province (in*

Thai). Tech. rep. Burirum, Thailand: Buriram Rajabhat University, pp. 1–89. URL: http://stdb.most.go.th/research_detail.aspx?ResearchId=105245.

World Bank (2020a). *The Worldwide Governance Indicator*.

— (2020b). *World Development Indicators*. URL: https://databank.worldbank.org/source/world-development-indicators/preview/on (visited on 06/06/2020).

Wu, Kang and Xiaonan Wang (2019). "Aligning pixel values of DMSP and VIIRS night-time light images to evaluate urban dynamics". In: *Remote Sensing* 11.12, pp. 1–18. ISSN: 20724292. DOI: 10.3390/rs11121463.

WWF (2015). "Asian Elephant". In: 1973.November, pp. 1–4.

Zeppelzauer, Matthias, Sean Hensman, and Angela S Stoeger (2015). "Towards an automated acoustic detection system for free-ranging elephants". In: *Bioacoustics* 24.1, pp. 13–29. ISSN: 21650586. DOI: 10.1080/09524622.2014.906321.

Zeppelzauer, Matthias and Angela S Stoeger (2015). "Establishing the fundamentals for an elephant early warning and monitoring system". In: *BMC Research Notes* 8.1. ISSN: 17560500. DOI: 10.1186/s13104-015-1370-y.

Zha, Y, J Gao, and S Ni (2010). "Use of normalized difference built-up index in automatically mapping urban areas from TM imagery". In: *International Journal of Remote Sensing* 24.3, pp. 583–594. DOI: 10.1080/01431160304987.

Zhang, Li et al. (2015). "Asian elephants in China: Estimating population size and evaluating habitat suitability". In: *PLoS ONE* 10.5, pp. 1–13. ISSN: 19326203. DOI: 10.1371/journal.pone.0124834. URL: http://dx.doi.org/10.1371/journal.pone.0124834.

Zhao, Chuang et al. (2017). "Temperature increase reduces global yields of major crops in four independent estimates". In: *Proceedings of the National Academy of Sciences of the United States of America* 114.35, pp. 9326–9331. ISSN: 10916490. DOI: 10.1073/pnas.1701762114.