Modeling Inter-annual and Seasonal Distribution of Crop Depredation by Wild Asian Elephants in Eastern Thailand during 2009 to 2017

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ABSTRACT: In Thailand, crop depredation by wild elephants have been intensified and negatively impacted local communities' quality of life as well as wild elephant's long-term conservation success. Despite increasing concern and urgent needs for solution, limited studies explore landscape-scale spatiotemporal pattern of this conflict. The goal of this study was, hence, to fill this gap and identify potential conflict distribution across season and year during 2009 to 2018. Specifically, we applied Maximum Entropy (Maxent) method and separately constructed models for resource-related scenario and direct human pressure scenario for wet and dry season (total of 4 models). Candidate predictors which characterize vegetation productivity (NDVI), meteorological drought condition (KBDI), landscape composition (standard deviation of NDVI), land cover (MODIS land cover and Landsat permanent water pixel). topographic condition (elevation and TRI), and human pressure (Human Density, Roads, and Built-up) were used. Then, we applied our proposed two-dimensional conflict matrix based on thresholding approach to categorized predictive results into four groups. These include 1) high conflict area, 2) attractive area with uncertain pressure, 3) occasional refuge, and 4) unattractive which can be linked to different management action. With high temporal availability of satellite-derived dataset, we project our model on each year from 2009 to 2017. Multivariate Environmental Similarity Surface (MESS) was calculated to identify dissimilarity between each year to the training models, while regression slope was used to identify trend. Differences in habitat preference during wet and dry season can be identified. Variable response implied higher tolerant to direct human pressure in dry season. We estimated over 500 km^2 of frequent conflict occurring yearly in part of Chantaburi and Chachoengsao provinces due to high habitat suitability in that areas. Across 9 years, our model did not predict visible changes in direct human pressure, but large variation in resource-related suitability. KBDI was the key limiting factors causing drastic inter-annual response in distribution of potential conflict especially during extreme climatic condition (El Nino), while land cover changes suggested a subtle influence causing gradual changes in potential conflict over time. Management of crop depredation by elephants should consider not only variation in seasonality, but also resilience to extreme climatic events occur internally. Our method and potential conflict matrix can be applied for wildlife conflict study in other regions.

1 Introduction

Human-elephant conflict (HEC) is a problem commonly faced by all countries habituated by wild elephants, with crop depredation as the most common issue (IUCN/SSC Asian Elephant Special ist Group, 2017). Across both Asia and Africa, approximately 10–15% of total agricultural output in some communities may be lost due to elephants and can created financial burden impacting security, livelihood and well-being of affected individual (Barua, Bhagwat, and Jadhav, 2013). HEC was defined as an incidence where wild elephants' needs and behavior become incompatible with goals of human, resulting in negative impact of one or both species. Asian elephants (*Maximas Elephas*) remain under an endangered list with its totally population estimated to remain at 30,000-45,000 individuals. However, due to fragmentation of habitat, the distribution of the population is not uniform led to local concentration in one area and extirpation in another (Choudhury et al., 2008).

Thailand has approximately 3,000 wild elephants in 69 areas, of which 41 are facing HEC. (Noonto, 2009). Historically, elephants were believed to retreat and move away when there is increasing human activities, (Sukmasuang, 2015). However, their natural habitats now situates mainly in protected areas surrounded by human-dominated landscape. Consequently, interaction between elephants and human became more frequent. Researches on HEC in Thailand are typically limited to people's attitudes and perceptions (Water and Matteson, 2018). Although a few studies existed on spatial distribution of conflict, their focus is localized within a single protected areas or a few villages (Sukmasuang, 2015)). Study on spatial patterns of elephant conflict over large areas remain limited and urgently needed (Gubbi et al., 2014).

Species distribution models (SDMs), mathematical models based on occurrence data of interested event and spatial environment characteristics, is widely used in ecology for predicting species spatial occurrence and pattern (Elith et al., 2011). SDM has been applied for other human-wildlife conflict (Mateo-Tomás et al., 2012), but remain relatively few in HEC application (Franklin and Miller, 2010). SDMs usually use environmental data that do not provide seasonality information, as well as utilize temporal resolution that do not match occurrence data collected. Additionally, common assumption in SDM is that response can be describe by a single function which likely oversimplifying the response by species (Naves et al., 2003)) and became difficult to identify what ultimately drives the predicted probability (Bleyhl et al., 2015). In addition to seasonal variation expected from established studies of elephants ecology (Sukumar, 1992; Santiapillai, Chambers, and Ishwaran, 1984), elephants distribution and related HEC response to inter-annual changes have not been studied. Large number of studies aimed for extrapolating into the future (Kanagaraj et al., 2019), but less focus on understanding recent historical changes.

1.1 Objectives

This study attempted to model spatial pattern of crop depredation by wild elephants in large landscape exploring both seasonal and inter-annual effects. To distinguish between resource-related and direct human disturbance condition, we applied two models in which each scenario is parameterized separately. To capture seasonal and annual resource-related and human disturbance factors, we utilized various satellite-derived and ancillary data.

2 Materials and Methods

2.1 Study Area

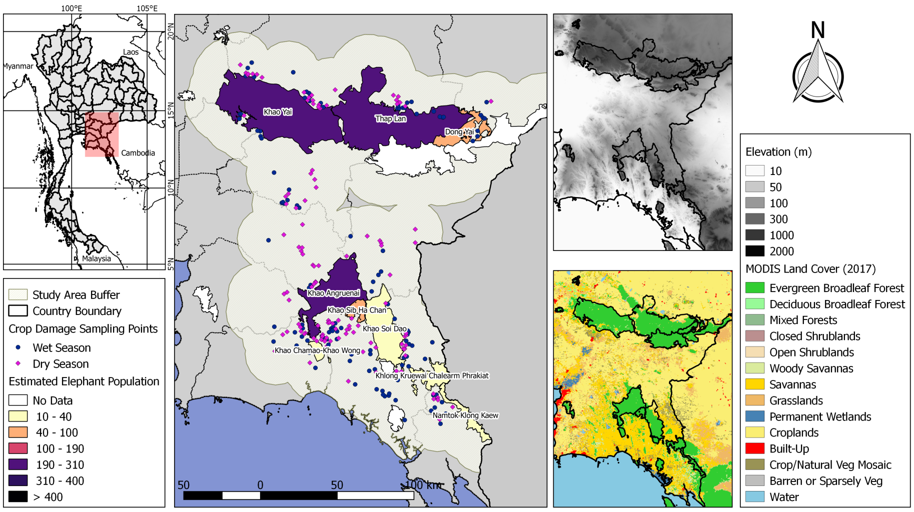

Figure 1: Study area located on the eastern region of Thailand reported with high density of elephants and increasing HEC trend. The 20km buffered zone was selected for modeling.

Eastern Thailand (Figure 1) is situated east of Bangkok. The area faces monsoon season during mid-May to mid-October with highest wettest month during July and September. The seasonal model is set according to this information with May to October representing wet season, while November to April representing dry season. Protected areas in Eastern region experienced highest density of wild elephants with 0.2 elephant/km^2 (Vinitpornsawan et al., 2013). Additionally, areas surrounding Khao-Angruinai are continuously low elevation allowing easy dispersal outside of protected areas. Consequently, the region is believed to be the HEC hotspot with highly reported interaction of elephants outside protected area. The region also contain 9 parks with elephants resident. Five most important crops in this region, in term of planting area, are rice, cassava, rubber plant, sugarcane, and maize. The region is also famous for various fruits such as pineapple and durian. To limit the study area with only those of potential elephant occurrences, a buffer of 20 km were created from protected areas with known elephants resident and village location with reports of crop damage incidents. All models and projection of potential conflict areas were performed within this buffered zone. Figure 5 shown overview of methodology.

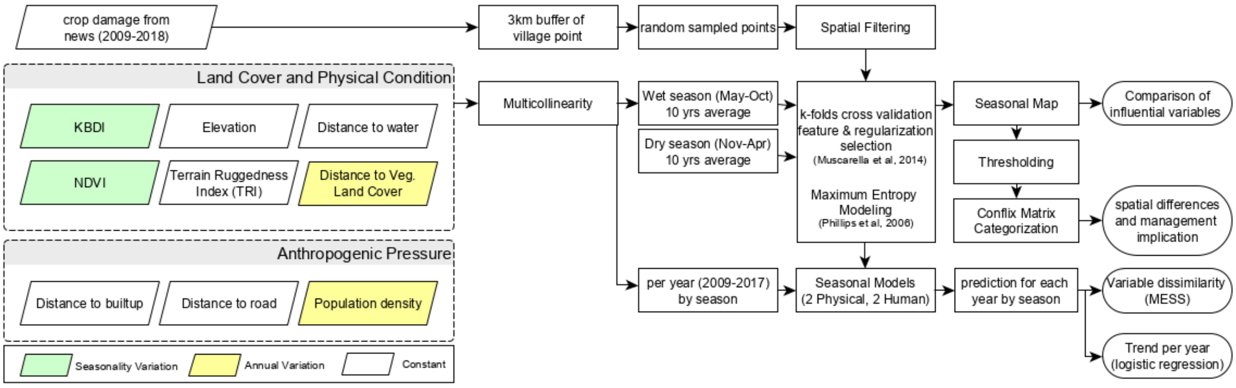

Figure 2: Flow chart data and methodology.

2.2 Data

2.2.1 Crop Damage Data

Data on crop damages caused by wild elephants were obtained through Google Search Engine under News section. A keyword '*wild elephants*' in Thai language was used as a search term and a customized time period was set for 2009 to 2018. Each search output was investigated manually to retain only incidents resulting in agriculture damaged or those occurred as a result of elephants entering agriculture land. The obtained data was without precise locations and only reported at a village level. To accommodate the lack of occurrence location, random points within a buffer of 3km-radius around village locations were sampled. Within the generated buffer, potential area for sampling were further restricted to exclude those that fell within the boundary of protected areas, large water bodies (e.g. reservoir), and permanent built-up area during 2009-2017, and major road network. The number of random occurrence point were generated according to the numbers of damage incidents reported within each village. The random sampling was performed separately for wet and dry season. Wilcoxon-Mann-Whitney test (Fay and Proschan, 2010) was applied on the generated occurrences to compare the distribution profile of these points for each independent variable to that of the other five subsets of occurrence record in order to evaluate that no statistically significant differences between subsets existed.

2.2.2 Prediction Variables

Candidate set of fifteen variables were selected based on their reported relevance to elephant ecology. These variables characterized vegetation productivity, meteorological drought condition, landscape composition, topographic condition, and human pressure. We grouped the predictors into two categories, 1) Landscape condition (12 variables) and 2) Direct human pressure group (3 variables). All the predictors were resampled to a 500-m resolution using bilinear interpolation method, and re-projected WGS 84/UTM zone 47N (EPSG32647).

Landscape condition were represented using Normalized Vegetation Index (NDVI), Keetch-Byram Drought Index (KBDI), distance to permanent water, land cover, vegetation heterogeneity, and aspect. NDVI and KBDI was used to capture seasonality characteristic of the landscape. NDVI was found to be an effective proxy of forage availability (Pettorelli et al., 2005) and African elephants showed to be dispersed according to the greening-up measured by NDVI (Bohrer, Beck, and Douglas-hamilton, 2014). We calculated the monthly median NDVI from MODerate Resolution Imaging Spectroradiometer (MODIS) product (MOD09Q1), and later computed the mean value across the months for wet and dry season. Drought has also shown to affect elephants mortality (Foley, Pettorelli, and Foley, 2008). Although the elephants' response to drought in tropical region is not clear, drought influences surface water availability and vegetation quality which govern elephants habitat usage (Sukumar, 1992). KBDI estimated dryness of soil layers and the product available from Takeuchi et al., 2015 was used. The scale of KBDI ranges from 0 (no moisture deficit) to 800 (extreme drought). The daily data from 2009 to 2018 was averaged by season. Elephants also need daily access to water and required to drink approximately 190 liter of water a day (Sukumar, 1992). To capture accessibility to water, we calculated euclidean distance to the mode of permanent water pixel obtained from Landsat Global Water Surface Product (Pekel et al., 2016). In addition, elephants were observed to use various land cover classes depending on the availability and quality of their environment. To capture land cover, the MODIS land-cover data (MCD12Q1) was used. We reclassified the original 17 land-cover categories into seven vegetation classes: forest, woody savanna, savanna, shrub, grassland, crop, and non-vegetation. Additionally, elephant preferred a mixed of land cover and were observed to heavily utilized forest edge (Rood, Ganie, and Nijman, 2010). .Hence, heterogeneity of the landscape was calculated from the standard deviation of mean NDVI value within each season using a moving window of 1.5km radius. Lastly, to capture topographic characteristics, we derived elevation and terrain ruggedness index (TRI) from the Shuttle Radar Topography Mission data (SRTM).

Direct human disturbance was measured from distance to main roads, distance to built-up areas, and population density. Euclidean distance to major roads (highway and primary) were computed using road network vector from Bureau of Highways Maintenance Management of Thailand. Built-up areas were obtain from Global Human Settlement Layers (GHSL) by considering all built-up from 1975 to 2014 (Pesaresi et al., 2015). Human population also influence alteration of landscape and intensity of anthropocentric activities. Mean population density was computed from 2009 to 2017 using yearly estimation from Landscan dataset.

2.3 Model Construction and Evaluation

Multicollinearity among each predictor was evaluated using Variance Inflation Factors (VIF) and Pearson correlation. Variables that showed VIF greater than 10 and more than 0.7 correlation with other variables were removed. Maximum Entropy algorithm from MaxEnt species distribution modeling package (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 et al., 2013). The algorithm chooses the distribution that fulfills the given constraints inferred from the presence data and minimizes the relative entropy for the model derived from the overall distribution of the predictors (Elith, Kearney, and Phillips, 2010). MaxEnt is a presence-background modeling method and has shown high performance even with few records available and least affected by location errors of occurrence (Mateo-Tomás et al., 2012).

Feature classes and regularization multiplier (RM) governed modeling results of Maxent and their selection is importance (Merow et al., 2013). To ensure optimal model balancing between complexity and over-fitting, model tuning was performed using EMNeval package in R (RobertMuscarella et al., 2014). Majority of the ecological response usually fall under uni-modal which equivalent to Quadratic-feature (Merow et al., 2013). Therefore, we selected only Linear-Quadratic and Hinge-Quadratic combination, then perform k-fold cross-validation with regularization ranging from 0.5 to 4 with 0.5 increment. We used Akaike Information Criterion The lowest (AIC) for model selection. A single parameters of features and regularization combination is chosen based on Delta AIC_C, average AUC_{TEST}, and average AUC_{DIFF}. After optimizing feature classes and RM, default settings of other parameters were then used to run the model, including 10,000 background points representing psudo-absent location, 500 iteration maximum, and convergence thresholds. Total of four models were created, two for resource-related condition and another two for direct human pressure representing wet and dry season. All model construction was done using dismo package in R with maxent version 3.3.4 (Hijmans et al., 2017).

The final models were evaluated based on k-fold cross validation based on the mean Area Under the Curve (AUC) of the Receiver Operating Curve (ROC) analysis. In addition, variable importance for constructed model was calculated from permutation contributions, while jackknife was used to identify important predictors when transferring to test dataset. Logistic link function was used to derive a relative probability of occurrence ranging between zero (low probability) and one (high probability) (Phillips, Anderson, and Schapire, 2006).

2.4 Potential Conflict Areas and Annual Distribution Changes

The relative probability of occurrence for both resource condition scenario and direct human pressure scenario were categorized into matrix of potential conflict areas. To categorized the results, we first separated into avoided matrix and potential occurrence following (Bleyhl et al., 2015) in which potential usage areas are where 5% of presence location occurred. Maximum testing sensitivity plus specificity thresholds for each model were used to further divide potential occurrence areas into good resource condition (value > threshold), marginal resource condition (value < threshold), peak human pressure (value > threshold), and unsure level pressure with under low predicted probability (value < threshold). Figure 3 shows the proposed two-dimensional conflict category based on resource suitability and potential human pressure: 1) conflict areas (good resource condition with peaked human pressure), 2) attractive areas with uncertain pressure (good resource condition with uncertain human pressure), 3) possible short refuge areas (marginal resource condition with uncertain pressure),and 4) unattractive areas (marginal resource condition with peaked human pressure).

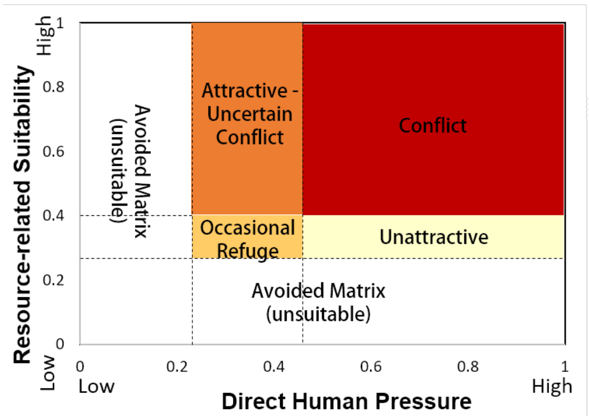

Figure 3: proposed two-dimensional matrix of potential conflict areas combining probability of resource-related suitability and level of direct human pressure

To obtain possible historical condition of potential conflict, we extrapolate the constructed models on the set of variables from each year between 2009 to 2017. The same threshold from the constructed model were used to categorize the historical prediction. To identify similarity and differences between historical conditions to the average values of the same variable, we applied Multivariate Environmental Similarity Surface (MESS) (Elith, Kearney, and Phillips, 2010). Negative MESS score indicates novel condition in variables, while positive score indicate similar conditions. Additionally, overall trend of potential conflict over 9 historical years were extracted from the slope of linear regression.

3 Results

3.1 Model Performance and Variable Responses

Total of 246 incidents of crop damage by wild elephants were reported between 2009 to 2018, 120 incidents during wet and 126 incidents during dry season. After applying spatial filtering, 120 and 125 occurrences remained for wet and dry season respectively. For the incident location randomly sampled, the distribution profile of values from each predictor did not have statistically differences when compared to that of additional five sets of random sampling points, Wilcoxon-Mann-Whitney test with lowest p-value > 0.15.

All four models had mean cross-validated AUC > 0.75 which indicates acceptable performance of models. For resource-related condition, important predictors based on permutation results for wet season are savanna (26%), TRI (20%), KBDI (16%), and distance to shrub (15%). In dry season model, KBDI (35%), elevation (16%), Savanna (15%), and heterogeneity (8.5%) were the important predictors. Distance to Water was a greater predictor during dry season (6.2%) compared to wet season (0.8%). For human pressure scenario, variable permutation results indicated that human density was the main predictor with 60% and 52% contribution in wet and dry season model respectively. Figure 4 listed response curves of each variable computed while keeping other variables at constant means for resource suitability condition (a) and direct human pressure (b), as well as percent contribution of each variable.

3.2 Potential Conflict Areas and Annual Changes

Our model and probability map of conflict indicated approximately 4,457 km^2 and 3,806 km^2 of high conflict areas in wet and dry season respectively over 5 years period. Although larger area of high conflict was predicted in wet season, overall areas with potential conflict was higher in dry season, 35% and 43% of total area in wet and dry season respectively (Table 1). Figure 5 showed a larger spatial extent potentially face with crop damages was

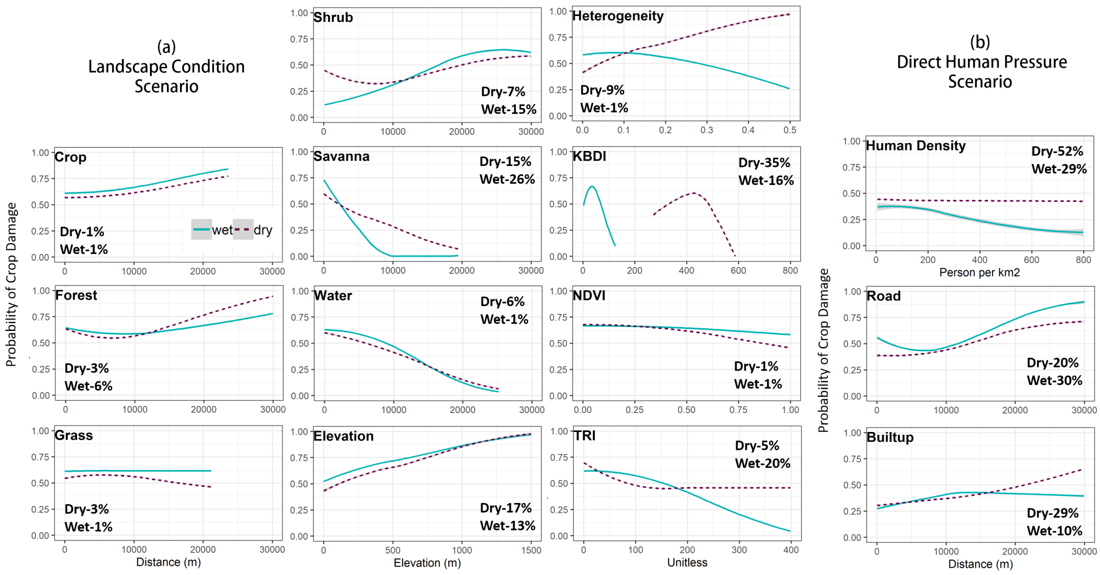

Figure 4: Response curves of each predictor for (**a**) resource-related suitability scenario and (**b**) direct human pressure scenario, variable contribution to final models are also listed

predicted for dry season. Areas frequently facing with high potential conflict were shown in Figure 5 as the last pair. Concentration of persistent conflict situated close to protected areas, with large areas predicted toward southern of study area near Khao Angruinai in Chantaburi and Chachoengsao provinces. Other sparsely distributed spots were in Trat province. For northern area, smaller clusters of persistent conflict hotspot were identified near Khao-Yai and Thablan.

Table 1: Summary of predicted areas under each group categorized using the conflict matrix for wet and dry season over 5-years period (2014-2018).

Conflict Habitat	Resource Suitability	Human Pressure	Area (km^2) Wet	Area (km^2) Dry	Area (%) Wet	Area (%) Dry
Conflict	High	High	4457	3806	12	10
Attractive	High	Uncertain	4716	4281	12	11
Occasional Refuge	Low	Uncertain	2659	5251	7	14
Unattractive	Low	High	1572	2998	4	8

During 2009 to 2017, the extrapolation using our model illustrated large variation for resource-related scenario, but rather constant situation for direct human pressure scenario. Large discrepancies were identified for 2010 and 2014 to 2016 in which high probability decreases drastically. MESS results identified large negative values for those years with high limiting factor from KBDI. Figure 6 showed an excerpt from 2013 to 2016 in wet season where large dissimilarity (negative MESS) was found and large anomaly in KBDI was also observed. El Nino events were recorded during those year with worst drought recorded for Thailand in 2015-2016. The impact of drought likely restrict dispersal ability of wild elephants, but may led to increase in conflict concentration and intensity of conflict within local areas may arise.

Besides extreme meteorological condition like El Nino that showed significantly affect on inter-annual variation in probability of elephants occurrence, changes in predicted probability over time remained after disregarding those extreme events. Overall increase in area with high resource suitability with +0.01 and + 0.03 in wet and dry season respectively. The trend is likely influenced by land cover changes which is an indirect pressure from human activities. Land cover changes impact the distribution of elephants and consequent conflict more subtly.

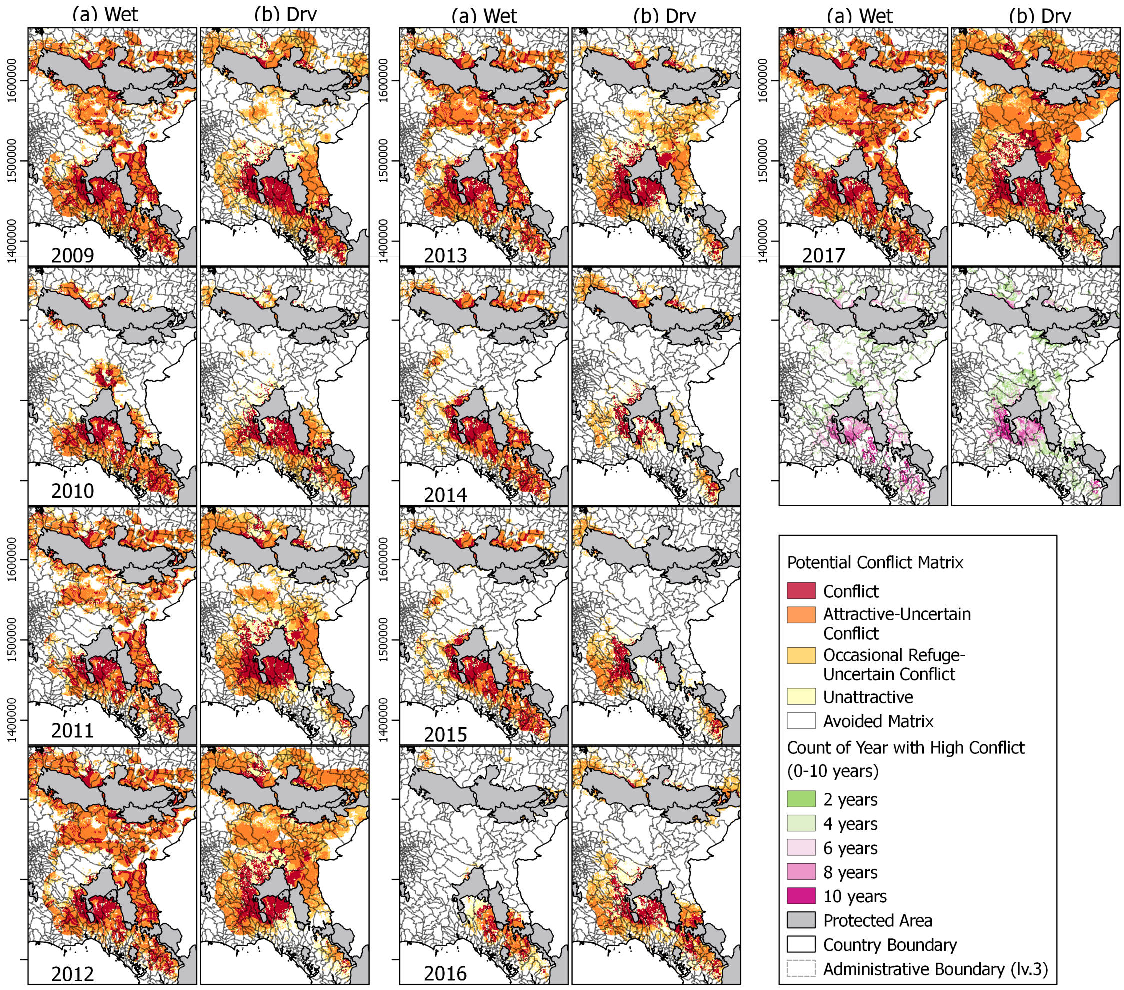

Figure 5: Predicted annual spatial distribution of potential conflict from 2009 to 2017 for (**a**) wet season, and (**b**) dry season. With count of years with high conflict to identify area persistent with high conflict across year

4 Discussion

In compare to resource-related predictor, direct human pressure contribution is small in combined model and likely be over-powered during model training. Our models were able to captured seasonality response of conflict within a single year, with differences in conflict distribution among season. This information can better prepare management response. Areas identified as high persistent conflict was due to its high resource-related suitability. Extended areas along southern and western boundary of Khao-Angruenai wildlife sanctuary was a clear hotspot with savanna is the dominant land cover class which represented perennial crop such as rubber. This is largely unique compared to the northern part dominated by cropland. Such situation may provide cover for elephants and assist in their movement. Study in India and China also identified perennial plantation to have high usage by elephants outside of protected areas (Kumar, Mudappa, and Raman, 2010; Liu et al., 2016; Li et al., 2018). Both mitigation and adaptation strategy should be used. For attractive area with uncertain conflict, management may response with prevention of spillover or use it as buffer from high conflict area depending on reality of human pressure within the area. Hence, further investigation and data collection on the ground is highly importance.

In addition, we demonstrated the usefulness of applying the same approach on past data to model previously unknown distribution. With yearly modeling, we captured substantial fluctuation in conflict distribution due to extreme events. Similarly, various studies in arid regions identified extreme drought alter concentration of elephants and even lead to mass starvation (Wato et al., 2016). However, such events were not usually considered during modeling and later management application. With potentially more frequent and intense extreme event due to climate change, response of conflict distribution in such event can be critical for management implication. Both elephants and human are affected by event like drought and further increase competition of resources. According to our model, KBDI is prominently govern inter-annual response. With its high temporal resolution of daily coverage, it has potential as

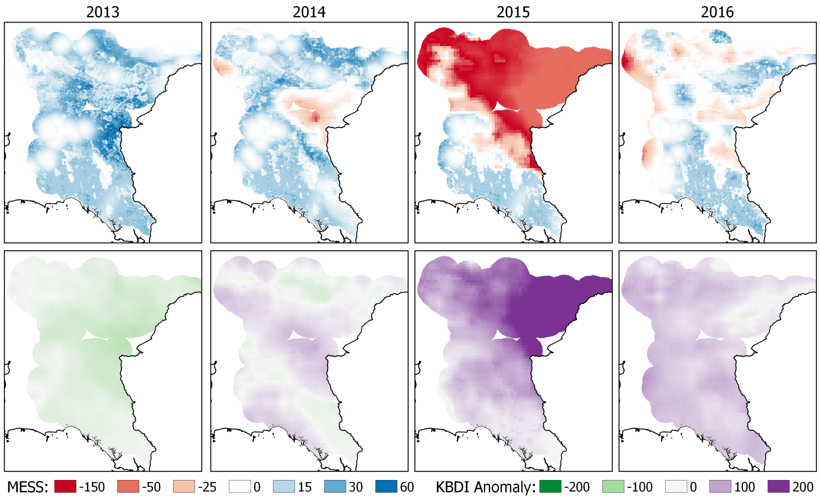

Figure 6: Example from 2013 to 2016 wet season showing MESS and KBDI anomaly. MESS indicated similarity of variables in 2013 and dissimilarity in 2014-2016 with corresponding to KBDI anomaly.

early warning indicator probability incorporation with other high spatial resolution dataset such as land use.

Although each individual variable response consistent with ecology of elephants and generally similar across other part of Asia, the transfer-ability of our model must be further tested. Predictive power of our model relied largely on distance to forest and savanna. Forest land cover can represent natural habitat within protected areas. However, savanna is mostly agricultural areas comprised of orchard and perennial plantation. This characteristic maybe specific to this region which reduce transfer-ability of our model into different location. Additionally, activity beyond land cover class was such as cropping pattern was identified as an important factor determining when and where crop field is raided by elephants. Studies of African elephants crop raiding behavior identified crop availability and ripening timing are important indicator for occurrence of crop damage (Chartier, Zimmermann, and Ladle, 2011). The study further suggested that temporal pattern of crop-raiding for elephants in forest habitat can be largely explained by crop, while seasonal fluctuation of foraging quality governed those in arid savanna habitat.

5 Conclusions

This study illustrated the importance of inter-annual and seasonal variation on distribution of potential HEC. Drastic changes of predicted HEC areas across each year was largely due to extreme event like drought during El Nino and was captured by KBDI. Although more subtle in level of changes, land cover seems to gradually influence the shift in conflict categories across long period of time. Our result suggested that HEC was largely governed by resource-related condition and less on direct human pressure. Within the same year, seasonality also influenced probability and distribution of conflict in which wet season illustrated higher clustered of conflict, while more larger special extent of conflict was predicted for dry season. Within the study region, savanna land cover contributed largely to HEC prediction. We applied two separate modeling based on landscape and direct human disturbance, and then proposed potential conflict matrix. Our finding is essential for future planning and management of resources and resilience to mitigate crop damages and conflict between human and elephants. Furthermore, this study highlighted the advantages of satellite-derived variables with high temporal resolution which can capture annual and seasonal variation.

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