Received: 23 January 2024 | Revised: 20 March 2024 | Accepted: 16 April 2024

DOI: 10.1002/ecs2.4922

ARTICLE

ECOSPHERE
AN ESA OPEN ACCESS JOURNAL

Drivers of human–tiger conflict risk and potential mitigation approaches

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Funding information
National Key R&D Program of China, Grant/Award Number: 2023YFF1305000; National Natural Science Foundation of China, Grant/Award Number: NSFC31872241; Fundamental Research Funds for the Central Universities, Grant/Award Number: 2572022DS04

Handling Editor: Joseph D. Holbrook

Abstract

Human–wildlife conflict has become a significant challenge for conservationists, particularly in areas where endangered species, such as large carnivores, are recovering. If we fail to keep a balance between the interests of humans and wildlife, the human–wildlife conflict can have adverse outcomes. However, the drivers of human–wildlife conflict, and how to mitigate conflict, are often poorly understood. In this study, we aimed to explore the possible causes for and potential mitigating approaches to human–tiger conflict risks through spatiotemporal niche partitioning. Based on data from the reports of Amur tiger (*Panthera tigris altaica*) preying on cattle and camera trap detection data from 2014 to 2019 in Hunchun, Northeast China, we predicted Amur tiger occurrence and created risk maps of human–tiger potential encounters. We found that Amur tiger occurrence was positively driven by prey distribution and negatively by the distribution of pastures used for domestic cattle grazing. Livestock was increasingly predated in areas with limited preferred prey, that is, wild pig (*Sus scrofa*) and sika (*Cervus nippon*), and in closer proximity to cattle-grazing land. On the basis of our models, we divided areas utilized by human and Amur tigers into low-, medium-, and high-risk areas across multiple spatiotemporal scales. We suppose that multiple spatiotemporal scale niche partitioning management might effectively reduce the risk of human–tiger encounters, prompt harmonized coexistence between humans and tigers, and provide new solutions to other areas experiencing human–wildlife conflicts.

KEYWORDS

Amur tiger, domestic cattle grazing, human–tiger conflict, prey distribution, spatiotemporal niche partitioning, variance inflation factor

INTRODUCTION

Human–wildlife interactions are a part of human life in rural and remote areas (Nyhus, 2016). While many interactions are benign or positive (Soulsbury & White, 2015), there are also many interactions that result in negative outcomes for both parties. The negative impacts of human–tiger conflict include the loss of human lives and livelihoods, which may result in negative attitudes toward tiger conservation, such as retaliatory killing and poaching of tigers (Figel et al., 2023; Tilson & Nyhus, 2009; Woodroffe et al., 2005). Among the big cats, tigers (*Panthera tigris*) are probably the most notorious for conflicts with humans, as they have historically killed large numbers of people (Tilson & Nyhus, 2009). In recent decades, conflicts between humans and tigers have been prevalent in almost all places where tigers have been present (Barlow et al., 2010; Tilson & Nyhus, 2009; Woodroffe et al., 2005).

In one study of human–tiger conflicts from 2000 to 2009 in parts of Russia, more than 200 incidents were reported in about 128,000 km^2 of Amur tiger habitat in the Russian Far East (Goodrich et al., 2011). The competitive exclusion principle states that two competing species cannot coexist in the same ecological niche for long periods of time. High levels of overlap in tiger habitat urgently demand solutions to mitigate human–tiger conflict, and although there are many available interventions, their effectiveness needs to be considered. Studies have shown that large carnivores and humans can share the same landscape (Malaney et al., 2018; Recio et al., 2020). The success of conservation efforts lies in legislation, public support, and practices, leading to the coexistence of humans and animals (Carter et al., 2012; Oberosler et al., 2020).

In China, Amur tiger mainly resides in the Hunchun area. In recent years, due to the extensive attention of the government and all sectors of society, the population and distribution of Amur tiger have been effectively restored (Wang et al., 2018), but human–tiger conflict remains an issue. Due to the continuous recovery of the population and distribution of Amur tiger (Qi et al., 2021), there are more direct human encounters with Amur tigers, which instils a sense of fear among local residents. This can have a negative impact on the long-term recovery and protection of Amur tiger.

If we cannot solve the problem of human–animal conflict, then the very concept of harmonious coexistence will be in danger. For the long-term survival of Amur tiger in the Hunchun area, and to develop a prosperous coexistence with local residents, as well as a model for restoration of large carnivores to other landscapes, we here use the competitive exclusion principle to alleviate human–tiger conflict. In this research, firstly, we predicted that Amur tiger occurrence is driven by prey distribution. Secondly, we predicted that the reason why Amur tigers prey on domestic animals is due to the lack of preferred natural prey. Thirdly, we expected that the separation of human and Amur tiger activities in both temporal and spatial ecological niche dimensions can mitigate conflict risk to some extent.

MATERIALS AND METHODS

Study area

Hunchun municipality is an area of 4899 km^2 in Jilin province, Northeast China. Most of the area belongs to the Northeast Tiger and Leopard National Park (Figure 1). It is connected to the Russian "Land of the Leopard National Park" to the east and to North Korea to the southwest. The area is a key corridor connecting the Amur tiger in China and Russia (Gu et al., 2018). The main animals include Amur tiger, Amur leopard (*Panthera pardus orientalis*), sika, wild boar, roe deer (*Capreolus pygargus*), and musk deer (*Moschus moschiferus*) (Li et al., 2017; Soh et al., 2014). There are 98 villages and 4 towns (Gu et al., 2018), and based on a questionnaire survey, 63 cattle-grazing pastures are present within the area covering 3066 cows (Li et al., 2017). The village economy relies heavily on livestock farming, collection of non-timber forest products, and crop cultivation (Li et al., 2009). Since the establishment of the Northeast Tiger and Leopard National Park, the state-owned forest and collective forest have been separately managed. Cattle grazing is prohibited in the state-owned forest at some local sites, while daily production and living activities can occur in the collective forest.

Data collection

We arranged automatic cameras on a 3.2×3.2 km grid in three large areas within the study area. These three areas were considered to be the most active areas for Amur tigers at that time, and the size of the three areas ranged from 261 to 760 km^2 (average 559 $\pm$ 263.3 km^2). There were 228 cameras distributed among 110 camera sites (Appendix S1: Table S1). Within a camera grid, we maximized the probability of detection by placing cameras in areas with signs of animal activity (e.g., animal trails, lying locations, feeding locations, water sources, and near scent-marked trees) and by setting up a pair of cameras. For camera data processing, we first screened all images and videos for animal or human activities.

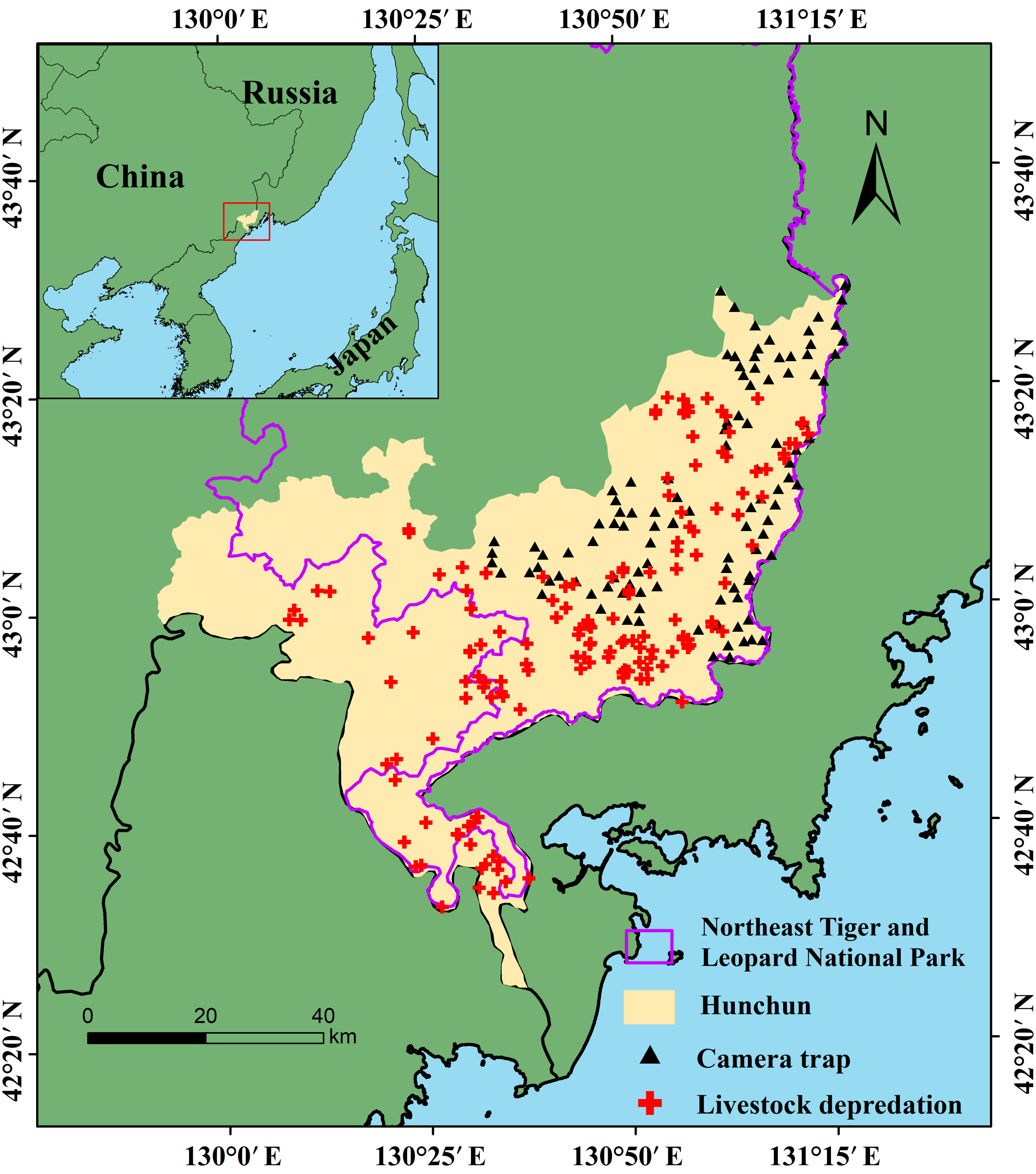


FIGURE 1 Camera trap and livestock depredation locations in the study area in Northeast China.

Then, we identified and classified species as well as behavioral activities. We also recorded the time, date, and temperature information of each image. To avoid duplicate recordings for analysis, we defined independent events as (1) consecutive photographs of different individuals, (2) consecutive photographs of individuals of the same species but requiring a time interval of more than 0.5 h between photographs, and (3) nonconsecutive photographs of individuals of the same species (O'Brien et al., 2003).

Data of livestock depredation by Amur tiger and the grazing sites were obtained from Hunchun Bureau of

Northeast Tiger and Leopard National Park. We analyzed 448 records of livestock depredation from 2014 to 2019 for which spatial coordinates were available. Each year, the local government takes census on residents' losses without any apparent time gaps or other inconsistencies caused by incomplete records, and all data were verified and georeferenced by reserve staff. Data of vegetation type, village, farmland, river, road, and Normalized Difference Vegetation Index (NDVI) were derived from the National Geographic Information Resource Directory Service System (http://www.webmap.cn). The digital elevation model (DEM) came from Geospatial Data Cloud (http://www.gsclod.cn). Slope and aspect were derived from DEM data using ArcGIS 10.7.

Modeling prey relative abundance

Relative abundance index (RAI) is the number of detections per 100 camera trap days of every species (Martin-Garcia et al., 2022; O'Brien et al., 2003; Rowcliffe et al., 2008). The RAI of three species of Amur tiger prey (i.e., wild boar, roe deer, and sika) were calculated based on each independent event at each camera point in each year. Pearson's correlation method was used to calculate correlation coefficients between independent variables such as elevation, slope, slope direction (aspect), NDVI, and nearest distance from camera point to different vegetation types, farmland, villages, roads, and rivers. When the Pearson's correlation coefficient was greater than 0.5, we considered that there was a strong correlation between the two variables, and therefore, one of them was removed so that none of the variables entering the model would affect the model because of correlation problems (Li et al., 2017; Ramsay et al., 2003). We used generalized linear models (GLMs) to test specific effect mechanisms (Carlson et al., 2007; Guisan et al., 2002). We used Akaike information criterion adjusted for small sample sizes (AIC_c) for model selection (Burnham & Anderson, 2002). The model with the least AIC_c was considered the optimal model. Then, the RAI of the three ungulates was predicted using the predict function in R according to the optimal model (R Core Team, 2022), and the model was verified by the method of 10-fold cross validation (Schouten et al., 2009).

Modeling prey occurrence probability

We used a Maxent model (Maximum Entropy Model) to predict the annual occurrence probability of three ungulate prey species in Hunchun area. The Maxent model maintains high accuracy even when the species occurrence data are few, and its prediction accuracy increases with increasing sample size and related ecological factors (Baldwin, 2009; Perkins-Taylor & Frey, 2020). The Jackknife test was used to analyze the importance of ecological factors. The Kernel Density Estimation was used to generate bias file for the sample area (Beck et al., 2014; Syfert et al., 2013). Band Collect Statistics were used to calculate co-variance, and variables with correlation greater than 0.5 were removed (Snedecor & Cochran, 1968). We used the Circuitscape Export tool to standardize cell size and the extent of all environmental variables in ArcGIS 10.7 (Anantharaman et al., 2019). Afterward, the processed data of distribution sites of target species and relevant environmental variables, as in our prey RAI modeling described above, were input into the Maxent model. A division of 25% test set and 75% training set was used to build the model. The regularization multipliers were set to 1, 2, and 3, and we obtained species distribution probability estimates ranging from 0 to 1, which can represent habitat suitability. The model was verified using cross validation, and the area under receiver operator characteristic curve (AUC) value was used to evaluate the accuracy of the Maxent models. Finally, the model with the maximum AUC value was selected as the optimal occurrence probability model (Tracy et al., 2019).

Modeling Amur tiger occurrence probability

We used grazing distance and prey factors to explore the activity patterns of Amur tigers. Distances between the camera trap sites and the nearest grazing sites were calculated using ArcGIS 10.7 (data from Forestry Bureau). At each camera trapping site, we extracted RAIs and probabilities of occurrence for the three ungulate species. A generalized linear mixed model (GLMM) was used to model Amur tiger occurrence as a function of RAI and probability of occurrence of the three prey species and distance from the grazing site. In the model, the number of Amur tiger occurrences at each camera trap site was used as the response variable, and year was considered as a random effect to distinguish the effects of nonindependent variables, such as environmental changes (van Doormaal et al., 2015). To increase the reliability of the model, we checked for multicollinearity using the variance inflation factor (Wang et al., 2017), and we considered the model multicollinear when variance inflation factor > 3. The correlation screening between independent variables was performed using the Cor function, and one of the variables was removed when $|r| > 0.5$ between two variables. Finally, the model with the minimum AIC value was selected as the optimal model (Johnson & Omland, 2004). The GLMM was fitted using the R package YawMMF (Zhang et al., 2020). Residuals and R^2 were calculated according to the scheme proposed by Nakagawa and Schielzeth (2013).

Modeling occurrence probability of Amur tiger predation on livestock

We compared the geospatial points of Amur tigers preying on livestock with the occurrence points of Amur tigers recorded by cameras. GLMMs were fitted to model Amur tigers preying on livestock (i.e., 1 for predation and 0 for non-predation) as a function of three prey species' RAI and probability of occurrence based on the results of the previous two models, as well as distance to grazing. Year was considered as a random effect to distinguish the effects of nonindependent variables, such as environmental changes (van Doormaal et al., 2015). Multicollinearity, correlation, GLMM fitting, and calculation of residual variance and R^2 are as described above in our Amur tiger occurrence modeling section. We drew model receiver operating characteristic (ROC) and calculated model area under the curve (AUC) values in R (Robin et al., 2011). The Wilcoxon test was used to test large ungulate biomass differences of three prey species (i.e., three ungulate species' RAI multiplied by their body mass) at predation and non-predation sites to assist in the validation of the model.

Modeling resident occurrence probability

As described in the prey RAI modeling above, the number of independent resident occurrence events captured by each camera was the response variable, and the probability of local resident occurrence was predicted using the GLM. Goodness of model fit was evaluated by cross validation of root mean square error (RMSE) (Willmott & Matsuura, 2005). Villages and farmland around residential areas were excluded from our prediction because most of the automatic cameras were located in the wilderness area far away from them.

Human–tiger spatial and temporal niche conflicts

In a spatial context, the underlying assumption is that places with a high overlap between human and Amur tiger occurrence are the areas expected to have the highest chance of potential conflicts. We overlayed the human occurrence probability raster and the Amur tiger occurrence probability raster produced in ArcGIS. We rescaled the predicted values in raster cells to between 0 (low occurrence probability) and 1 (high occurrence probability) and then multiplied the predicted values of the resident and Amur tiger overlap to obtain a map of conflict risk (Oliveira-Santos et al., 2021); risk was reclassified as medium ($0.25 \leq$ coefficient < 0.36), high ($0.36 \leq$ coefficient < 0.49), and focal risk area (coefficient < 0.49). At the same time, in order to further reveal the causes of human–tiger encounters, we drew a buffer zone of 7-km radius around the points where female Amur tiger occurrence was detected with cubs from 2014 to 2019. The radius of the buffer zone is equal to the daily activity distance of Amur tiger (Goodrich et al., 2010) and was superimposed on the conflict risk map.

We used kernel density estimation methods to analyze the temporal data collected for each species to obtain daily activity patterns by species (Linkie & Ridout, 2011; Ridout & Linkie, 2009). Temporal niche overlap coefficients, ranging from 0 to 1, were used between two species to assess the temporal niche overlap between species at different times. Because local residents are rarely active in the mountains during winter and because many cameras do not work due to low winter temperatures, we only considered potential conflicts in spring (March–May), summer (June–August), and fall (September–November). For the kernel density analysis, we chose the D4 method for large sample sizes (minimum sample size > 75), the D1 method for small sample sizes (minimum sample size < 50), and the D5 method for sample sizes from 50 to 75. CIs were calculated using 10,000 bootstrap samples.

We make a reasonable classification of the human–tiger conflict risk map based on the overlap value and also find the time period with less overlap of human–tiger activities based on the human–tiger activity pattern to minimize the risk of human–tiger conflict. Analyses were performed using the overlap package (Ridout & Linkie, 2009) and the stats package (R Core Team, 2009).

RESULTS

Probability of Amur tiger occurrence

Using the RAI of the three ungulate species predicted by the models (Appendix S1: Tables S2 and S3) and the Maxent model results (Appendix S1: Table S4), we found that the occurrence probability of Amur tiger was positively correlated with the RAI of wild boar, the probability of occurrence of sika, and the distance to grazing land. Amur tiger probability of occurrence was negatively correlated with the RAI of roe deer (Appendix S1: Tables S5 and S6). About 11.9% (584 km^2) of Hunchun

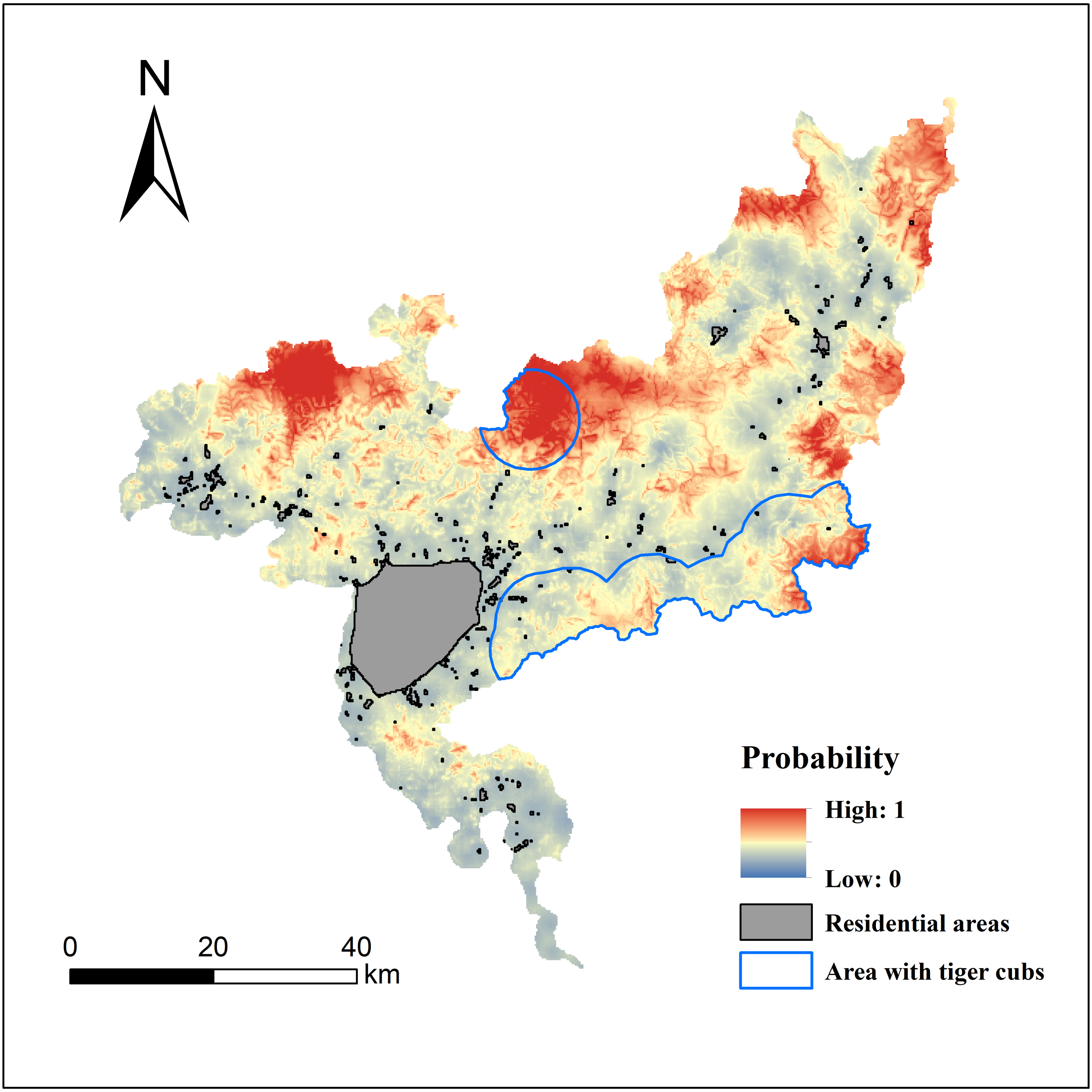
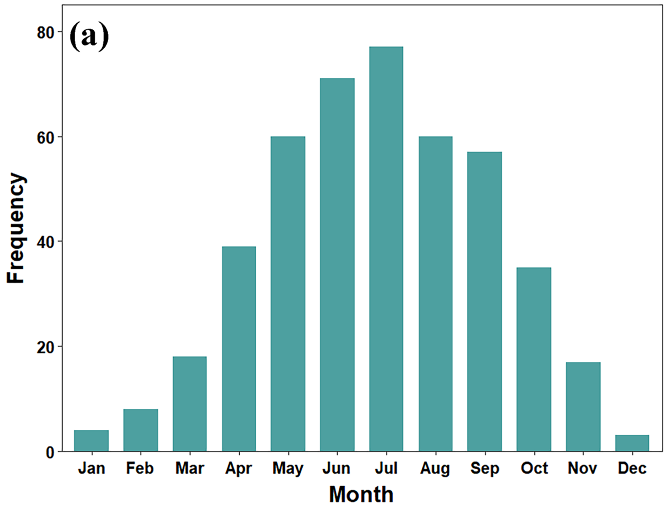


FIGURE 2 Probability map of Amur tiger occurrence based on Amur tiger occurrence points in Hunchun area, 2014–2019.

appeared to have high probability for Amur tiger occurrence above the threshold of 0.5 (Figure 2). Predicted areas did not include residential areas.

Probability of livestock predation by the Amur tiger

Among the 448 reported cases of Amur tigers preying on livestock, the annual peak period occurred from May to September (Figure 3a); the number was greatest in 2014–2016, with 109, 125, and 102 cases per year, respectively (Figure 3b). The probability of Amur tiger preying on livestock was negatively correlated with the RAI of wild boar, the RAI of sika, the probability of occurrence of roe deer, and the distance to grazing land (Appendix S1: Tables S5 and S7). Most of the high probability areas were close to residential areas (Figure 4). Large ungulate biomass at sites where Amur tigers did not prey on livestock was significantly greater than at sites where Amur tigers preyed on livestock ($p < 0.001$).



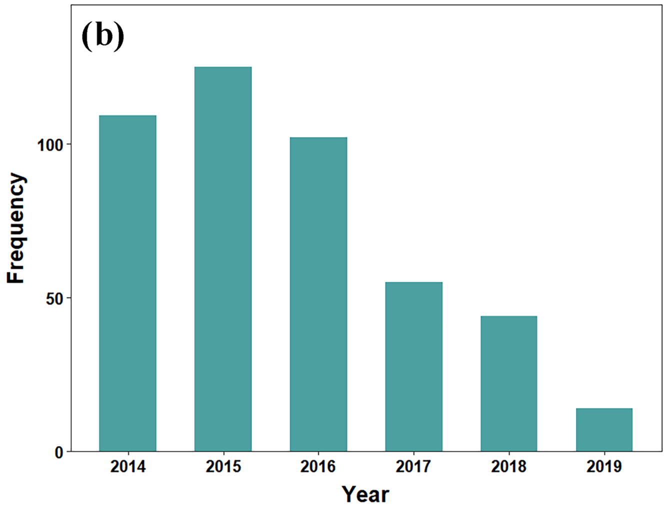


FIGURE 3 Amur tigers preying on cattle in Hunchun region, 2014–2019. The number of cattle killed by Amur tigers (a) each month and (b) each year.

Spatiotemporal human–tiger conflict risk

On a spatial scale, the risk coefficient for human–tiger conflict ranged from 0 to 0.569 (Appendix S1: Table S8), resulting in 851.88 km^2 (17.39% of the Hunchun area) in medium risk, 91.36 km^2 (1.86% of the Hunchun area) in high risk, and 2.24 km^2 (0.05% of the Hunchun area) in focal risk, the highest risk level (Figure 5). In areas where Amur tiger cubs were found, the area of medium conflict risk was 219.92 km^2 (25.82% of the total medium conflict area) and 39.44 km^2 of high risk (43.17% of the total high conflict risk area). Amur tiger cubs were found in nine of the villages, and 10 were at risk of conflict (Figure 5).

Temporally, the overlap index of residents and Amur tigers was 0.38 in spring, 0.37 in summer, and 0.33 in autumn. During spring, the intersections of human–tiger activity where Amur tiger activity was less than human activity were 5:25 h and 15:35 h. The least activity of Amur tiger was noted at 12:35 h. During summer, these above intersections of human–tiger activity were 5:40 h and 16:35 h, with the Amur tiger least active time 9:40 h, and during autumn, the intersections of human–tiger activity pattern were 5:55 h and 16:35 h, with the least activity of Amur tiger noted at 9:28 h. We quartered the difference in y values between each human–tiger time intersections and the lowest peak of Amur tiger activity to demarcate the different intensities of tiger activity. Hence, the time period between the two points on the tiger activity line at $y = 1/4\ (y_{peak} - y_{trough}) + y_{trough}$ was the recommended activity time for residents in the high-risk area, corresponding to spring: 8:25 h–13:55 h, summer: 8:40 h–15:00 h, and autumn: 9:28 h–14:04 h. For medium-risk areas, determined as the time period between the two points at $y = 1/2\ (y_{peak} - y_{trough}) + y_{trough}$, the recommended activity time for residents was 7:25 h–14:35-h, summer: 8:00 h–15:40 h, and autumn: 7:00 h–15:05 h. For low-risk areas, determined as the full time period between the two human–tiger activity intersections, the recommended activity time for residents was 5:25 h–15:35 h, summer: 5:40 h–16:35 h, and autumn: 5:55 h–16:35 h (Figure 6).

DISCUSSION

Occurrence of Amur tiger driven by ungulate prey

As with other large carnivores, the availability of prey is one of the main drivers of tiger distribution and abundance (Harihar et al., 2014; Petrunenko et al., 2016; Xiao et al., 2018; Yang et al., 2019). This is particularly the case for Amur tiger, where both Amur tiger and prey densities are least within the species' range. In this study, the relationship between the occurrence probability of Amur tiger and ungulate prey further confirmed this hypothesis (Figure 2). In terms of prey selection, previous research of fecal diet analysis has revealed that wild boar is preferred, but sika, and especially roe deer, was avoided by Amur tiger, relative to its availability (Bagchi et al., 2003; Gu et al., 2018; Hayward et al., 2012). This is likely because there is no significant difference in energy expenditure between Amur tiger predation on large-sized prey, such as wild boar and sika, and small-sized prey, such as roe deer, but there is a large difference in energy return. Hence, tigers appear to prefer prey species which match their weight, similar to other solitary predators (Carbone et al., 1999; Hayward et al., 2007).

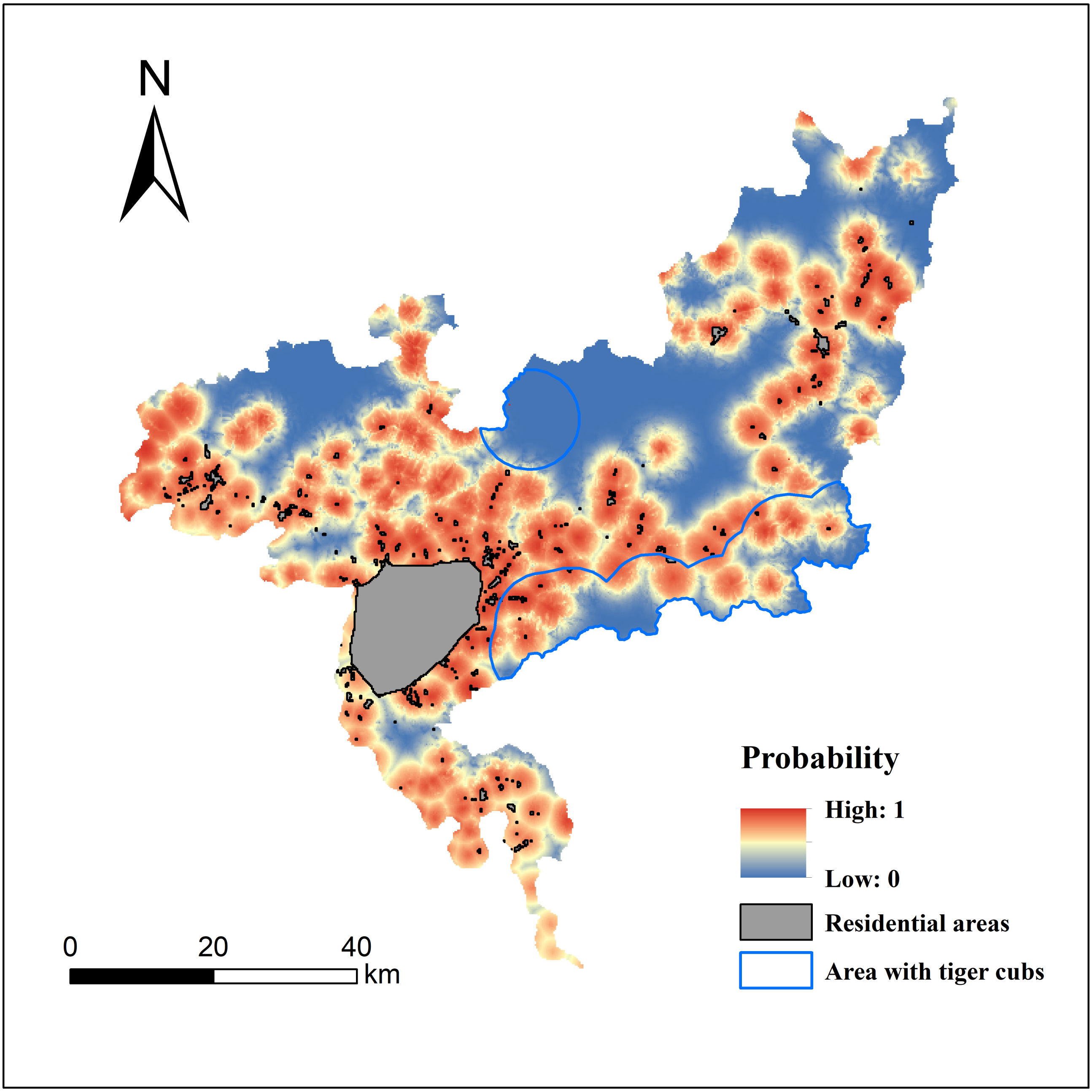


FIGURE 4 Probability map of Amur tiger killing livestock based on Amur tiger prey on cattle points in Hunchun area, 2014–2019.

Amur tiger predating livestock due to lower population of large ungulate

Tiger attacks on people and its predation on are persistent from time immemorial (Tilson & Nyhus, 2009). Today, as human activities continue to expand, livestock often move into the forest to forage (Margulies & Karanth, 2018), which greatly increases the likelihood of livestock being predated and becoming an alternative food source for wild carnivores (Karanth, Gopalaswamy, et al., 2013; Karanth, Naughton-Treves, et al., 2013). We found that the Amur tigers preyed on livestock in areas where the population of wild ungulate RAI was low and close to cow-grazing sites. Therefore, we speculate that the lack of wild ungulate prey in these areas is the most important reason for the Amur tigers preying on livestock and foresee continuous pressure on livestock as the African swine fever continues to decrease populations of wild boar (i.e., the main food for Amur tigers; Luskin et al., 2023).

Previous studies found that the biomass contribution of livestock to the feeding habits of the Amur tiger was much greater in Hunchun than in Russia. In spite of this overestimation, 25% of the livestock they kill are

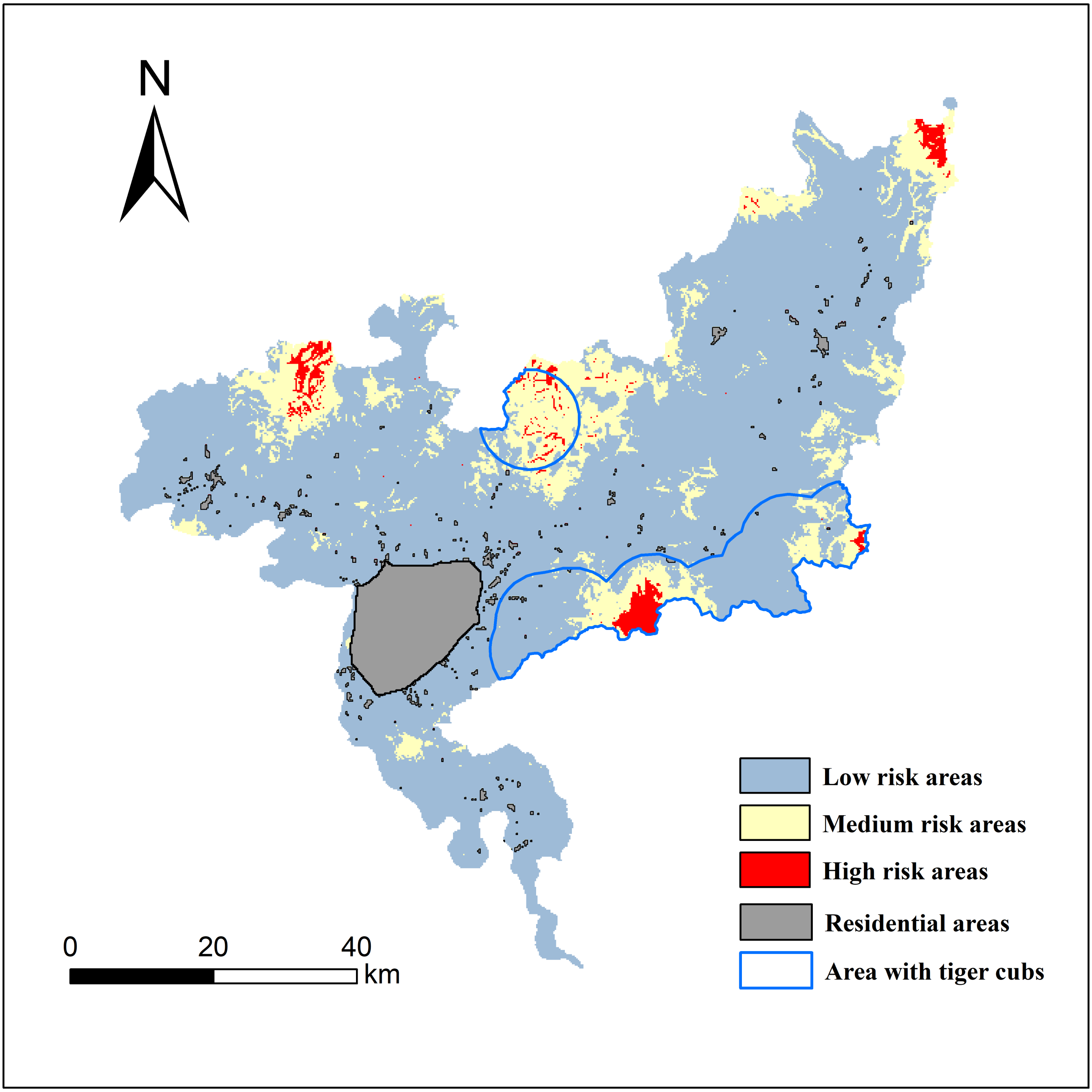


FIGURE 5 Human–tiger conflict risk area map of Hunchun region.

not eaten by Amur tigers, and in the 42% of the livestock killed, less than half of the carcass is eaten (Gu et al., 2018; Wang et al., 2018). This situation seems to be associated with human presence in the area causing Amur tigers to abandon predating or feeding. Our Amur tiger occurrence probability model reveals that the Amur tiger is avoiding grazing areas, but if the higher the abundance of the Amur tiger, the greater the depredation of livestock as young or weak Amur tigers are forced to be led into human-dominated landscapes to find territory (Goodrich et al., 2011; Karanth & Gopal, 2005).

The data we presented show a significant decline in the number of cattle killed by Amur tigers since 2016. This was also the time when the Northeast Tiger and Leopard National Park implemented "two pilot projects" to ban grazing in state-owned forests. It appears that these pilot projects have not only reduced cattle depredation by Amur tigers but also the income of local residents (Han et al., 2022). For the residents of the reserve, the reduction in income may be largely due to the change in the attitude toward the protection of the Amur tiger, and if the residents are not compensated in time, they may intent to hurt the Amur tiger due to hatredness (Karanth

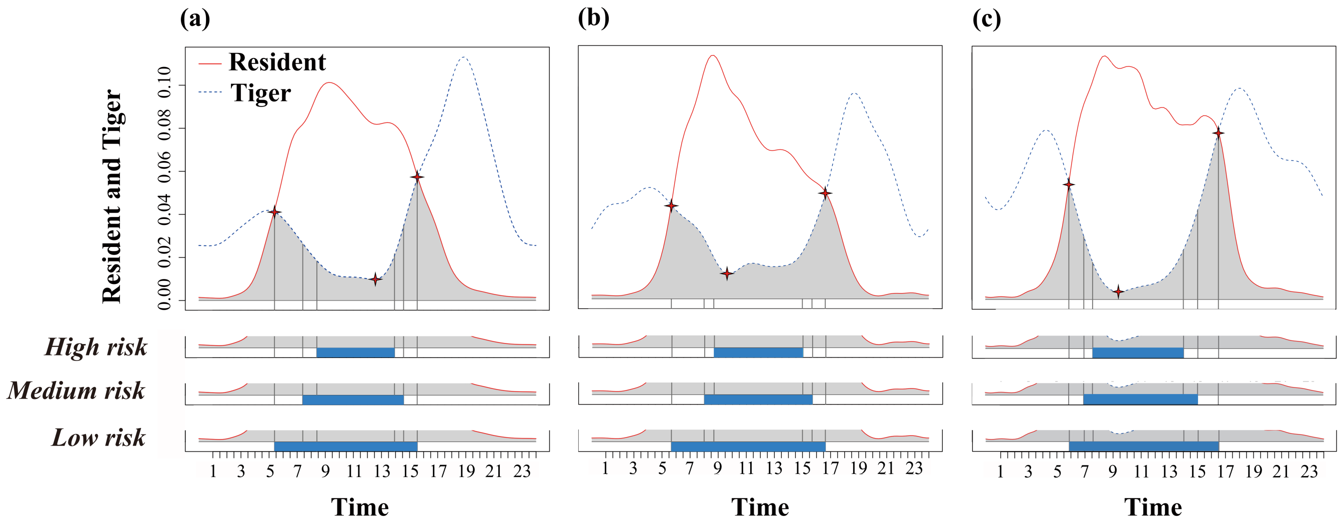


FIGURE 6 Human and tiger activity patterns during three seasons in Hunchun area. Red stars indicate the two human–tiger time intersections and the lowest point of tiger activity. (a) Spring. (b) Summer. (c) Autumn.

& Gopal, 2005). As such, holistic approaches are required, including efforts to increase incomes from other activities (e.g., plants and plant products, mushrooms, ecological landscapes, and ecological services).

Spatiotemporal management of human–tiger conflict

In Hunchun area, in addition to livestock predation, direct encounters between humans and Amur tigers in the wild cause conflict as has been reported in Russia (Goodrich et al., 2011). Local residents are involved in rearing livestock and other food-producing activities such as picking wild mushrooms or vegetables, which increase the possibility of direct encounters between humans and Amur tigers. Thus, in order to protect the safety of humans and Amur tigers and to prevent the occurrence of Amur tiger attacks, it is necessary to identify the areas prone to conflict at the landscape scale. Evidently, Amur tigers are predominantly activein the morning and dusk; this activity pattern can be better separated from human activities, which provides a basis for further spatial and temporal zoning management. Humans should avoid the activities of Amur tigers in time and space, and give both sides enough space to survive, in order to maximize long-term coexistence.

Based on the spatiotemporal analysis results above, we developed recommendations for different risk areas: (1) For high-risk conflict areas, human activities should be strictly reduced or prohibited. If not, activities such as scientific research, monitoring, or habitat management, should be carried out in groups during the recommended time periods. (2) For medium-risk areas, human activities should occur during the recommended time periods and avoid acting alone. (3) For low-risk conflict areas, various production activities can occur, but it is best to do so during the suggested time period (Figures 5 and 6). Such division of spatiotemporal zones and corresponding recommendations should be reviewed and revised as necessary, including under circumstances of changing tiger populations and presence of female tigers with cubs. Areas where Amur tiger cubs occur are the breeding grounds of female Amur tigers which need to hunt prey more frequently to feed their cubs (Goodrich et al., 2010), and hence, this may increase the risk and danger of human–tiger encounters. Further, it is essential to remind that even during the periods when Amur tigers are least active, there is still a small amount of activity, and the chance of encounter between humans and Amur tigers cannot be avoided entirely.

Finally, elsewhere in the Amur tiger range in Russia, a tiger response team has been operating since 1999 in order to cope with the conflict between Amur tigers and humans. In the future, to learn from this experience, technologies such as infrared cameras, vibration optical fiber, anchor-free detectors (Liu & Qu, 2023), and other equipment to monitor the protected area, and to timely detect and deal with emergency conflict situations should be utilized effectively, which ultimately requires the joint efforts of local communities, governments, and wildlife conservationists.

Conservation implications

To harmonize the coexistence of humans and large carnivores, there is an urgent need to understand the spatial and temporal use of resources by large carnivores and humans in the same landscape. Here, we found the drivers of spatiotemporal conflicts between humans and Amur tigers and revealed that the occurrence of the Amur tiger is mainly driven by natural preferred prey, that Amur tiger predation is associated with a lack of large natural ungulate prey in the area, and that utilizing different breadths and portions of the temporal dimension can mitigate risk of encounter and conflict. To reduce human–tiger conflict, we put forward the following recommendations: (1) The long-term and effective recovery of the Amur tiger population first needs to increase the local population of large ungulates as primary food, in turn reducing the predation of livestock by the Amur tiger. This could be achieved by reintroducing large preferred ungulates, supplementary feeding for ungulates in winter, and regularly clearing ungulate hunting traps (snares). (2) Formulate scientific and reasonable cow-grazing and non-timber product collection policies and improve management methods. This includes limiting the grazing areas, returning cattle to the cattle pen every night, and reasonably planning permitted and prohibited grazing areas (Roberts et al., 2021). (3) For different zones of human–tiger conflict risk, scientific management of human activities should be implemented according to the risk map, limiting the time of human activities to when tigers are least active in an effort to reduce the occurrence of human–tiger conflict. (4) Set up a special emergency team to strengthen the monitoring of human and Amur tiger conflict and to reduce the possibility of direct encounters in high-risk areas between humans and Amur tigers to the best extent possible. This approach to spatiotemporal niche partitioning can provide ideas, too, for conflict resolution in other human-inhabited protected areas.

AUTHOR CONTRIBUTIONS

Guangshun Jiang designed the study. Jiayin Gu, Dusu Wen, and Wannian Cheng contributed to field survey. Dusu Wen, Wen She, Heng Bao, Jinzhe Qi, Xuankai Liang, Heng Bao, and Wannian Cheng contributed to model validation. Wannian Cheng, Heng Bao, Wentao Zhang, and Nathan J. Roberts contributed to data analysis and paper writing, and Nathan J. Roberts, Thomas NE Gray, and Heng Bao contributed to paper revisions.

ACKNOWLEDGMENTS

This research was supported by the National Key R&D Program of China (2023YFF1305000), National Natural Science Foundation of China (NSFC31872241), and Fundamental Research Funds for the Central Universities (2572022DS04).

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data, other than Amur tiger occurrence data, and code are available from Figshare: https://doi.org/10.6084/m9.figshare.23714373.v3. Datasets of Amur tiger occurrences are sensitive and cannot be shared publicly. Qualified researchers may contact Guangshun Jiang, Feline Research Center of National Forestry and Grassland Administration, at jgshun@126.com.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Cheng, Wannian, Thomas N. E. Gray, Heng Bao, Dusu Wen, Xuankai Liang, Wen She, Wentao Zhang, et al. 2024. "Drivers of Human–Tiger Conflict Risk and Potential Mitigation Approaches." *Ecosphere* 15(7): e4922. https://doi.org/10.1002/ecs2.4922