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Mapping crop damage by wild boars using multi-scale risk modeling in Northeast China

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ABSTRACT Balancing development and conservation is one of the major challenges for modern societies. Negative human–wildlife interactions, especially crop raiding by wildlife, greatly undermine this objective. Jilin Province in Northeast China encompasses ecosystems of high biodiversity value but endures serious losses in crop yields due to wild boars (*Sus scrofa*). Mitigation measures have been hindered by knowledge gaps in wild boar damage patterns. This study aimed to investigate how wild boar damage responded to human-

dominated landscapes, evaluating landscape patterns of damage at multiple ecological scales, thus providing a provincial map of damage risk to assist with damage mitigation. We used 1,144 coordinates of wild boar damage from 2009 to 2013 to train multi-scale risk models with the MaxEnt algorithm. We found that damage risk was highest on gentle slopes and in heterogenous landscapes composed of fragmented plantations and cropland, high edge density among small discontinuous patches, with dense settlements presence in countryside areas with sporadic road networks. The scale had substantial effect on relationships between damage and landscapes. We recommend mitigating the conflict risk by improving the compensation system and reducing the damage frequency through repelling, electric fencing, and dissuasive feeding.

KEYWORDS crop raiding, damage hotspots, human–wildlife interactions, Jilin Province, Maxent, *Sus scrofa*, wild boar

The unlimited expansion of human activities, together with exploitation of limited natural resources, have represented a major contradiction of modern societies (O'Connor 1998, Harris and Roach 2017, Tietenberg and Lewis 2018). Negative human–wildlife interactions (HWI) are a typical representation of this issue, referring to any negative impact that human or wildlife has on the other (IUCN SSC HWCTF 2020). Human disturbance and exploitation of ecosystems have led to habitat loss or local extinction of wildlife, increasing encounters between human and wildlife and the frequency of wildlife damage (Ravenelle and Nyhus 2017, Torres et al. 2018, IUCN 2022). Such damage could have unignorable influence on livelihoods of individual households, and often can make communities less supportive of conservation (McLennan and Hill 2012, Sponberg and Mathiesen 2022). Damage episodes

may include personal injury, traffic collision, and disease transmission, but livestock depredation and agriculture destruction have been undoubtedly the most relevant (Gren et al. 2018, Torres et al. 2018). These factors increase the risk of retaliation on wildlife and can deteriorate the coexistence of human with wildlife into conflict (Gubbi et al. 2014, Moreto 2019, Viollaz et al. 2021). Whilst damage to livestock is usually attributable to large predators (Ugarte et al. 2019), crop raiding animals are represented by a heterogeneous array of species, including elephants, bears, ungulates, primates, and birds (Nyhus 2016). Since agriculture occupies half of global habitable land (Ritchie and Roser 2013), damage to crops could be even more common than reported.

Studies on HWI generally focus on social influence or mitigation techniques (Dickman 2010). However, in many cases, conditions failed to be improved despite increasing interest and effort in this domain (Anand and Radhakrishna 2017, Montgomery et al. 2018). A probable reason was the difficulty for traditional studies to contribute to mitigation actions (Gray et al. 2019). The link between HWI and social factors, e.g., religion, income, and education, have been proved by many studies (Dickman 2010). However, the improvement of these factors was rather complex and could hardly be achieved in a short timeframe.

Technical studies, i.e., studies on damage mitigation techniques (Fall and Jackson 2002, Dickman 2010), focused on the application of technological devices, such as electronic collars (Rossler et al. 2012) and injectable contraceptives (Massei et al. 2012). However, such technological mitigation is often neither available (Fall and Jackson 2002) nor affordable (Webber et al. 2007) in undeveloped regions. In recent years, risk models have been developed as the integration of HWI and species distribution models (SDM; Rostro-García et

al. 2016, Jin et al. 2021). Given locations of previous damage, the application of SDM methods enables spatial analysis of damage and visualization of risk (Miller 2015). For wildlife managers and policy makers, a map of damage risk represents a direct means to evaluate patterns of negative interactions and developed proactive mitigation interventions.

Scale has become a core tenet of ecological modeling (McGarigal et al. 2016). However, despite many studies incorporating the effect of scale in studies of wildlife distribution (McGarigal et al. 2016, Atzeni et al. 2020, Chen et al. 2022), the effect of scale in risk modeling has received little attention. Only a small number of studies focusing on risk modeling incorporated multiple-scale approaches (Guerbois et al. 2012, Rostro-García et al. 2016, Bautista et al. 2021). It is commonly accepted that organisms respond to their natural habitat at multiple scales (Wiens 1976, Wiens 1989). Therefore, if we consider wildlife damage as an adaptation to disturbance in human-dominated landscapes, the principles of multiple scales distribution modeling can be extrapolated to risk models and HWI. For example, Rostro-García et al. (2016) found that the importance of landscape variables to livestock predation by tigers (*Panthera tigris*) and leopards (*Panthera pardus*) varied with scale, reporting different conflict patterns from those generated by single-scale models. Malviya and Krishnamurthy (2022) found that livestock predation risk by tigers were mainly affected by prey encounter rate and shrub abundance at fine scales. Bautista et al. (2021), focusing on brown bear (*Ursus arctos*) damage to apiaries, found that the risk map predicted by multi-scale models was more accurate than those at single scales. In other words, multi-scale risk models were likely be more sensitive to factors that only affected damage risk at certain scales, identifying real damage hotspots more reliably, and consequently providing

90 applicable advice for mitigation actions.

91 Wild boars (*Sus scrofa*) are native to Eurasia but have expanded to all continents except
92 Antarctica (Lewis et al. 2017). Their rooting behavior has dramatic influence on seeding of
93 plants (Sanguinetti and Kitzberger 2010), diminish food availability for sympatric animals
94 (Focardi et al. 2000) and can affect even aquatic communities (Doupé et al. 2010). Most
95 importantly, wild boars are the cause of a large proportion of crop raiding in Europe, Asia,
96 and North America (Schlageter 2015, Gren et al. 2018, Jin et al. 2021). The annual damage
97 cost by wild boars in the United States was estimated at 1.5 billion USD (Pimentel 2007). An
98 indirect measure of damage severity can be represented by total compensation amounts,
99 which are proportional to economic losses (Schley et al. 2008, Bobek et al. 2017, Kong
100 2019). In Luxembourg, wild boar damage accounted for 4.7 million USD in compensation
101 schemes between 1997 and 2006 (Schley et al. 2008). Compensation schemes amount
102 millions of USD each year in other European countries as well (Lombardini et al. 2017,
103 Cappa et al. 2021).

104 Jilin Province, in Northeast China, is widely recognized as a biodiversity hotspot. There
105 are more than 4,900 wildlife species in Jilin (Jilin Forestry and Grassland Bureau 2022).
106 Together with a neighboring province, Jilin harbors the only stable population of tigers in
107 China (Panthera 2023). 167 protected areas have been established in Jilin, which covers 17%
108 of the provincial area (Jilin Forestry and Grassland Bureau 2022) and provide high
109 biodiversity and genetic values (Fan et al. 2018). However, crop raiding by wild boar is
110 particularly severe and widespread in the province (Kong 2019, Jin et al. 2021), which ranks
111 one of the highest in the whole of China for number of wild boar damage (Wang et al. 2023).

A total of 16 million USD compensation for wildlife damage in 2015 was mostly attributed to wild boars (Wei 2015, Kong 2019). Over 3,000 wild boar damage incidents were recorded from 2007 to 2018 in Hunchun, a city in Northeast Jilin (Kong 2019). Furthermore, little is known about the ecology of wild boar, and their interactions with human in Northeast China. Due to the great flexibility of their diet and behavior (Schlageter 2015, Stillfried et al. 2017), the patterns of damage and effectiveness of mitigation measures found in Europe or North America may not be applicable to other contexts. Jin et al. (2021) produced the first risk map of wild boar damage in Hunchun; however, their study covered only 0.03% of Jilin's provincial area. This knowledge gap hindered conservation and mitigation actions in one of the China's most important biodiversity hotspots.

The objectives of this study were to use multi-scale risk modelling to provide an accurate map of wild boar damage risk covering the entire Jilin province, and to reveal the interactions between landscape and risk patterns, in terms of influential variables, scales of effect and magnitudes of effect. We hypothesized that damage risk responded to topography, land cover patterns, and human disturbance, and these relationships were scale dependent.

STUDY AREA

Our study area covers the entirety of Jilin Province, located in Northeast China (Figure 1). Jilin Province's topographic characteristics allowed us to subdivide this administrative unit into a mountainous area located predominantly in the eastern part, and large plains in the central and western parts. Its altitude gradients showed a pattern of gradual increase from northwest to southeast, whose range spans 280 to 2,691 m. In the western plain, vast croplands characterizes the landscape, and the 2 main cities (the capital Changchun, and Jilin

City) are in the center of the province. Jilin has a temperate monsoon climate and 4 seasons. Although it is one of the coldest regions in China, there is a large annual temperature difference (-15°C in winter and 15°C in summer; Kou 2019). Precipitations are mostly concentrated in the east and in summer. Forest areas are found in mountainous areas on the eastern part of the province and are fragmented by cropland patches. Scattered plantations interspersed with forest patches are found in the southeast part of the province. The total provincial area is $187,400\text{ km}^2$ and cropland, forests and cities amount 38%, 47%, and 4% of the total province, respectively (Natural Resources Department of Jilin Province 2014).

During the period of this study (2010–2013), the human population in Jilin amounted over 27 million, of which 53% lived in cities or towns, and 47% in rural areas (Statistic Bureau of Jilin 2021). Heavy industries were the dominant department of Jilin's economy, followed by service industries, and by traditional and less mechanized agriculture (Statistic Bureau of Jilin 2012, HKTDC Research 2022). Maize, rice, and soybeans were the major products of agriculture (Li 2019), supplemented by fruits and herbs from plantation. The land cover pattern has been relatively stable for decades, but there has been a relocation of 3 million people from rural to urban areas over ten years (Statistic Bureau of Jilin 2021).

METHODS

Damage records and landscape variables

We obtained records of wild boar damage compensation from Jilin Academy of Forestry's document library. We gather records in 5 prefectures in the middle and east of Jilin Province: Baishan, Changchun, Jilin City, Tonghua and Yanbian (Figure 1). Each prefecture had a compensation office responsible for recording damage information. The compensation office

needed to send no less than two professional investigators to verify reported incidents, evaluate economic losses, and record details of damage, including targets, environmental characteristics and coordinates (People's Government of Jilin Province 2006). Landscape variables for modeling damage hotspots involved land cover, topography, and linear or point features (Table 1). We resampled each variable at 500m pixel size from their original resolution, projected to UTM 52N, and calculated metrics at 12 different circular focal neighborhoods (henceforth scales) (0.5, 1, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20 km). We set the largest scale at 20 km as the daily travelling distance of wild boars under human disturbance was estimated at 6–19 km (Podgórski et al. 2013). The vector of Jilin's bound was rasterized and used as the mask to clip raster. Dimensions of all the variables were unified by functions crop and mask in the R (R Core Team 2021) package terra (Hijmans 2023).

We used the Shuttle Radar Topography Mission (SRTM) digital elevation model version 4.1 (CGIAR-CSI 2022) as elevation variable. SRTM was merged and resampled at 500 m × 500 m resolution by the Resource and Environment Science and Data Center of Chinese Academy of Sciences (Institute of Geographical Sciences and Resources 2022). We calculated slope (in degrees) from the SRTM data by the function terrain in the package terra (Hijmans 2023). Mean elevation and mean slope were then calculated by the Focal Statistics tool at all radii evaluated in this analysis in ArcGIS Pro version 2.8 (Esri, Redlands, CA, USA). We download vectors of river, human settlements, and roads on a scale of 1:250,000 from National Catalogue Service for Geographic Information (National Basic Geographic Information Center 2022). We calculated density of river (km/km²), density of human

settlements (number/km²), and density of roads (km/km²) by the line density tool or the point density tool in ArcGIS Pro, at all radii evaluated in this analysis.

We obtained visually interpreted land cover data of China from Landsat Thematic Mapper 8 at 30 m × 30 m resolution from Resource and Environment Science and Data Center (Institute of Geographical Sciences and Resources 2018). The classification system had 6 general levels, which were further classified into several specific levels (Table 2). We used general classification for all the land cover types except forest. We extracted the specific level of plantation from the general forest level (Table 2), because economic losses from damage to herbs and fruits in plantation were known to be much more severe and thus deserved additional attention. Using the tool buffer of package terra, we generated a buffer with a width of 20 km, i.e., the largest scale around the boundary of Jilin Province. The land cover data of China was clipped by this buffer, using functions crop and mask in the package terra (Hijmans 2023). We used Fragstats 4 (McGarigal et al. 2002) to calculate landscape metrics at landscape and class levels, using the 8-cell neighborhood rule and the round moving window approach for each scale considered in this analysis. We selected metrics based on results of previous studies. Wild boar damage was known to be associated with fragmented landscapes (Rutten et al. 2019). The abundance of wild boars was also found to be highest in a diverse landscape (Acevedo et al. 2006), and to prefer edges and narrow landscape elements in winter and spring (Thurfjell et al. 2009). Therefore, our metrics at landscape level were aggregation, elongation, edge density, continuity, fragmentation, and diversity of landscapes (Table 1). Aggregation (%) measures the aggregation level of patches in the landscape. Elongation is an index assessing stretching of patches. Long and narrow

patches thus are expected to have high elongation values. Edge density (m/ha) calculated the density of edge segments in the landscape. Continuity (m) was the area-weighted mean of patches extend in the landscape. It measures both patch size and compaction. Fragmentation (number/100 ha) equaled the density of patches in the landscape. Diversity (unit:information) or the Shannon diversity index indicated the richness and evenness of patches in the landscape. Landscape aggregation, elongation, and continuity increase, whilst edge density, landscape fragmentation and landscape diversity decrease, as the landscape becomes progressively more aggregated or less fragmented (Table 1).

Class-level metrics of Fragstats described characteristics of a particular land category. Acevedo et al. (2006), Olofsson (2015), and Caruso et al. (2018) found that wild boar damage was affected by the proportion and fragmentation of land cover categories. In addition to plantation, Jin et al. (2021) found forest and cropland to affect wild boar damage in Jilin Province. Thus, we enabled forest, cropland, and plantation in the class descriptor of Fragstats. We calculated class-level metrics of aggregation, area, core area, core proportion, and proportion of land cover types. Aggregation was the aggregation level of patches corresponding to a particular land type. Area represented the area-weighted mean of patch area corresponding to a particular land type. Core area (in hectares) represents the area-weighted mean of core areas, which was the area in a patch whose distance to the edge of the patch equals the edge depth. In this study, the edge depth was a constant (500 m), which was equal to the pixel size of variables. Core proportion (%) calculated the sum of core areas of patches belonging to a particular type, divided by the total landscape area. Proportion (%) calculated the sum of patch area belonging to a particular type, divided by the total landscape

area. All the metrics at the class level increase when patches become larger (Table 1).

Modeling procedures

The records of wild boar damage consist of presence-only data. There are several presence-only methods in SDM. The Maximum Entropy model has become one among the most popular (Qazi et al. 2022), as it is robust to spatial errors and requires relatively fewer presence locations (Baldwin 2009). Therefore, we adopted the Maximum Entropy algorithm (Phillips et al. 2006) implemented in MaxEnt version 3.4.1 (Phillips et al. 2022) to predict damage hotspots. The cloglog output of MaxEnt represents the habitat suitability of the target species (Elith et al. 2011). Since species presence was replaced with wild boar damage data, the occurrence probability of species was thus translated into the occurrence probability of damage, and the output can thus be interpreted as damage risk (Saito et al. 2012, Bautista et al. 2021, Jin et al. 2021).

We performed scale selection by single-variable Maxent modeling in the package dismo (Hijmans et al. 2021). We trained models by all damage coordinates and one scale for one landscape variable at a time, i.e., 312 single-variable models (26 variables assessed at 12 scales). Model settings included removing duplicate records, linear and quadratic features, 5,000 maximum iterations, and 10-k fold cross-validation of data. Other settings were kept as default. We evaluated models at different scales for each variable by the area under the receiver operating characteristic curve (AUC; Fielding and Bell 1997). For each variable, we determined the scale that resulted in a model with highest test AUC value as the optimal scale of this variable.

We carried out variable selection and parameter optimization of multi-variable models

according to the workflow of package SDMtune (Vignali et al. 2020). We partitioned damage coordinates into 10 random folds using ENMeval (Kass et al. 2021) for cross-validation. We used partitioned occurrence data and all variables at their optimal scales to train unoptimized multi-variable models with the same settings as the single-variable models. Using the varSel function in the package SDMtune (Vignali et al. 2020), we ranked variables according to their permutation importance. We calculated Spearman's correlations between the most important variable and other variables. If the correlation between a pair of variables was higher than 0.7, we took a Jackknife test and left out one variable of the pair. Removal of variables always caused decrease of models' AUC values. Therefore, we dropped the variable whose removal led to less drop of test AUC values and retained the other correlated variable of this pair. Then we calculated the correlation between the second important variable and others and dropped correlated variables similarly. The process was repeated until all retained variables were uncorrelated.

We used the retained uncorrelated variables to train a new multi-variable model with the same unoptimized settings. After this, we optimized parameters, i.e., regularization multipliers (from 1 to 5 with an increment of 0.1) and iterations (from 500 to 5,000 with an increment of 100) of this model by optimizeModel function in the package SDMtune (Vignali et al. 2020). The function used the genetic algorithm with 5 generations and a population size of 20. The genetic algorithm applied the principles of natural selection to parameter optimization (Holland 1992). It treated models with different parameters as a population and selected the top model after several generations of evolution (Vignali et al. 2020). The parameter settings resulting in the highest test AUC value were selected as the optimal

settings.

After the optimization of settings, we trained another model and ranked variables from highest to lowest permutation importance. We applied the function `reduceVar` in the package `SDMtune` (Vignali et al. 2020) and dropped variables whose importance was less than 5% and removal did not decrease test AUC. Hence, we optimized parameters of a new model with the reduced variable list using the `optimizeModel` function. We compared this optimized multi-scale model with models trained with the same variables but at single scales and calculated 3 indices for every model. We calculated test AUC values by the function `auc` of the package `SDMtune` (Vignali et al. 2020); Boyce indices by the function `ecospat.boyce` of the package `ecospat` (Broennimann et al. 2022); Areas under the precision recall gain curve (AUPRG) by the function `create_prg_curve` of the package `prg` (Kull and Flach 2022). Models were evaluated preliminarily according to Test AUC and AUPRG, with reference also to the Boyce index. A model with good performance should have higher values for all these metrics.

We mapped the wild boar damage risk for the multi-scale and single-scale models. Using the function `global` of package `terra` (Hijmans 2023), we calculated the mean and coefficient of variation of damage risk. We obtained maximum training sensitivity and specificity (MTSS training) thresholds, test omission rates of MTSS training thresholds, and test omission rates of maximum test sensitivity and specificity (MTSS test) thresholds by the function `thresholds` of package `SDMtune` (Vignali et al. 2020). A well performing model should have low omission rates. Then we reclassified risk maps by MTSS training thresholds and identified pixels with damage risk value over the MTSS training threshold as damage hotspots. We calculated hotspot areas by multiplying the number of hotspot pixels and the pixel resolution.

We corrected the sampling bias of wild boar damage occurrences through the bias file of Maxent GUI. The bias file was a raster representing the relative sampling effort across the study area (Elith et al. 2011). We created bias files by the tool Gaussian Kernel Density of Sampling Localities in SDM toolbox (Brown and Anderson 2014), exploring all radii used for the environmental variables. We copied the results of variable selection and parameter optimization in the package SDMtune to Maxent GUI. We added Gaussian Kernel Density bias files at each radius to models. We regarded the model with best performance as the top model of this study. Again, the evaluation was mostly determined by Test AUC and AUPRG and assisted by the Boyce index and MTSS omission rates. We ranked variables of the top model by their permutation importance. We plotted the response of damage risk to each variable while keeping other variables at average. We mapped the top model's damage risk and identified damage hotspots by the same method above.

RESULTS

Damage occurrence

We obtained 6,239 records of wild boar damage from 2009 to 2013, among which 1,144 had coordinates (Table 3). A large proportion (39.2%) of damage occurred in cropland near forest. Autumn was the season when most damage occurred (73.2%). Over half of incidents with coordinates occurred in the prefecture Baishan (58.8%). The major target of damage was maize (89.3%). The lowest and highest mean compensation were for maize (232 USDs per incident) and herbs (18,559 USDs), respectively.

Single-variable models

The selection of scale for variables were markedly different (Table 4). About half (52%) of the variables had their optimal scales at fine scales (≤ 4 km) whilst the others were optimal at coarse scale (≥ 14 km; Table 4). None of the variables was optimal at moderate scales (6–12 km; Table 4).

Multi-variable models

The function varSel selected forest aggregation, plantation aggregation, cropland area, landscape elongation, cropland core proportion, edge density, landscape continuity, river, road, settlement, landscape diversity, and slope (Table 4, Table 5). The first optimized model had regularization multiplier of 1 and iterations of 2,600. The function reduceVar retained plantation aggregation, cropland core proportion, edge density, landscape continuity, road, settlement, and slope. The second optimized model also had a regularization multiplier of 1 and iterations of 2,600. Three of the 7 retained variables were at fine scales (edge density, settlement, and slope), whilst 4 (plantation aggregation, cropland core proportion, landscape continuity and road) were at the coarsest scale (20 km).

Multiple scales versus single scales

All the single-scale models except the coarsest-scale (20 km) model (test AUC = 0.898, AUPRG = 0.964) had lower test AUC and AUPRG values than the multi-scale model (test AUC = 0.897, AUPRG = 0.958). The coarsest-scale model had a higher test AUC value, a lower MTSS training omission rate, a lower MTSS test omission rate, but a substantially lower Boyce index (0.754) than the multi-scale model (0.928; Table 6). Overall, the performance of single-scale models increased as the scale became coarser. The single-scale model with the lowest test AUC value (0.777) was at the finest scale (500 m), whilst the

highest one (0.897) was at the coarsest scale. Risk maps were greatly influenced by the scale of models (Figure 6). The mean damage risk predicted by the finest-scale model (0.371) was markedly higher than the prediction of the multi-scale model (0.144). The risk map made by the finest-scale model was less heterogenous (CV = 68.0%) than the map made by the multi-scale model (CV = 155.6%). The predicted risk was mostly different in regions where no damage incidents had been recorded (Figure 2C). The mean damage risk (0.134) and the spatial pattern of risk map predicted by the coarsest-scale model were consistent with the prediction of the multi-scale model. However, the risk values predicted by the coarsest-scale model were higher near damage occurrences (Figure 2G).

The MTSS threshold of the finest-scale model (0.487) was much higher than that of the multi-scale model (0.261). The MTSS threshold of the coarsest-scale model (0.284) was similar to the threshold of the multi-scale model (0.261). Dividing by the MTSS thresholds, the finest-scale model identified much larger damage hotspots (29.2% of the provincial area) than the area the multi-scale model did (18.6 %). The finest-scale model identified most regions in the southeastern half of the province as hotspots (Figure 2D), whilst the coarsest-scale model identified more hotspots near damage locations (Figures 2B, H).

The Maxent GUI model with the bias file at 500 m radius was the top model. As the radius of bias files increased, Test AUC, AUPRG and the Boyce index all dropped, but so did MTSS training omission rate and MTSS test omission rate (Table 6).

Predictors and maps of damage risk

According to the top model, slope was the most important variable to the wild boar damage risk (42.6%), followed by plantation aggregation (14.2%), settlement (12.9%), cropland core

proportion (11.1%), edge density (7.5%), road (7.3%), landscape continuity (4.4%; Table 7). The damage risk was positively associated with slope when the mean slope in a 4-km radius was lower than 4° , and negatively associated with mean slope steeper than 4° . The damage risk was positively associated with the plantation aggregation when the index was smaller than 50%, and negatively associated with it after it exceeded 50%. The damage risk responded positively to edge density less than 35 m/ha and was negatively correlated with edge density higher than 35 m/ha. The damage risk was negatively associated with cropland core proportion, road, and landscape continuity, and positively associated with settlement (Figure 3). In brief, the damage risk was highest on gentle slope, in fragmented cropland or plantation, and in relatively heterogeneous landscape, with few roads despite relatively dense human settlements.

We identified regions where the wild boar damage risk was above the MTSS threshold (0.523) as damage hotspots (Figure 4). Most hotspots were in Baishan, Jilin City, Tonghua, and Yanbian. Yanbian had the largest area of hotspots (9,716.8 km²), whilst the proportion of hotspots (39.3%) was highest in Baishan (Table 8).

DISCUSSION

This study supports the conclusion that damage resulting from human–wildlife negative interactions can be described as an ecological process occurring at multiple spatial scales (Guerbois et al. 2012, Rostro-García et al. 2016, Bautista et al. 2021, Jin et al. 2021), as it is the case for habitat suitability and drivers of wildlife distribution (McGarigal et al. 2016, Atzeni et al. 2020, Chen et al. 2022). In fact, our results confirmed that different variables were influential at different spatial scales, and that a multi-scale description of damage

occurrence resulted in more accurate discrimination measures. Our findings suggest that wild boar-induced damage is a process occurring both at fine and coarse scales, with either category revealing important characteristics of wild boar damage ecology. The contrasting effect of scales across different variables indicates that the interaction between wild boars and a human-dominated landscape could be rather complex (Table 4, Table 7). Fine-scale variables, i.e., slope, human settlement density, and edge density, operated at the level of feeding site (Johnson 1980), mainly characterizing the environment in which wild boars perform damage behavior (Deng et al. 2008, Osugi et al. 2019, Jin et al. 2021). In our study area, gentle slopes are often typical of the edges between forest and cropland (spreadsheet in Supporting Information), where damage is most likely to happen (Cai et al. 2008, Thurfjell et al. 2009, Bobek et al. 2017). By contrast, coarse-scale variables, i.e., plantation aggregation, cropland core proportion, and road density reflect interactions between wild boars and human-dominated landscapes at the home range level (Johnson 1980). They indicate that the distribution of damage hotspots is driven by a broad accessibility and availability of landcover types, and diffuse patterns of human encroachment. These landscape associations suggest therefore that large, homogeneous, and highly human-dominated landscapes, like vast cropland or extensive road networks are unlikely to become the hotspots of damage.

As shown elsewhere in other studies comparing single and multiple scale optimizations of habitat maps (McGarigal et al. 2016, Atzeni et al. 2020, Chen et al. 2022), the performance of multiple scale models was superior to unscaled models in all respects (Table 6). In fact, multi-scale models exhibited better performance in discriminating damage occurrence from the background dataset (as measured by AUC), identifying occurrence more precisely (as

measured by AUPRG), and reducing the rate of omission errors (as measured by the Boyce's index and MTSS omission rates; Table 6). Single-scale models had remarkably lower discrimination and identification abilities, hugely overestimating the extent of damage hotspots, especially at finer scales (Figure 2). This is a recurring observation in studies comparing scales of ecological effect in for habitat suitability (Shirk et al. 2012, Wasserman et al. 2012, Mateo Sanchez et al. 2014) and confirms that studies of damage hotspots should routinely assess covariates in this fashion, as the multiple scale evaluation will results in more realistic predictions and more accurate models. However, there were a few instances in which coarse-scale models performed equally well as the multi-scale model. This fact may be attributable to the home range requirements of wild boars, which has been seen to increase when accounting also for crop raiding behavior (Keuling et al. 2009). Additionally, the similar performance between coarse-scale and multi-scale models can be dictated by the large extent of our study area such as that large scales overall were better discriminating an ecological process operating at the level of the entire province.

Slope was the predominant driver of wild boar damage risk in this study (Table 7, Figure 3). Both damage records and model predictions supported that damage risk is higher on gentle slopes (Table 3, Figure 3). Similarly, Min et al. (2018) also found that slope affected crop damage by wild boars in Korea. As we mentioned, in our study area, gentle slopes are the border between farmlands and forests, where the damage risk was often found to be highest (Cai et al. 2008, Thurfjell et al. 2009, Li et al. 2012, Bobek et al. 2017). Another explanation of this phenomenon may lie in the feeding requirements of wild boars. Animal proteins serve as a critical part in the nutrition requirement of wild boars. After consuming

crops, which are rich in carbohydrates but lacks proteins, wild boars are known to dig more actively for invertebrates (Schley et al. 2008). Osugi et al. (2019) suggested that the humus on gentle slopes is thicker and contains more invertebrates, and wild boars prefer gentle slopes for this reason. Thus, consuming crops on mild slopes and rooting for invertebrates in proximity becomes an efficient feeding strategy for wild boars, which makes damage more likely to occur on such terrain.

Wild boars prefer moving along landscape edges and linear elements (e.g., stream and hedges; Thurfjell et al. 2009). Therefore, the importance of landscape edges in our results was quite expectable (Table 7, Figure 3). Due to the homogeneous nutrition of crops, wild boars need to commute between different types of habitats to fulfil their requirement of different food resources (Schley et al. 2008, Keuling et al. 2009), and we assume that shifting along edges might be the optimal strategy to reduce the movement effort. For the same reason, wild boar damage is unlikely to occur over large homogeneous landscapes, as high aggregation of landcover patches over large extents implies low heterogeneity and low amount of edge between land cover classes.

The responses of damage risk to plantation aggregation and cropland core area were nearly opposite. We found that damage was unlikely to occur in aggregated plantation or in extensive cropland (Figure 3). This supports our assumption that wild boars need to move between land cover types for different resources when feeding on crops and exemplifies the importance of heterogenous landscapes to wild boars. However, we found the highest damage risk in medium-sized plantations, rather than in small and fragmented ones. This can be related to the fact that plantations in our study area were transformed from natural forest and

are usually found in their vicinity, which increases the accessibility to, and damage risk in, plantations.

Human settlements and road density possibly represent elements of human disturbance for wild boars. As shown by our response curves (Fig. 3) wild boars damage is concentrated where the density of road networks is low on large extents and tend to decrease with increasing density. This is an indirect indication of damage risk mostly occurring in countryside areas, with few roads connecting human settlements. Given knowledge of the ecological requirements of the species (Keuling et al. 2008, Amendolia et al. 2019), we did not expect however to find a positive strong relationship to density of human settlements. However, we also noticed that the peak of settlement density was relatively low in the response curve (Figure 3). It represents an array of small villages and their territories, with low human population and scattered farmlands, where wild boars perceive little danger. Furthermore, most studies which found wild boars avoided human disturbance were in regions where hunting was part of management (Ohashi et al. 2012, Ikeda et al. 2019, Cappa et al. 2021, Rosalino et al. 2022). By contrast, harvest of wild boards had been prohibited in Jilin Province for decades. As a result, wild boars could flexibly adjust their perception of danger, adopt less prudent activity patterns (Johann et al. 2020), and move closer to human settlements (Stillfried et al. 2017).

In addition to environmental variables, we also noticed that there was seasonality within wild boar damage (Table 3). Previous studies often found that damage by wild boars concentrated after grains growing and before harvesting (Schley et al. 2008, Keuling et al. 2009). In our study area, most damage occurred in summer and autumn, when maize, the

food item most often targeted by wild boars, was available in the field. We suggest that damage was more frequent in autumn because ripe corns are more appealing than green ones (Thurfjell et al. 2009). However, we could not further investigate the seasonality by splitting our data into seasons, because most damage records occurred in autumn.

A limitation of this work is that technicians only investigated regions where damage had occurred, implying a considerable sampling bias. Therefore, we could not meet the assumption of unbiased sampling of presence-only models. We addressed this problem by applying bias grids proportional to the sampling effort (Elith et al. 2011), and conservatively interpreted the model output as damage risk rather than the probability of damage occurrence (Yackulic et al. 2013). Should the local government implement unbiased sampling for systematical records of damage information, future studies could generate more robust prediction of damage probability.

Another limitation is that we referred to studies conducted in other countries when interpreting the ecological meaning of variables, because of a knowledge gap in wild boars' ecology (e.g., movement and feeding) in Northeast China. As we mentioned, results from other contexts may not be fully comparable to ours for very adaptable animals like wild boars. Therefore, we suggest more studies on the ecology of this animal in Northeast China and surrounding regions, to provide a better basis for understanding human–wild boar interactions.

Overall, this study mapped wild boar damage risk across Jilin Province and analyzed the relationship between damage risk and landscape patterns through multi-scale risk modeling. We found that these relationships are scale dependent and that damage risk is highest on

gentle slopes and in heterogeneous landscapes composed of fragmented plantations and croplands, high edge density between small discontinuous patches, with dense settlement presence in rural areas with sporadic road networks.

MANAGEMENT IMPLICATIONS

Based on the results of this study, we recommend a series of measures to mitigate economic loss resulting from wild boar damage. We suggest improving the efficiency and simplifying the process of the current compensation system. This could alleviate dissatisfaction of the local community and reduce the risk of conflict. To reduce the frequency of crop damage, we recommend acoustic or visual repelling. The duration should be restricted within the bearing season of crops in case wild boars get accustomed to them. The locations could be set up around farmlands or on edges between farmlands and forests. In regions where tigers (the major predator of wild boars in our study area) are present, we suggest playing recordings of tiger calls and wild boars screams (Cui and Liu 2020b). Following their landscape of fear, wild boars could perceive the danger near farmlands and avoid approaching them. For regions outside the tiger range, we recommend setting solar blinkers (Cui and Liu 2020a) or electric fences. They are worth consideration for plantation, given their small area but high economic value. Dissuasive baiting could also be performed, but the baiting duration should be carefully controlled, and the location should be far from forest edges, in case that bait increases wild boar population size or attracts them to cropland. We recommend starting experiments of repelling, fencing, and baiting in damage hotspots that we identified, adjusting measures if needed, and then generalizing to other regions.

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ETHICS STATEMENT

In this study, signs of crop raiding were recorded after the fact. No animals had to be handled according to the animal welfare standards of the Institutional Animal Care and Use Committee (reference number 07-024-15 assurance number 3375).

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Figures Captions

Figure 1. Wild boar damage incidents recorded by compensation offices in Jilin, China, 2009–2013.

Figure 2. Wild boar damage risk and damage hotspots at multiple scales (A), the finest scale (500 m; B), a moderate scale (8km; C), and the coarsest scale (20 km; D). Damage risk was the cloglog output of Maxent models trained with damage coordinates recorded by compensation offices in Jilin, China, 2009–2013. Damage hot spots were regions with risk values over the maximum training sensitivity plus specificity thresholds. Black lines indicate prefecture bounds.

Figure 3. Responses of wild boar damage risk to retained variables in the top model of this study. The model was trained with damage coordinates recorded by compensation offices in Jilin Province, Northeast China, along with multi-scale landscape variables in the plot. The curve shows mean damage risk of 10 k-fold cross validation. The shadow indicates one standard deviation + /- the mean value. The optimal scale and permutation importance of each variable are also reported for each variable.

Figure 4. Wild boar damage risk and damage hotspots from the top model. The model was trained with damage coordinates recorded by compensation offices in Jilin Province, Northeast China, along with multi-scale landscape variables in the plot. Damage hot spots were regions with risk values over the maximum training sensitivity plus specificity threshold (0.523). Black lines indicate prefecture bounds.

824 Tables

825

826 Table 1. Variables used for modeling wild boar damage risk in Jilin, China, 2009–2013. Class
 827 level metrics were calculated for each land cover type. Definitions of land cover metrics were
 828 abbreviations used by Fragstats. Positive signs (+) mean the land cover metric increases in a
 829 fragmented or heterogenous landscape. Negative signs (–) mean the opposite. When
 830 calculating edge density, none of any boundary/background were counted and the edge depth
 831 was 500 m.

Category	Variable	Definition	Unit	Source
Land cover (landscape level)	Aggregation (+)	AI	%	Resource and Environment Science and Data Center
	Elongation (–)	CIRCLE_AM	NA	
	Edge density (+)	ED	m/ha	
	Continuity (–)	GYRATE_AM	m	
	Fragmentation (+)	PD	number/100 ha	
	Diversity	SHDI	Information	
Land cover (class level)	Aggregation (–)	AI	%	National Catalogue Service for Geographic Information
	Area (–)	AREA_AM	ha	
	Core area (–)	CORE_AM	ha	
	Core proportion (–)	CPLAND	%	
	Proportion (–)	PLAND	%	
Topography	Elevation	Mean elevation	m	
	Slope	Mean slope	°	
Linear or point features	Road	Road density	km/km ²	
	River	River density	km/km ²	
	Settlement	Human settlement density	number/km ²	

832 Table 2. Reclassification of land cover data from Resource and Environment Science and
833 Data Center.

Landsat Thematic Mapper 8		Reclassification	
Category	Description	Category	Description
11	Wet cropland	10	Cropland
12	Dry cropland		
21	Dense forest	20	Forest
22	Shrubland		
23	Open forest		
24	Plantation	30	Plantation
31–33	Grassland	40	Grassland
41–46	Waters	50	Waters
51–53	Urban areas	60	Urban areas
61–67	Unused land	70	Unused land

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836 Table 3. Summary of wild boar damage incidents in Jilin, China, 2009–2013. Total numbers in different fields did not match because there were
837 missing values. spring: (Mar–31 May), summer (1 Jun–31 Aug), autumn (1 Sep–30 Nov), and winter (1 Dec–28 Feb). We regarded
838 compensation as a surrogate of economic loss. Compensation cost was proportional to the economic loss and was converted from CNY to USD
839 by the annual exchange rate in 2012 (6.31:1).

		Object (incident number × mean compensati on per incident)				Environment	
Season	City						
Spring (7)	Baishan	673	Maize	5,573	232	Near forest	2,450
Summer (1,482)	Yanbian	335	Vegetables	436	\$881	Slope	762
Autumn	Jilin	117	Fruits	58	\$4,061	Steep	41

<hr/>							
(4,568)							
Winter	Tonghua	16	Herbs	44	\$18,559	Gentle	417
(3)							
						Little human activity	668
						Away from human settlements	228
						Extensive cropland	2
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841 Table 4. Scale selection by single-variable models and variable selection by R package SDMtune. Models were trained with damage coordinates
842 recorded by compensation offices in Jilin, China, 2009–2013. Marked by a cross (†): variables removed by the function varSel; marked by an
843 asterisk (*): variables removed by the function reduceVar. Test AUC = Area under the receiver operating characteristics curve for test data
844 generated by cross-validation.

Category	Variables	Class	Optimal scale (km)	Test AUC
Topography	Elevation		18†	0.742
	Slope		4	0.791
Linear or point features	River		20*	0.630
	Road		20	0.629
	Settlement		4	0.684
Land cover (landscape level)	Aggregation		0.5†	0.578
	Elongation		1*	0.607
	Edge density		0.5	0.592
	Continuity		20	0.592
	Fragmentation		20†	0.666
	Diversity		4*	0.598
Land cover (class level)	Aggregation	Cropland	20†	0.743
		Forest	1*	0.728
		Plantation	20	0.705
	Area	Cropland	2*	0.695
		Forest	2†	0.767
		Plantation	18†	0.650
	Core area	Cropland	20†	0.692

Core proportion	Forest	4†	0.737
	Plantation	0.5†	0.500
	Cropland	20	0.688
Proportion	Forest	4†	0.744
	Plantation	0.5†	0.500
	Cropland	18†	0.752
	Forest	2†	0.773
	Plantation	20†	0.671

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846 Table 5. Variable selection and parameter optimization in R package SDMtune. Models were trained with damage coordinates recorded by

847 compensation offices in Jilin, China, 2009–2013. RM = regularization multiplier. Features were kept as linear and quadratic.

Step	Results
Initial setting	RM = 1, iterations = 5000
Variable selection	16 variables removed
First optimization	RM = 1, iterations = 2600
Variable reduction	4 variables removed
Second optimization	RM = 1, iterations = 2600

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850 Table 6. Performance of the multi-scale model and single-scale models trained with the same variables. Models were trained with damage
851 coordinates recorded by compensation offices in Jilin, China, 2009–2013. Marked by an asterisk (*): multi-scale models with bias files at different
852 radius. AUC = area under the receiver operating characteristic curve; AUPRG = area under the precision recall gain curve. CV = coefficient of
853 variation. MTSS = maximum training sensitivity plus specificity.

Scale	Test AUC	AUPRG	Boyce index	MTSS training omission	MTSS test omission	MTSS threshold	MTSS area percentage (%)	Mean	CV (%)
500 m	0.777	0.792	0.964	0.284	0.239	0.487	29.2	0.371	68.0
1 km	0.827	0.825	0.978	0.201	0.171	0.436	28.0	0.295	93.5
2 km	0.840	0.884	0.969	0.196	0.184	0.411	27.3	0.260	106.2
4 km	0.856	0.918	0.942	0.171	0.168	0.350	26.1	0.220	121.1
6 km	0.856	0.937	0.837	0.142	0.137	0.293	29.1	0.211	124.4
8 km	0.859	0.936	0.831	0.131	0.106	0.248	31.0	0.203	128.0
10 km	0.871	0.936	0.917	0.135	0.118	0.230	29.2	0.186	134.9
12 km	0.875	0.947	0.893	0.155	0.142	0.236	26.4	0.174	138.8
14 km	0.878	0.943	0.917	0.165	0.143	0.291	22.6	0.175	138.6
16 km	0.884	0.949	0.913	0.135	0.116	0.250	23.7	0.162	143.2
18 km	0.893	0.957	0.861	0.117	0.107	0.222	23.4	0.146	154.3
20 km	0.898	0.964	0.754	0.128	0.129	0.284	19.0	0.134	161.0
multi-scale	0.897	0.958	0.928	0.170	0.161	0.261	18.6	0.144	155.6

500 m*	0.861	0.942	0.953	0.242	0.201	0.523	14.0	0.234	101.5
1 km*	0.861	0.916	0.940	0.240	0.216	0.599	13.2	0.274	90.1
2 km*	0.856	0.845	0.901	0.239	0.207	0.675	12.9	0.334	76.3
4 km*	0.840	0.776	0.928	0.239	0.215	0.689	17.2	0.398	63.8
6 km*	0.807	0.760	0.960	0.201	0.159	0.667	24.5	0.434	57.3
8 km*	0.761	0.714	0.883	0.158	0.132	0.625	31.4	0.461	51.9
10 km*	0.737	0.650	0.811	0.136	0.124	0.601	34.5	0.481	47.2
12 km*	0.717	0.623	0.761	0.127	0.120	0.583	39.5	0.496	44.0
14 km*	0.695	0.651	0.720	0.114	0.099	0.562	45.8	0.507	41.6
16 km*	0.678	0.693	0.710	0.092	0.079	0.547	50.4	0.516	39.6
18 km*	0.664	0.740	0.707	0.085	0.076	0.536	53.7	0.523	37.9
20 km*	0.653	0.788	0.692	0.077	0.069	0.522	57.8	0.530	36.3

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856 Table 7. Permutation importance of variables to the top model in this study. The top model was trained with damage coordinates recorded by
857 compensation offices in Jilin, China, 2009–2013. It had linear and quadratic features, regularization multiplier = 1, 2,600 iterations and a bias
858 file of 500-m radius.

Variable	Scale	Permutation importance (%)
Slope	4 km	42.6
AI plantation	20 km	14.2
Human settlement density	4 km	12.9
CPLAND cropland	20 km	11.1
ED	500 m	7.5
Road density	20 km	7.3
GYRATE_AM	20 km	4.4

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861 Table 8. Areas of wild boar damage hotspots in cities of Jilin Province, predicted by the top model. The top model was trained with damage
862 coordinates recorded by compensation offices in Jilin, China, 2009–2013. It had linear and quadratic features, regularization multiplier = 1, 2,600
863 iterations and a bias file of 500-m radius.

Name	The area of wild boar damage hotspots (km ²)	Hotspot percentage (%)
Yanbian	9,716.8	22.5
Baishan	6,838.8	39.3
Jilin City	5,359.3	19.3
Tonghua	4,529.5	29.1
Siping	190.8	1.3
Baicheng	48.3	0.2
Liaoyuan	27.5	0.5
Changchun	5.3	0.0
Songyuan	0.0	0.0
Jilin Province	26,716.0	14.0

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