

Forecasting Environmental Hazards and the Application of Risk Maps to Predator Attacks on Livestock

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*Environmental hazards are distributed in nonrandom patterns; therefore, many biologists work to predict future hazard locations from the locations of past incidents. Predictive spatial models, or risk maps, promise early warning and targeted prevention of nonnative species invasion, disease spread, or wildlife damage. The prevention of hazards safeguards both humans and native biodiversity, especially in the case of conflicts with top predators. Top predators play essential ecological roles and maintain biodiversity, but they can also threaten human life and livelihood, which leads people to eradicate predator populations. In the present article, we present a risk map for gray wolf (*Canis lupus*) attacks on livestock in Wisconsin between 1999 and 2006 that correctly identified risk in 88% of subsequent attack sites from 2007 to 2009. More-open habitats farther from any forest and closer to wolf pack ranges were the riskiest for livestock. Prediction promotes prevention. We recommend that the next generation of risk mappers employ several criteria for model selection, validate model predictions against data not used in model construction before publication, and integrate predictors from organismal biology alongside human and environmental predictors.*

Keywords: animal damage management, carnivore conservation, human–wildlife conflict, probability surface, spatial model

Environmental hazards, such as emerging diseases and wildlife damage, are distributed in nonrandom patterns. Therefore, many biologists work to predict hazards' future locations from their past patterns. Risk maps (also known as probability surfaces or predictive spatial models) can help predict where hazards will occur, whether they concern invasive species, emerging diseases, or predator–prey ecology (Jones et al. 2008, Kaartinen et al. 2009, Venette et al. 2010). Thus risk maps promise early warning and a way to target preventive action, which can safeguard both humans and ecosystems. Such prevention is particularly important when humans react to hazards by destroying the environment or retaliating against species, as is seen in conflicts between people and predators (Treves and Naughton-Treves 2005, Woodroffe and Frank 2005, Treves 2009). Predators play essential roles in ecosystems by exerting direct and indirect control of the numbers of herbivores and smaller predators, which in turn influence vast food webs (Estes et al. 1998, Terborgh et al. 2001, Smith et al. 2003, Ripple and Beschta 2004, Berger J 2007, Wallach et al. 2010). Yet predators sometimes pose threats to human life and livelihoods, which makes it difficult for most people to coexist with them (Gompper 2002, Treves and Naughton-Treves 2005, Shivik 2006, Treves 2009). Over the past two centuries, people have eradicated numerous populations of predators, including two species driven to extinction (Woodroffe and Ginsberg 1998, Woodroffe and Frank 2005, Woodroffe et al. 2005, Dickman et al. 2007, Sillero-Zubiri et al. 2007). Preventing

conflicts between people and predators at the outset would support worldwide efforts to conserve biodiversity and to restore ecosystems (Terborgh and Estes 2010, Walston et al. 2010). Prevention of conflicts with predators would also protect human life and livelihood.

Risk-mapping procedures

In this article, we present a risk map for conflicts between people and predators that includes several advances beyond past efforts. We describe novel methods usable in addressing other environmental hazards, from nonnative species invasions to emerging infectious diseases (Jones et al. 2008, Venette et al. 2010). Foremost, we verified the model's predictions on "future" data that were not used in model construction: We constructed a model for gray wolf attacks on livestock that took place from 1999 to 2006 in Wisconsin, and its predictions were verified by the data from subsequent affected sites from 2007 to 2009. Because the latter sites played no part in the model's construction, we concluded that the risk map is valid and predictive. We also integrated the organism's biology (wolf demographic and ecological variables) into the model, alongside human land-use and vegetation-cover predictors. Finally, we used exacting criteria for the retention of predictors so as to avoid overfitting our model with spurious predictors.

Locations of environmental hazards and the landscape features of these locations are the essential starting points for risk mapping. Wisconsin's wolf range contains temperate

forests interspersed with open areas, wetlands, and many bodies of water (Mladenoff et al. 1997). Livestock farms ($n = 42$) averaged 136 ha and 86 cattle kept on fenced private pastures, some partly forested (Treves et al. 2004). The Wisconsin Department of Natural Resources (WDNR) mapped and verified wolf attacks on domestic animals (depredate) statewide, using methods described previously (Treves et al. 2002, Ruid et al. 2009). The livestock ($n = 283$) involved in these attacks were bovinds (89%, mostly calves), ovids (14%), equids (4%), or two of the preceding types (7%). Livestock losses in this period resembled those from 1976 to 2000 (Treves et al. 2002). We examined 211 incidents recorded between 28 August 1999 and 22 May 2009. Before 2002, the WDNR recorded depredation locations ($n = 29$) in standard legal coordinates (direction, township, range, and section) at a resolution of 2.56 square kilometers (km^2). From 2002 to 2009, the verifiers from the WDNR used ground-based global positioning system (GPS) coordinates

to record locations more precisely ($n = 104$). Therefore, we had 133 affected sites from 1999 to 2006 (figure 1) and 60 affected sites from 2007 to 2009. We discarded 18 additional depredation records from 1999 to 2009, because another had occurred on the same property within 48 hours, the location data were missing, or the GPS and legal coordinates were irreconcilable. The WDNR estimated the ranges of wolf packs every year, using direct and indirect methods (Wydeven et al. 2009). They located radio-collared wolves weekly in the winter with aerial telemetry (GPS location error was estimated at 142 m, in the range of error reported by Devault et al. 2003) and directly observed associated pack members in 40 to 60 packs annually. The WDNR used minimum convex polygons to estimate the ranges of wolves that had more than 20 radio locations. Two or fewer outliers more than 5 km from other locations were excluded from the range estimates, so the range polygons are underestimates (Wydeven et al. 2009). The WDNR estimated the

ranges of packs without radio-collared individuals by repeated track surveys during snow-cover periods. These wolf pack ranges should therefore be considered estimates with error margins that vary among packs and among years. We assume that this uncertainty affects both our affected and our comparison unaffected sites because of their proximity (see below).

To discriminate high-risk from low-risk sites for risk mapping, one needs a comparison set that minimizes framing bias—that is, a comparison set in which *absence* or *unaffected* sites are representative of the available landscape (Keating and Cherry 2004, Alexander et al. 2006, Venette et al. 2010). When one is finding the appropriate comparison set of unaffected sites, the biology of the study organism should be taken into account. We knew that wolves have crossed virtually all habitat types, except perhaps dense urban areas or deep water that never freezes (Wydeven et al. 1998, Kohn et al. 2009), so we did not set a habitat criterion other than to exclude Lake Superior and neighboring states (for which landscape data collection differed). However, framing bias can still arise. At one extreme, comparison sites might be inaccessible to the organism, thereby leading to trivial conclusions (e.g., wolves do not cause problems where wolves rarely occur, such as areas remote from wolf packs, which are only entered by the rare, dispersing wolf; Martin 2007, Treves et al. 2009a). At the other extreme

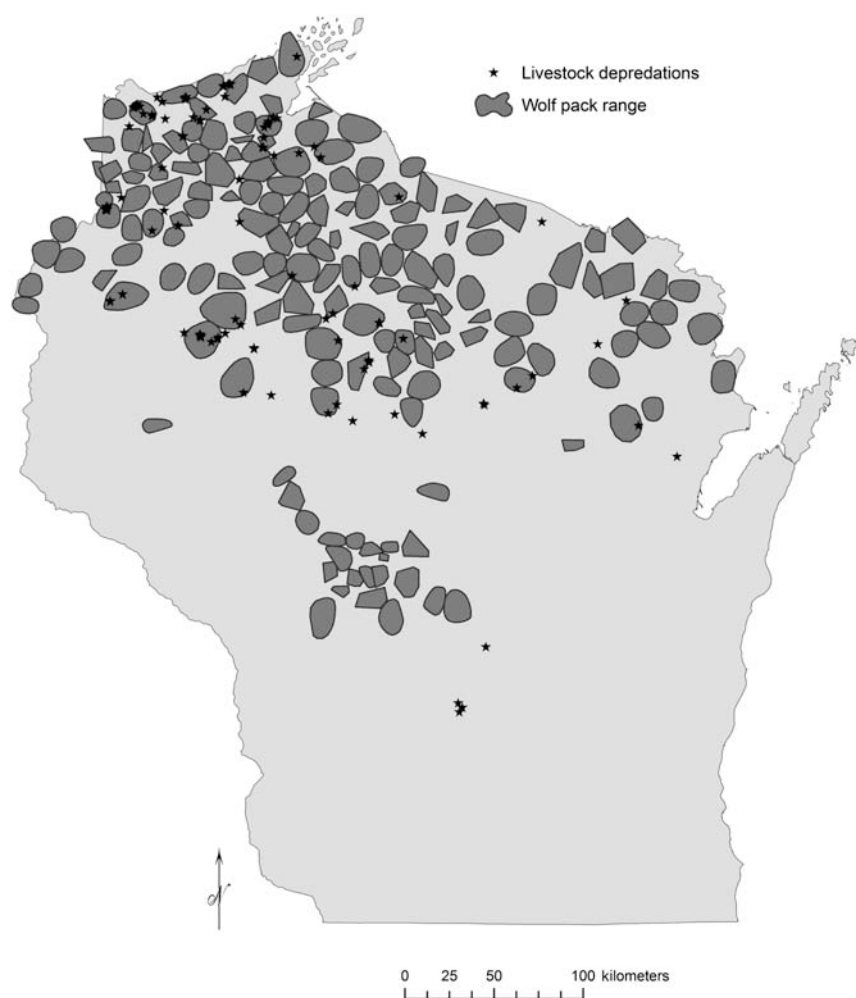


Figure 1. Sites of wolf attacks on livestock (stars) in Wisconsin, between 1999 and 2006. The small gray polygons are the estimated wolf pack ranges. Cumulatively, 47 wolf packs were implicated in such attacks during this period; expressed as a percentage of the total number of packs, between 4% and 17% of the packs attacked livestock annually.

of framing bias, one's comparison set should not resemble the affected sites too closely, lest one nullify significant predictors of risk. To balance these extremes of framing bias, we stipulated that unaffected sites not overlap affected sites but that they must be nearby. Distance is a known predictor of risk in other species (Naughton-Treves 1998, Hoare 1999), so we randomly chose unaffected sites from a ring-shaped area around each affected site, no farther than 10.2 km away, irrespective of the location of the nearest wolf pack (see the supplementary figure at <http://dx.doi.org/10.1525/bio.2011.61.6.7>). We also assigned unaffected sites to a year, in the same distribution observed for the affected sites, so that we could calculate wolf pack attributes for each unaffected point. Because packs change, appear, or disappear over time, the pattern of wolf demographics in the unaffected set was not identical to that in the affected sites. After model construction, we verified that our unaffected sites were representative of the unaffected area as a whole (see the supplementary figure at <http://dx.doi.org/10.1525/bio.2011.61.6.7>).

We identified the best predictors of the differences between the affected and unaffected sites from an array of variables collected over a 23.3-km² buffer area around the affected and unaffected sites (table 1). The wolf pack attributes were the averaged prior and subsequent winter counts (Wydeven et al. 2009) for the following four measures: (1) the distance to the nearest wolf pack range in kilometers (*DW*), (2) the number of pack members, (3) the area of the pack range, and (4) the number of wolves per square kilometer. We also collected the percentage of the area in each of nine land-cover classes (30-meter [m] resolution; Homer et al. 2007) and derived two new measures using ArcGIS Version 9.1 (ESRI, Redlands, California): (1) the length of the edge of all forest types in kilometers and (2) the distance to the closest forest of any type in kilometers (*DF*). A recent finding of

systematic error in the forest-cover estimates (Nowak and Greenfield 2010) should influence the affected and unaffected sites equivalently. Finally, we estimated the density of people, houses, farms, roads, deer, cattle, and livestock premises in various geopolitical units (Mladenoff et al. 1997, US Census 2000, Treves et al. 2004). The buffers often spanned more than one geopolitical unit (census block, county, or township), so we calculated the average areal densities from each overlapped unit.

Previous efforts at risk mapping have involved single-model inference or multimodel inference with one or two criteria for selection of the best models (for a review, see Garamszegi 2011). We used two criteria before including a predictor in a multivariate model: The univariate logistic regression had to be significant, and the predictor could not be collinear with a stronger predictor. For multivariate modeling, we employed four additional criteria before adding a "surviving" predictor to the model. That predictor had to have a beta coefficient (\pm the standard error) that did not include zero (i.e., a "stable direction of relationship," after Mazerolle 2006), which was also significant at $p < .025$ (correction for the second use of the predictor in a logistic regression); it had to improve Akaike's information criterion (AIC) by two; and it had to improve the receiver operating characteristic (ROC), which is an estimate of discriminating power, by $\geq 1\%$. We used JMP Version 8 (SAS Institute, Cary, North Carolina) for statistical tests.

If the newest predictor met the preceding conditions, we retained it in the model and tested its interactions with prior predictors. These stringent criteria helped us to avoid overfitting the model and to hold each model to a performance criterion rather than to an arbitrary AIC criterion (Arnold 2010). Following Alexander and colleagues (2006) and Arnold (2010), we compared our final model with two

Table 1. Predictors that discriminate sites of wolf attack on livestock from unaffected sites in Wisconsin between 1999 and 2006.

Predictor	Affected		Unaffected		Goodness of fit ^a	ROC
	Mean	Standard deviation	Mean	Standard deviation		
Grass/pasture/hayfield (percentage of area)	15	11	5	7	65***	.81
Distance to forest (in kilometers)	0.08	0.09	0.03	0.09	18***	.74
Distance to nearest wolf pack (in kilometers)	4	9	11	16	22***	.70
Open water (percentage of area)	1	3	3	4	9**	.70
Wooded wetlands (percentage of area)	5	7	12	12	28***	.68
Length of the forest edge (in kilometers)	5	1	4	2	16***	.66
The number of wolves per 10 square kilometers	0.8	0.6	0.6	0.7	8**	.62
Coniferous forest (percentage of area)	10	9	7	10	7**	.61
Emergent wetlands (percentage of area)	5	6	3	4	4*	.60
Deciduous forest (percentage of area)	51	15	56	22	4*	.58

^aUnivariate logistic regression (χ^2), $n = 266$, degrees of freedom = 1.

ROC, receiver operating characteristic (predictive discrimination power analogous to sensitivity and specificity).

* $p < .05$, ** $p < .01$, *** $p < .001$

previously published models, one from Michigan (Edge et al. 2011) and one from Wisconsin and Minnesota (Treves et al. 2004). Finally and most importantly, we verified the best model against sites of predator attacks between 2007 and 2009 ($n = 60$) and mapped risk across Wisconsin's wolf range.

Out of 21 initial predictors, 10 were significant in univariate logistic regression (table 1). Although prior work suggested that livestock density would be important, our measures of cattle per county and livestock premises per township were both collinear with the percentage of cropland cover (Pearson's $r > .7$), so we retained the latter variable because it had finer resolution. No other predictors used in multivariate tests were collinear in pairwise comparisons ($|r| > .7$). We began with the strongest predictor—the percentage of the area that was grass, pasture, or hayfield (table 1), which had also been the strongest in 2004 (Treves et al. 2004)—then added the next-strongest predictor, in order of ROC.

We found only one model with high likelihood (equation 1; table 2; $n = 266$, $\chi^2(4) = 105$, $r^2 = .284$, $p < .0001$; no lack-of-fit $\chi^2 = 264$, $p = .29$),

$$P(\text{affected}) = \frac{1}{(1 + e^{-.7948 - 9.7366G - 12.0753DF + .0681DW + .6065(DW - 7.1806)(DF - .0544)})}, \quad (1)$$

where $P(\text{affected})$ is the probability that a given area of 23.3 km² will be affected by wolf attack on livestock; G is the percentage of the area under grass, pasture, or hayfield; DF is the distance to the nearest forest; and DW is the distance to the nearest wolf pack range.

The probability of wolf attack on livestock was higher at open habitat sites (which may correlate with livestock availability on pastures), closer to a known wolf pack range, and farther from any type of forest, with an interaction between

the last two predictors such that sites far from forest and far from wolf packs were less risky. The mechanism underlying this interaction remains obscure.

Comparing new models with models derived from theory or with those in prior publications will help advance understanding and management. We did so, and the results are in table 2: The previously published models were not likely by AIC, nor did they improve the ROC, and equation 1 significantly outperformed each one. This result suggests either that temporal or regional variation exists in the sites of wolf attack on livestock or that our current model's inclusion of DW and DF improved the predictive performance of equation 1. We feel that DW in particular reflected the probability of wolf attack more closely than had variables in previous models.

We set the threshold between the affected and unaffected sites at $P(\text{affected}) = .365$ in order to maximize the model's sensitivity and the specificity for past sites. At that threshold, equation 1 discriminated past sites of wolf attack on livestock with 87% sensitivity for the affected sites (115 of the 133 affected sites were identified correctly) and 77% specificity for the unaffected sites (103 of the 133 unaffected sites were identified correctly), which is significantly greater than would be expected from chance (assuming $P(\text{affected}) = 63.5\%$, binomial exact $p < .0001$).

Model verification against future data is essential if we wish to disseminate risk maps with confidence. Therefore, we tested the predictive ability of our model using 60 sites of verified depredation between 2007 and 2009, which played no part in our model construction. Of these sites, equation 1 identified 53 (88%) correctly as affected ($p < .0001$). Therefore, the model appears robust to interannual variation and has real predictive power.

We made post hoc comparisons of classification errors ($n = 25$) and the correct predictions ($n = 168$) for all affected sites between 1999 and 2009. There was a higher

Table 2. Alternative models of wolf attack on livestock in Wisconsin 1999–2006.

Predictors added	Log likelihood ^a	K	AIC	ΔAIC	ROC
The present study					
None	184	1	371	97	.500
Grass/pasture/hayfield (percentage of area)	152	2	308	33	.813
Distance to forest (in kilometers)	149	3	303	29	.825
Distance to nearest wolf pack (in kilometers)	138	4	283	9	.841
Distance to wolf pack × distance to forest	132	5	274	0	.867
Saturated (predictors from table 1 added)	129	11	280	6	.874
Alternative models from the literature					
Treves et al. 2004 (for Minnesota and Wisconsin townships)	149	7	313	39	.802
Treves et al. 2004 (for Minnesota and Wisconsin farms)	149	8	314	40	.805
Edge et al. 2011 (for Michigan)	151	4	309	35	.810

^aFrom ordinal logistic regression ($n = 266$), all p -values $< .0001$.

K , one more than the number of predictors; AIC, Akaike's information criterion (lower values of AIC are more probable); ΔAIC, the difference in AIC relative to best model; ROC, receiver operating characteristic.

proportion of errors associated with large-livestock than small-livestock losses (28% versus 10%; $\chi^2(1) = 6$, $p = .012$; *small* refers to ovids, calves or foals, whereas *large* refers to adult cattle or adult equids). A similar analysis for type (ovid, equid, or bovid) was weaker ($\chi^2(2) = 5$, $p = .077$). A higher proportion of classification errors occurred when the verifiers had not implicated a specific wolf pack (29%, 11%, and 10% for *none implicated*, *uncertain*, and *confident* ratings, respectively, on the verification form: $\chi^2(2) = 7$, $p = .028$). Although such patterns deserve further attention in the field, they are probably not useful in predicting wolf attacks on livestock, because they are measured after an attack has occurred.

To disseminate the verified and validated model, we mapped risk within 100 km of every wolf pack from 2009 across 125,125 km² of Wisconsin. We calculated risk for each 30-m pixel as an average of landscape predictors in a 23.3-km²-radius moving window. We mapped risk in six

color categories within 100 km of the wolf pack ranges (figure 2). By visual inspection, high-risk clusters (areas larger than a few square kilometers with a >75% probability of being affected by equation 1) in red or orange occur near the coast of Lake Superior and the edge of the wolf range to the south, as was previously noted (figure 1; Treves et al. 2004). In addition, new high-risk clusters appear from the western to the south-central portions of the wolf range that were more recently recolonized (Wydeven et al. 2009). Two hot spots just south of Lake Superior had verified attacks between 2007 and 2009, but a third high-risk cluster somewhat inland did not. The two highest-risk categories with $P(\text{affected}) > 75\%$ covered 10.5% of the map pixels, the next three covered 22.1%, and the lowest-risk unaffected pixels covered 67.4% of the map (figure 2).

Interpreting risk maps requires care. These maps are correlational, not causal; therefore, any landscape predictor is best interpreted as a complex association of environmental variables. In our case, we cannot disentangle a wolf pack's history and individual membership from its landscape correlates, because the wolf pack ranges did not change much from year to year. Nevertheless, the predictive power of the associations that we demonstrated leads us to recommend that wildlife managers and livestock owners act to mitigate the risk posed by high concentrations of grassland, pasture, or hayfield far from forest and near wolf packs.

Interpreting the predictive power of land cover, we found ostensibly high-risk areas of northwest Wisconsin containing extensive open areas (barrens, savannas, and recent clearcuts) that are likely mostly devoid of livestock (figure 2). Our map suggests that bringing livestock into these areas would generate a high risk of wolf attack. Lower-risk areas are where forest is largely unbroken by open land covers (north) or far from wolf packs (northeast and south). The higher risk associated with open areas may reflect the presence of livestock, although our other estimators of livestock presence were not independently predictive (tables 1 and 2). In any case, this greater risk for livestock in open areas should not necessarily be interpreted as predators being attracted to livestock (Treves et al. 2004). Predators follow

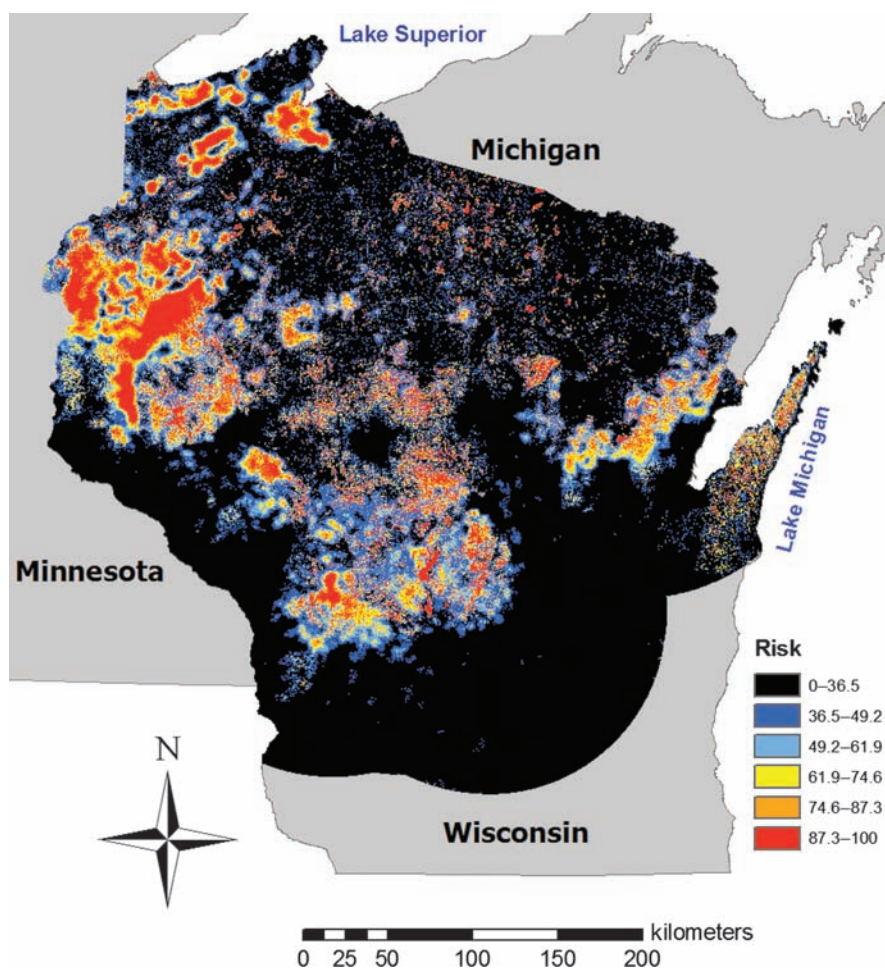


Figure 2. Predicted percentage of future risk of wolf attack on livestock in Wisconsin from equation 1. The colors categorize risk by pixel (30-meter resolution) such that unaffected pixels are black (67.4% of the map); other colors represent $P(\text{affected}) > .365$ in evenly sized bins. The raster layer used to map risk introduced shifts of up to 30 meters in distance from forest (DF; equation 1), producing a 3% average mapping error.

their wild prey and may thereby incidentally encounter humans or their property (Bradley and Pletscher 2005, Packer et al. 2005). For example, Norwegian *Lynx lynx* did not select sites with sheep, but rather those with many roe deer (*Capreolus capreolus*; Odden et al. 2008). The same may be true in Wisconsin after wolf movements are related to distributions of both deer and livestock with the greater spatial resolution afforded by GPS collars.

The proximity of wildlife habitat to crops and livestock is a known farm-level risk factor in species as diverse as elephants (*Loxodonta africana*), chimpanzees (*Pan troglodytes*), and brown bears (*Ursus arctos*) (Naughton-Treves 1998, Hoare 1999, Wilson et al. 2006). Our results emphasize the risk associated with raising livestock near a wolf pack. Indeed, we found classification errors by our model when the verifying agent did not implicate a specific wolf pack, which may reflect the distance from the known, established wolf packs. For example, four of the errors in the 2007–2009 verification were 47 to 58 km from the nearest wolf packs, which might be explained by the presence of new, unidentified wolf packs; nonpack wolves (loners or dispersers); or some other canid misidentified as a wolf (e.g., feral dog, wolf–dog hybrid, coyote [*Canis latrans*]). Although some loners or dispersers have attacked livestock (Treves et al. 2002, Wydeven et al. 2010), our map and model suggest that a few wolf packs are more likely livestock predators than others. Incorporating the distance from an animal's range and the histories of known individuals or groups seems a reasonable next step for other wildlife hazard models. Likewise, we recommend that those aiming to construct risk maps for other organismal hazards pay attention to any organism's sensory capacities and movements within its environment.

Most of the world's carnivores are recovering in less-glamorous landscapes such as Wisconsin's mixed-use agroecosystem, rather than in wildernesses. So the relevance of our work extends beyond the Great Lakes, or even the United States, to Scandinavia, Western Europe, and India (for wolves) and to many other regions for other large carnivores: Andean bears (*Tremarctos ornatus*), leopards (*Panthera pardus*) and tigers (*P. tigris*), to name just a few. Furthermore, we mapped risk across 125,125 km², which showed that approximately 10% of the state's wolf range is at high risk. Preventive intervention can be more focused and cost effective when high-risk clusters are targeted than when risk is assumed to be ubiquitous. Finally, gray wolves are the subjects of intense research interest and public policy debate in Europe and the United States as these governments deliberate over how to manage predators so as to reduce conflicts with recovering populations of various species. Our work offers a scientific path to minimizing conflicts and restoring top predators in areas beyond wilderness and vast protected areas.

Around the world, it is common for people to kill wildlife indiscriminately when they perceive them as threats (Karanth and Madhusudan 2002, Treves and Naughton-Treves 2005, Woodroffe and Frank 2005, Woodroffe et al. 2005). Predator attack prevention would be a preferable

approach and would safeguard rare animals, such as top predators or keystone species with disproportionate or essential roles in ecosystem function. Selective responses to problem individuals are needed, whether these individuals are livestock producers or predators. To date, people have been largely unable or unwilling to discriminate between individual culprits and nonculprits when addressing problems with wild animals (Treves and Naughton-Treves 2005, Treves 2009). As a result, indiscriminate killing has been perceived as cost effective. Research on coyotes near sheep suggests that decades of government-financed, lethal coyote control with a variety of methods have not succeeded in reducing sheep losses (Knowlton et al. 1999, Bartel and Brunson 2003, Berger KM 2006). Indeed, routine elimination of large numbers of nonculprits can exacerbate sheep losses (Knowlton et al. 1999). Risk maps point the way to more selective interventions in conflicts between wild animals and people (Wilson et al. 2006, Kaartinen et al. 2009). First, private citizens may be able to modify activities, animal husbandry, or habitats to reduce their vulnerability with a diverse array of antipredator deterrents (Treves et al. 2009b). Second, managers can work proactively with residents on cost-effective preventions in areas where conflicts are most likely. Third, policymakers may use risk maps to promote selective treatment of both problem predators and problem properties. Prevention of most human–wildlife conflict promises to preserve the ecological function and aesthetic or recreational benefits of wildlife in mixed-use landscapes. However, a key prerequisite is for policymakers, managers, and the public to relinquish the outdated view that all predators are problems.

For others constructing risk maps, we recommend four steps that have not always been included in prior efforts: (1) Stringently filter predictors by multiple criteria that reflect their contributions to predictive power. (2) Incorporate human land uses, organismal biology, and land cover simultaneously. (3) Move beyond simple land cover to derived measures that can approximate the organism's movements through the environment (e.g., the distance to forest cover rather than the percentage of forest cover). Finally, (4) verify any model with subsequent data, because internal validation may not suffice. The idea that risk is ubiquitous and ever present must give way to a more nuanced understanding of the factors that make environmental hazards predictable and preventable.

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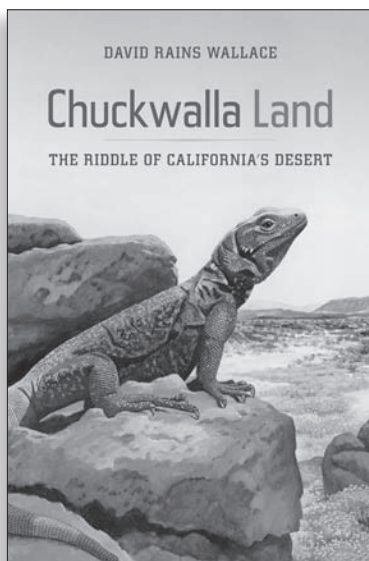
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