SPATIOTEMPORAL TENDENCIES OF HUMAN – BLACK BEAR CONFLICTS AND THE EFFECTS OF CURRENT CONFLICT MITIGATION STRATEGIES IN WISCONSIN

By

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"Examine each question in terms of what is ethically and aesthetically right, as well as what is economically expedient. A thing is right when it tends to preserve the integrity, stability, and beauty of the biotic community. It is wrong when it tends otherwise."

— *Aldo Leopold*

"Science can only ascertain what is, but not what should be, and outside of its domain value judgments of all kinds remain necessary."

— *Albert Einstein*

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Spatiotemporal Effects of Nuisance Black Bear Management Actions in Wisconsin, USA

ABSTRACT

Black bears (*Ursus americanus*) and humans commonly come into conflict throughout the Northern Great Lakes Region, including Wisconsin. From 2008 to 2010, wildlife managers working under Wisconsin's US Department of Agriculture – Animal and Plant Health Inspection Service, Wildlife Services, provided technical assistance and live-trapping to mitigate nuisance complaints from residents. I examine the spatial and temporal effects of these management responses using hazard analysis. I estimate the hazard for subsequent complaints by estimating the latency period between a management response and a future complaint. I show that as one expands outward in distance from the original complaint site, latency period decreases. Additionally, the number of bears that were translocated from a conflict location was not associated with decreased hazard. I discuss hypotheses for why this might have occurred. The percentage of locations that did not have a subsequent complaint was nearly identical for both technical assistance and live-trapping.

Keywords

Conflict, American black bear, live-trapping, technical assistance, mitigation, hazard analysis, complaints, nuisance

INTRODUCTION

Human-black bear conflict (*i.e.*, complaint from an encounter between an American black bear(s) (*Ursus americanus*) and a person or person's property) is an issue natural resource agencies face annually across the United States and Canada. Wisconsin is no exception, and there are many areas where black bear activities directly or indirectly intersect human activity. Successful conflict mitigation and an ability to abate future conflict are a high priority for both the public and wildlife managers.

Recently, researchers have tested the effectiveness of various non-lethal bear-human conflict mitigation techniques (*e.g.*, Peine 2001, Beckmann et al. 2004, Ziegltrum 2004). Black bears are expanding across much of their range and human populations continue to rise (Williamson 2002, IUCN 2012). Evaluating the spatiotemporal effects of management responses to mitigate conflicts is vital to the advancement of methods and techniques for reducing human-bear conflict.

Here, I compare the spatiotemporal effects of two mitigation actions performed by the US Department of Agriculture – Animal and Plant Health Inspection Service, Wildlife Services (WS) in response to black bear nuisance complaints from 2008 through 2010. WS carried out two primary mitigation actions – technical assistance and live-trapping. I define the spatiotemporal effects of a management action as the hazard for a subsequent complaint in the vicinity (≤ 9 mi^2 area) of a management response. A long latency period between a management response and a subsequent complaint would correlate with a low hazard rate within the vicinity of the management response.

Summary of Nuisance Black Bear Management

A primary method for mitigating damage caused by black bear throughout the U.S. and Wisconsin is live-trapping and relocation (translocation) of nuisance bears (Stowell and Willging 1992, Linnell et al. 1997, Witmer and Whittaker 2001, Spencer et al. 2007)[1]. Wisconsin has translocated problem bears since the 1950s (Hygnstrom and Hauge 1989). The efficacy of translocating carnivores, generally, has been questioned in recent

[1] Approximately 75% of North American wildlife management agencies (*n*=48) relocate problem bears (Spencer et al. 2007)

years (Fontúrbel and Simonetti 2011). Biologists have noted the extraordinary ability of black bears to home back to their capture site after relocation (Harger 1970, Rutherglen and Herbison 1977, Massopust and Anderson 1984, Rogers 1986, Fies et al. 1987, Linnell et al. 1997, Landriault 1998). A close alternative to translocation is on-site release, where trapped bears are not moved but released at the site of capture. On-site release of black bears has been shown to be effective under certain circumstances, such as for day-active bears and non-family groups (Shull 1994, Clark et al. 2002). As of 2007, 42% of states and provinces with black bears regularly practiced on-site release of black bears (Spencer et al. 2007). Wisconsin WS prefers translocation, although on-site release may be practiced if partial family groups are caught (Spencer et al. 2007, Koele 2010)[2]. Evaluating the success of black bear translocations has been measured by monitoring translocated bears post-release (Alt et al. 1977, McArthur 1981, Massopust and Anderson 1984, Fies et al. 1987, Shull 1994, Linnell et al. 1997, Landriault 1998). Results vary, even within studies, indicating the potential for translocated bears to either cease or continue causing problems. For example, Landriault (1998) found that anywhere from 10% to 48% of relocated nuisance bears in South Ontario were repeat offenders. Opinions on translocation also vary, but many managers continue to rely on it as a method for mitigating human-bear conflict. Spencer et al. (2007) found that 94% of agencies practicing translocation in North America monitored bears post-release at least some of the time; Wisconsin ceased ear tagging bears post-release in 2003 (WDNR 2003).

Public agencies regularly provide educational materials to help the public

[2] On-site release is practiced if young cubs are caught and the mother cannot be captured (Willging, *pers. comm.*)

coexist with bears. I view technical assistance as a particular form of education, being aimed at the individual rather than a mass audience. Past research has shown that educational programs with goals of mitigating or preventing human-bear conflict are rarely critically reviewed by the groups that administer them, and when they are explored complaints commonly serve as the measure of effectiveness (Gore et al. 2006). Despite bear managers' reliance on education, assessing the efficacy of the technique at regional scales is rarely attempted. In Wisconsin, nearly three quarters (71%) of an annual average of 947 nuisance complaints were handled solely with technical assistance from 2008 to 2010. In these instances, WS staff assessed a complaint over the telephone and provided brief consultation, during which recommendations for avoiding future conflict were provided. In some instances, a visit to the complainant's property was made. Site visits were made at the discretion of WS staff. To my knowledge, no empirical measure of area-wide effects of technical assistance in Wisconsin has been performed other than comparing annual sums of complaints (Engstrom et al. 2008, 2009, 2010). Gore (2006) suggests that management efforts could serve as an explanatory variable to provide a more reliable measure of effectiveness beyond mere complaint counts. Howe et al. (2010) suggests that complaints may not be a reliable indicator of conflict if they are not examined in context. Thus, throughout my analyses I remained cognizant of possible contributing factors external of complaints.

I analyzed black bear complaints in Wisconsin from 2008-10 by compiling WS complaint records. My analyses attempt to evaluate the effects of management responses by taking into account the type of response and the interval between successive complaints at three spatial scales. The question I asked regards the longevity of two management responses – technical assistance & live-trapping – as measured by the latency period between a management response and a subsequent complaint. Management response to a human-black bear conflict at location *x* at time *t* is not expected to prevent future conflict indefinitely. Therefore, I predicted the latency period to be longer over a narrow spatiotemporal window (*e.g.*, a complainant's property during a week's time) than a wider spatiotemporal window (*e.g.*, a township over the course of a month). This is the rationale behind hypothesis one.

> *Hypothesis 1:* The time interval (t_1-t_0) between a management response and a subsequent complaint is negatively correlated with the distance between the management response location x_0 and the subsequent nearest complaint location x_1.

With these data, it would be unwise to make a direct comparison between these two management responses because of the difference in the rationales behind their implementation. For minor conflicts, technical assistance is standard protocol. If the conflict is perceived by WS as dangerous for an individual or a bear, then live-trapping is preferred. And, in the rare case of an extreme safety concern, bears are euthanized. But, a more detailed look at live-trapping is still warranted. Although bears are not always captured when live-trapping is used, most (> 90%) successful captures result in bear relocation. It is unknown, however, the degree to which live-trapping bears may affect the hazard of a subsequent conflict in the area. This is the rationale behind hypothesis two.

> *Hypothesis 2:* The time interval (***t_1-t_0***) between when a live-trap is set and a subsequent complaint differs based upon the number of bears translocated from the vicinity.

METHODS

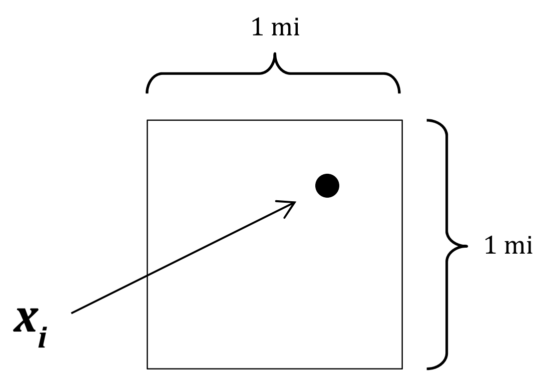
In 1990, the Wisconsin Department of Natural Resources (WDNR) entered into a cooperative agreement with WS to manage nuisance bears (Engstrom et al. 2010). WS has been recording public complaints since. From 2008 to 2010, black bear complaints were telephoned into WS offices in Rhinelander and Waupun, Wisconsin. WS recorded ~2,840 complaints from 2008 to 2010, and live-trapped ~725 bears. Sixty-eight percent (± 9% annually, n = 3 years) of first-time nuisance bear complaints were addressed by technical assistance. This is consistent with pre-1990 rates reported by WDNR staff, which were estimated to be 75% for Northwest Wisconsin in 1986 (Hygnstrom and Hauge 1989). Repeat complaints within the same year at the same property were referred to a WS field technician provided the complainant reported he or she had complied with previous recommendations given by telephone. For repeat complaints, a technician either offered further technical assistance (41% ± 7%) or provided live-trapping (58% ± 6%). Approximately 25% (± 1%) of first-time calls were mitigated with live-trapping, bypassing technical assistance altogether. These were primarily in situations that were believed by WS to involve health and human safety. In sum, live-trapping was typically dependent upon prior technical assistance which accompanied live-trapping also, so I could not compare the two directly.

When WS implemented live-trapping on a property, 61% (± 5%, n = 3 years) of those resulted in bear capture. Then, 93% (±3%) of captured bears were translocated, and the remaining captured bears were either euthanized (3% ± 1%) or were released on-site or taken to a rehabilitation center (*i.e.*, orphaned cubs) (3% ± 1%). WS addressed complaints involving agricultural damage using a distinctly different set of procedures for a complainant's property (Wildlife Damage Abatement and Claims Program, WDACP) and are therefore excluded from this analysis.

I obtained addresses of complainants from WS reports and entered them into an excel spreadsheet. Per USDA and UW-Madison rules regarding personally identifiable information, addresses and names were anonymized. Thus, I generalized addresses to a previously agreed upon area equal to one square mile using the Public Land Survey System (PLSS) section as the geographical unit (Fig. 1). Addresses that could not be geo-located to at least an 80% level of accuracy were not mapped but did remain in the analysis if the property could be uniquely identified (ESRI 2009). Records that documented subsequent complaints at a location in less than a 24-hour window were omitted. I did this to allow WS enough time to respond to a bear complaint and to help avoid pseudoreplication by artificially inflating the sample. I also removed repeat complaints that originated from the same property to avoid taking multiple measures of longevity for any one location. Of approximately 3,460 complaints reported by WS from 2008-10 (Engstrom et al. 2008, 2009, 2010), I was able to record 2,697 (78%) using the preceding criteria with an additional 143 (4%) that could not be mapped reliably, but were identifiable as a unique property. Lastly, for hypothesis two I excluded properties with live-trapping that had on-site release, euthanasia, or cubs taken to a rehabilitation center (these cases remained for my analysis of hypothesis one). A total of 38 locations from 2008-10 were excluded for those reasons, which approximated to 5% of all live-trapping observations.

(Figure 1) *Management response location generalized to 1 mi²*

A complainant's property (x_i) and the corresponding generalized Wisconsin PLSS section (1 mi²).



My approach to answering the question of latency period was to identify a nuisance complaint at a given location and year and then identify any subsequent nuisance complaint in the vicinity after the management response within the same year. Essentially, each location entered the study at the time of management response and left the study either when a subsequent complaint was reported in the vicinity or was set to the maximum Julian date of 365 and its latency period censored if there was no subsequent complaint. These were not dropped from the analysis but were coded in a way that indicated whether or not a complaint was made. Censoring provides a more reliable estimate of longevity by taking into consideration those locations having a default t_1 value of 365. I used ArcMap v. 10.0 to perform a spatial query to locate x_1t_1 at the PLSS levels, and a logical query in Excel to locate x_1t_1 for the anonymized properties. The resulting time intervals (t_1-t_0) measured the latency period between a management response and a subsequent complaint.

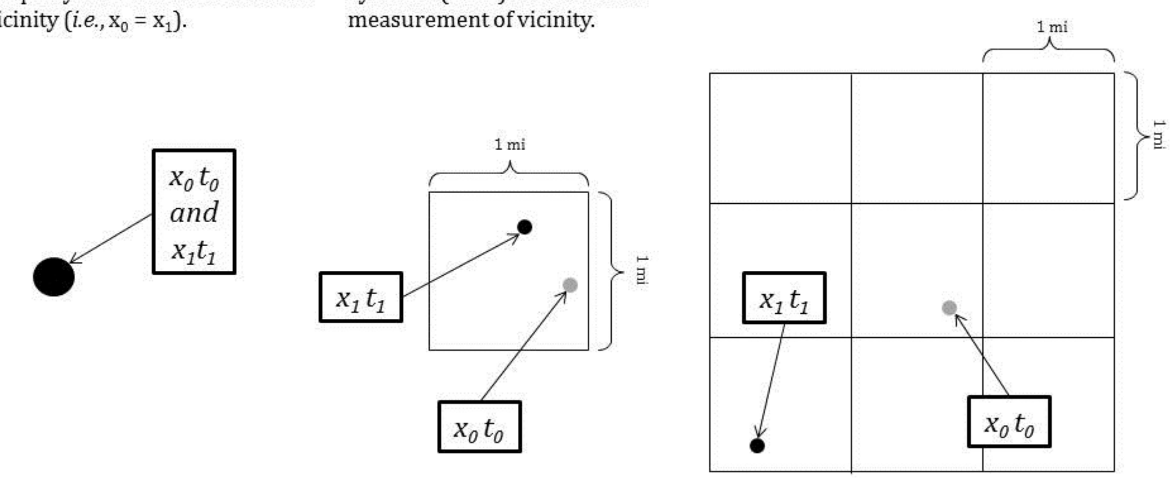
I chose three spatial scales for vicinities: A) complainant's property (n = 2,846); B) PLSS section of 1 mi^2 (n = 2,697); and C) 9 mi^2 block of PLSS sections (n = 2,697) (Fig. 2). Complaints from 2008 to 2010 were examined, each having received a Julian date that ranged from January 1 to December 31 (maximum possible value = 365). I assumed independence of management responses both within and among years. This is reasonable, because WS responds to all complaints regardless of whether a complaint has previously been reported at a property or in an area. However, I acknowledge that there are instances where my assumption of independence would be violated if, for example, a single bear or family group generated multiple complaints. I attempted to address possible non-independence of complaints by using the date of the complaint as the measure rather than the sum number of complaints in an area or at a location.

(Figure 2) *Management response location and subsequent complaint location for Wisconsin 2008-2010*

A. The initial management response location (x_0t_0) and subsequent complaint location (x_1t_1) using the complainant's property as the measurement of vicinity (*i.e.*, $x_0 = x_1$).

B. The initial management response location (x_0t_0) and subsequent complaint location (x_1t_1) using the Public Land Survey System's (PLSS) section as the measurement of vicinity.

C. The initial management response location (x_0t_0) and subsequent complaint location (x_1t_1) using a block of 9 PLSS sections as the measurement of vicinity.



My methods follow those of event history analysis (EHA) (Brostram 2012). The Nelson – Aalen estimator of the cumulative hazard function is used in survival analyses and allows for censoring (*i.e.*, incorporating unobserved responses into the estimate). Rather than estimating survival (*s*), though, it provides a hazard estimate (*1-s*). It is a conditional measure of hazard; which in this case means that given a management response, it estimates the cumulative proportion of locations at risk for a subsequent complaint at time *t*. The estimator is given as

$$\widehat{H}(t) = \sum_{t_j \le t} \left[\left(\frac{Number\ of\ subsequent\ complaints\ at\ time\ j = d_j}{Number\ of\ locations\ at\ risk\ at\ time\ j =\ r_j} \right) \right]$$

I refined the hazard estimator, adding variables using a Cox proportional hazards regression (Brostram 2012). I incorporated vicinity (z_1) and the number of bears translocated (z_2) in the vicinity of x_0 from t_0 to t_1 into the estimators. A possible confounding factor was that some PLSS sections and blocks of 9 PLSS sections had multiple management responses within a season, and thus had multiple measures latency periods. I added a categorical variable (z_3) for sections (1 mi^2) and section blocks (9 mi^2) to indicate whether an area had previous management responses in the same year (1) or not (0). Another confounding variable involves the seasonal variation in bear damage. Black bear complaints transition from being primarily nuisance to agricultural close to the month of August (see Chapter II). Wisconsin WS mitigation efforts and techniques undergo a dramatic shift at this time. Therefore, I ran an additional regression using a binary variable (z_4) to code for management responses that happened at a given property either before 1 August (0) or after 1 August (1). Cox's regression formula, which in this case measures conditional hazard at time t given variable z is

$$h(t|z) = h_0(t)\, e^{\{\beta' z\}}$$

To test for an effect of vicinity (z_1) on hazard or management response longevity (hypothesis one), I performed a Wald test using statistical packages *'eha'* and *'survival'* in R 2.15.1. To test hypothesis two, I compared differences in hazard as explained by the number of bears captured (z_2) also using a Wald test. Finally, I regressed the two binary variables (z_3 & z_4) independently and interpreted significance using Wald tests. All tests of significance were performed with alpha (α) set to 0.05. Tendency was defined as having a probability where $\alpha < p < 2\alpha$.

RESULTS

There were 2,532 conflict locations monitored post-management response at the two larger spatial scales (1 mi^2 & 9 mi^2) between 2008 and 2010 and 2,669 conflict locations at the property level (smallest spatial scale). The number of locations having no subsequent complaint (*i.e.*, censored) showed an inverse relationship with vicinity (Table 1). A Cox regression, where hazard was a function of vicinity (z_1) yielded a significant positive correlation with distance (Table 2). Regardless of management response type, the relative hazard for a subsequent complaint was higher by a factor of 3.6 when I expanded the vicinity from the property level to 1 mi^2; and by a factor of 8.7

when I expanded it to 9 mi^2. Relative hazard is a ratio of two hazards, with the relative hazard being in reference to 1. In the case of categorical variables, one of the categories serves as the reference, whereas for a continuous variable a value of '0' serves as the default reference.

(Table 1) *Management's response and observed outcome post-intervention*
Number of management responses to black bear complaints, subsequent complaints and the proportion of locations censored (having no subsequent complaint and thus maximum longevity) for each vicinity level and management response type in Wisconsin 2008-2010.

Vicinity Response	Mgmt. Response (x_0t_0)	Subs. Complaints (x_1t_1)	Percentage Censored
Property	**2,669**	**178**	**93.3%**
Live-trapping	722	68	90.9%
Technical assistance	1,947	112	94.2%
Section = 1 mi^2	**2,532**	**557**	**78.0%**
Live-trapping	720	145	80.0%
Technical assistance	1,812	412	77.3%
Block = 9 mi^2	**2,532**	**1,134**	**55.2%**
Live-trapping	720	322	55.3%
Technical assistance	1,812	812	55.2%

(Table 2) *Relative complaint hazards for areas in the vicinity of a management response*
Cox regression analysis using vicinity as a predictor variable for hazard of a subsequent complaint in the vicinity from 2008-10 in Wisconsin. Rel. hazard is hazard relative to the reference (property level). Significance is defined at α = 0.05.

Variable z_1	Mean	Coefficient	Rel. Hazard	S.E.	Wald p
Property	0.418	0	1 (*reference*)		
1 mi^2	0.337	1.283	3.608	0.086	$< 0.001^{***}$
9 mi^2	0.244	2.162	8.685	0.081	$< 0.001^{***}$

(Table 3) *Relative complaint hazards and associations with bear translocations*
Cox regression analysis using the number of translocated bears from 2008-10 in Wisconsin as a predictor for hazard of a subsequent complaint in the vicinity. Rel. hazard is hazard relative to zero bears having been translocated. Significance is defined at $\alpha = 0.05$.

Variable z_2	Mean	Coefficient	Rel. Hazard	S.E.	Wald p
Per translocation from property	0.863	0.248	1.282	0.09	0.004**
Per translocation from 1 mi^2	0.878	-0.024	0.976	0.08	0.766
Per translocation from 9 mi^2	0.876	0.005	1.005	0.05	0.932

Hazard at the property level was significantly higher when more bears were removed (Rel. hazard = 1.28, S.E. = 0.09, $p = 0.004$). That is, relative hazard for a property increased by a factor of 1.28 per translocated bear. There was no significant association between the number of translocations and hazard at either the 1 mi^2 or 9 mi^2 levels (Table 3). When I tested for an effect of previous management action (z_3) within a PLSS section on relative hazard, I found an approximate 2- to 3-fold increase if that section had prior management response that year (Table 4). Allowing for standard error, the hazard at the 9 mi^2 level was approximately 2.0 times higher for locations having had either prior technical assistance or live-trapping (S.E. = 0.087, $p < 0.001$; S.E. = 0.208, $p = 0.003$). Hazard was also higher within the 1 mi^2 section, although the increase differed between technical assistance and live-trapping (2.9 for 1 mi^2 areas having had technical assistance prior, and 2.0 for 1 mi^2 areas having had live-trapping prior; S.E. = 0.109, $p < 0.001$; S.E. = 0.281, $p = 0.011$).

(Table 4) *Relative complaint hazards and associations with previous management intervention*
Cox regression analysis using previous management response (yes or no) from 2008-10 in Wisconsin as the predictor variable for hazard of a subsequent complaint. Rel. hazard is hazard relative to the reference (no previous management response). Significance is defined at α = 0.05. Vicinities having had a previous response are coded '1'; those not are '0'.

	Variable z_3	Mean	Coefficient	Rel. Hazard	S.E.	Wald p
1 mi²	Live-trapping					
	0	0.957	0	1 *(reference)*		
	1	0.043	0.716	2.045	0.281	0.011
	Technical assistance					
	0	0.903	0	1 *(reference)*		
	1	0.097	1.073	2.924	0.109	< 0.001**
9 mi²	Live-trapping					
	0	0.963	0	1 *(reference)*		
	1	0.037	0.622	1.863	0.208	<0.01*
	Technical assistance					
	0	0.911	0	1 *(reference)*		
	1	0.089	0.691	1.996	0.087	< 0.001**

Season and hazard for subsequent complaints were not significantly associated. However, I did see a tendency for season to be associated with property-level-hazard when WS responded with live-trapping. Hazard for a subsequent complaint was nearly two-thirds less if live-trapping took place after 1 August (Rel. hazard = 0.353, S.E. = 0.592, p = 0.078).

DISCUSSION

Human-bear conflict mitigation strategies fit into two broad categories. Management actions may either be reactive or proactive. An example of reactive management includes translocation, which is the most used method of on-the-ground direct mitigation by Wisconsin WS. Technical assistance, too, is reactive in practice. Only when an individual has had a conflict does that person call for assistance.

Proactive management includes actions directed to the public *en masse*, like the provisioning of educational materials, as well as one-on-one interactions such as providing fencing for apiaries and calving areas in anticipation of conflict. These proactive measures, while practiced in Wisconsin, were beyond the scope of this study. My study evaluated the effects of two reactive measures: technical assistance delivered by telephone and live-trapping on complainants' properties.

My results support hypothesis one. At larger spatial scales, hazard was higher for a subsequent complaint within the same year in the vicinity of an initial complaint (*i.e.*, location of management response). Hazard was consistently less and spatiotemporal longevity greater at the property level. My results also support hypothesis two with limitations. There was no appreciable effect of the number of bears translocated on hazard at the larger spatial scales of 1 mi^2 or 9 mi^2 (Table 3). However, bear translocations from a property were associated with an increased hazard for a subsequent complaint. This may seem counterintuitive since the management goal was to reduce hazard via translocation. There are several alternative hypotheses for why I observed an increased hazard. The increase in hazard with each translocated bear at the property level may have been an artifact of those properties being prone to conflict (*i.e.*, high risk properties). There is also a possibility that persons who had live-trapping in the past were more likely to seek management assistance in the future, and thus the increased hazard was not due to management action directly but rather was a byproduct of an individual's tendency to complain. The increased hazard could also be due in whole or part to higher bear densities in some areas.

The percentage of locations not having a subsequent complaint after a management response within the same year (*i.e.*, maximum attainable latency) are presented in Table 1. A minority of PLSS sections had multiple management responses within a year. However, if managers did intervene, the vicinity around the property (1 mi^2 and 9 mi^2) was 2 to 3 times' more likely to have a subsequent complaint. This is not surprising, and could indicate that locations requiring management intervention are inherently more hazardous. Many factors determine the risk of conflict at a site (see Chapter II). Although I found no statistically significant effect of season on hazard, I did observe a tendency (p = 0.078) for properties that had live-traps placed after 1 August to have a relative hazard of 0.35 (or about two-thirds less) for a subsequent complaint later that year compared to properties prior to 1 August. This is probably due at least in part to complaints reported after to 1 August having less time to experience future conflict. It might also be due in part to the seasonality of bear conflicts in Wisconsin, with non-agricultural complaints being higher prior to 1 August before field corn reaches the palatable milk stage and before hard mast becomes available.

My results suggest that latency periods between technical assistance or live-trapping and subsequent complaints were influenced by time and space. The chances of either of these management responses preventing a future complaint within a year decreased when I increased the vicinity around a management response (Table 2). When I examined individual properties only, the hazard for a subsequent complaint was less (*i.e.*, latency period was longer). When I broadened the spatial focus to 1 mi^2

or 9 mi^2, I saw increased hazard (*i.e.*, latency period was shorter). In essence, 3 of 5 complaint locations did not have a subsequent complaint within 2 months' time in the 9 mi^2 area surrounding it; and, 4 of 5 did not have a subsequent complaint within 2 months' time in the surrounding 1 mi^2. Spatiotemporal effects were exemplified by my finding that 2 months after an initial complaint, more than 90% of properties did not report a subsequent conflict. But, ~ 20% of 1 mi^2 sections and ~ 40% of 9 mi^2 blocks did (Table 5). Managers should not expect efforts directed toward an individual property to necessarily translate to fewer complaints for other properties in the vicinity. If we want to increase management effectiveness, we must acknowledge its spatial limitations.

(Table 5) *Percentage of locations having no subsequent complaints*
Percent of locations not having a subsequent complaint post-management response (technical assistance or live-trapping) from 2008-10 in Wisconsin as measured within the given distance of the initial response (vicinity) and within a certain time interval (t_1-t_0) in days.

Vicinity/ Response	**1 day**	**7 days**	**14 days**	**30 days**	**45 days**	**60 days**
Property /						
Technical assistance	99.8%	98.6%	97.2%	95.9%	95.5%	94.9%
Live-trapping	100%	99.2%	97.0%	93.4%	92.0%	92.0%
1 mi^2 /						
Technical assistance	98.4%	93.2%	88.4%	83.7%	81.1%	79.9%
Live-trapping	99.0%	95.1%	91.3%	84.5%	82.4%	82.2%
9 mi^2 /						
Technical assistance	96.1%	83.6%	75.2%	65.9%	61.7%	59.4%
Live-trapping	97.1%	86.3%	76.5%	63.8%	60.0%	58.4%

The majority (> 90%) of individuals receiving technical assistance or live-trapping between 2008 and 2010 did not report subsequent complaints. It is unknown, however, whether this was because people rarely had more than one conflict in any given year or because management actions prevented subsequent conflicts or because subsequent conflicts were not reported (*i.e.*, no one complained). In reality, it was likely a combination of factors.

Technical assistance and live-trapping are not typically used under the same circumstances. That is, more severe complaints often warranted more direct intervention like live-trapping whereas less severe complaints did not. However, the percentage of locations that did not have a subsequent complaint afterward was nearly identical for both types of management response (Table 5) and for all three spatial scales. This could indicate equivocal effects and begs the question of whether technical assistance might be preferred by managers under certain circumstances due to cost-effectiveness.

I would recommend future research incorporate a randomized trial in which properties were assigned a treatment in order to directly compare the effects of technical assistance to live-trapping. Additionally, I recommend research be directed towards understanding the impacts of perceived conflict severity on management responses. Finally, latency periods might be better understood if a hazard analysis was expanded to include areas not having experienced prior management intervention. This would provide a control measure that could expand spatiotemporal interpretations beyond a property and its immediate vicinity (*i.e.,* 1 mi^2 & 9 mi^2).

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Spatiotemporal Variation of Human - Black Bear Conflict and Predicting Complaints in Wisconsin, USA

ABSTRACT

Complaints about black bears in Wisconsin differ by the type of complaint and between seasons. I examine the associations of several landscape and human demographic variables with the probability of complaints (risk) at the Public Land Survey System (PLSS) 36 mi^2 township level between 2008 and 2010. Using a mixed methods approach that accommodates for an over-dispersion of zero count observations, I show that both the probability of risk and the predicted level of risk vary from March 1^{st} to July 31^{st} and August 1^{st} to November 30^{th}. Separating complaints by whether they received technical assistance, direct control or were agricultural in nature affects which variables are the best risk predictors. Average annual hunter harvest proved the best predictor for probability of risk; and, seasonal homes, corn, hunter harvest and low level land development proved the best predictors for the number of complaints recorded. By mapping predicted risk levels and the probabilities of risk, I illustrate how human-black bear conflicts vary across Wisconsin's multiple-use landscapes and between seasons. And, the utility of such risk maps can help to direct management intervention to locations that need it most.

Keywords

Conflict, American black bear, complaints, nuisance, Zero inflated Poisson, mixed models, risk map

INTRODUCTION

Human-bear (family Ursidae) conflicts vary over both space and time (*i.e.*, spatiotemporally). They vary from year to year, season to season, and place to place. This is not new knowledge[1]; however, only recently has this phenomenon been investigated empirically. Factors contributing to spatial and temporal variation of

[1] See (Schorger 1947) for a review of historical frontier black bear encounters.

human-bear conflicts have recently begun to interest managers and scientists. Human-black bear (*Ursus americanus*) conflicts in Wisconsin are no exception. My objective for this study was to uncover the drivers of human-bear conflict in Wisconsin with respect to location and season. Using complaint data collected between 2008 and 2010, I create multivariate predictive models capable of predicting when and where conflicts occurred in Wisconsin. In addition, the models themselves help to clarify associations between certain landscape and demographic variables and human-bear conflicts.

Given the many environmental factors that may influence human-bear conflict, it is logical to assume that spatiotemporal variation of human-bear conflicts may be forecasted. There is a widespread assumption among the public and still held by some wildlife professionals that the recipe for human-carnivore conflict is twofold. Simply put, an individual and a carnivore inhabiting the same place in space and time is a supposed recipe for conflict. This has been shown not to be the case, however. Recently Treves et al. (2011) showed that livestock depredations by wolves in Wisconsin were not uniform and could be forecasted with accuracy. Further, several studies have elucidated spatiotemporal factors as drivers or indicators of human-carnivore conflict. These factors are numerous and have been associated with a host of carnivore species including: African lions (*Panthera leo*), gray wolves (*Canis lupus*), black and grizzly bears (*Ursus americanus* & *Ursus arctos horribilis*), coyotes (*Canis latrans*), Amazonian felids (*Panthera onca* & *Puma concolor*), Iberian wolves (*Canis lupus signatus*), Amur tigers (*Panthera tigris altaica*), and South African carnivores (*Caracal caracal, Canis mesomelas, Acinonyx jubatus, Hyaena brunnea, Panthera pardus*

pardus) (Treves et al. 2004, Bradley and Pletscher 2005, Kapp 2005, Packer et al. 2005, Michalski et al. 2006, Wilson et al. 2006, Baruch-Mordo et al. 2008, Treves et al. 2010, Goodrich et al. 2011, Lukasik and Alexander 2011, Merkle et al. 2011, Llaneza et al. 2012, Thorn et al. 2012).

Complaints as indicators of human-black bear conflict

Wisconsin is an excellent state in which to examine spatiotemporal variation of human-black bear conflict. Complaints about negative interactions are reported by citizens and recorded by US Department of Agriculture – Animal and Plant Health Inspection Service, Wildlife Services (WS) technicians. It has been rightly suggested that complaints do not, *per se*, directly indicate conflicts (Poulin et al. 2003, Howe et al. 2010). Reporting rates may vary due to factors external to conflict. However, Poulin et al. (2003) found "general agreement" between nuisance complaints and other measures of nuisance bear activity, noting complaints were reliable provided they are "interpreted in light of changes to reporting rates."

From 2008-10 there were no appreciable differences in total complaint numbers reported by WS (μ = 1,332, SD = 45) (Engstrom et al. 2008, 2009, 2010). In fact, there has been no appreciable long-term change in the number of complaints over the 22-year history of WS management of Wisconsin's nuisance black bear program. But, it should be emphasized that while complaints may not have decreased over the years, neither have they increased. When viewed in light of the dramatic rise of the bear population, it becomes evident that factors aside from the sheer number (and/or density) of black bears has contributed to human-bear conflict in Wisconsin (Appendix, Fig A.1). I am unaware of any direct way to measure past reporting rates of human-bear conflict in Wisconsin. I would argue it isn't necessary, though. While the concern of nuisance bear managers is human-bear conflict, management responses can only be assured for those individuals who report conflict. In practice, then, complaints are often the closest thing managers have to assess conflict. And, while I acknowledge that complaints and conflicts may not share a 1:1 relationship, the relationship appears to have remained constant in Wisconsin.

Black bear nuisance conflicts in Wisconsin range in severity, and complaints by themselves are not reliable indicators of severity. However, there are standard operating procedures for mitigating nuisance black bear conflicts in Wisconsin (WDNR 2010). Complaints may be handled with technical assistance given over the phone or through some form of direct control. Direct control methods include live-trapping, translocation and euthanasia. If WS judges a complaint as trivial (*e.g.*, a bear walking through a back yard) they mitigate with technical assistance. There is a good chance that many such encounters go unreported. In cases where the safety of people or bears is threatened, or in repeated offenses where significant bear damage is occurring, WS prefers direct control measures. In the case of agricultural complaints, a separate set of procedures are used (WDNR 2010). Here, technical assistance is less-often used, and direct control methods are preferred. This is especially true during the peak agricultural damage season which occurs when field corn is in its "milk" stage. This period generally lasts two months and begins in either early or mid-August.

Factors contributing to human-bear conflict

The factors contributing to human-bear conflict are myriad, and human-bear conflicts are thus complex. A large portion of the complexity is a result of the interplay between human and natural systems. More and more, a non-isolationist view of our natural world is becoming necessary to understand it. For better or worse, humans have an impact on earth's systems, and any attempts to accurately model their workings require that scientists recognize and assimilate the two systems in the pursuit and transmission of scientific knowledge (Liu et al. 2007). Human-bear conflict is no exception.

After a thorough investigation of the literature on human-bear conflicts, I classified factors contributing to conflict into five general categories. These factors are both "natural" and anthropogenic, tangible and opaque. Note that some of these factors fit into multiple categories and that the categories are, therefore, not mutually exclusive (*e.g.*, natural mast production varies seasonally which can alter foraging behavior (Eagle and Pelton 1983). I also want to note that equivocal results have been found among studies on human-bear conflict (*e.g.*, hunter harvest has been found to both reduce and have no effect on black-bear nuisance complaints (Forbes et al. 1994, Treves et al. 2010). So, factors I present under the following subheadings are presented as plausible rather than prescribed factors contributing to human-black bear conflict.

1. The human factor

Where we live, how we think, and what we do are central to human-bear conflict. Often these factors – such as how we feel – cannot easily be measured at a landscape or local level and require social surveys. For example, Gore et al. (2006) showed that knowledge and perception of a wildlife agency's capacity to manage black bears accounts for 59% of an individual's perception of bear-associated risk in New York. Our past experiences and awareness of bears may affect the likelihood for conflict, as well. It has been shown that persons who have experienced bear damage have an increased risk perception while those persons having non-negative encounters have a decreased risk perception (Siemer et al. 2009). Our awareness of conflict, such as increased public awareness due to fatal attacks in media coverage, may also influence our response to conflict (Poulin et al. 2003). How we perceive the severity of a conflict may also impact our feelings towards different management responses (Don Carlos et al. 2009).

At a group or community level, other variables come into play. The net capacity for groups to accept negative and positive impacts associated with wildlife and its management is known, generally, as wildlife stakeholder acceptance capacity (WSAC) (Carpenter et al. 2000, Decker et al. 2002). Our acceptance capacity for a species is best measured through social surveys, much as it is for measuring individual perceptions. However, some of the driving factors behind human-bear conflicts can be spatiotemporally extrapolated. For example, Kretser et al. (2009) found that socio-demographic variables were good indicators for spatial variation in perceptions of human-black bear interactions in New York, with a spatial clustering of like-minded individuals. Socioeconomic factors such as age, education, sex, and community type have been shown to influence support for black bear recovery (Morzillo et al. 2010). At a fundamental level, the mere density of humans may be a risk factor for conflict. For example, significant relationships have been found between peak summer tourist seasons and the number of human-black bear conflicts (Singer and Bratton 1980, Landriault 1998). "Increasing human population, increasing human activity in bear habitat, [and] new generations of humans less-savvy to black bears" are commonly cited by wildlife professionals to contribute to increased human-black bear conflict (Witmer and Whittaker 2001). Unfamiliarity with black bears is an often cited factor for conflict, as well. For example, Kapp (2005) found that the number of seasonal homes was a significant predictor of nuisance complaints in Wisconsin. She hypothesized that it was due in part to persons being unfamiliar with living among black bears (*e.g.*, seasonal residents and tourists).

2. Habitat suitability

The quality of bear habitat is another factor important in human-bear conflict. Our manipulation of the landscape for purposes of growing food, building homes and traveling to work have fragmented the landscape and altered bear habitat. Throughout the contiguous US, black and grizzly bears are recolonizing historic ranges after being displaced by humans in previous decades (Bader 2000, Garshelis and Hristienko 2006, MacFarland 2009). Our landscape alterations and bears' subsequent range reclamation has resulted in a mosaic of human dominated and natural landscapes that are serving the needs of both people and bears.

Perhaps no other feature serves to fragment the landscape as much as roadways. And roads, it appears, have an incredible impact on habitat quality. Mueller (2004) found that sub-adult grizzly bears in Alberta frequented areas closer to high-use roads more often than adults, suggesting that dominant individuals prefer areas further from roadways. Lewis and Rachlow (2011) found a positive correlation between black bear highway crossings and the area of forested landscape and a negative correlation between human development and highway crossings, indicating that when bears cross roads they prefer to do so far from humans. And, in Shenandoah National Park, both male and female bears were shown to avoid primary roads year round (Garner and Vaughan 1989). Numerous habitat suitability studies and models for black bears include road density as an indicator (Rogers and Allen 1987, Van Manen and Pelton 1997, Vander Heyden and Meslow 1999, MacFarland 2009)

Consistently, research finds that safe refuge is necessary for bears if they live in proximity to humans. Recently, Baruch-Mordo (2007) found clustering of inter-urban black bear-human conflicts near high quality habitat. Garner (1989) found black bears consistently left Shenandoah National Park (presumably high quality habitat) to forage in rural developed and agricultural areas. And, Ordiz et al. (2011) found that Scandinavian brown bears (*Ursus arctos arctos*) avoided human settlements, preferring more concealed bedding areas during seasons of increased human activity. A recent investigation of human-black bear conflicts in Missoula, Montana, found housing density, distance to large forest patches and distance to water bodies to be significant predictors for human-bear interactions, all of which are habitat quality indicators (Merkle et al. 2011). Mattson (1990) notes bear populations that rely regularly on human foods only do so when sufficient amounts of quality refuge are near, and McLean and Pelton (1990) attributed the amount of "panhandler" activity in Great Smoky Mountains National Park to habitat quality. An inverse relationship between habitat and home range size for black bears has also been found, indicating that bears may range farther in poorer habitats, thus increasing the chances of human-bear interaction (Smith and Pelton 1990).

All of the above studies indicate a close relationship between habitat quality and conflict. It appears that the poorest of habitats theoretically have minimal conflict because bears are few or non-existent. On the other hand, the best habitats offer smaller home ranges and more easily achieved seclusion from human development. One may hypothesize that somewhere in the middle of the habitat quality spectrum is where conflicts are highest. Either small areas of prime habitat or large areas of mediocre habitat that are in proximity to human development would be at risk for human-bear conflict. I say bear conflict rather than black-bear conflict because this pattern seems to hold for other bear species as well. Wilson et al. (2005 & 2006) found that human-grizzly conflict hot-spots from 1986-2001 in west-central Montana were strongly associated with nearness to agricultural attractants like sheep pastures and unfenced beehives, as well as, wetland and riparian areas. And, Dyck (2006) showed defense of life and property (DLP) kills for polar bears varied seasonally from 1970-

2000 in Nunavut, Canada, with more conflicts occurring between late August and early September during periods of peak open water (*i.e.*, minimal pack ice and thus poorer habitat).

3. Availability and productivity of natural foods

Natural foods are closely associated with habitat quality. For black bears, this means hard mast species such as oaks, hickories and beeches (*Quercus* spp., *Carya* & *Juglans* spp., and *Fagus* spp.) and wild berries such as raspberries, blackberries and blueberries (*Rubus* spp. & *Vaccinium* spp.). Poulin et al. (2003) found a significant negative correlation between nuisance complaints[2] and summer and fall natural food availability in Ontario, and Landriault (1998) noted higher nuisance capture rates in the same region when natural foods were scarce. Poor natural food production was purported as a primary factor for an historical record-high number of nuisance complaints in Wisconsin (Stowell and Willging 1992). In Minnesota, mast productivity in late-summer and fall was observed to be negatively correlated with nuisance activity (Garshelis 1989). Also, in Northern Minnesota sub-adult males may hasten their dispersal if food availability is low (Rogers 1987). And, this is a representative demographic in human-black bear conflicts (*e.g.*, Treves et al. 2010, Mattson 1990). However, poor food productivity does not preclude bears to nuisance activity. Noyce and Garshelis (2011) found that bears were more apt to leave their home range in late-summer and fall if substantial food crops were available outside of it. Also, bears

[2] The authors log-transformed the complaints to normalize the data due to an unusually high number of complaints in 2001.

tended to remain within their home ranges in times of food scarcity. In cases of food abundance, then, black bears may travel further increasing the likelihood of their crossing paths with people. However, black bears' proclivity to seek anthropogenic food sources is unlikely in such cases because non-food-conditioned black bears prefer natural foods when available[3] (Beeman and Pelton 1980, Costello and Sage 1994, Thiemann et al. 2008).

4. Seasonal variation

The discussion of food productivity transitions easily into the next factor, which is, generally speaking: time. As I have already stated, conflicts are not uniform in space nor are they uniform in time. As an obvious example, human-bear conflicts dramatically drop during the period of winter dormancy, and complaints tend to increase in the Midwest around mid-May, shortly after black bears emerge from their dens (Garshelis 1989). Less obvious is the variability in complaints during the summer and fall months between and within years. However, evidence suggests changing weather patterns may influence nuisance bear activity. Recently, Zack et al. (2003) showed La Niña events were a strong predictor for human-black bear encounters in New Mexico, and Baruch-Mordo (2007) found that measurements of frost, precipitation, and relative humidity were significant predictors for black bear-human conflict hotspots. Also, in Wisconsin, drought has contributed to higher black bear agricultural damage complaints (Stowell and Willging 1992). For black bears, Witmer

[3] Note that baiting for black bears may have the opposite effect, with bears frequenting hunter bait stations more often during weeks of peak mast production (Johnson 2007).

and Whittaker (2001) suggests both long- and short-term weather patterns are plausible drivers of bear complaints. Garshelis (1989) found snow depth during the last two weeks of March to be strongly negatively correlated with the level of nuisance activity for the upcoming spring and summer.

Bear foraging behavior also varies between seasons. Jonker (1998) showed monthly variability in black bear depredation of crops, apiaries, and livestock in Massachusetts. In addition, crop damage in Minnesota occurs primarily in August and September – much as it does in Wisconsin (Garshelis 1989, this study). Variation in daily activity patterns vary by season, too. Black bears are known to increase diurnal activity in summer months, for example (Garshelis and Pelton 1980). Other bear-human conflicts seem to exhibit similar temporal variation. Wilson (2005, 2006) found there was a significant seasonal (spring, summer, fall) component to the likelihood for grizzly depredation events in Montana. In Greece, Karamanlidis et al. (2011) found that agricultural damage by brown bears (*Ursus arctos arctos*) varied by season. Similarly, Charoo et al. (2011) found agricultural damage and human attacks by Asiatic black bears (*Ursus thibetanus*) varied seasonally.

5. Black bear behavior and demographics

Individual black bears vary in their tendencies to damage property. This is not extraordinary, and has been shown to be true for many large carnivore species (Sacks et al. 1999, Odden et al. 2002, Treves and Naughton-Treves 2005, Woodroffe and Frank 2005). The tendency for black bears, specifically, to cause damage is likely due to learned behavior[4]. For example, Mazur and Seher (2008) found that 81% of black bear cubs reared on anthropogenic foods by food-conditioned mothers continued the behavior into adulthood in Sequoia Kings and Yosemite National Parks. Studies have shown that black bears may alter their entrance into winter dens when anthropogenic or natural food availability is high (Rogers 1987, Beckmann and Berger 2003a, Beckmann and Berger 2003b). Beckman and Berger (2003a) noted that urban-interface black bears shift from diurnal to crepuscular and nocturnal foraging behavior when habituated to anthropogenic foods. A large body of literature exists to support the importance of learned behavior in mammalian development (see Box & Gibson 1999 for a comprehensive treatment of mammalian social learning; see Maestripieri & Mateo 2009 for a comprehensive treatment of mammalian maternal effects). And, it has been shown that in black bears, there is no clear genetic inheritance or mother-offspring learning that predisposes an individual to being food-conditioned (Breck et al. 2008).

Although studies vary in their conclusions on which groups (age and sex) are primarily responsible for nuisance behavior (Garshelis 1989, Mattson 1990, Beckmann and Berger 2003b), the theoretical framework of nuisance bear demographics tends accurate. Mattson (1990) suggests that the bears most likely to seek human food sources differ based upon their demographic (age/sex) metabolic requirements and behavioral (dominance/security) prerogatives[5]. He suggests that the disproportionate representation of sub-adult males and adult females with cubs that feed near humans

[4] See Breck et al. (2008) about the role of genetics and family lineages in black bear nuisance behavior
[5] A copy of Mattson's framework is presented in the Appendix, Fig. A.4.

may be a direct result of these metabolic needs and behavioral prerogatives and regulated in part by the presence of adult males.

Treves et al. (2010) & Kapp (2005) found age and sex differences of nuisance bears in Wisconsin to be comparable to this framework, with 64% of nuisance bears live-trapped from 1995-2004 being male, and 71% of those were 1-3 years of age. This is not restricted to the upper Midwest, however. Matthews et al. (2006) found that sub-adult males were significantly closer to developed areas than all other age-sex groups in Yosemite NP and Beeman and Pelton (1976) found that 87% of translocated bears in GSM NP were male; and while only 20% were juveniles, 100% of juveniles were male**.**

METHODS

Response variable identification

I obtained addresses of complainants from WS records and entered them into an excel spreadsheet. Per USDA and UW-Madison rules on personally identifiable information, addresses and names were anonymized. I proceeded to generalize addresses to 1 mi^2 using the Public Land Survey System (PLSS) section as the spatial unit of measure. I omitted addresses that could not be geo-located to at least an 80% level of confidence from my analysis (ESRI 2009). Additionally, records that documented subsequent complaints at a location in less than a 24-hour window were omitted. I did this to allow WS enough time to adequately respond to a bear complaint. All complaint records were subsequently classified as either agricultural or nuisance and spilt into two separate datasets. Nuisance complaints were classified further, separated by type of management response. Nuisance complaints fell into one of two groups, being classified as either having received technical assistance or direct control. After generalizing complaint locations to 1 mi^2 (2.59 km^2) and classifying complaints by type (*i.e.*, agricultural, nuisance with technical assistance, nuisance with direct control), I aggregated them by PLSS townships (n = 1,699, μ = 33.9 mi^2, SD = 7.2 mi^2)[6]. The township level is more practical for management purposes, and it more closely aligns with black bear ecology. For example, female black bear home ranges are estimated at 18.3 km^2 (3.2–36.5 km^2, n = 19, SD = 8.3 km^2) for Northern Wisconsin and approximately 25 km^2 for bears in the upper Midwest (Baker 1983, Sadeghpour and Ginnett 2011). A township is much more likely, therefore, to contain an individual bear's home range. At a spatial unit of 1 mi^2 attributing multiple measurements (*e.g.*, a 20 km^2 home range would include approximately eight 1 mi^2 sections) to one bear's home range would be unavoidable and unadvisable. Were complaints aggregated at a smaller scale, like the PLSS section (1 mi^2) level, assumptions of independence may be violated. For example, if one bear generated many complaints or one person complained multiple times in a township, it would give those locations undue influence. So, to further avoid a violation of independence, I used a range of complaints to define a conflict severity level for each township (Table 1). In theory, this should diminish any overdue influence a single bear generating multiple complaints may have had. In addition, it should help improve the models' predictive power.

[6] 77.0% of townships range between 35 and 37 mi^2

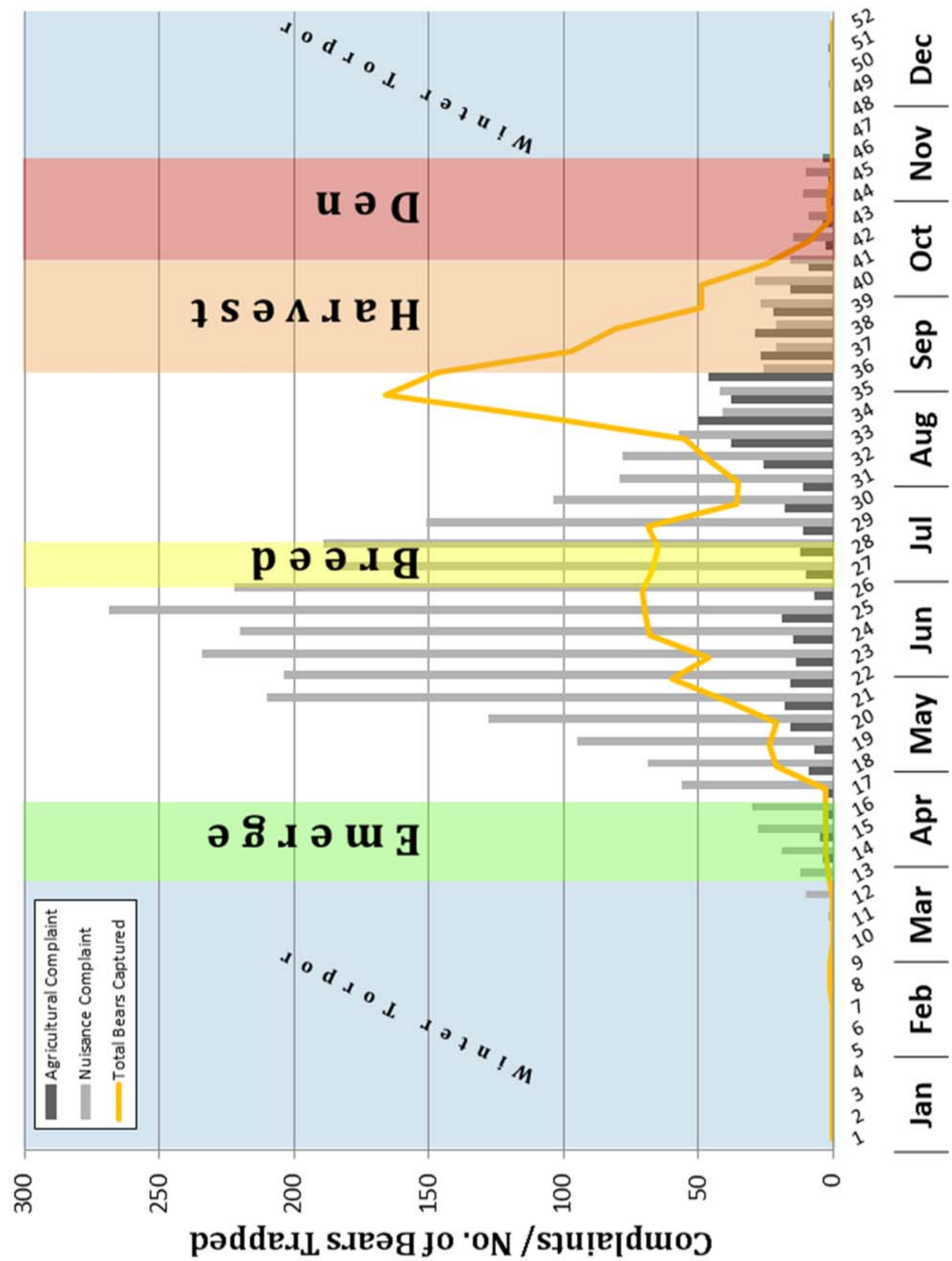
(Table 1) *Complaints generalized to risk levels*
Showing the number of complaints received in Wisconsin from 2008-10 at a township level on the left and the associated risk level assigned to each township on the right.

NUISANCE	*Risk Level*
None.	0
1.	1
2-3.	2
4-10	3
>10	4
AGRICULTURAL	*Risk Level*
None.	0
1.	1
2.	2
≥3	3

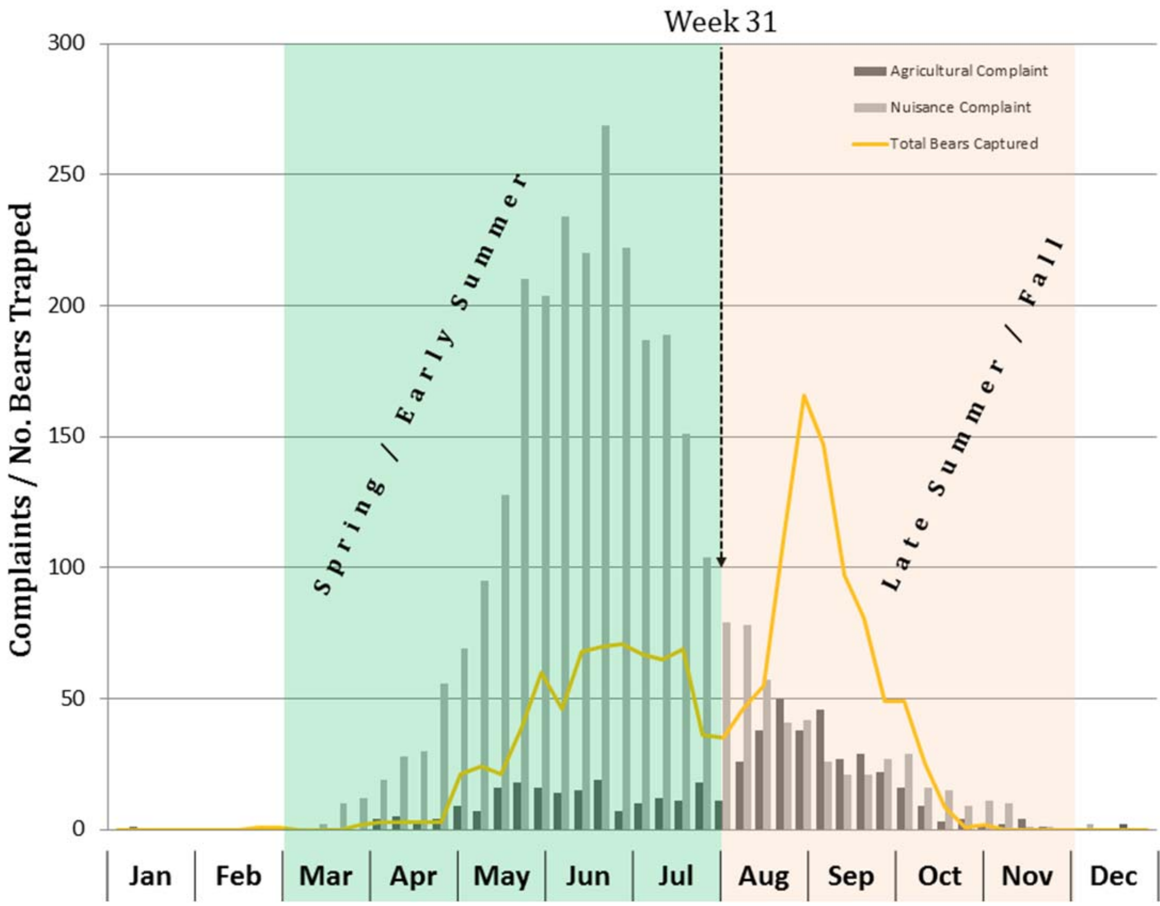
My next step was to include a seasonal component to complaints by classifying them as either having taken place between March 1st and July 31st (spring – early summer) or August 1st and November 30th (late summer – fall), similar to Noyce & Garshelis's (2011) study in Northern Minnesota. Wisconsin black bear foraging behavior closely mirrors that of Northern Minnesota. This was apparent when I examined WS trapping data from 2008 to 2010 (FIGURE 1). There was a clear drop in bears translocated in late July and early August. The number waned as the "nuisance" season came to a close and wild berries ripened across Northern Wisconsin. Additionally, the breeding season ended sometime in in mid-July (FIGURE 2) and family groups are known to have broken up by the end of June. Subsequently, in late August and early September field corn reached its peak "milk" stage at which time it is most palatable to black bears. Trapping efforts to remove black bears from farmers' fields increased dramatically as a result. The mean Julian date between these two seasons is the transitional window into late summer, which was the 31st week of the year or roughly one month past the summer solstice for 2008-2010. I excluded winter months (December, January, and February) due to bear inactivity[7].

[7] There was only one nuisance complaint during this time (Feb. 2010) and two livestock complaints (Jan. 2010 & Dec. 2008).

(Figure 1) *Observed black bear nuisance behavior and annual bear ecology*
A yearly timeline delineated by month and week showing the total number of agricultural and nuisance complaints and bears live-trapped that were recorded from 2008-10 with an overlay showing the life story of the black bear in Wisconsin.



(Figure 2) *Observed black bear nuisance behavior and the representative seasonal divide*
A yearly timeline showing the number of agricultural and nuisance complaints in Wisconsin from 2008-10 by month and the total number of black bears live-trapped. The division of the data into two seasons is shown with week 31 being the division between seasonal assignments of the data.



Predictor Variable Identification

After a review of the literature (previous section) on the factors that contribute to human-black bear conflict, I identified the following eight variables as candidates for my analysis: Mean annual hunter harvest (No. bears harvested per TWP), seasonal homes (No. seasonal homes per TWP), mean annual corn crop cover (hectares per TWP), developed land cover (3 categories, hectares per TWP), oak (*Quercus* spp.) cover (hectares per TWP), and a habitat suitability index (probability of occupancy from 0 to 1)(MacFarland 2009). All variables were imported to ArcMap v. 10.0 and data extracted by PLSS townships using ArcMap (ESRI 2011) and the extensions Hawth's Tools (Beyer 2004), and Spatial Ecology (Beyer 2012).

1: Hunter harvest

Hunter harvest is the 5th most cited management strategy to reduce human-black bear conflicts in North America[8] (Spencer et al. 2007). Harvesting black bears has been hypothesized as a way to directly reduce nuisance complaints by Witmer and Whittaker (2001) and by Forbes et al. (1994). The WDNR Black Bear Committee regularly reviews past human-bear conflicts when deliberating upcoming annual harvest quotas (Voyles, unpublished data 2010 & 2012). Further, Noyce and Garshelis (1997) found that hunter success in Minnesota was inversely related to natural food productivity[9]. In other words, higher hunter harvest success correlated with local food stresses; and so, harvest numbers may indirectly predict human-black bear conflict. While harvest success and the number of bears harvested in an area are undoubtedly linked, the measures are not equal. Since Wisconsin hunter success is only known for large areas (bear management units), interpolating success to the township scale would

[8] The four more common strategies, in order from most-common to least are: site visit, translocation, euthanasia, and kill permits (Spencer et al. 2007).

[9] The study also found that the bear population size had no significant effect on hunter success though it can, in some cases, be a factor contributing to hunter success (Noyce and Garshelis 1997)

be ill-advised[10]. Therefore, I did not include hunter success as one of my candidate predictor variables and chose to only use harvest outright.

Bear hunter harvest in Wisconsin is recorded by Deer Management Unit (DMU). These units vary in size, measuring between 2 km^2 and 3,284 km^2 with a mean size of 1,052 km^2 (n = 138, SD = 676 km^2). I first calculated the mean annual harvest for each DMU from 2008-10. To standardize mean annual harvest, I divided harvest for each DMU by its area, yielding an areal average. I proceeded by calculating the area weighted mean for each township.

2: Seasonal homes

The number of seasonal homes is a measure that could be associated with myriad factors. For one, it could be associated with bear habitat quality and/or the availability of natural foods. From an anthropogenic standpoint, the number of seasonal homes could serve as an estimate for the degree of seasonal recreation. Seasonal homes might also be indicators of rural areas. Kapp (2005) found that the number of seasonal homes was a significant predictor of annual black bear complaints for Wisconsin counties.

I used 2010 National Decennial Census data downloaded from the University of Wisconsin's Applied Population Laboratory to estimate the number of seasonal homes (UW Extension 2012). These data are aggregated by census blocks which vary in size, measuring between 0.04 km^2 and 1,080 km^2, with an average size of 32.59 km^2 (n =

[10] There are four bear management units in Wisconsin: A, B, C & D. Their sizes are: A) 15,918 km^2; B) 14,854 km^2; C) 97,998 km^2; D) 16,471 km^2.

4456, SD = 73.04 km^2). To standardize the number of seasonal homes, I took the areal average for each township.

3: Corn crop cover

Agricultural cereal crops can be strong attractants for bears. In Wisconsin, corn is the most highly depredated grain crop (Koele 2008, 2009, 2010). It makes intuitive sense to use corn crop cover as a predictor for agricultural conflict, although it may not be as intuitive to use it as a predictor for nuisance complaints. It is possible, though, that nuisance complaints (*i.e.*, non-agricultural) are spatiotemporally linked to crop cover. I cite several sources above where conflicts are linked to the nearness of agriculture lands.

Corn crop cover was identified using the USDA – National Agricultural Statistics Service, Cropland Data Layer (CDL). Satellite imagery was compiled annually for each annual growing season as a raster file with a ground resolution of 56 meters for 2008 and 2009 and 30 meters for 2010. I summed cover estimates at the township level for each year and then calculated an annual average for each township. Corn classification had producer accuracies[11] of 92.5%, 95% and 95% for 2008-10 respectively. User accuracies[12] were 94.4%, 94.6% and 94.2% for 2008-10 respectively.

[11] Producer's accuracy is 100% minus omission error.
[12] User's accuracy is 100% minus commission error (*i.e.*, false attribution).

4 - 6: Developed land

I used 2006 National Land Cover Data (NLCD) to identify degrees of land development[13]. Initial NLCD data was compiled from satellite imagery in 2001. The 2001 products were later refined using 2006 imagery. There are three classes of land development: low, medium, and high intensity. The definitions as defined in the NLCD metadata are:

> Low intensity "includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20-49 percent of total cover. These areas most commonly include single-family housing units."
>
> Medium intensity "includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50-79 percent of the total cover. These areas most commonly include single-family housing units."
>
> High intensity "includes highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80 to100 percent of the total cover." (USGS 2011)

The latest NLCD data date from 2006, but a regional class accuracy assessment is not available for the 2006 data. Regional accuracy assessments for the previous 2001 NLCD are available, and the method of satellite data collection was very similar to procedures performed in 2001(Wickham et al. 2010, Wickham et al. 2013; TABLE 2). Thus, these accuracy estimates are assumed to be representative of the 2006 data.

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[13] Official estimates indicate a ≤ 1.0% annual increase in the number of housing units developed in Wisconsin between the years of 2006 and 2010 (Wisconsin DOA 2000 & 2010).

Ground resolution of the 2001 and 2006 data is 30 meters. I estimated land cover by summing coverage per intensity level across townships.

(Table 2) *Accuracy assessment for NLCD data used to model Wisconsin bear complaints 2008-10* National land cover data land development classifications showing producer's (100% - omission error) and user's (100% - commission error) accuracies. Accuracies were assigned to 2001 NLCD data (Wickham et al. 2010).

Accuracy assessments for NLCD developed classes

Class	***Producer's Accuracy (%)***	***User's Accuracy (%)***
Developed, low intensity	80.1	87
Developed, medium intensity	90.5	88
Developed, high intensity	98.5	83

7: Hard mast availability (Quercus spp.)

To account for hard mast crops, I used the WISCLAND raster file produced by a consortium of governmental and private organizations across Wisconsin. I used estimates for oak species coverage to quantify areas with the potential to produce acorns for black bears. WDNR does not maintain annual records of oak mast productivity. Thus, oak coverage serves as a rough approximation for this measure.

The WISCLAND raster file identifying oak species was produced using LANDSAT Thematic Mapper satellite imagery taken between 1991 and 1993. Although the age of this data is >20 years, the coverage estimates for most classes – including oak coverage – were accurate (WDNR 1999), and changes since this time in forest assemblages are assumed to be minimal at a township scale. Nonetheless, it should be recognized that the data represent species compositions as they were circa 1992. Ground resolution for this data is 30 meters. User's accuracy for the oak classification was 90% and the producer's accuracy was 93%. I estimated land cover by summing oak coverage across townships.

8: Habitat Suitability Index (HSI)

I used an index measure of habitat suitability generated by MacFarland (2009) for the Upper Great Lakes region. The primary factors selected to estimate HSI included forest and wetland type, road density, stream density and crop cover. Each township was attributed with probability of black bear occupancy (0 to 1). The HSI layer was developed at the township level and no spatial transformation was necessary.

Sub-setting the data for future validation

In order to validate the final regression models, I set aside 20% of the townships (*i.e.*, 340 of 1,699) to use after model selection to compare predicted risk to observed risk. I randomly chose which townships to reserve for validation. The remaining townships were used in the regression analyses using zero-inflated mixed-effects techniques.

Zero-Inflated Mixed-Effects Model (ZIP)

The zero-inflated Poisson model (ZIP) is a mixed-effects model that better fits data with excessive zeros. Statistically, it is a way to overcome over-dispersion effects of zeros (*i.e.*, more zeros than would be expected in a Poisson distribution) and avoid biased parameter estimates (Zuur 2009). A central tenet of the Poisson distribution is that variance equals the mean[14]. When the deviance of the residuals is greater than the degrees of freedom for the residuals (like when there are too many zeros), the assumption of mean-equals-variance is broken (Kabacoff 2011). ZIP is commonly used to account for this violation.

The ZIP model assumes that there are two types of zeros. There are those that fit into the normal distribution of observed counts (aka, structural zero group), and there is another group of zeros which could never be anything but zero (aka, false zero group). The regression model is thus expanded beyond the Poisson distribution to include a logistic regression. The logistic portion of the model measures the probability of zero assuming there are two types of zeros. In the instance of bear complaints per township across the state of Wisconsin, there are a very high number of zeros. It is easy to see that there are two types of zeros in this case. There are some townships, for instance, which never received a complaint but well could have. These townships would belong in the structural zero group. There are other townships – such as those that encompass Lake Winnebago or the city of Kenosha, for example – that never received a complaint because there were no resident bears in the area, and thus could never have experienced a complaint (with the exception of the rare ambitious bear). Zeros such as these belong to the false zero group. The ZIP model includes a logistic model to help differentiate these two types of zeros.

The probability distribution of a ZIP model is conditional on the value of y. In the case of bear complaints, we are making an assumption that the probability of

[14] $\lambda = E(X) = Var(X)$

measuring a bear complaint in township *i* is a combination of the probability of a zero being structural or false "mixed" with the Poisson-based probability of measuring a complaint. In the end, the ZIP model produces a response value that has been adjusted to account for the effects of false zeros. For this study, the ZIP model estimates the probability of measuring 0 complaints under a binomial distribution (risk level = 0; false or structural) mixed with the probability of measuring ≥ 0 complaints under a Poisson distribution (risk level ≥ 0).

$$\Pr(Y_i = 0) = \Pr(False\ zeros) + \Pr(1 - False\ zeros) \times \Pr(We\ measure\ a\ true\ zero)$$

$$\Pr(Y_i = y_i) = \Pr(1 - False\ zeros) \times \Pr(Count\ process)$$

Where μ is the mean of the positive counts and π the probability of false zeros, the probability functions of a ZIP are expressed as[15],

$$f(y_i = 0) \qquad = \pi_i + (1 - \pi_i) \times e^{-\mu_i}$$

$$f(y_i \mid y_i > 0) = (1 - \pi_i) \times \frac{\mu^{y_i} \times e^{-\mu_i}}{y_i!}$$

And introducing covariates to account for the probability of a false zero and mean count value yields,

$$\pi_i = \frac{e^{\nu+\gamma_1 \times Z_{i1} + \cdots \gamma_q \times Z_{iq}}}{1 + e^{\nu+\gamma_1 \times Z_{i1} + \cdots \gamma_1 \times Z_{iq}}}$$

AND

$$\mu_i = e^{\alpha+\beta_1 \times X_{i1} + \cdots \beta_q \times X_{iq}}$$

[15] All expressions are identical to those explained in Zurr (2009)

Model selection and validation

I checked each of the previous eight predictor variables against each other to test for collinearity. If two predictor variables showed $|r| \geq 0.7$, I kept the stronger predictor. The stronger predictor was determined via its association with the response variable. The predictor with the higher $|r|$ shared with the response variable was retained. Those variables passing the collinearity test were kept for further modeling.

Using the identified non-collinear predictor variables, I proceeded by regressing each predictor against the six risk response variables (spring – early summer nuisance / technical asst.; spring – early summer nuisance / direct control; summer – late fall nuisance / technical asst.; summer – late fall nuisance / direct control; spring – late summer agricultural; and summer – late fall agricultural) using statistical software R 3.0.0 (R Core Team 2013) and packages '*pscl*' (Zeileis et al. 2008) and '*lmtest*' (Zeileis & Hothorn 2002). The predictors were examined one-at-a-time beginning with the logistic part of the model. Predictors were evaluated using a likelihood ratio test and the model AIC values were compared to the null. The best predictor for each risk type (*i.e.*, most negative Δ AIC) was chosen as the initial predictor for the logistic portion of the ZIP model. I subsequently added the other predictor variables one-at-a-time in two forms – once as an additional predictor and once to create an interaction term. I compared each expanded model against the previous model using likelihood ratio tests. If Δ AIC $\leq$ - 2, the new variable was retained. I continued to add variables in additive and interactive forms until the difference between the expanded and the previous model was insignificant ($-2 < \Delta$ AIC). This resulted in six mixed-effects models with predictor(s) for the logistic portion and only an intercept term for the count portion. The logistic side of the models at this point remained set and unchanged.

Next, I added each predictor one-at-a-time to the count side of the model. All of the predictors re-entered the building process at this point, regardless of whether it was included in the logistic portion of the model. A significant predictor of zero may, in theory, not be a predictor for the level or risk, or vice versa. The predictor leading to the largest decrease in AIC was retained as the initial predictor for the count portion of the model. I added each remaining predictor one-at-a-time in two forms (additive and interactive forms). If AIC decreased by > 2, the new variable was retained. I continued to add variables until the difference between the larger and the previous models was insignificant ($-2 < \Delta$ AIC).

This resulted in six ZIP models, one for each type of risk. Using the techniques above, the selected variables could either be identical or different among (risk types) and within (logistic and count) models. The final variables selected for the logistic portion of the model predict the probability of a false zero. The variables selected for the count portion of the model predict the level of risk (0-4 for the nuisance sets and 0-3 for the agricultural set; Table 1). The fully mixed model predicts the level of risk after determining whether a zero is a false zero. I used the final models to predict the probability of zero risk focusing on the logistic side of the model first[16].

[16] Note the model predicts the probability of a false zero (π). $1 - \pi$ is therefore the probability of not being a false zero, and thus equates to probability of complaint.

I subsequently adjusted the threshold value for determining affected and unaffected townships minimizing the probability of producing false negatives (*i.e.*, model predicts zero risk, but there was observed risk). This is a common alteration to logistic regression models and results in higher accuracy than using the default threshold of 0.5 (Stokland et al. 2011, Olson et al. 2012). The theoretical framework of risk mapping and the statistical methodology of this research assume some risk is unobserved but aims to illustrate where risk could potentially occur (Zuur 2009, Venette et al. 2010). Adjusting the threshold value allows us to appropriately interpret model outputs to recognize these areas. Statistically, adjusting the threshold in this manner decreases type II errors (*i.e.,* false negatives). I assessed the accuracy of the six logistic models by calculating the odds of predicting risk correctly. The entire model in its mixed form (logistic and count) predicts a level of risk as a continuous response variable ranging upward of zero. I tested predicted risk against observed risk using a Welch's paired t-test. My last step was to use the previously removed validation set to see if the models predicted risk level approximate to the observed risk level. I assessed the logistic predictions of the model against the validation set with an odds ratio and the predictions of the mixed model against the validation set using a Welch's paired t-test, as well.

RESULTS

Out of 3,595 total complaint records from 2008-10, 604 (μ = 201, SD = 35, n = 3) were identified as agricultural, whereas 2,992 (μ = 997, SD = 19) were nuisance complaints. Proportionally, nuisance complaints made up 83% of all complaints from

2008-10 (μ = 83.3, SD = 2.6). 185, or 6.2%, of nuisance complaints could not be mapped and 18, or 3.0%, of agricultural complaints could not be mapped (TABLE 3). Mapped nuisance complaints could be attributed to 552 unique townships from 2008-10 (μ = 340, SD = 21) and mapped agricultural complaints to 278 townships (μ = 124, SD = 11).

(Table 3) *Summary of mapped black bear nuisance complaints*
Complaints across Wisconsin from 2008-10 classified by type and season and whether the origination of the complaint could or could not be mapped to a PLSS 1 mi^2 section.

Mapped Complaints				
NUISANCE	*2008*	*2009*	*2010*	*All Years*
Number of complaints	1007	1014	971	2992
Unmapped complaints *(removed)*	53	63	69	*185*
Mapped complaints	954	951	902	2807
Unknown season *(removed)*	13	19	22	*54*
Winter season *(removed)*	-	-	1	*1*
Mapped complaints w/ seasonal info	941	932	879	**2752**
AGRICULTURAL	*2008*	*2009*	*2010*	*All Years*
Number of complaints	217	153	233	603
Unmapped complaints *(removed)*	6	6	6	*18*
Mapped complaints	211	147	227	585
Unknown season *(removed)*	40	7	38	*85*
Winter season *(removed)*	1	-	1	*2*
Mapped complaints w/ seasonal info	170	140	188	**498**

Frequency distributions of the annual nuisance and agricultural complaints per township by risk type showed that a minority of townships from 2008-10 had ≥ 1 reported complaint and needed only technical assistance between March 1st and July 31st (spring – early summer season) from 2008-10 (μ =252 , SD = 28). Townships with ≥ 1 complaint which needed only technical assistance was lower from August 1st to November 31st (late summer – fall season) (μ = 73, SD = 19). Similarly, comparatively more townships reported ≥ 1 complaint and needed direct control in the spring and early summer seasons from 2008-10 (μ = 142 , SD = 8) than during the late summer and fall seasons (μ = 34 , SD = 3). The annual average number of townships receiving management assistance because of agricultural complaints from 2008-10 was higher in the late summer and fall seasons (μ = 80, SD = 17) than during the spring and early summer seasons (μ = 52, SD = 2). From 2008-10, 83% of nuisance complaints took place during the spring and early summer season, while 36% of agricultural complaints took place during this time. Only 17% of nuisance complaints took place during the late summer and fall season, while 64% of agricultural complaints took place during this time (TABLE 4).

In total, 521 affected townships (those receiving ≥ 1 complaint between 2008 and 2010) remained for the nuisance spring and early summer set; 215 nuisance late summer and fall set; 147 for the agricultural spring and early summer set; and 175 affected townships for the agricultural late summer and fall set. When I examined all affected townships by nuisance management response type from 2008-10, I found that 456 of 521 (87.5%) affected townships received technical assistance during the spring and early summer seasons of 2008-10, and 282 of 521 (54.1%) received direct control during this season. During the late summer and fall seasons, 173 of 215 (80.5%) of affected townships received technical assistance, and 87 of 215 (40.5%) received direct control (Table 5).

(Table 4) *Seasonal summary of black bear nuisance complaints*
Mapped complaints in Wisconsin between 2008 and 2010 previously classified by type and season at the PLSS 1 mi^2 section level attributed to PLSS 36 mi2 townships.

Complaints by season

NUISANCE	*2008*	*2009*	*2010*	*All Years*
Spring-summer complaints	791	831	664	2286
Summer-fall complaints	150	101	215	466
Spring-summer only TWPs	246	293	202	337
Summer-fall only TWPs	28	24	38	31
SS & SF TWPs	62	51	77	184
Total SS TWPs	308	344	279	**521**
Total SF TWPs	90	75	115	**215**
AGRICULTURAL	*2008*	*2009*	*2010*	*All Years*
Spring-summer complaints	60	62	56	178
Summer-fall complaints	110	78	132	320
Spring-summer only TWPs	39	49	39	103
Summer-fall only TWPs	69	57	86	131
SS & SF TWPs	15	0	13	44
Total SS TWPs (n_{AG_SS})	54	49	52	**147**
Total SF TWPs (n_{AG_SF})	84	57	99	**175**

(Table 5) *Management response summary of black bear nuisance complaints*
Nuisance complaints from 2008 to 2010 in Wisconsin distinguished by management response (technical assistance or direct control) and classified by season and their subsequent attribution to PLSS 36 mi^2 townships.

Nuisance complaints by management response

COMPLAINTS	*2008*	*2009*	*2010*	*All Years*
Spring-summer complaints	791	831	664	2286
Technical assistance	561	587	451	1599
Direct control	230	244	213	687
Summer-fall complaints	150	101	215	466
Technical assistance	106	61	163	330
Direct control	44	40	52	136
TOWNSHIPS (TWPs)	*2008*	*2009*	*2010*	*All Years*
Spring-summer TWPs	308	344	279	521
Technical assistance (n_{TA_SS})	255	285	216	**456**
Direct control (n_{DC_SS})	137	153	135	**282**
Summer-fall TWPs	90	75	115	215
Technical assistance (n_{TA_SF})	73	49	96	**173**
Direct control (n_{DC_SF})	31	33	39	**87**

The three levels of land development proved to be highly correlated and exceeded my threshold of |r| < 0.7. So, I removed two of the candidate variables – medium level land development and high level land development. The predictor I retained was low development. It had strongest association with risk level for every type of complaint. . A correlation matrix is presented in Appendix, Fig. A.2. Habitat suitability and harvest proved to be highly collinear, but did not exceed my threshold of |r| > 0.7 (r = 0.649).

After using likelihood ratio tests to test each predictor against the null for the logistic portion of the ZIP models, mean annual hunter harvest proved to be the best single predictor for the logistic model for all risk types, having had a positive association with risk for all risk types and seasons. Once the initial logistic predictor had been chosen, I added variables beginning with the logistic portion and proceeding to the count portion (TABLE 6).

(Table 6) *Risk model building process and validity of variable selection*
Showing the model selection process building up from a null model with zero predictors. The left side of the model corresponds to the Poisson distributed count portion of the mixed ZIP model, and the right side corresponds to the binomially distributed logistic portion of the mixed ZIP model. Variables were retained if Δ AIC ≤ -2.

Mixed model = count | logistic

Spring - Early Summer Technical Assistance	*df*	AIC	Δ AIC	Likelihood ratio test	
Null	2	2586.05	0	χ^2	*df, p*
1 | harvest	3	2330.78	-255.27	275.3	1, $p < .0001$***
1 | harvest X ldev	3	2239.82	-346.23	91.0	0, $p < .0001$***
1 | harvest X ldev + occ	4	2182.80	-403.25	59.0	1, $p < .0001$***
1 | harvest X ldev + occ + corn	5	2165.13	-420.92	19.7	1, $p < .0001$***
1 | harvest X ldev + occ + corn + seashome	6	2158.66	-427.4	8.5	1, $p = .0036$**
seashome | harvest X ldev + occ + corn + seashome	7	2133.10	-452.96	27.6	1, $p < .0001$***
seashome + corn | harvest X ldev + occ + corn + seashome	8	2128.60	-457.46	6.5	1, $p = .0108$*

Late Summer -Fall Technical Assistance	*df*	AIC	Δ AIC	Likelihood ratio test	
Null	2	1167.46	0	χ^2	*df, p*
1 | harvest	3	1127.48	-39.982	42.0	1, $p < .0001$***
1 | harvest X ldev	3	1056.31	-111.15	71.2	0, $p < .0001$***
1 | harvest X ldev + occ	4	1043.50	-123.96	14.8	1, $p < .0001$***
seashome | harvest X ldev + occ	5	1030.65	-136.81	14.9	1, $p < .0001$***
seashome + harvest | harvest X ldev + occ	6	1021.14	-146.32	11.5	1, $p < .0001$***
seashome + harvest + corn | harvest X ldev + occ	7	1009.43	-158.03	13.7	1, $p = .0002$***
seashome + harvest + corn + oak | harvest X ldev + occ	8	1002.36	-165.10	9.1	1, $p = .0026$**
Spring - Early Summer Direct Control	*df*	AIC	Δ AIC	Likelihood ratio test	
Null	2	1801.18	0	χ^2	*df, p*
1 | harvest	3	1523.99	-277.2	279.2	1, $p < .0001$***
1 | harvest X seashome	3	1487.59	-313.6	36.4	0, $p < .0001$***
1 | harvest X seashome + corn	4	1473.52	-327.67	16.1	1, $p < .0001$***
1 | harvest X seashome + corn + occ	5	1464.75	-336.43	10.8	1, $p = .0010$**
ldev | harvest X seashome + corn + occ	6	1448.30	-352.89	18.5	1, $p < .0001$***
ldev X harvest | harvest X seashome + corn + occ	6	1435.94	-365.24	722.2	0, $p < .0001$***
Late Summer - Fall Direct Control	*df*	AIC	Δ AIC	Likelihood ratio test	
Null	2	694.72	0	χ^2	*df, p*
1 | harvest	3	630.58	-64.142	66.1	1, $p < .0001$***
1 | harvest X seashome	3	606.58	-88.138	24.0	1, $p < .0001$***
1 | harvest X seashome + occ	4	598.04	-96.676	10.5	1, $p = .0012$**
corn | harvest X seashome + occ	5	591.00	-103.71	9.0	1, $p = .0026$**
Spring - Early Summer Agricultural	*df*	AIC	Δ AIC	Likelihood ratio test	
Null	2	972.27	0	χ^2	*df, p*
1 | harvest	3	917.42	-54.852	56.9	1, $p < .0001$***
1 | harvest X ldev	3	895.75	-76.524	21.7	1, $p < .0001$***
corn | harvest X ldev	4	891.73	-80.541	534.2	1, $p < .0001$***
Late Summer - Fall Agricultural	*df*	AIC	Δ AIC	Likelihood ratio test	
Null	2	1172.13	0	χ^2	*df, p*
1 | harvest	3	1079.76	-92.371	94.4	1, $p < .0001$***
1 | harvest X ldev	3	1063.75	-108.38	16.0	1, $p < .0001$***
1 | harvest X ldev + occ	4	1044.20	-127.93	21.5	1, $p < .0001$***
ldev | harvest X ldev + occ	5	1033.74	-138.39	12.5	1, $p < .0001$***
ldev X occ | harvest X ldev + occ	5	1029.23	-142.9	4.5	1, $p < .0001$***

*** indicates significance at the $\alpha = 0.0001$ level
** indicates significance at the $\alpha = 0.0050$ level
* indicates significance at the $\alpha = 0.0200$ level

The 'R' output (abbreviated) for AIC and likelihood ratio tests are provided in the appendix along with model coefficients and significance. All regression terms for all model components were significant at the $\alpha = 0.05$ level. All likelihood ratio tests comparing models were significant at the $\alpha = 0.02$ level (Table 6). For the logistic models, an interaction between harvest and low level development was the best term to predict technical assistance regardless of season; the interaction between harvest and seasonal homes was the best term to predict direct control regardless of season; and, the interaction between harvest and low level development was the best term to predict direct control regardless of season. For all of the logistic models, the harvest interaction terms had a net positive correlation with risk (*i.e.*, negative correlation with false zeros).

For the count model, seasonal homes proved the best single predictor for the level of risk for technical assistance, having a positive correlation with risk. Low level land development was the single best predictor for spring – early summer direct control and late summer – fall agricultural risk. The interaction between low development and harvest had a net positive association with spring – early summer direct control risk. The interaction between low development and habitat suitability had a net negative association with late summer – fall agricultural risk. Corn was the only significant predictor for the risk of late summer – fall direct control and spring and summer agricultural risk[17].

[17] Note that corn would be an indicator of agricultural lands (fields) in this case. Corn would not be palatable to bears in the spring in early summer months.

Using the final logistic models, I tested the predicted risk against the observed risk to assess how well they fit the data (excluding the validation set). Using only the logistic portion of the models and an adjusted threshold for distinguishing between affected and unaffected sites, each model was able to identify risk with high accuracy. Odds ratios for the models, which assess the ratio of correct predictions to false predictions yielded ratios of 11.7 (95% CI = 8.7 to 16.0; $p < 0.01$) for spring and early summer technical assistance; 9.0 (95% CI = 4.9 to 16.5; $p < 0.01$) for late summer and fall technical assistance; 19.4 (95% CI = 12.8 to 29.4; $p < 0.01$) for spring and early summer direct control; 36.9 (95% CI = 5.1 to 266.2; $p < 0.01$) for late summer and fall direct control; 7.3 (95% CI = 3.9 to 13.6; $p < 0.01$) for spring and early summer agricultural; and, 7.9 (95% CI = 4.8 to 12.8; $p < 0.01$) for late summer and fall agricultural. Relatively speaking, direct control models performed most accurate, technical assistance second-most, and agricultural third-most.

I tested the accuracy of the count models at identifying the correct level of risk by performing Welch's paired t-tests between the predicted risk and the observed risk level for each type of risk. These tests showed all models predicted risk levels that were not significantly different from what was observed (spring – early summer technical assistance: $t = -0.1236$, $p = 0.9016$; late summer – fall technical assistance: $t = 0.0079$, $p = 0.99$; spring – early summer direct control $t = 0.3590$, $p = 0.72$; late summer – fall direct control $t = 0.0458$, $p = 0.96$; spring – early summer agricultural $t = 0.0174$ $p = 0.99$; late summer – fall agricultural $t = 0.0633$, $p = 0.95$). Likely due to the large number of zeros in each sample, the predicted risk level was almost always less than observed risk level (83% ± 13 of affected townships have risk that is predicted lower than the observed risk, while 1% ± 2 were predicted higher).

Using the risk models for the validation set yielded similar results. The odds ratios for the logistic model yielded ratios of 21.0 (95% CI = 10.0 to 44.1; $p < 0.01$) for spring and early summer technical assistance; 36.1 (95% CI = 4.9 to 268.7, $p < 0.01$) for late summer and fall technical assistance; 4.8 (95% CI = 0.28 to 81.2; $p = 0.28$) for spring and early summer direct control; 17.4 (95% CI = 2.2 to 137.7; $p < 0.01$) for late summer and fall direct control; 39.2 (95% CI = 5.2 to 294.5; $p < 0.01$) for spring and early summer agricultural; and, 8.1 (95% CI = 2.8 to 23.3; $p < 0.01$) for late summer and fall agricultural. Relatively speaking, the spring and early summer agricultural model performed best followed by late summer and fall technical assistance, spring and early summer technical assistance, late summer and fall direct control, and late summer and fall agricultural. The spring and early summer model produced an odds ratio that with 95% confidence intervals did not cross zero, however, the test of this ratio proved insignificant.

A Welch's paired t-test showed no significant difference between the validation set predictions and observations (spring – early summer technical assistance: $t = -0.1733$, $p = 0.86$; late summer – fall technical assistance: $t = 0.0008$, $p = 0.99$; spring – early summer direct control $t = 0.0000$, $p = 0.99$; late summer – fall direct control $t = 0.0954$, $p = 0.92$; spring – early summer agricultural $t = - 0.0183$ $p = 0.99$; late summer – fall agricultural $t = 0.415$, $p = 0.97$). The 340 validation townships also had many zeros, so risk level was consistently under-predicted (86% ± 2 of affected townships have risk that is predicted lower than the observed risk, while 1% ± 2 were predicted higher).

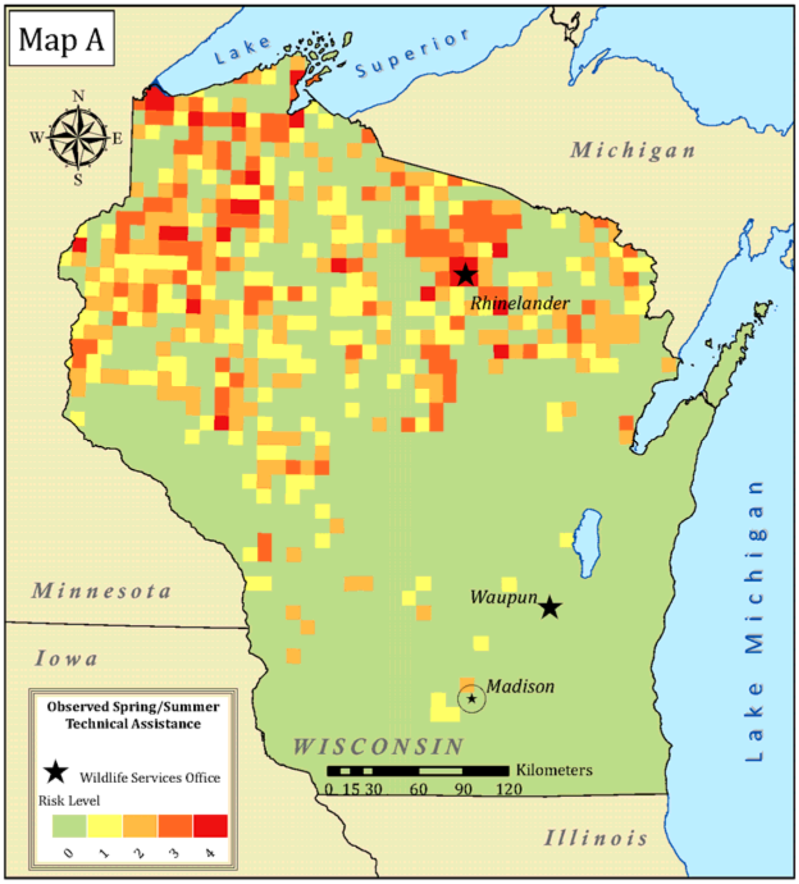
Mapping using models

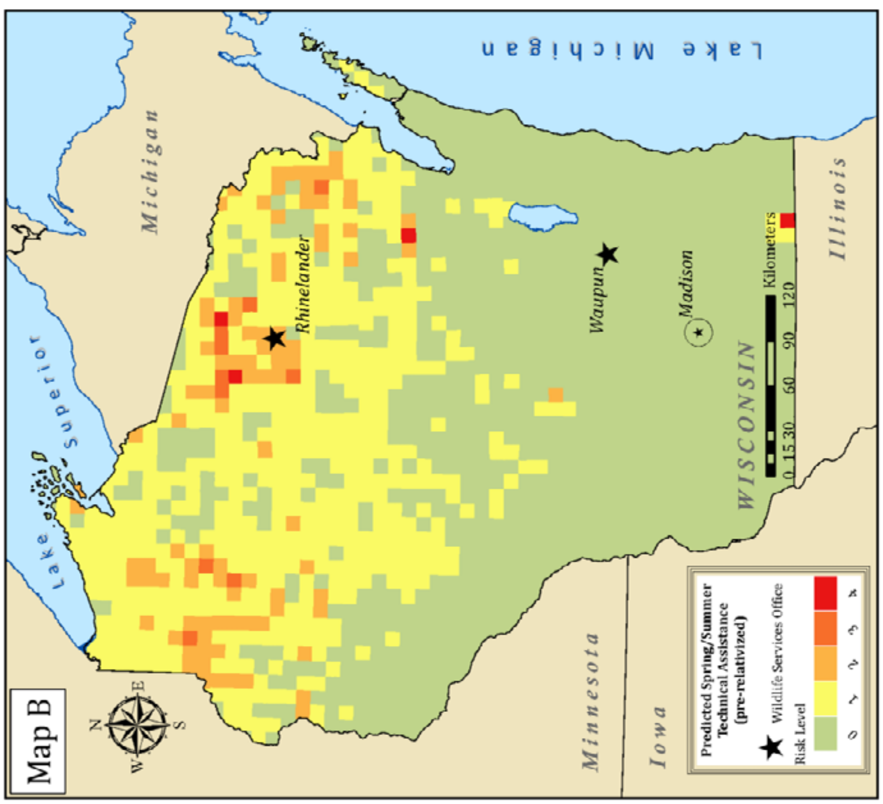
While I suggest that Wisconsin's human-black bear conflicts are not uniform in space or time, presenting complaint information in an interpretable form is key to understanding spatiotemporal relationships. Tables and graphs are informative but limit our ability to quickly assess and interpret data *spatially*. In addition to the tables above, I now present maps generated using my validated models. I elucidate connections between the data presented above in tabular form with the data presented in these maps.

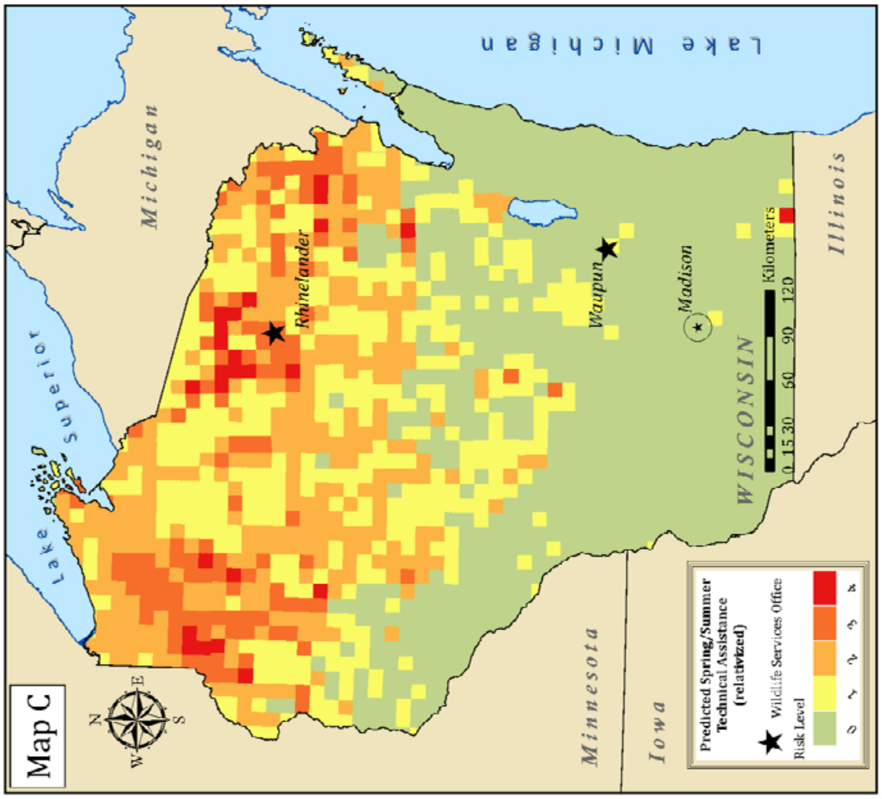
It is important to note the strengths and limitations of the models I generated before proceeding. First, there is general agreement between the model risk sets (using data from 1,359 randomly chosen townships) and the validation risk sets (data withheld from 340 townships, or 20% of the total 1,699). Second, the predictors used in the mixed regression models were all significant at the $\alpha = 0.05$ level. And, all final full models were significantly better at predicting risk than in their reduced forms. Third, the logistic portions of the models showed the odds of making correct predictions about whether or not a township was at risk (1) or not (0) and were highly significant save for the spring and early summer direct control validation set (Limitation 1). Fourth, although Welch's paired t-tests showed no significant difference between predicted risk level and observed risk level (for any risk type), the high number of zero observations must be considered. In short, the ability to accurately predict the level of risk was limited by this high number of zeros. Predicted risk levels were often less than observed risk levels (Limitation 2). Relatively speaking, the models show proper delineation of predicted risk levels and align with observed risk levels. In other words, while risk level was consistently under-predicted due to the high number of zeros, the levels – when relativized – appear accurate. This becomes evident when I compare the observed spring and early summer technical assistance risk levels (Map A) to the predicted risk levels before and after being relativized (*i.e.*, rescaled) according to their deviations from mean predicted risk level (Maps B & C)[18].

[18] I present only spring and early summer technical assistance risk as a case-in-point. Other risk levels mirror the relationship depicted in Maps B and C.

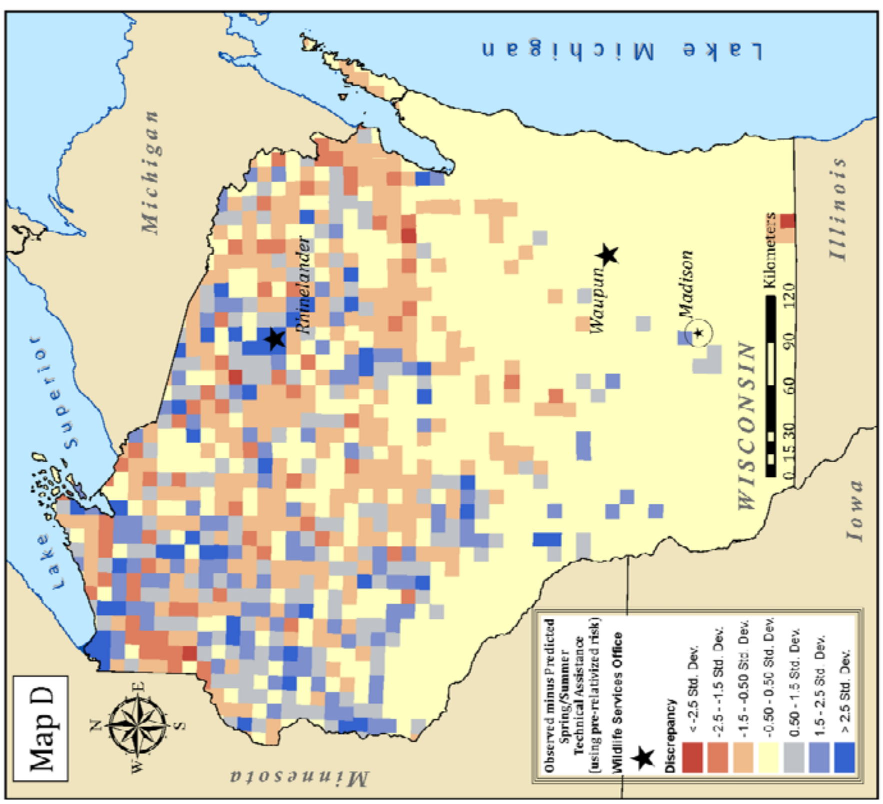
Spring & Early Summer Technical Assistance (Maps A – E)

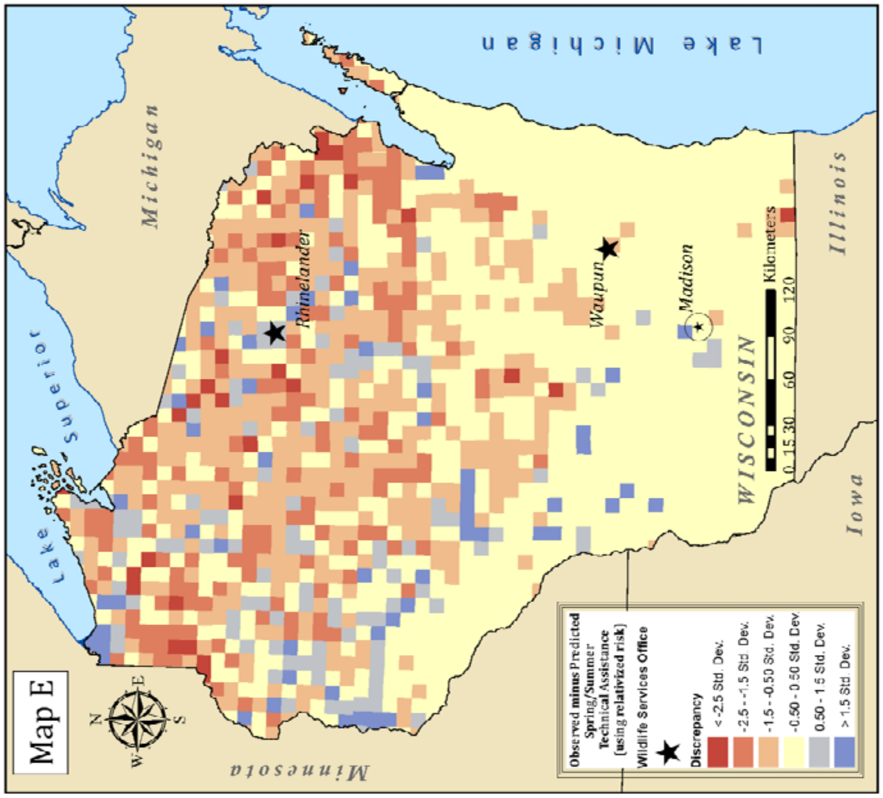



Map B
Lake Superior
Michigan
Lake Michigan
Rhinelander
Waupun
Madison
WISCONSIN
Minnesota
Iowa
Illinois
0 15 30 60 90 120
Kilometers
Predicted Spring/Summer Technical Assistance (pre-relativized)
Wildlife Services Office
Risk Level
0
1
2
3
4


Map C
Lake Superior
Michigan
Lake Michigan
Rhinelander
Waupun
Madison
WISCONSIN
Minnesota
Iowa
Illinois
0 15 30 60 90 120
Kilometers
Predicted Spring/Summer Technical Assistance (relativized)
Wildlife Services Office
Risk Level
0
1
2
3
4

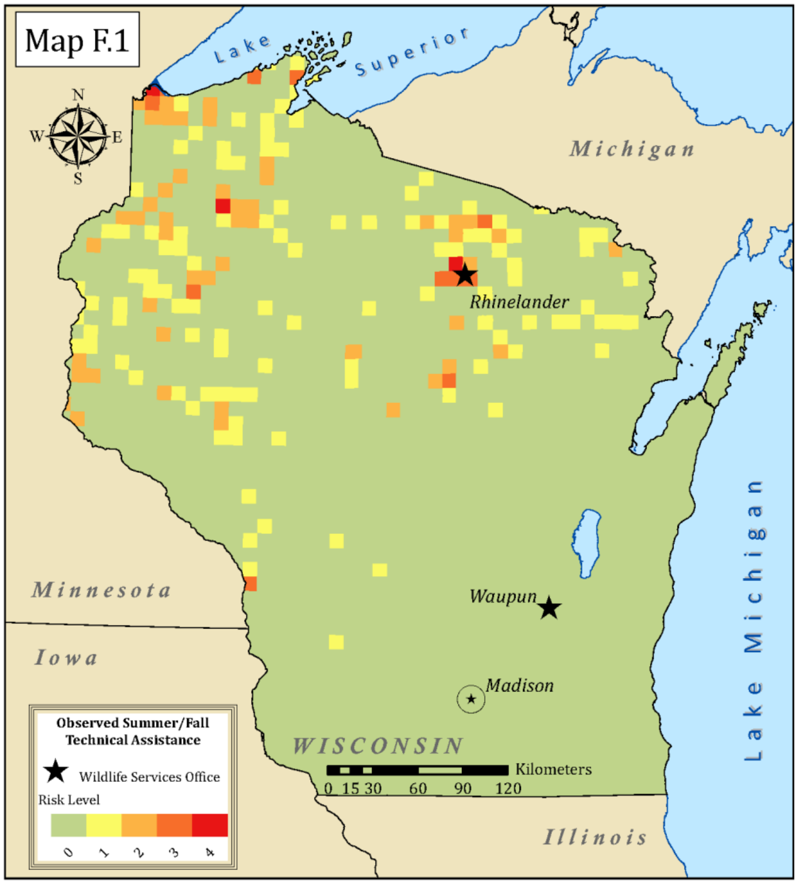
While Map C appears to be a more complete picture of Map A, I would caution using my models to predict risk *level* without first verifying the models using other data (*i.e.*, model verification). By using data obtained from other years (*e.g.*, 2011 to 2013) one could see if relativizing risk levels post-prediction consistently produced results consistent with observed risk levels. Since the logistic portion of the mixed models proved consistently accurate across the board, I would advise they serve as the models on which to base interim interpretations (see Maps K – O). The following two maps show the discrepancy between observed risk level and predicted risk levels. The first discrepancy map (Map D) was created by taking observed risk level minus predicted risk level. The second (Map E) was created by taking observed risk level minus the *relativized* predicted risk level. Under-predicting risk level is minimized (*i.e.*, false negatives are reduced) when I use relativized risk level. This increases the utility of the second map (Map E) and the model because they become more useful for forecasting purposes and less likely to overlook risky areas (refer to pages 46-7 of this document). The darker shade of blue a township is, the greater the positive difference between observed and predicted risk. This means that the model predicted the area to have a lesser risk level than was observed from 2008-10. The darker shade of red a township is, the greater the negative difference between observed and predicted risk. This means the model predicted risk in an area to be higher than was observed from 2008-10.

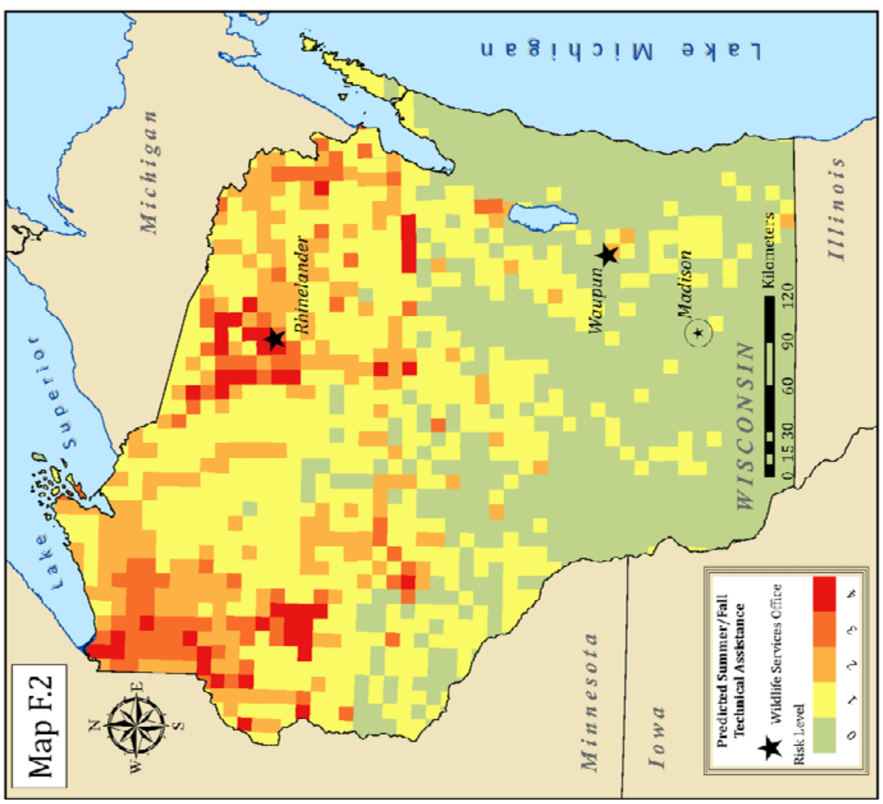

Map D
Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
0 15 30 60 90 120
Kilometers
Observed minus Predicted Spring/Summer Technical Assistance (using pre-relativized risk)
Wildlife Services Office
Discrepancy
< -2.5 Std. Dev.
-2.5 - -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev.
0.50 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.

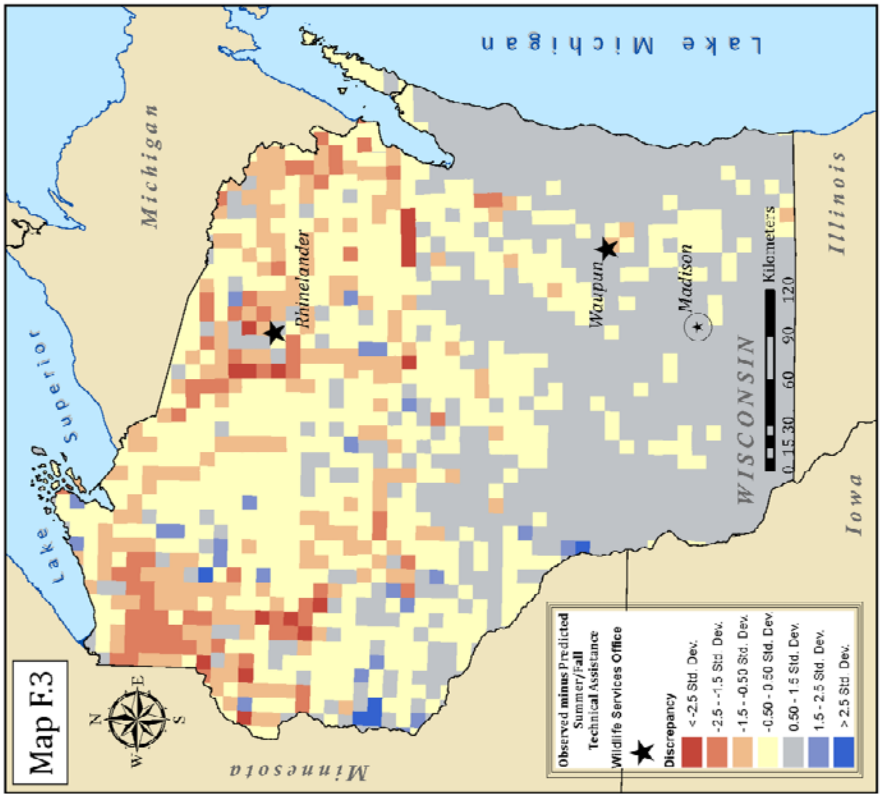

Map E
Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
0 15 30 60 90 120
Kilometers
Observed minus Predicted Spring/Summer Technical Assistance (using relativized risk)
Wildlife Services Office
Discrepancy
< -2.5 Std. Dev.
-2.5 - -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev.
0.50 - 1.5 Std. Dev.
> 1.5 Std. Dev.

The following series of maps depict risk in three forms. The first map of each set (F.1-J.1) in the series depicts the observed risk level per township from 2008-10 by risk type. The second map for each set (F.2 – J.2) depicts the predicted risk level relativized by the predicted risk's deviation from the mean. And finally, the third map for each set shows the degree of difference between the relativized predicted risk level and observed risk level (F.3 – J.3). The discrepancy maps should be interpreted with care and not without consulting the first and second maps in each set and the corresponding probability map (Maps K – O). Maps A, C & E depicting spring and early summer technical assistance risk levels are identical to the series of maps that follow.

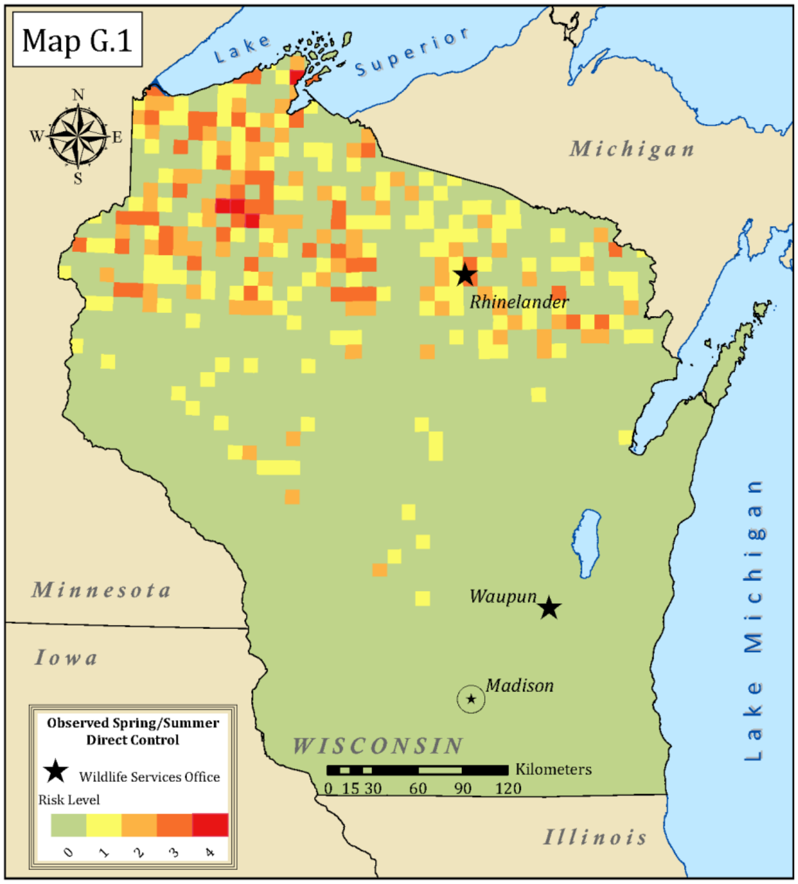
Late Summer & Fall Technical Assistance (Maps F.1 – F.3)

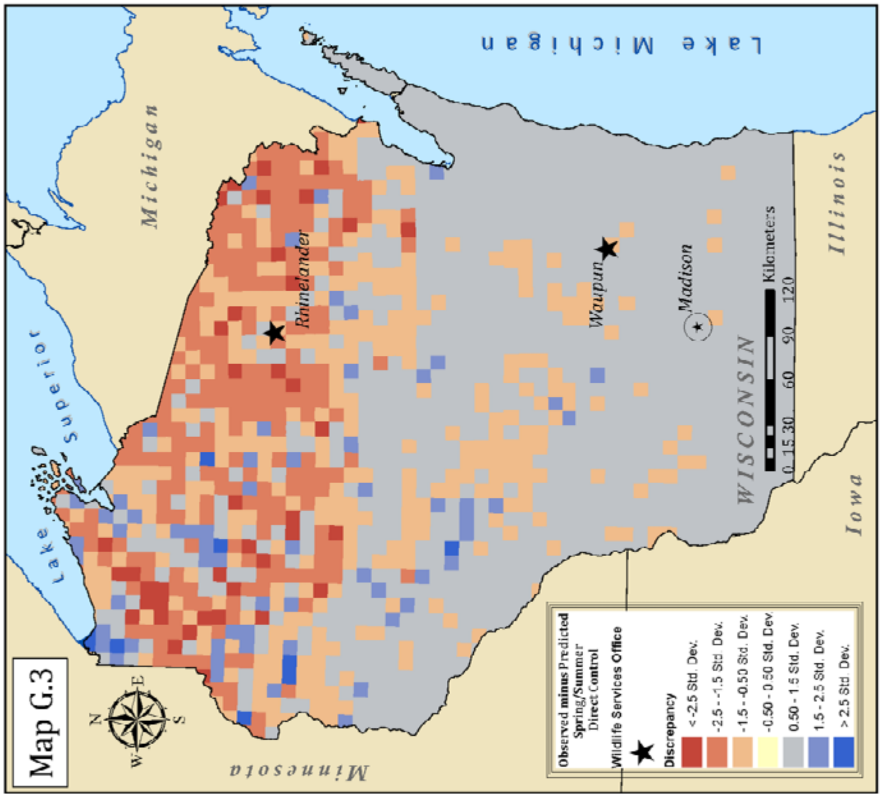



Map F.2
Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
0 15 30 60 90 120
Kilometers
Predicted Summer/Fall Technical Assistance
Wildlife Services Office
Risk Level
0
1
2
3
4

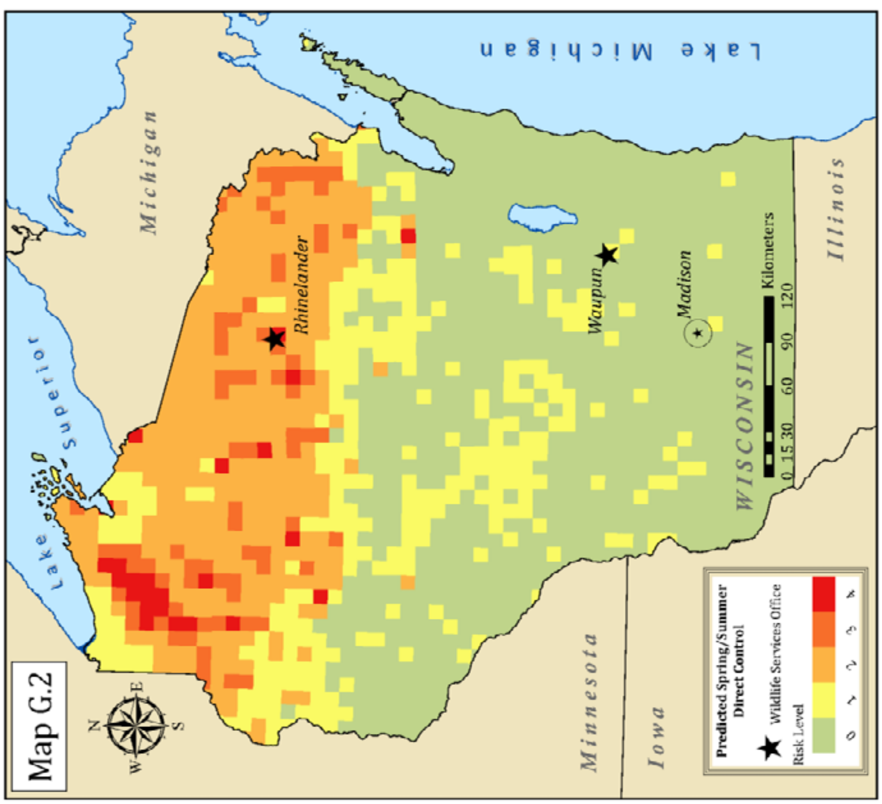

Map F.3
Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
0 15 30 60 90 120
Kilometers
Observed minus Predicted Summer/Fall Technical Assistance
Wildlife Services Office
Discrepancy
< -2.5 Std. Dev.
-2.5 - -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev.
0.50 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.

Spring & Early Summer Direct Control (Maps G.1 – G.3)



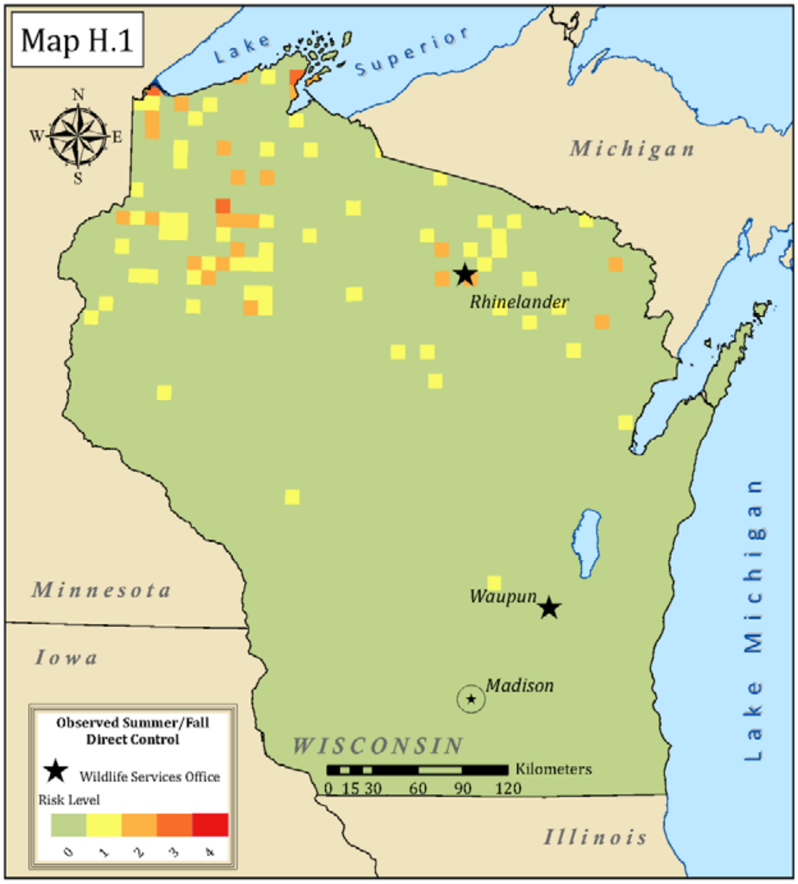

Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
0 15 30 60 90 120 Kilometers
Observed minus Predicted Spring/Summer Direct Control
Wildlife Services Office
Discrepancy
< -2.5 Std. Dev.
-2.5 - -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev.
0.50 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.

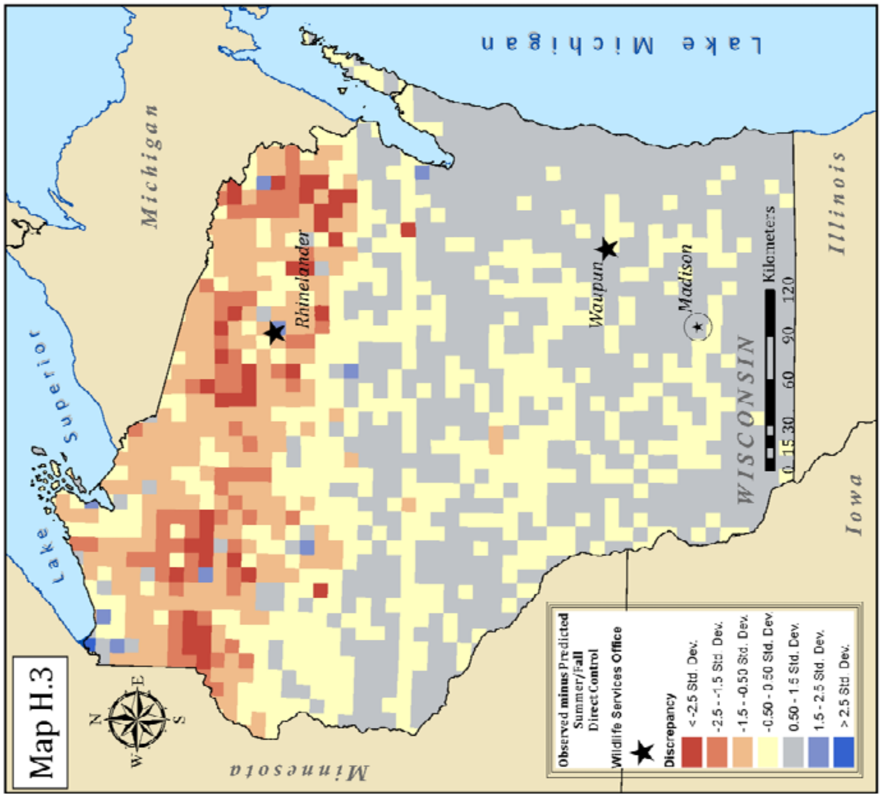
Map G.3

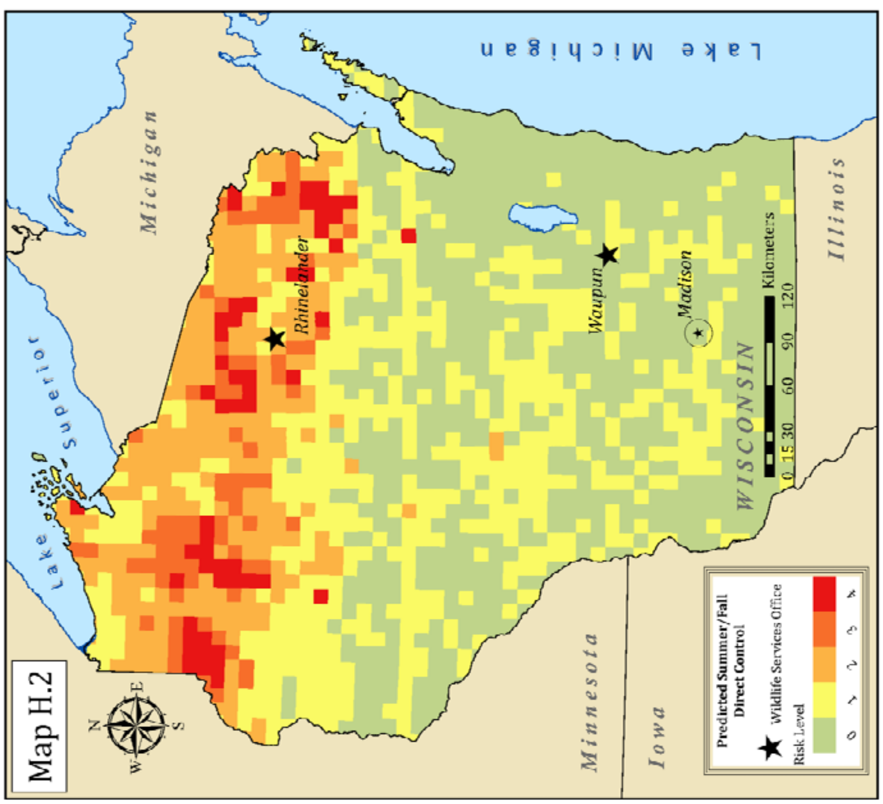

Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
0 15 30 60 90 120 Kilometers
Predicted Spring/Summer Direct Control
Wildlife Services Office
Risk Level
0
1
2
3
4

Map G.2

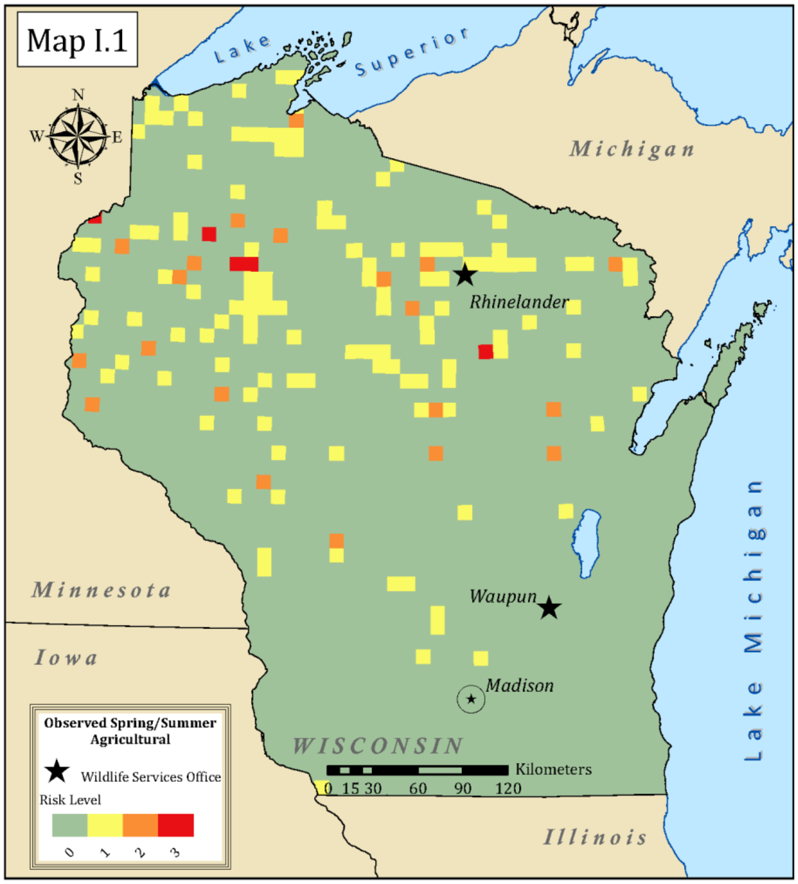
Late Summer & Fall Direct Control (Maps H.1 – H.3)

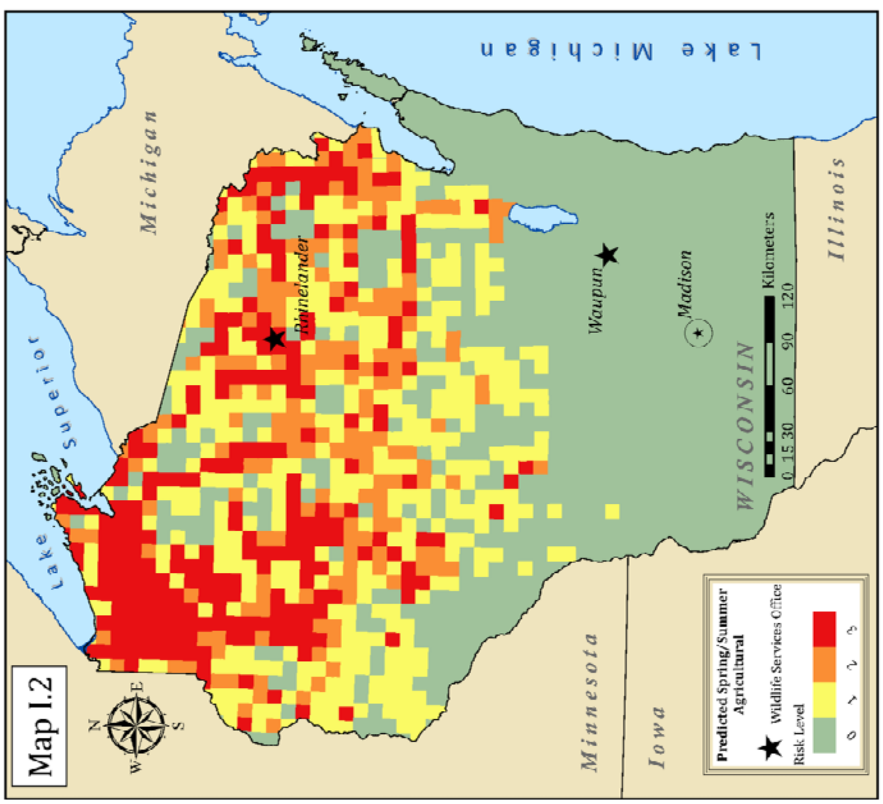



Map H.3
Observed minus Predicted Summer/Fall Direct Control
Wildlife Services Office
Discrepancy
< -2.5 Std. Dev.
-2.5 - -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev.
0.50 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.
Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
0 15 30 60 90 120 Kilometers

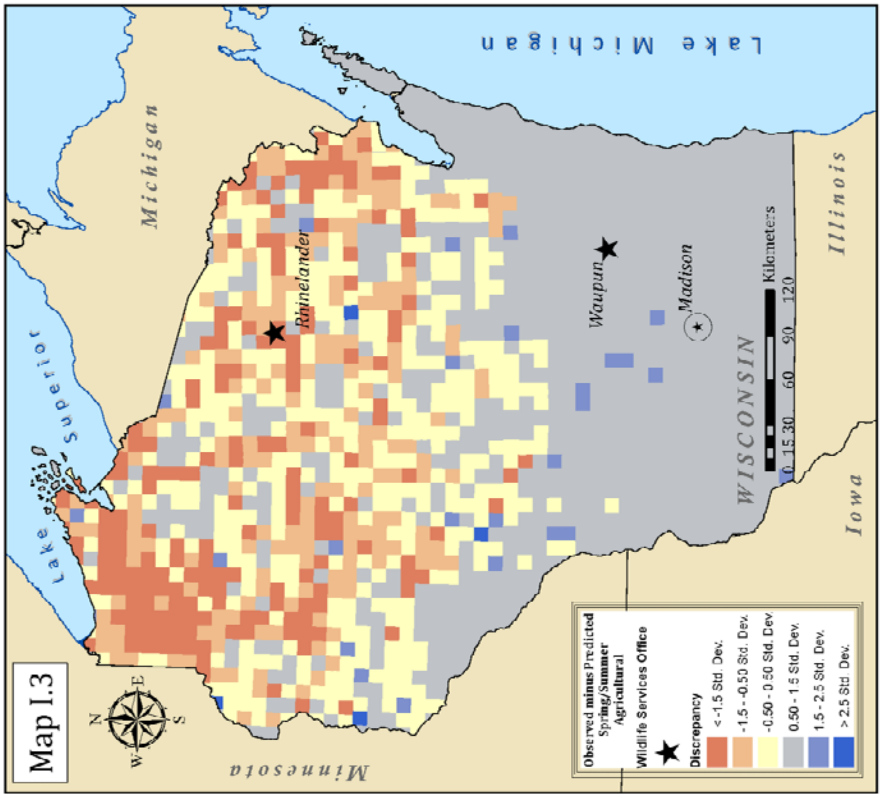

Map H.2
Predicted Summer/Fall Direct Control
Wildlife Services Office
Risk Level
0
1
2
3
4
Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
0 15 30 60 90 120 Kilometers

Spring & Early Summer Agricultural (Maps I.1 – I.3)



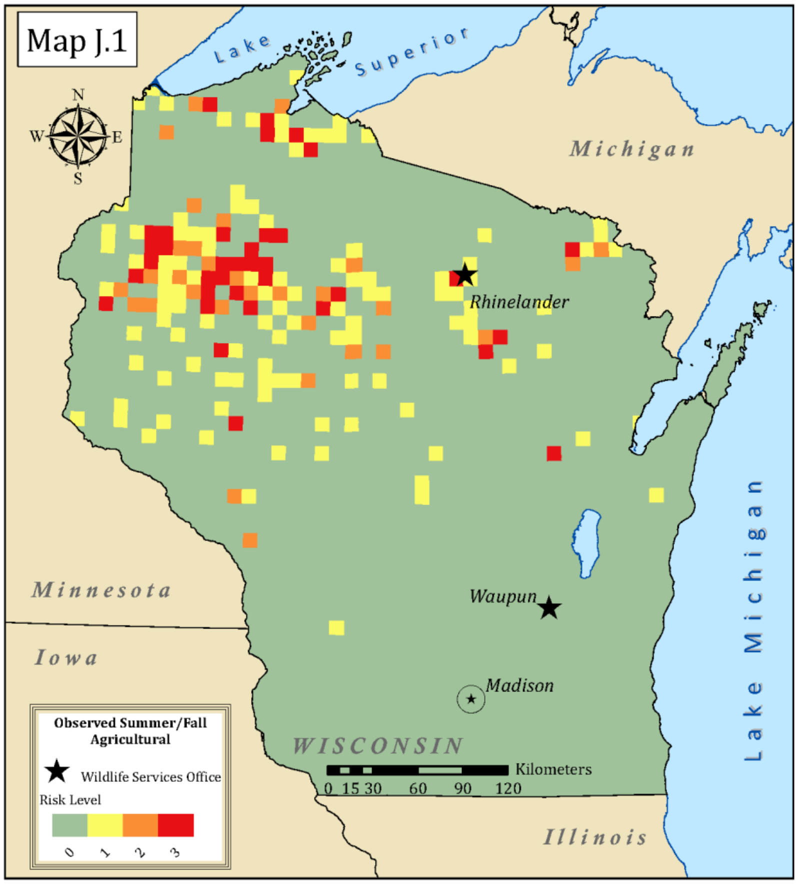


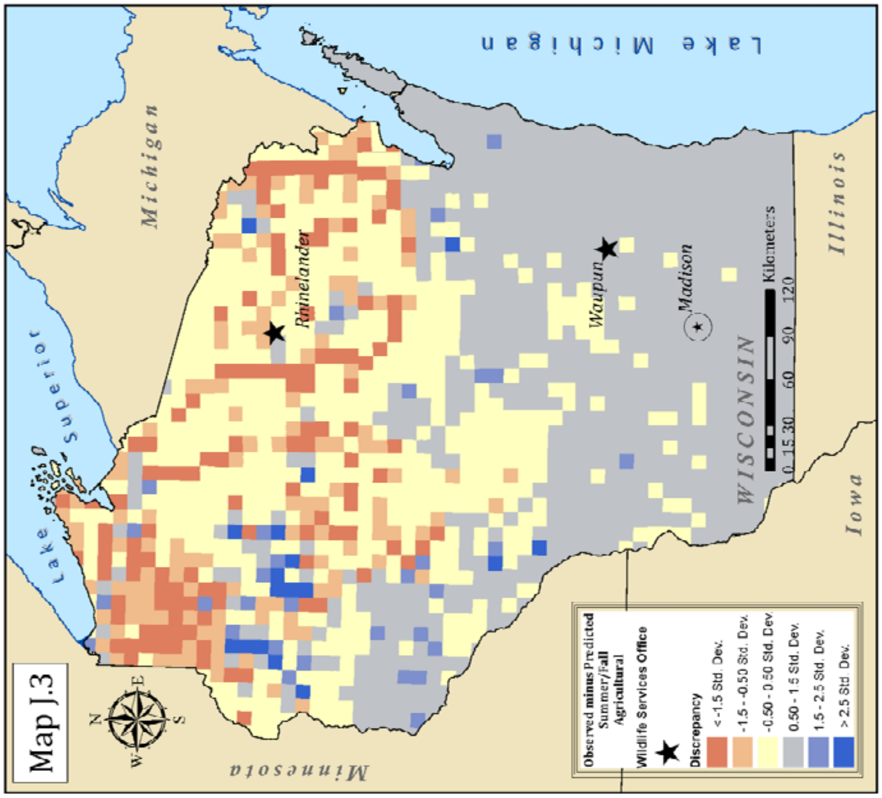
Map I.2
Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
Kilometers
0 15 30 60 90 120
N
E
S
W
Predicted Spring/Summer Agricultural
Wildlife Services Office
Risk Level
0
1
2
3

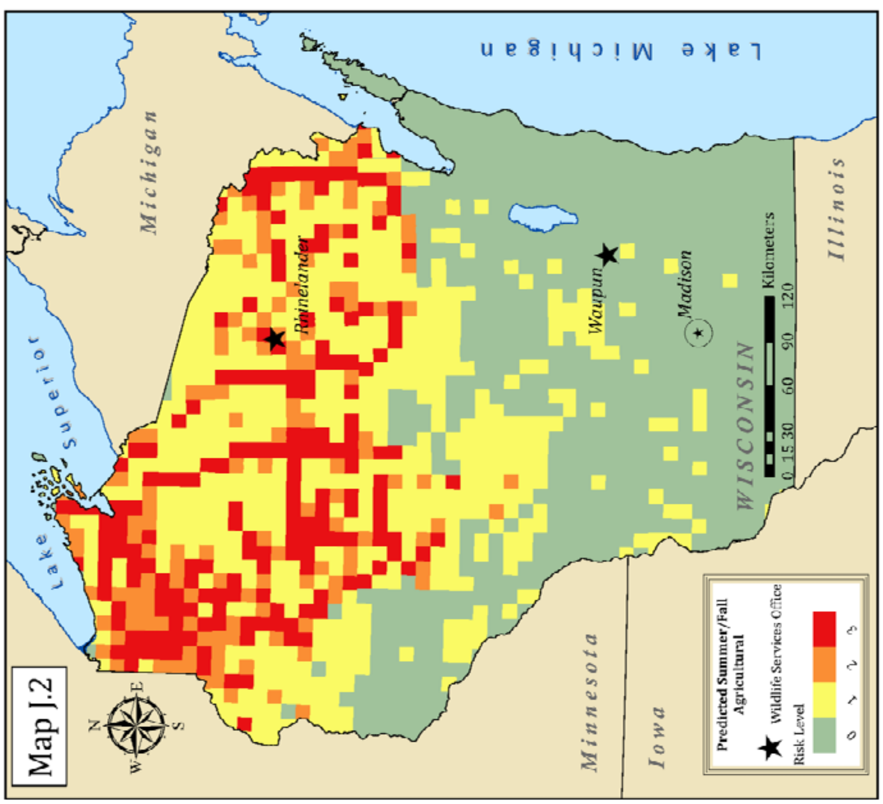


Map I.3
Lake Superior
Michigan
Lake Michigan
Minnesota
Iowa
Illinois
WISCONSIN
Rhinelander
Waupun
Madison
Kilometers
0 15 30 60 90 120
N
E
S
W
Observed minus Predicted Spring/Summer Agricultural
Wildlife Services Office
Discrepancy
< -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev
0.50 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.

Late Summer & Fall Agricultural (Maps J.1 – J.3)

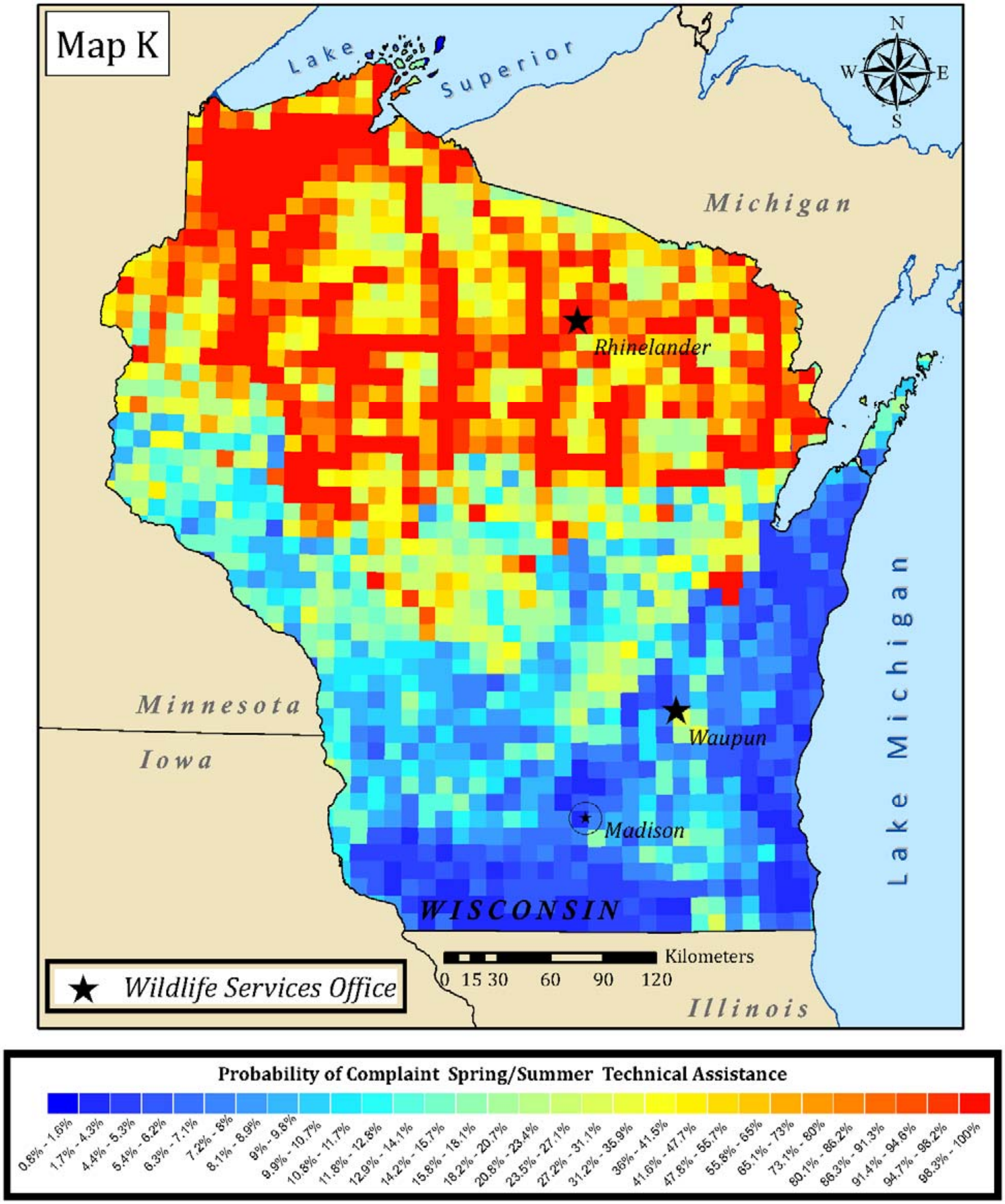



Map J.3
N
E
S
W
Lake Superior
Michigan
Lake Michigan
Rhinelander
Waupun
Madison
WISCONSIN
Illinois
Iowa
Minnesota
0 15 30 60 90 120 Kilometers
Observed minus Predicted Summer/Fall Agricultural
Wildlife Services Office
Discrepancy
< -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev
0.50 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.

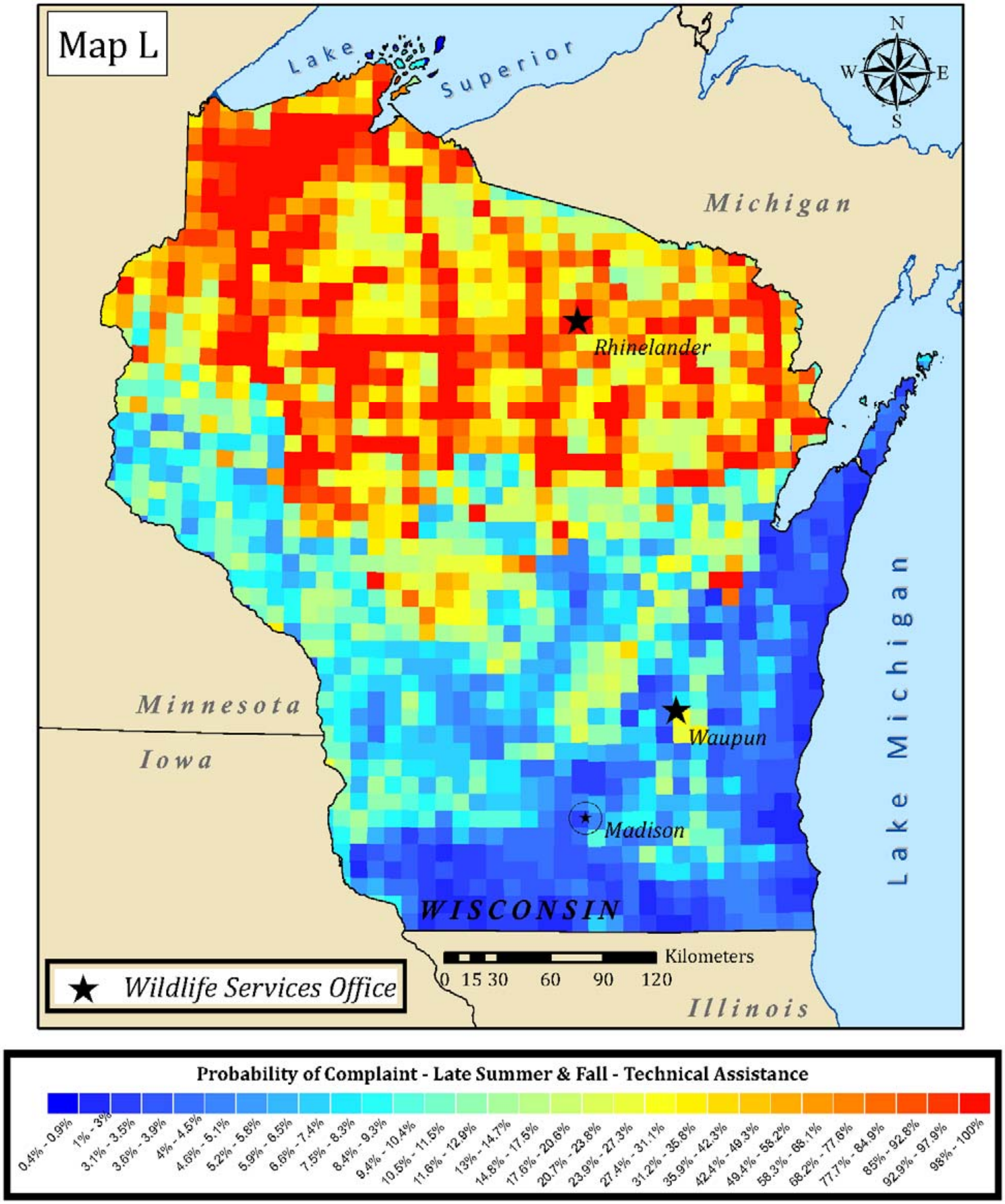

Map J.2
N
E
S
W
Lake Superior
Michigan
Lake Michigan
Rhinelander
Waupun
Madison
WISCONSIN
Illinois
Iowa
Minnesota
0 15 30 60 90 120 Kilometers
Predicted Summer/Fall Agricultural
Wildlife Services Office
Risk Level
0
1
2
3

This final series of maps (K – O) depict the probability of risk on a scale of 0-1 for each risk type from 2008-10. The probability of risk was determined using the logistic portion of the mixed models. The reader may compare the predicted risk to observed risk by comparing the maps that follow to the maps above (A, F.1 – J.1) which depict observed risk level to make a visual comparison. The reader should see that risk appears more widely spread in the following probability maps. This is fine. The maps that follow do not depict where complaints took place, but rather where they are likely to take place given the parameters of each model. These maps show which townships were most likely to have had a nuisance black bear complaint sometime between 2008 and 2010.

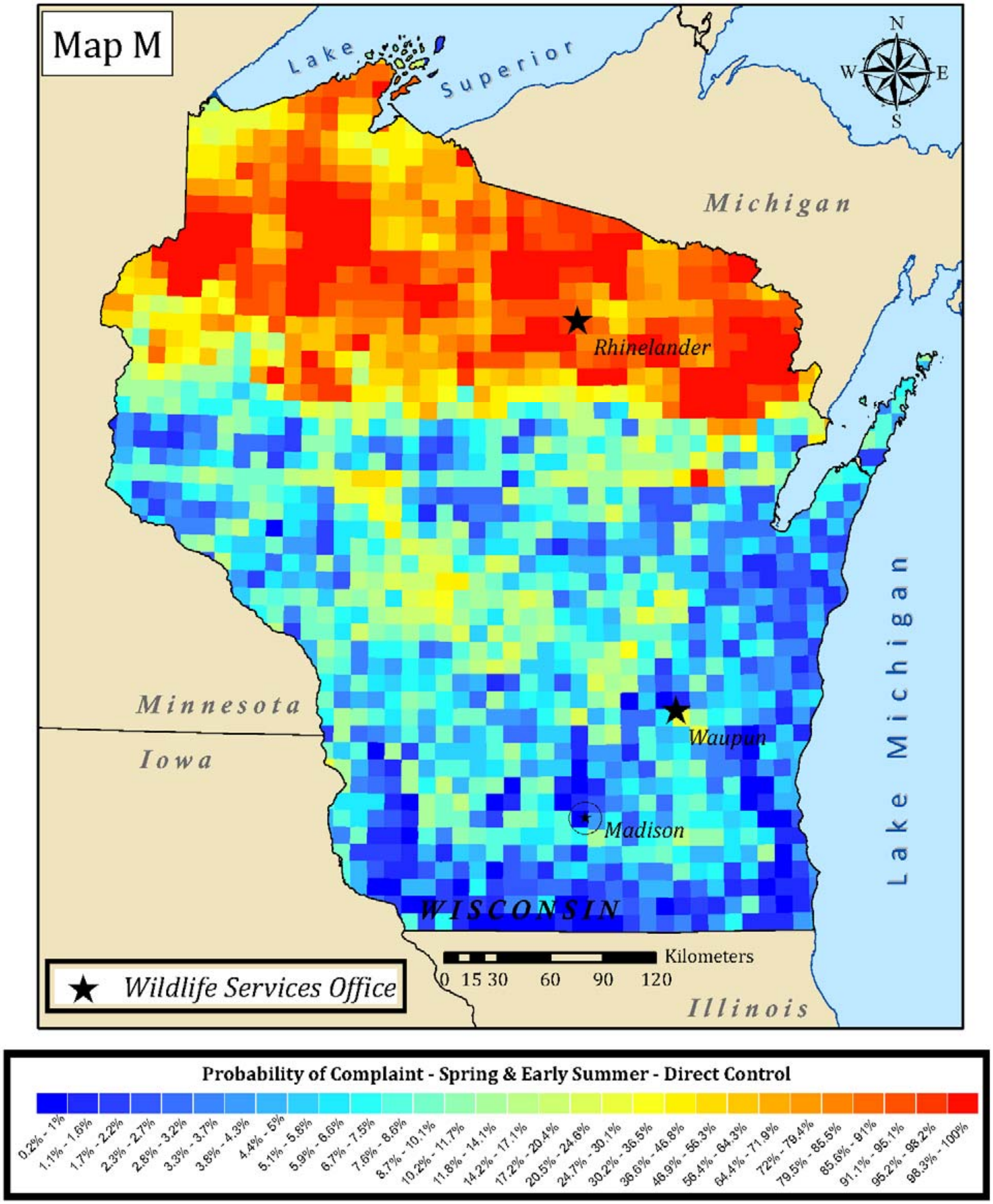
Technical Assistance Spring & Early Summer



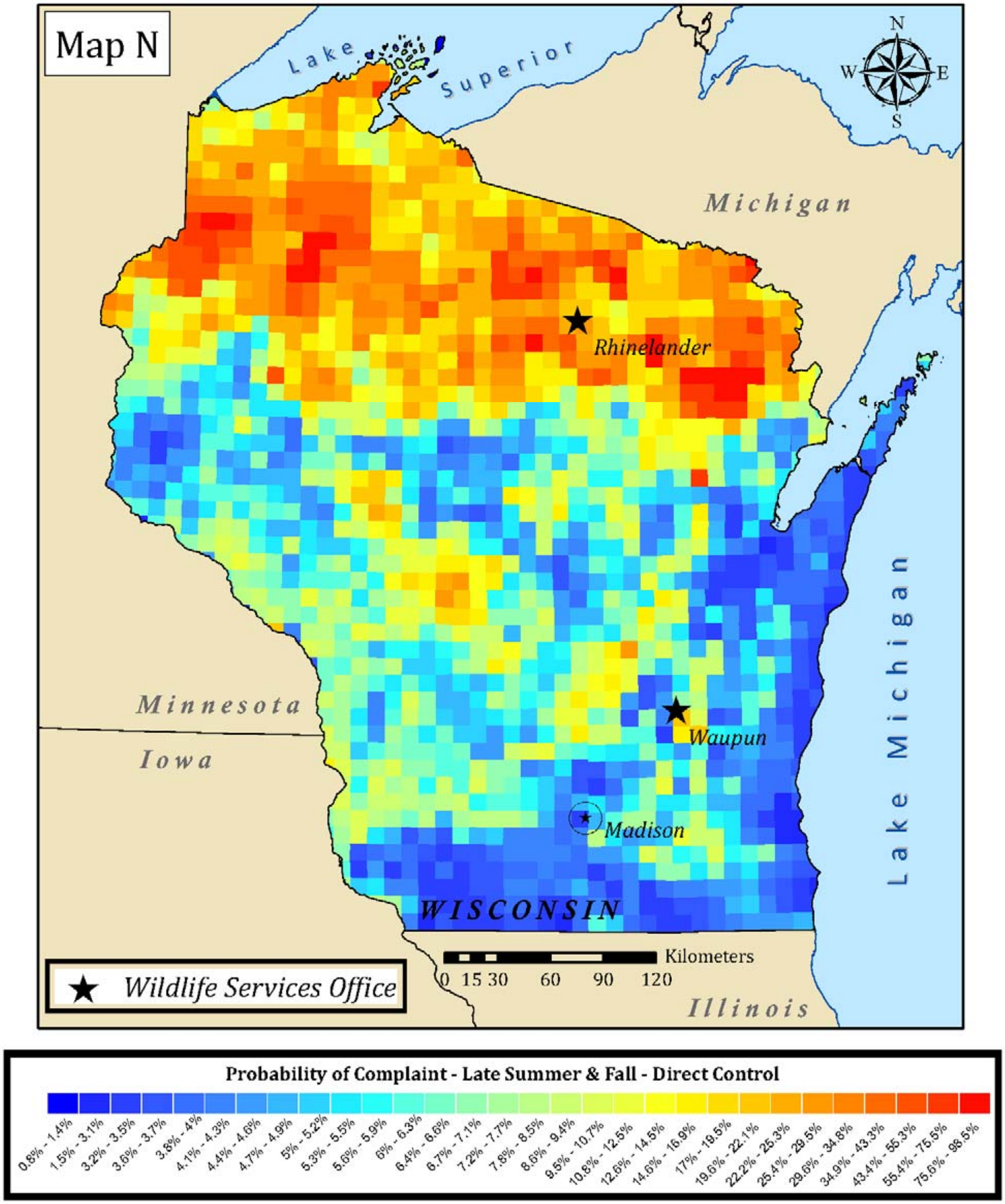
Technical Assistance Late Summer & Fall



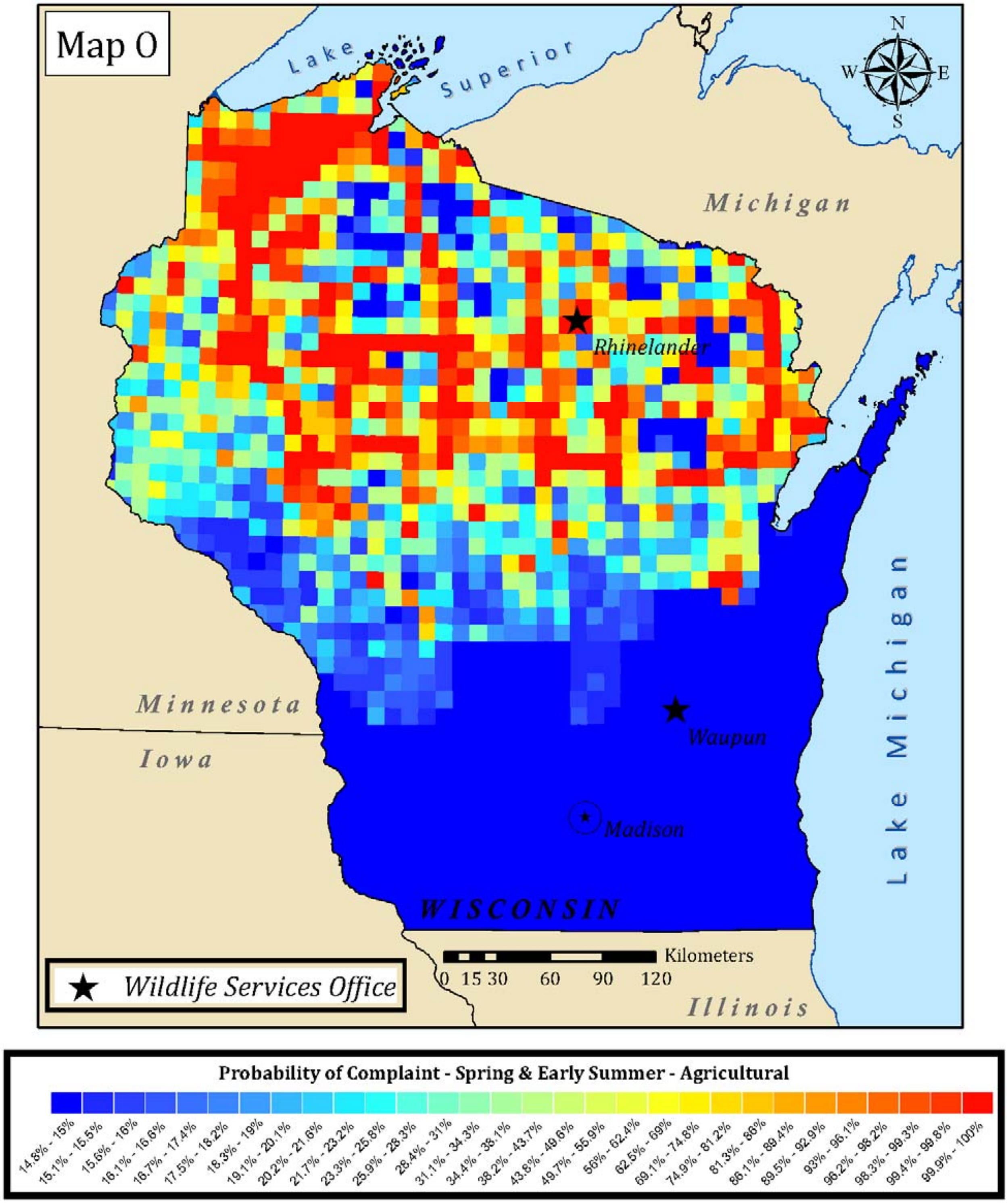
Direct Control Spring & Early Summer



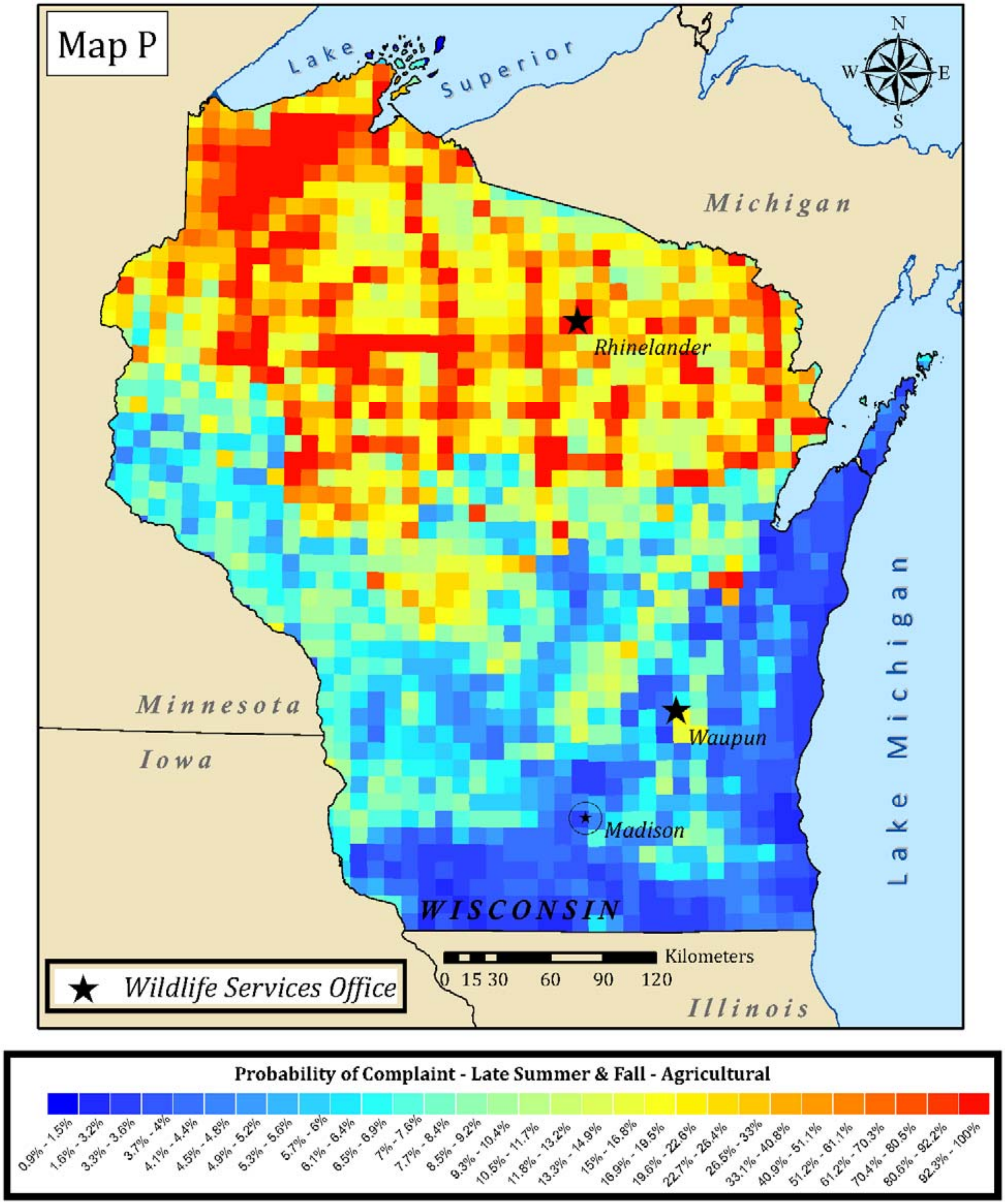
Direct Control Late Summer & Fall



Agricultural Spring & Early Summer



Agricultural Late Summer & Fall



DISCUSSION

Not surprisingly, there were similarities and differences among the six models predicting risk for bear complaints across Wisconsin from 2008 to 2010. For the logistic portion of the models, each conflict type had the same strongest predictors (interaction terms) regardless of season. For technical assistance and agricultural complaint risks, the term was hunter harvest multiplied with the area of low level land development (landscapes dominated by single-family households and impervious surfaces covering between 20% and 49% of the total land area). And, for direct control risk, the term was harvest multiplied with seasonal homes. For all risk types and seasons, the coefficient was negative and thus increased the probability of a complaint (decreased the probability of a false zero, π). Neither land development or hunter harvest or habitat suitability varied substantially from 2008 to 2010 at a state-wide level (Wisconsin DOA 2000 & 2010, Dhuey et al. 2008, 2009, 2010).

Harvest could be a reflection of the size or density of the local bear population[19], which is also supported by the fact that occupancy (*i.e.*, habitat suitability index) was present in 5 of the 6 logistic risk models. In 4 of these, it was the second strongest predictor. In addition, activities surrounding the fall bear harvest in Wisconsin occur throughout much of the summer months. For example, training bear hounds is permitted throughout the state from July 1st through August 31st. Also, baits may be placed from mid-April through the general harvest in September and early October

[19] Examining the correlation between complaints and hunter harvest from 1990 to 2011, I calculated a correlation coefficient of 0.82 (n = 21, $p < 0.001$; Voyles 2012).

(WDNR 2008, 2009, 2010). It is quite possible that these activities altered bear habits and thus had an impact on complaint risk for the seasons before and after 1 August. And, the effects of bear harvest likely extend beyond the general fall harvest. For example, fall harvest has been shown to correlate positively with future bear population estimates (Voyles 2012); and, bear harvest at the county level has been shown to be positively correlated with the number of complaints in subsequent years (Kapp 2005). Finally, the bear harvest structure in Wisconsin has been shown to affect bear which demographics are most at risk (Malcom 2010).

The probability maps for technical assistance and agricultural complaints differ little between the spring and early summer (Maps K & O) and late summer and fall (Map L & P) seasons. This is likely at least partially due to the fact that harvest, land development and habitat suitability remained constant. Seasonal homes, however, while likely remaining in place from 2008 to 2010, were probably occupied at higher capacities during the summer holidays which occurred between the end of May (Memorial Day weekend) and July 4th (Independence Day). This could help explain why spring and early summer direct control risk was relatively higher than during the late summer and fall seasons (Maps M & N).

Interpreting the risk for a complaint beyond probability required the entire mixed-effect ZIP model. These revealed further insight into when, where and possibly why the level of risk (*i.e.*, the number of complaints reported) varied among risk types and between seasons. One benefit of the mixed ZIP model is that predictors used to construct the logistic model need not have been the same for the Poisson distributed count model. The variables introduced into the count portion of the models indicate they had an influence on risk level, or in other words, helped explain the difference between few and many complaints.

The discrepancies between observed and predicted risk levels were not consistent, however. After relativizing predicted risk levels (which were biased low), the problem of underestimating risk was minimized. Still, there were townships that were observed to have had more complaints than predicted. This could mean that the years 2008-2010 were anomalous for those locations, and that they experienced an unusually high number of complaints. It could also indicate that the models lacked one or more variables that affected risk levels between 2008 and 2010. Either way, it is clear that while all predictor variables I selected were statistically significant for each model, the predictors are not prescriptive for the number of complaints at all locations or under all circumstances.

For technical assistance, seasonal homes and corn were strong predictors for the level of risk in both seasons. Seasonal homes were positively associated with risk level and corn negatively associated. One might conclude from this that seasonal homes (prevalent in parts of Northern Wisconsin) indicate the presence of seasonal residents and tourists who may be unfamiliar with black bears. There is also a possibility that bears in these areas had become accustomed to them in the spring months prior to when people occupied them. And, those bears may have been unwilling to relocate despite the influx of seasonal occupants (who may also provide ample anthropogenic foods) as a result (*e.g.*, Olson 1997, Mattson 1990, and McCullough 1982). Maps C and

F.2 show that some of the townships with the highest predicted risk levels appear to coincide with areas known for their upscale lake homes and lakeside resorts. Corn, on the other hand, is generally associated with Southern Wisconsin and tends not to be a strong correlate with black bear occupancy (MacFarland 2009). Its strong negative association with risk level was likely due in part to this. Still, it would be beneficial to examine the effects of corn in areas where it is not common. Areas such as Sawyer County, Wisconsin have high complaint levels and also relatively numerous amounts of corn (Koele 2010). Any positive association between corn and risk level in such areas might have been inundated by corn crops in the South. Oak was shown to have a negative association with late summer and fall technical assistance risk level which might indicate that these areas provided fall mast and were thus less likely to experience high complaint levels. This would correspond to findings in Northern Minnesota by Garshelis (1989). Hunter harvest was negatively associated with late summer and fall technical assistance complaints. This is the only instance where hunter harvest had a negative association with risk. It could be that hunting reduced these types of complaints or that areas with higher bear harvests were less likely to experience high levels of complaints.

An interaction between low level land development and hunter harvest was significant for spring and early summer direct control risk. This interaction had a positive association with risk level between 2008 and 2010. This suggests that low level developed areas near areas with higher harvests were more likely to experience higher complaint levels. This could be a product of baiting for bears in the late spring and summer months which occurs extensively on small chunks of forested land relatively close to human habitation (MacFarland, pers. comm.) For late summer and fall direct control risk, corn was the best single predictor having had a negative association with risk (*i.e.*, more corn indicated less risk). This could have been due to high numbers of bears exploiting corn fields in August and September (Appendix, Fig. A.3). It may be that bears in areas with much corn were more likely to be implicated for agricultural damage than for residential nuisance behavior. This would also help explain the negative association between corn and technical assistance complaints during the late summer and fall season. Another explanation similar to one already put forth, is that corn is strongly associated with Southern Wisconsin and the negative association between corn and risk level is a product of this.

Spring and early summer agricultural complaints primarily involved small domestic animals (*e.g.*, chickens and rabbits) and apiaries. Risk levels for these types of complaints were fairly scattered and showed no obvious pattern (Map I.2). This is not surprising since these types of agricultural practices or hobbies likely occur throughout rural Wisconsin. Corn was the best single predictor of spring and early summer agricultural risk level. The association between corn and risk level in this model was negative. It might be that cropland agriculture provides poor habitat (*e.g.*, no food and little cover) for bears in the spring and early summer months, and so they avoid these areas then. This could also help explain why corn had a negative association with spring and early summer technical assistance risk level. Additionally, it is important to remember that corn is not uniform across Wisconsin, and many areas with high corn production are devoid of black bears. An interaction between low level land development and black bear occupancy was the best predictor for late summer and fall agricultural risk level. This was the only time this interaction term was selected for any model. This term had a negative association with expected risk level. This could indicate that townships with higher quality habitat near low level developed areas were less likely to have experienced agricultural damage in late summer and early fall. Since the vast majority of these complaints involved corn, one might expect that such areas generally either lacked crop fields and/or that more suitable habitat decreased the likelihood for high levels of crop damage.

In sum, it is evident that different predictors came into play for predicting risk from 2008 to 2010. These predictors varied between seasons and among types of complaints. It is interesting to see that many predictors were most significant when included as part of an interaction term. This suggests that it is not cut and dry when it comes to predicting when or where black bears may generate complaints. My modeling methods were limited to a degree by their spatial and temporal generalizations. However, I would argue that by averaging complaints across years, I present models that are more representative of a "typical" year in Wisconsin. In addition, by extending my study area beyond occupied bear range, I provided some insight into where bear conflict could occur in the future should bears expand their range into previously unoccupied areas.

I would suggest future research be conducted to investigate risk at a finer geographic scale (*e.g.*, examining landscape attributes at individual conflict sites or for hunting zones). One purpose for these models was the risk maps they produced. I intended these to be of use for managers who must optimize their management efforts in space and time due to budgetary and staff constraints. When interpreting my models and their accompanying risk maps, I would strongly suggest each be examined in relation to the others and not in isolation.

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Concluding Remarks

Let me recommend first and foremost that the Wisconsin Department of Natural Resources (WDNR) and Wisconsin USDA-APHIS, Wildlife Services (WS) review current policies on bear complaints. Despite a steadily increasing bear population since the late 1980s, the number of bear complaints has not increased. It is good to know that the rising population has not been mirrored by a dramatic increase in complaints. The next step forward would be to investigate if and how bear complaints might be reduced.

WDNR hopes that hunting will reduce nuisance complaints. But, there is no evidence to suggest that increased hunter take has reduced complaints in Wisconsin. There are at least two reasons for this. First, Wisconsin's bear harvest is not designed at a spatial scale on par with nuisance bears or bear complaints. Quotas are set at a spatial scale much too large to have any local impact on nuisance complaints, and my research (and that of others) suggests that complaints are regional or local. Second, I am unaware of any current efforts to assess the effectiveness of harvest on reducing conflict. I recommend future research address the question of whether increased hunting pressure has reduced bear complaints in recent years. My research (and that of Kapp 2005 & Treves et al. 2010) indicates a positive correlation between bear harvest and bear complaints at several spatial scales. But, these studies are limited to correlation at larger-than-optimal spatial scales. Harvest data are collected by deer management unit (DMU) and complaint locations are known precisely. By focusing in on the appropriate scale of analysis (individual bears and individual properties) the cooperating agencies have a better chance of understanding the effect of harvest on bear behavior. This is surely a project worth undertaking if harvest quotas continue to be justified by the number of nuisance bear complaints in a region.

Secondly, I recommend that policies regarding nuisance live-trapping and translocation be compared to those surrounding technical assistance. My research suggests the impacts of translocation do not extend far beyond an individual's property in that they do not reduce subsequent complaints near that property. I suggest WS and WDNR investigate the current biological and economic impacts of translocation and determine to what degree its continued use is warranted. To help answer these questions, I suggest live-trapped bears be identified in some way (*e.g.*, ear-tagged). There would be multiple benefits to this. For one, it would help answer whether hunters harvest nuisance bears. It would also serve to help managers understand the degree to which trapped bears repeat or continue nuisance behavior.

Third, I would recommend the imminent revision of Wisconsin's Bear Management Plan incorporate a social acceptance survey by which to measure public opinion regarding *nuisance* bear management. Questions in the survey could help managers understand public attitudes toward translocation, euthanasia, agricultural compensation, and harvesting to reduce conflict.

Regarding the nuisance bear program, providing technical assistance to complainants is far and away the most common type of agency-public interaction. Some of these interactions are negative and serve little more than to enhance inimical attitudes toward natural resource agencies and staff (*e.g.*, Berman 1997). I recommend technical assistance be optimized to reduce negative interactions. By refocusing efforts on proactive measures – like community workshops – to prevent conflict and alter perceptions about preventative strategies, time spent responding to conflicts might be minimized (*e.g.*, Wilson et al. 2008, Bannister et al. 2003). No doubt, there will be a continued need for a conflict response hotline because no reasonable amount of abatement can prevent every human-bear conflict. It may, however, reduce the need for multiple calls with individual property owners and perhaps ensuing reactive management.

My last recommendation is not wholly separate from those I have already mentioned. In essence, my final recommendation is a way to help implement my previous suggestions. My research suggests human-black bear conflict in Wisconsin is not ubiquitous in time or space. There are drivers of conflict that vary across landscapes, among communities and between seasons. Response protocols should attempt to mimic these variations. I recommend the nuisance bear program retain a strong agency head, but allow communities to do more of the legwork. There is a host of knowledgeable and dedicated agency staff that spends much of their time addressing inane complaints like "bear sightings." Designating community personnel who could encourage their communities to use bear-proof garbage containers, to take down their feeders during summer months, and to learn to coexist with local wildlife (and perhaps being allowed to assume regulatory powers) would relieve many existing burdens that higher-level state and federal agency staff now shoulder. The current black bear nuisance program asks citizens to rely on a centralized support structure that is often stretched thin. As counterintuitive as it sounds, a reduction in complaints might be attainable if WDNR and WS are willing to do less.

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Appendix

Figure A.1

A trending upward Wisconsin black bear population estimate and hunter harvest alongside a seemingly cyclical trend in nuisance complaints from the beginning of USDA-APHIS, Wildlife Services nuisance bear program contract to 2010 (WDNR 2010, USDA-APHIS, Wildlife Services Wisconsin 1990 through 2010).

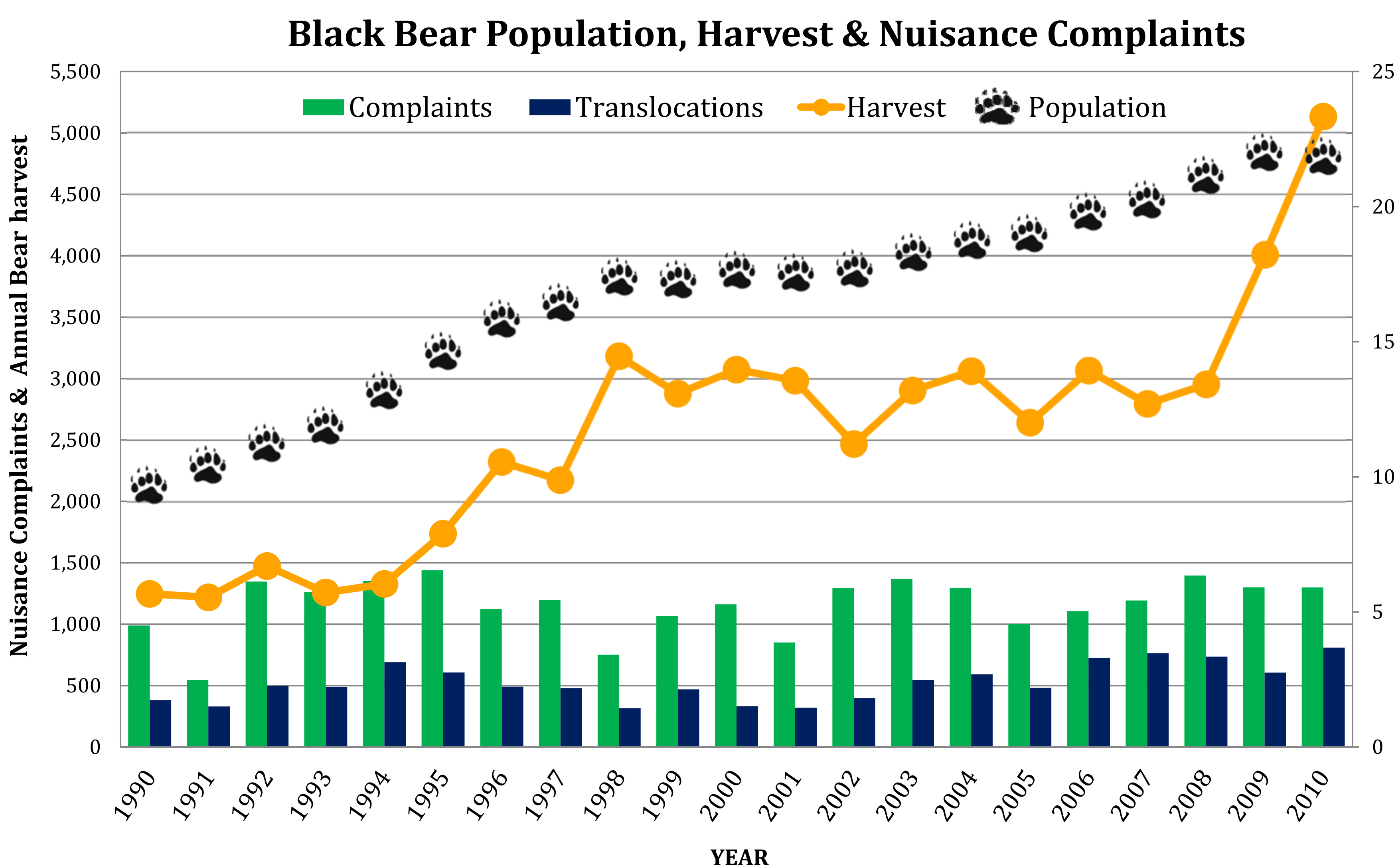

Figure A.2

Correlation Matrix between Variables

Strength of the relationship between two variables is color-coded. Red indicates a negative correlation and blue a positive correlation. All variables were measured at the PLSS township level. Predictor variables were, when applicable, measured as an annual average for 2008-10 (indicated by *). Response variables were measured as the average annual risk level for 2008-10 (indicated by †). Response variables removed due to collinearity are indicated by ′. Refer to pages 31-42 for complete variable descriptions.

Key to variables:

Reponse	***Description***
TA_SS†	technical assistance; spring - early summer
TA_SF†	technical assistance; late summer - fall
DC_SS†	direct control; spring - early summer
DC_SF†	direct control; late summer - fall
AG_SS†	agricultural; spring - early summer
AG_SF†	agricultural; late summer - fall

Predictor	***Description***
harvest*	average annual hunter harvest
seashome	estimated number of seasonal homes
corn*	average annual corn crop coverage
ldev	low level land development
mdev′	medium level land development
hdev′	high level land development
oak	oak tree coverage
occ	occupancy probability / habitat suitability index

	TA_SS	TA_SF	DC_SS	DC_SF	AG_SS	AG_SF	harvest	seashome	corn	ldev	mdev	hdev	oak	occ	
TA_SS	1.0000	0.5155	0.5810	0.3905	0.2457	0.2722	0.3595	0.0545	-0.2805	-0.0686	-0.0453	-0.0402	-0.1162	0.2764	TA_SS
TA_SF	0.5155	1.0000	0.4273	0.4227	0.1262	0.1921	0.1545	0.0334	-0.1776	0.0073	0.0197	0.0159	-0.1068	0.1284	TA_SF
DC_SS	0.5810	0.4273	1.0000	0.4302	0.1987	0.2289	0.4354	0.0413	-0.2659	-0.0927	-0.0626	-0.0562	-0.1259	0.3360	DC_SS
DC_SF	0.3905	0.4227	0.4302	1.0000	0.1722	0.1723	0.2015	0.0275	-0.1570	-0.0284	-0.0141	-0.0170	-0.0716	0.1882	DC_SF
AG_SS	0.2457	0.1262	0.1987	0.1722	1.0000	0.2264	0.1821	0.0150	-0.1346	-0.0549	-0.0366	-0.0359	-0.0684	0.1066	AG_SS
AG_SF	0.2722	0.1921	0.2289	0.1723	0.2264	1.0000	0.3018	0.0171	-0.1448	-0.0759	-0.0523	-0.0450	-0.0784	0.1594	AG_SF
harvest	0.3595	0.1545	0.4354	0.2015	0.1821	0.3018	1.0000	0.0538	-0.4374	-0.2698	-0.1662	-0.1486	-0.2736	0.6287	harvest
seashome	0.0545	0.0334	0.0413	0.0275	0.0150	0.0171	0.0538	1.0000	-0.1443	0.0286	0.0182	0.0168	0.0244	0.1051	seashome
corn	-0.2805	-0.1776	-0.2659	-0.1570	-0.1346	-0.1448	-0.4374	-0.1443	1.0000	0.1868	0.1237	0.1185	0.1284	-0.4163	corn
ldev	-0.0686	0.0073	-0.0927	-0.0284	-0.0549	-0.0759	-0.2698	0.0286	0.1868	1.0000	0.8700	0.8474	-0.0868	-0.3512	ldev
mdev	-0.0453	0.0197	-0.0626	-0.0141	-0.0366	-0.0523	-0.1662	0.0182	0.1237	0.8700	1.0000	0.9727	-0.0791	-0.2529	mdev
hdev	-0.0402	0.0159	-0.0562	-0.0170	-0.0359	-0.0450	-0.1486	0.0168	0.1185	0.8474	0.9727	1.0000	-0.0831	-0.2384	hdev
oak	-0.1162	-0.1068	-0.1259	-0.0716	-0.0684	-0.0784	-0.2736	0.0244	0.1284	-0.0868	-0.0791	-0.0831	1.0000	0.0154	oak
occ	0.2764	0.1284	0.3360	0.1882	0.1066	0.1594	0.6287	0.1051	-0.4163	-0.3512	-0.2529	-0.2384	0.0154	1.0000	occ
	TA_SS	TA_SF	DC_SS	DC_SF	AG_SS	AG_SF	harvest	seashome	corn	ldev	mdev	hdev	oak	occ	

Figure A.3

The summed agricultural complaints and sum number of trapped bears from 2008 to 2010. Overlaid are the estimate average corn developmental stages in Southern Wisconsin for those years. Shown is kernel "milk" content and the average week (XX) in which the corn cob reached that stage of development (UW Department of Agronomy, 2008, 2009, &2010).

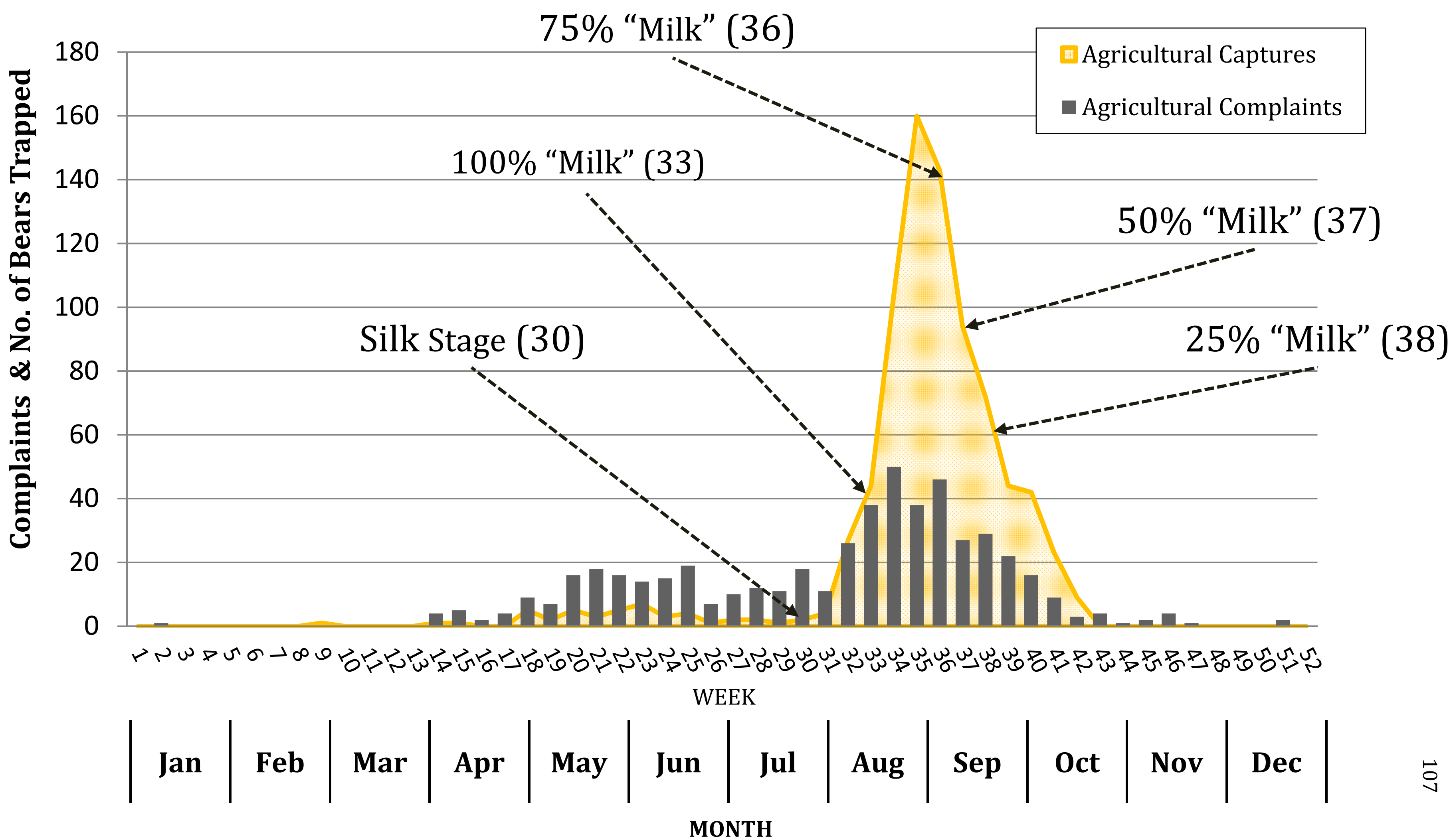

Figure A.4

Theoretical framework depicting the relative likelihood of an individual bear to be willing to tolerate humans given its age, sex and net relative predicament (*i.e.*, stress level). A lower number may indicate a higher likelihood of seeking anthropogenic food sources (*from* Mattson 1990).

Table 1. Rank order of bear classes according to security-dominance mediated access to food and habitat (A), unit-mass energy requirements (B), and the relative predicament of bear classes in meeting their energy requirements (differences between B and A).

(A) Security-dominance mediated access	(B) Unit-mass energy requirements	(B-A) Relative predicament	
1. Adult males	1. Females with COY	Adult males	(2)
2. Lone adult females	(lactation)	Lone adult females	(2)
3. Females with yearlings	2. Females with yearlings	Subadult females	(1)
Subadult females	(food-sharing)	Subadult males	(-1)
4. Females with COY[a]	3. Adult males	Females with yearlings	(-1)
(security mediated)	Subadult males	Females with COY	(-3)
Subadult males	4. Lone adult females		
(dominance mediated)	Subadult females		

[a] COY = cubs-of-the-year.

```
##########ta.ss = Technical assistance Spring / Early Summer

>ta.ss.null=zeroinfl(ta.ss~1|1,data=resp,dist="poisson")
>ta.ss.a=zeroinfl(ta.ss~1|harvest,data=resp,dist="poisson")
>ta.ss.b=zeroinfl(ta.ss~1|I(harvest*ldev),data=resp,dist="poisson")
>ta.ss.c=zeroinfl(ta.ss~1|I(harvest*ldev)+occ,data=resp,dist="poisson")
>ta.ss.d=zeroinfl(ta.ss~1|I(harvest*ldev)+occ+corn,data=resp,dist="poisson")
>ta.ss.e=zeroinfl(ta.ss~1|I(harvest*ldev)+occ+corn+seashome,data=resp,dist="poisson")
>ta.ss.f=zeroinfl(ta.ss~seashome|I(harvest*ldev)+occ+corn+seashome,data=resp,dist="poisson")
>ta.ss.g=zeroinfl(ta.ss~seashome+corn|I(harvest*ldev)+occ+corn+seashome,data=resp,dist="poisson")

>lrtest(ta.ss.null,ta.ss.a)
>lrtest(ta.ss.a,ta.ss.b)
>lrtest(ta.ss.b,ta.ss.c)
>lrtest(ta.ss.c,ta.ss.d)
>lrtest(ta.ss.d,ta.ss.e)
>lrtest(ta.ss.e,ta.ss.f)
>lrtest(ta.ss.f,ta.ss.g)
>lrtest(ta.ss.null,ta.ss.g)

Likelihood ratio test

Model 1: ta.ss ~ 1 | 1
Model 2: ta.ss ~ 1 | harvest
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -1308.6
2   3 -1141.1  1 335.08  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Likelihood ratio test

Model 1: ta.ss ~ 1 | harvest
Model 2: ta.ss ~ 1 | I(harvest * ldev)
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -1141.1
2   3 -1108.2  0 65.675  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ta.ss ~ 1 | I(harvest * ldev)
Model 2: ta.ss ~ 1 | I(harvest * ldev) + occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -1108.2
2   4 -1066.9  1 82.704  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ta.ss ~ 1 | I(harvest * ldev) + occ
Model 2: ta.ss ~ 1 | I(harvest * ldev) + occ + corn
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   4 -1066.9
2   5 -1055.3  1 23.143  1.504e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Likelihood ratio test

Model 1: ta.ss ~ 1 | I(harvest * ldev) + occ + corn
Model 2: ta.ss ~ 1 | I(harvest * ldev) + occ + corn + seashome
  #Df  LogLik Df Chisq Pr(>Chisq)
1   5 -1055.3
2   6 -1046.7  1 17.31  3.176e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ta.ss ~ 1 | I(harvest * ldev) + occ + corn + seashome
Model 2: ta.ss ~ seashome | I(harvest * ldev) + occ + corn + seashome
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   6 -1046.7
2   7 -1028.6  1 36.145  1.832e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ta.ss ~ seashome | I(harvest * ldev) + occ + corn + seashome
Model 2: ta.ss ~ seashome + corn | I(harvest * ldev) + occ + corn + seashome
  #Df  LogLik Df Chisq Pr(>Chisq)
1   7 -1028.6
2   8 -1025.0  1 7.273      0.007 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Likelihood ratio test

Model 1: ta.ss ~ 1 | 1
Model 2: ta.ss ~ seashome + corn | I(harvest * ldev) + occ + corn + seashome
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -1308.6
2   8 -1025.0  6 567.33  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>AIC(ta.ss.null,ta.ss.a,ta.ss.b,ta.ss.c,ta.ss.d,ta.ss.e,ta.ss.f,ta.ss.g)

           df      AIC
ta.ss.null  2 2621.239
ta.ss.a     3 2288.156
ta.ss.b     3 2222.481
ta.ss.c     4 2141.776
ta.ss.d     5 2120.633
ta.ss.e     6 2105.324
ta.ss.f     7 2071.179
ta.ss.g     8 2065.906
```

```
>summary(ta.ss.g)

Call:
zeroinfl(formula = ta.ss ~ seashome + corn | I(harvest * ldev) + occ +
    corn + seashome, data = resp, dist = "poisson")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-1.39029 -0.40058 -0.18092 -0.06056 12.24889

Count model coefficients (poisson with log link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  2.821e-01  6.217e-02   4.538 5.67e-06 ***
seashome     1.116e-02  1.754e-03   6.363 1.98e-10 ***
corn        -2.576e-04  8.985e-05  -2.867  0.00415 **

Zero-inflation model coefficients (binomial with logit link):
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        5.153e+00  6.391e-01   8.063 7.47e-16 ***
I(harvest * ldev) -2.364e+01  4.229e+00  -5.589 2.28e-08 ***
occ               -5.263e+00  8.546e-01  -6.158 7.36e-10 ***
corn               5.444e-04  1.992e-04   2.733 0.006281 **
seashome          -1.423e-02  4.309e-03  -3.302 0.000961 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 25
Log-likelihood: -1025 on 8 Df
Likelihood ratio test
```

```
##########ta.sf = Technical assistance Late Summer / Early Fall

>ta.sf.null=zeroinfl(ta.sf~1|1,data=resp,dist="poisson")
>ta.sf.a=zeroinfl(ta.sf~1|harvest,data=resp,dist="poisson")
>ta.sf.b=zeroinfl(ta.sf~1|I(harvest*ldev),data=resp,dist="poisson")
>ta.sf.c=zeroinfl(ta.sf~1|I(harvest*ldev)+occ,data=resp,dist="poisson")
>ta.sf.d=zeroinfl(ta.sf~1|I(harvest*ldev)+occ+corn,data=resp,dist="poisson")
>ta.sf.e=zeroinfl(ta.sf~seashome|I(harvest*ldev)+occ+corn,data=resp,dist="poisson")
>ta.sf.f=zeroinfl(ta.sf~seashome+harvest|I(harvest*ldev)+occ+corn,data=resp,dist="poisson")
>ta.sf.g=zeroinfl(ta.sf~seashome+harvest+oak|I(harvest*ldev)+occ+corn,data=resp,dist="poisson")

>lrtest(ta.sf.null,ta.sf.a)
>lrtest(ta.sf.a,ta.sf.b)
>lrtest(ta.sf.b,ta.sf.c)
>lrtest(ta.sf.c,ta.sf.d)
>lrtest(ta.sf.d,ta.sf.e)
>lrtest(ta.sf.e,ta.sf.f)
>lrtest(ta.sf.f,ta.sf.g)
>lrtest(ta.sf.null,ta.sf.g)

Likelihood ratio test

Model 1: ta.sf ~ 1 | 1
Model 2: ta.sf ~ 1 | harvest

  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -593.80
2   3 -564.98  1 57.636  3.154e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Likelihood ratio test

Model 1: ta.sf ~ 1 | harvest
Model 2: ta.sf ~ 1 | I(harvest * ldev)

  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -564.98
2   3 -531.81  0 66.335  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ta.sf ~ 1 | I(harvest * ldev)
Model 2: ta.sf ~ 1 | I(harvest * ldev) + occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -531.81
2   4 -511.41  1 40.796   1.69e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ta.sf ~ 1 | I(harvest * ldev) + occ
Model 2: ta.sf ~ 1 | I(harvest * ldev) + occ + corn
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   4 -511.41
2   5 -498.56  1 25.701  3.987e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Likelihood ratio test

Model 1: ta.sf ~ 1 | I(harvest * ldev) + occ + corn
Model 2: ta.sf ~ seashome | I(harvest * ldev) + occ + corn
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   5 -498.56
2   6 -488.14  1 20.849  4.971e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ta.sf ~ seashome | I(harvest * ldev) + occ + corn
Model 2: ta.sf ~ seashome + harvest | I(harvest * ldev) + occ + corn
  #Df  LogLik Df Chisq Pr(>Chisq)
1   6 -488.14
2   7 -479.15  1 17.97  2.244e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ta.sf ~ seashome + harvest | I(harvest * ldev) + occ + corn
Model 2: ta.sf ~ seashome + harvest + oak | I(harvest * ldev) + occ +
    corn
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   7 -479.15
2   8 -476.08  1 6.1477    0.01316 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Likelihood ratio test

Model 1: ta.sf ~ 1 | 1
Model 2: ta.sf ~ seashome + harvest + oak | I(harvest * ldev) + occ +
    corn
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -593.80
2   8 -476.08  6 235.43  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>AIC(ta.sf.null,ta.sf.a,ta.sf.b,ta.sf.c,ta.sf.d,ta.sf.e,ta.sf.f,ta.sf.g)

           df       AIC
ta.sf.null  2 1191.5920
ta.sf.a     3 1135.9559
ta.sf.b     3 1069.6204
ta.sf.c     4 1030.8246
ta.sf.d     5 1007.1240
ta.sf.e     6  988.2755
ta.sf.f     7  972.3051
ta.sf.g     8  968.1574
```

```
>summary(ta.sf.g)

Call:
zeroinfl(formula = ta.sf ~ seashome + harvest + oak | I(harvest * ldev) +
    occ + corn, data = resp, dist = "poisson")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-1.53221 -0.34820 -0.12155 -0.03626  9.46450

Count model coefficients (poisson with log link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.1060153  0.2151190  -0.493   0.6221
seashome     0.0128261  0.0029350   4.370 1.24e-05 ***
harvest     -1.2276725  0.2774070  -4.426 9.62e-06 ***
oak         -0.0010258  0.0004397  -2.333   0.0196 *

Zero-inflation model coefficients (binomial with logit link):
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        6.095e+00  1.149e+00   5.303 1.14e-07 ***
I(harvest * ldev) -1.617e+01  4.925e+00  -3.283  0.00103 **
occ               -6.809e+00  1.596e+00  -4.266 1.99e-05 ***
corn               1.844e-03  4.301e-04   4.289 1.80e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 33
Log-likelihood: -476.1 on 8 Df
```

```
##########dc.ss = Direct control Spring / Early Summer

>dc.ss.null=zeroinfl(dc.ss~1|1,data=resp,dist="poisson")
>dc.ss.a=zeroinfl(dc.ss~1|harvest,data=resp,dist="poisson")
>dc.ss.b=zeroinfl(dc.ss~1|harvest+corn,data=resp,dist="poisson")
>dc.ss.c=zeroinfl(dc.ss~1|harvest+corn+seashome,data=resp,dist="poisson")
>dc.ss.d=zeroinfl(dc.ss~1|harvest+corn+seashome+occ,data=resp,dist="poisson")
>dc.ss.e=zeroinfl(dc.ss~ldev|harvest+corn+seashome+occ,data=resp,dist="poisson")
>dc.ss.f=zeroinfl(dc.ss~I(ldev*harvest)|harvest+corn+seashome+occ,data=resp,dist="poisson")

>lrtest(dc.ss.null,dc.ss.a)
>lrtest(dc.ss.a,dc.ss.b)
>lrtest(dc.ss.b,dc.ss.c)
>lrtest(dc.ss.c,dc.ss.d)
>lrtest(dc.ss.d,dc.ss.e)
>lrtest(dc.ss.e,dc.ss.f)
>lrtest(dc.ss.null,dc.ss.f)

Likelihood ratio test

Model 1: dc.ss ~ 1 | 1
Model 2: dc.ss ~ 1 | harvest
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -973.33
2   3 -833.96  1 278.73  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: dc.ss ~ 1 | harvest
Model 2: dc.ss ~ 1 | harvest + corn
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -833.96
2   4 -811.27  1 45.395  1.611e-11 ***
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Likelihood ratio test

Model 1: dc.ss ~ 1 | harvest + corn
Model 2: dc.ss ~ 1 | harvest + corn + seashome
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   4 -811.27
2   5 -799.42  1 23.691  1.131e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: dc.ss ~ 1 | harvest + corn + seashome
Model 2: dc.ss ~ 1 | harvest + corn + seashome + occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   5 -799.42
2   6 -791.19  1 16.459  4.971e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: dc.ss ~ 1 | harvest + corn + seashome + occ
Model 2: dc.ss ~ ldev | harvest + corn + seashome + occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   6 -791.19
2   7 -780.68  1 21.029  4.524e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Likelihood ratio test

Model 1: dc.ss ~ ldev | harvest + corn + seashome + occ
Model 2: dc.ss ~ I(ldev * harvest) | harvest + corn + seashome + occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   7 -780.68
2   7 -774.59  0 12.167  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: dc.ss ~ 1 | 1
Model 2: dc.ss ~ I(ldev * harvest) | harvest + corn + seashome + occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -973.33
2   7 -774.59  5 397.47  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>AIC(dc.ss.null,dc.ss.a,dc.ss.b,dc.ss.c,dc.ss.d,dc.ss.e,dc.ss.f)

           df      AIC
dc.ss.null  2 1950.652
dc.ss.a     3 1673.927
dc.ss.b     4 1630.532
dc.ss.c     5 1608.840
dc.ss.d     6 1594.381
dc.ss.e     7 1575.353
dc.ss.f     7 1563.186
```

```
>summary(dc.ss.f)

Call:
zeroinfl(formula = dc.ss ~ I(ldev * harvest) | harvest + corn + seashome +
    occ, data = resp, dist = "poisson")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-1.06187 -0.38996 -0.13834 -0.04841  6.33777

Count model coefficients (poisson with log link):
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.17671    0.11633  -1.519    0.129
I(ldev * harvest)  0.35416    0.05626   6.295 3.08e-10 ***

Zero-inflation model coefficients (binomial with logit link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  5.3842335  1.1016852   4.887 1.02e-06 ***
harvest     -3.5668251  0.8327486  -4.283 1.84e-05 ***
corn         0.0010445  0.0002335   4.474 7.69e-06 ***
seashome    -0.0262019  0.0068484  -3.826  0.00013 ***
occ         -5.4834962  1.7225747  -3.183  0.00146 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 24
Log-likelihood: -774.6 on 7 Df
```

```
##########dc.sf = Direct control Late Summer / Fall

>dc.sf.null=zeroinfl(dc.sf~1|1,data=resp,dist="poisson")
>dc.sf.a=zeroinfl(dc.sf~1|occ,data=resp,dist="poisson")
>dc.sf.b=zeroinfl(dc.sf~1|occ+seashome,data=resp,dist="poisson")
>dc.sf.c=zeroinfl(dc.sf~1|occ+I(seashome*harvest),data=resp,dist="poisson")
>dc.sf.d=zeroinfl(dc.sf~corn|occ+I(seashome*harvest),data=resp,dist="poisson")

>lrtest(dc.sf.null,dc.sf.a)
>lrtest(dc.sf.a,dc.sf.b)
>lrtest(dc.sf.b,dc.sf.c)
>lrtest(dc.sf.c,dc.sf.d)
>lrtest(dc.sf.null,dc.sf.d)

Likelihood ratio test

Model 1: dc.sf ~ 1 | 1
Model 2: dc.sf ~ 1 | occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -383.06
2   3 -353.24  1 59.641  1.138e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Likelihood ratio test

Model 1: dc.sf ~ 1 | occ
Model 2: dc.sf ~ 1 | occ + seashome
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -353.24
2   4 -345.12  1 16.249  5.555e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Likelihood ratio test

Model 1: dc.sf ~ 1 | occ + seashome
Model 2: dc.sf ~ 1 | occ + I(seashome * harvest)
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   4 -345.12
2   4 -336.53  0 17.175  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: dc.sf ~ 1 | occ + I(seashome * harvest)
Model 2: dc.sf ~ corn | occ + I(seashome * harvest)
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   4 -336.53
2   5 -330.98  1 11.093  0.0008664 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: dc.sf ~ 1 | 1
Model 2: dc.sf ~ corn | occ + I(seashome * harvest)
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -383.06
2   5 -330.98  3 104.16  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
>AIC(dc.sf.null,dc.sf.a,dc.sf.b,dc.sf.c,dc.sf.d)

           df      AIC
dc.sf.null  2 770.1281
dc.sf.a     3 712.4871
dc.sf.b     4 698.2384
dc.sf.c     4 681.0632
dc.sf.d     5 671.9700

>summary(dc.sf.d)

Call:
zeroinfl(formula = dc.sf ~ corn | occ + I(seashome * harvest), data = resp,
    dist = "poisson")

Pearson residuals:
     Min       1Q   Median       3Q      Max
-0.78014 -0.27650 -0.14074 -0.08996 13.58828

Count model coefficients (poisson with log link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -0.3657187  0.1826337  -2.002   0.0452 *
corn        -0.0009401  0.0002979  -3.156   0.0016 **

Zero-inflation model coefficients (binomial with logit link):
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)            4.86893    0.84724   5.747  9.1e-09 ***
occ                   -4.10616    1.19339  -3.441 0.000580 ***
I(seashome * harvest) -0.08437    0.02448  -3.447 0.000567 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 33
Log-likelihood:  -331 on 5 Df
```

```
##########ag.ss = Agricultural Spring / Early Summer

>ag.ss.null=zeroinfl(ag.ss~1|1,data=resp,dist="poisson")
>ag.ss.a=zeroinfl(ag.ss~1|harvest,data=resp,dist="poisson")
>ag.ss.b=zeroinfl(ag.ss~1|I(harvest*ldev),data=resp,dist="poisson")
>ag.ss.c=zeroinfl(ag.ss~1|I(harvest*ldev)+occ,data=resp,dist="poisson")
>ag.ss.d=zeroinfl(ag.ss~corn|I(harvest*ldev)+occ,data=resp,dist="poisson")
>ag.ss.e=zeroinfl(ag.ss~I(corn*ldev)|I(harvest*ldev)+occ,data=resp,dist="poisson")

>lrtest(ag.ss.null,ag.ss.a)
>lrtest(ag.ss.a,ag.ss.b)
>lrtest(ag.ss.b,ag.ss.c)
>lrtest(ag.ss.c,ag.ss.d)
>lrtest(ag.ss.null,ag.ss.d)

Likelihood ratio test

Model 1: ag.ss ~ 1 | 1
Model 2: ag.ss ~ 1 | harvest
  #Df LogLik Df Chisq Pr(>Chisq)
1   2 -482.9
2   3 -440.2  1  85.4  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ag.ss ~ 1 | harvest
Model 2: ag.ss ~ 1 | I(harvest * ldev)
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -440.20
2   3 -430.54  0 19.311  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Likelihood ratio test

Model 1: ag.ss ~ 1 | I(harvest * ldev)
Model 2: ag.ss ~ 1 | I(harvest * ldev) + occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -430.54
2   4 -427.79  1 5.4947    0.01907 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ag.ss ~ 1 | I(harvest * ldev) + occ
Model 2: ag.ss ~ corn | I(harvest * ldev) + occ
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   4 -427.79
2   5 -424.55  1 6.4904    0.01085 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ag.ss ~ 1 | 1
Model 2: ag.ss ~ corn | I(harvest * ldev) + occ
  #Df  LogLik Df Chisq Pr(>Chisq)
1   2 -482.90
2   5 -424.55  3 116.7  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
>AIC(ag.ss.null,ag.ss.a,ag.ss.b,ag.ss.c,ag.ss.d)

            df      AIC
ag.ss.null  2 969.7938
ag.ss.a     3 886.3937
ag.ss.b     3 867.0829
ag.ss.c     4 863.5882
ag.ss.d     5 859.0978

>summary(ag.ss.d)

Call:
zeroinfl(formula = ag.ss ~ corn | I(harvest * ldev) + occ, data = resp,
    dist = "poisson")

Pearson residuals:
    Min      1Q  Median      3Q     Max
-0.5659 -0.3522 -0.1787 -0.1258  9.8886

Count model coefficients (poisson with log link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.1386885  0.1202373  -9.470  < 2e-16 ***
corn        -0.0004183  0.0001604  -2.609  0.00909 **

Zero-inflation model coefficients (binomial with logit link):
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)         3.2174     0.9414   3.418 0.000632 ***
I(harvest * ldev) -25.7541     7.9182  -3.253 0.001144 **
occ                -2.1596     1.4490  -1.490 0.136129
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 23
Log-likelihood: -424.5 on 5 Df
```

```
##########ag.sf = Agricultural Late Summer / Fall

>ag.sf.null=zeroinfl(ag.sf~1|1,data=resp,dist="poisson")
>ag.sf.a=zeroinfl(ag.sf~1|harvest,data=resp,dist="poisson")
>ag.sf.b=zeroinfl(ag.sf~oak|harvest,data=resp,dist="poisson")
>ag.sf.c=zeroinfl(ag.sf~I(oak*harvest)|harvest,data=resp,dist="poisson")
>ag.sf.d=zeroinfl(ag.sf~I(oak*harvest)+corn|harvest,data=resp,dist="poisson")

>lrtest(ag.sf.null,ag.sf.a)
>lrtest(ag.sf.a,ag.sf.b)
>lrtest(ag.sf.b,ag.sf.c)
>lrtest(ag.sf.c,ag.sf.d)
>lrtest(ag.sf.null,ag.sf.d)

Likelihood ratio test

Model 1: ag.sf ~ 1 | 1
Model 2: ag.sf ~ 1 | harvest
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -628.76
2   3 -566.00  1 125.51  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Likelihood ratio test

Model 1: ag.sf ~ 1 | harvest
Model 2: ag.sf ~ oak | harvest
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   3 -566.00
2   4 -564.08  1 3.8347     0.0502 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Likelihood ratio test

Model 1: ag.sf ~ oak | harvest
Model 2: ag.sf ~ I(oak * harvest) | harvest
  #Df  LogLik Df Chisq Pr(>Chisq)
1   4 -564.08
2   4 -562.68  0 2.812  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ag.sf ~ I(oak * harvest) | harvest
Model 2: ag.sf ~ I(oak * harvest) + corn | harvest
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   4 -562.68
2   5 -560.39  1 4.5736    0.03247 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Likelihood ratio test

Model 1: ag.sf ~ 1 | 1
Model 2: ag.sf ~ I(oak * harvest) + corn | harvest
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   2 -628.76
2   5 -560.39  3 136.73  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
>AIC(ag.sf.null,ag.sf.a,ag.sf.b,ag.sf.c,ag.sf.d)

           df      AIC
ag.sf.null  2 1261.512
ag.sf.a     3 1138.001
ag.sf.b     4 1136.166
ag.sf.c     4 1133.354
ag.sf.d     5 1130.781

>summary(ag.sf.d)

Call:
zeroinfl(formula = ag.sf ~ I(oak * harvest) + corn | harvest, data = resp,
    dist = "poisson")

Pearson residuals:
    Min      1Q  Median      3Q     Max
-0.7349 -0.3335 -0.1817 -0.1624  8.0254

Count model coefficients (poisson with log link):
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)       0.0179217  0.1197107   0.150  0.88099
I(oak * harvest)  0.0013087  0.0004409   2.969  0.00299 **
corn             -0.0003154  0.0001396  -2.258  0.02392 *

Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   2.6547     0.2041  13.008   <2e-16 ***
harvest      -2.6354     0.3060  -8.613   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 12
Log-likelihood: -560.4 on 5 Df
```

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