Appendix: Differentiated drivers in wildlife-induced damage necessitate species-specific mitigation strategies in the western Serengeti, Tanzania

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March 21, 2023

A1 Trends in livestock loss

Livestock losses are monitored and verified by the Grumeti Fund through two primary sources. The first is through partnership with Village Agricultural Officers (VAOs) in ten adjacent villages, who provide records of verified livestock losses on a monthly basis. This mode of monitoring was implemented in January 2017. The second is through reporting via a hotline and accessible to all adjacent communities. Calls are verified in the field and records maintained in a database. The hotline was implemented in March 2018. Reports from both sources are summarized here for the purpose of providing local context with respect to the seasonal trends of livestock damage and species preferences.

Reports of lion damage were most common (Table A1). On average lions killed 3.4 livestock per report, and 60% of animals killed were cattle. Hyena killed 5 livestock per report on average, but only 7% of animals killed were cattle (76% sheep) (Table A2).

Table A1: Total reports by species

Species	**Reports**
Hyena	106
Leopard	15
Lion	163
Total	284

Table A2: Number of livestock killed by species

Type	**Hyena**	**Leopard**	**Lion**
Cow kill	38	5	326
Sheep kill	399	34	86
Goat kill	93	19	128
Donkey kill	0	0	2
Dog kill	0	2	4
Other kill	0	0	1
Total	530	60	547

Reports of livestock depredation by lion were rarely received during the dry season (June - October). Depredation by hyena occurred throughout the year, but was most common during the traditional 'long rains' between March and May (Figure A1).

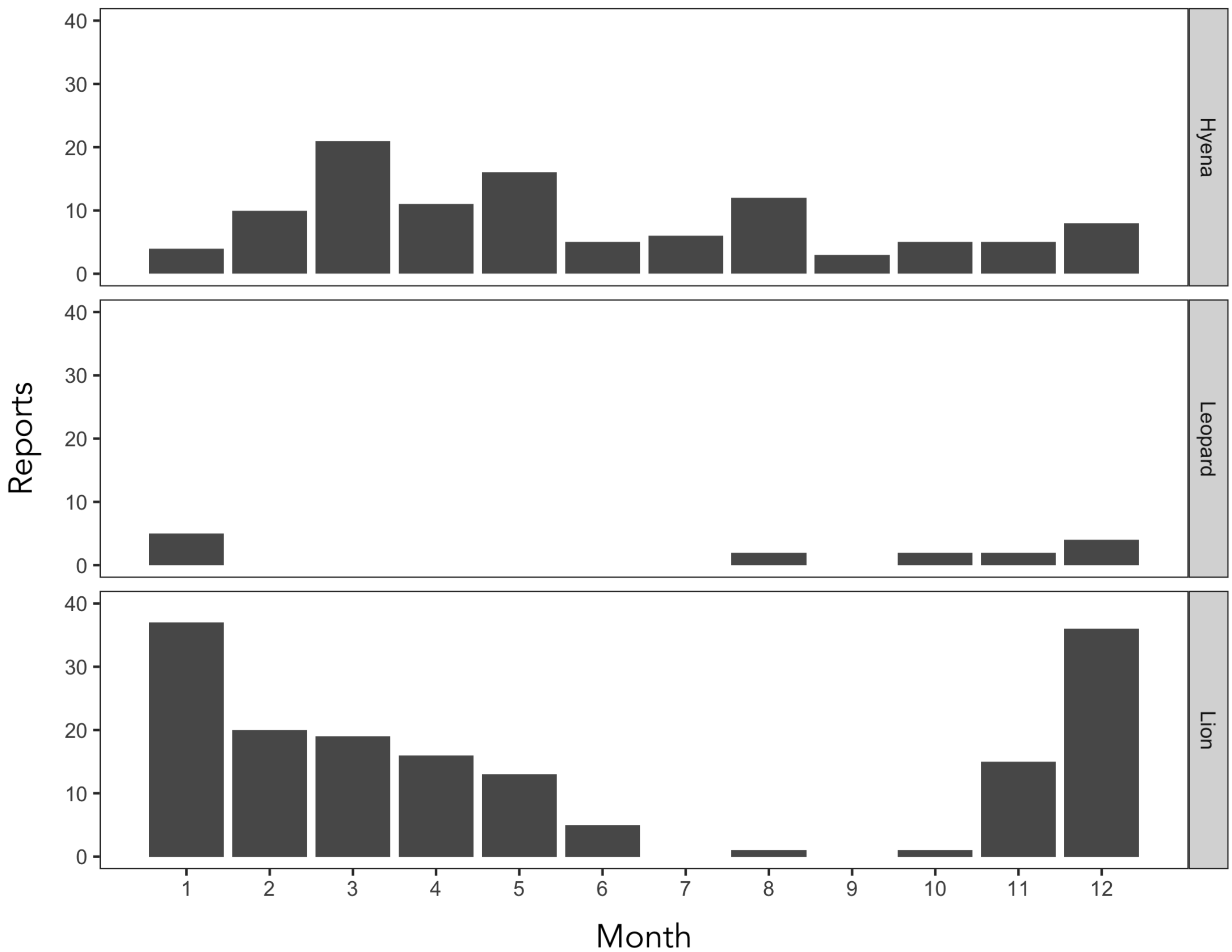


Figure A1: Reports of livestock depredation by month between Jan 1, 2017 and June 30, 2020

A2 Survey Instrument

Section 1. Respondent Characteristics Information					
Village					
Age					
Gender	M ☐	F ☐			
Ethnicity					
Education (highest level completed)	None ☐	Primary ☐			
	O-level ☐	A-level ☐			
	Post-secondary ☐				
Were you born in either Bunda or Serengeti Districts?	Yes ☐	No ☐			
Household size (number of individuals living in compound for 6 months or more out of the year)					
Household composition – Include number of all that apply	Young boys (less than 10 years old)	Adolescent boys (10-17)	Men (18+)		
	Young girls (less than 10 years old)	Adolescent girls (10-17)	Women (18+)		
In 2016 how often did you experience uncertainty over whether the household food supply would be enough to meet basic needs?	1 ☐ (never uncertain)	2 ☐ (rarely uncertain)	3 ☐ (sometimes uncertain)	4☐ (often uncertain)	5 ☐ (always uncertain)
In 2016 how often did you sell household possessions that you did not wish to in order to support your household?	Never ☐	Once or twice ☐	A few times (3-4) ☐	Frequently (several times) ☐	
Section 2. General Information					
In 2016 did you farm crops?	Yes ☐	No ☐			
In 2016 did you keep livestock?	Yes ☐	No ☐			
In 2016, what types of conflict with wildlife did your household experience? ** med/large = cattle, sheep, goat, donkey, dog*	Crop damage ☐	Livestock injury (med / large) ☐	Livestock death (med / large) ☐	Livestock injury (small) ☐	
	Livestock death (small) ☐	Structural damage ☐	Human injury ☐	Human death ☐	No conflict ☐

<table>
<tr><td>** small – chicken, duck</td><td colspan="2"></td><td colspan="3"></td><td colspan="2"></td><td colspan="3"></td><td colspan="2"></td></tr>
<tr><th colspan="13">Section 3. Farming practice questions</th></tr>
<tr><td rowspan="2">Which of these threats do you consider as the greatest threat to successful crop production?</td><td colspan="4">Damage by wildlife ☐</td><td colspan="4">Weather (eg drought) ☐</td><td colspan="4">Disease ☐</td></tr>
<tr><td colspan="4">Soil health ☐</td><td colspan="4">Labor requirements ☐</td><td colspan="4"></td></tr>
<tr><td>What is the estimated total size of your farm, in acres?</td><td colspan="12"></td></tr>
<tr><td>Can you see your fields from your home?</td><td colspan="6">Yes ☐</td><td colspan="6">No ☐</td></tr>
<tr><td rowspan="2">How long does it take you to walk from your home to your fields?</td><td colspan="4">0-15 minutes ☐</td><td colspan="4">15-30 minutes ☐</td><td colspan="4">30-45 minutes ☐</td></tr>
<tr><td colspan="4">45 minutes – 1 hour ☐</td><td colspan="4">More than 1 hour ☐</td><td colspan="4"></td></tr>
<tr><td rowspan="2">In 2016 how many months out of the year were you actively cultivating crops?</td><td colspan="2">1 ☐</td><td colspan="2">2 ☐</td><td colspan="2">3 ☐</td><td colspan="2">4 ☐</td><td colspan="2">5 ☐</td><td colspan="2">6 ☐</td></tr>
<tr><td colspan="2">7 ☐</td><td colspan="2">8 ☐</td><td colspan="2">9 ☐</td><td colspan="2">10 ☐</td><td colspan="2">11 ☐</td><td colspan="2">12 ☐</td></tr>
<tr><td>In 2016, how many unique crop types did you plant?</td><td colspan="12"></td></tr>
<tr><td rowspan="4">What crop protection strategies do you use?</td><td colspan="4">Guarding ☐</td><td colspan="4">Fire ☐</td><td colspan="4">Shouting ☐</td></tr>
<tr><td colspan="4">Chasing ☐</td><td colspan="4">Playing music ☐</td><td colspan="4">Sisal ☐</td></tr>
<tr><td colspan="4">Bee hive fence ☐</td><td colspan="4">Wire fence ☐</td><td colspan="4">Chili pepper fence ☐</td></tr>
<tr><td colspan="4">Dogs ☐</td><td colspan="4">Other ☐</td><td colspan="4">None ☐</td></tr>
<tr><td>What other crop protection strategies do you use?</td><td colspan="12"></td></tr>
<tr><th colspan="13">Section 4. Crop damage questions</th></tr>
<tr><td rowspan="2">Which wildlife species have you observed damaging your crops in 2016? *** limit to mammals</td><td colspan="4">Baboon ☐</td><td colspan="4">Buffalo ☐</td><td colspan="4">Elephant ☐</td></tr>
<tr><td colspan="4">Hippo ☐</td><td colspan="4">Other ☐</td><td colspan="4"></td></tr>
<tr><td>Name other</td><td colspan="12"></td></tr>
<tr><td rowspan="2">What species are you most concerned about damaging crops?</td><td colspan="4">Baboon ☐</td><td colspan="4">Buffalo ☐</td><td colspan="4">Elephant ☐</td></tr>
<tr><td colspan="4">Hippo ☐</td><td colspan="4">Other ☐</td><td colspan="4"></td></tr>
<tr><td>Name other</td><td colspan="4"></td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td rowspan="2">In 2016, when elephants damaged crops, did you report the incident to the local authorities (VAO or VEO)?</td><td colspan="4">Yes – always (100%) ☐</td><td colspan="4">Yes – often (75%) ☐</td><td colspan="4">Yes – sometimes (50%) ☐</td></tr>
<tr><td colspan="4">Yes – rarely (25%) ☐</td><td colspan="4">No – never (0%) ☐</td><td colspan="4"></td></tr>
<tr><th colspan="13">Section 5. Livestock Practice Questions</th></tr>
<tr><td rowspan="2">What types of livestock do you own that are housed</td><td colspan="3">Cattle ☐</td><td colspan="3">Sheep ☐</td><td colspan="3">Goat ☐</td><td colspan="3">Donkey ☐</td></tr>
<tr><td colspan="3">Dog ☐</td><td colspan="3">Chicken ☐</td><td colspan="3">Duck ☐</td><td colspan="3">Other ☐</td></tr>
</table>

<table>
<tr><td>and cared for on your local property? (select all that apply)</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Number of cattle owned</td><td colspan="4"></td></tr>
<tr><td>Number of sheep owned</td><td colspan="4"></td></tr>
<tr><td>Number of goats owned</td><td colspan="4"></td></tr>
<tr><td>Number of donkeys owned</td><td colspan="4"></td></tr>
<tr><td>Number of dogs owned</td><td colspan="4"></td></tr>
<tr><td>Number of chickens owned</td><td colspan="4"></td></tr>
<tr><td>Number of ducks owned</td><td colspan="4"></td></tr>
<tr><td>Number of other livestock owned</td><td colspan="4"></td></tr>
<tr><td rowspan="2">Which of these threats do you consider as the greatest threat to successful livestock production?</td><td>Damage by wildlife ☐</td><td>Weather (eg drought) ☐</td><td colspan="2">Disease ☐</td></tr>
<tr><td>Availability of grazing land ☐</td><td>Theft ☐</td><td colspan="2">Low productivity ☐</td></tr>
<tr><td rowspan="3">Which of these strategies do you use to prevent wildlife from damaging small livestock?
* small = chicken, duck</td><td>Guarding - day ☐</td><td>Keeping contained – day ☐</td><td>Dogs – day ☐</td><td>Other - day ☐</td></tr>
<tr><td>Guarding - night ☐</td><td>Keeping contained – night ☐</td><td>Dogs – night ☐</td><td>Other – night ☐</td></tr>
<tr><td>None – day ☐</td><td>None – night ☐</td><td></td><td></td></tr>
<tr><td>Describe other strategies used during the day (small)</td><td colspan="4"></td></tr>
<tr><td>Describe other strategies used during the night (small)</td><td colspan="4"></td></tr>
<tr><td rowspan="3">Which of these strategies do you use to prevent wildlife from damaging medium or large livestock?</td><td>Guarding - day ☐</td><td>Keeping contained – day ☐</td><td>Dogs – day ☐</td><td>Other - day ☐</td></tr>
<tr><td>Guarding - night ☐</td><td>Keeping contained – night ☐</td><td>Dogs – night ☐</td><td>Other – night ☐</td></tr>
<tr><td>None – day ☐</td><td>None – night ☐</td><td></td><td></td></tr>
<tr><td>Describe other strategies used during the day (med/large)</td><td colspan="4"></td></tr>
<tr><td>Describe other strategies used during the night (med/large)</td><td colspan="4"></td></tr>
</table>

Who is responsible for guarding med/large livestock during the day?	Young boys (less than 10 years old) ☐	Adolescent boys (10-17) ☐	Men (18+) ☐
	Young girls (less than 10 years old) ☐	Adolescent girls (10-17) ☐	Women (18+) ☐
How many people typically guard med/large livestock at a single time during the day?			
Who is responsible for guarding med/large livestock during the night?	Young boys (less than 10 years old) ☐	Adolescent boys (10-17) ☐	Men (18+) ☐
	Young girls (less than 10 years old) ☐	Adolescent girls (10-17) ☐	Women (18+) ☐
How many people typically guard med/large livestock at a single time during the night?			
Section 6. Small-sized Livestock Damage Questions			
Which types of small-sized livestock were damaged in 2016?	Chicken ☐	Duck ☐	Other ☐
How many chickens were lost to wildlife? (Estimate)			
How many ducks were lost to wildlife? (Estimate)			
How many other small livestock were lost to wildlife? (Estimate)			
In 2016, which wildlife species damaged small-sized livestock belonging to your household?	Jackal ☐	Honey badger ☐	Weasel ☐
	Civet ☐ / Genet ☐	Mongoose ☐	Other ☐
Name other			
What species are you most concerned about damaging small-size livestock?	Jackal ☐	Honey badger ☐	Weasel ☐
	Civet ☐ / Genet ☐	Mongoose ☐	Other ☐
Name other			
Section 7. Medium and Large-sized Livestock Damage Questions			
Which types of medium and large size livestock were damaged in 2016?	Cattle ☐	Goat ☐	Other ☐
	Sheep ☐	Dog ☐	Donkey ☐

How many cattle were lost to wildlife?			
How many sheep were lost to wildlife?			
How many goats were lost to wildlife?			
How many donkeys were lost to wildlife?			
How many dogs were lost to wildlife?			
How many other medium and large livestock were lost?			
In 2016, which wildlife species contributed to the loss of medium and large sized livestock belonging to your household?	Elephant ☐	Hyena ☐	Leopard ☐
	Lion ☐	Other ☐	
Name other			
What species are you most concerned about damaging medium and large size livestock?	Elephant ☐	Hyena ☐	Leopard ☐
	Lion ☐	Other ☐	
Name other			
When elephants damaged medium and large sized livestock, how often did you report the incident to the local authorities (eg. VAO or VEO)?	Always (100%) ☐	Often (75%) ☐	Sometimes (50%) ☐
	Rarely (25%) ☐	Never (0%) ☐	
When hyenas damaged medium and large sized livestock, how often did you report the incident to the local authorities (eg. VAO or VEO)?	Always (100%) ☐	Often (75%) ☐	Sometimes (50%) ☐
	Rarely (25%) ☐	Never (0%) ☐	
When lions damaged medium and large sized livestock, how often did you report the incident to the local authorities (eg. VAO or VEO)?	Always (100%) ☐	Often (75%) ☐	Sometimes (50%) ☐
	Rarely (25%) ☐	Never (0%) ☐	
When leopards damaged medium and large sized livestock, how often did you report the incident to	Always (100%) ☐	Often (75%) ☐	Sometimes (50%) ☐
	Rarely (25%) ☐	Never (0%) ☐	

the local authorities (eg. VAO or VEO)?			
Section 8. Structural Damage Questions			
What species were responsible for the structural damage?	Baboon ☐	Buffalo ☐	Elephant ☐
	Hippo ☐	Hyena ☐	Leopard ☐
	Lion ☐	Other ☐	
Name other			
Section 9. Location			
Location	Longitude		
	Latitude		
	Accuracy		

A3 Environmental Variables

Linear Features

Linear features include rivers and roads in the Serengeti-Mara. The river layer was derived from 1:50,000 topographic maps and is comprised of major and minor rivers and streams with clearly defined banks (Serengeti GIS and Data Center, 2008). The road data were derived from multiple sources and included publicly available mapped roads from Open Street Maps (OSM) and those mapped by the Grumeti Fund via field survey and digitized from satellite imagery. Rivers and roads were rasterized and feature density was calculated at the pixel-level (30 m) within each species-specific search radius.

Settlements

We used the distance to the leading edge of settlement as an estimate of distance traveled into human-dominated areas. We digitized a linear path along the leading edge of settlements and then calculated distance to this edge in ArcMap using the Euclidean distance tool. This measure gives an estimate of how proximate a household is to the household nearest the reserve. We elected to use this measurement, rather than distance to protected area, because many community grazing areas and other open areas border formally protected areas. These areas are used extensively by wildlife and domesticated animals.

Built Footprint

The building footprint of the Serengeti and Mara regions was extracted from OpenStreetMap (www.openstreetmap.org). This area was the focus of a Humanitarian Open Street Map Team (HotOSM) project in 2017, where volunteers traced buildings in this region. In 2018, we made further, systematic improvements to this layer. For modeling purposes, we calculated the point density of buildings (extracted on March 30, 2020) within the species-specific search radius at 30 m resolution.

Landcover and terrain

A landcover classification was created using Landsat 8 satellite data with a Random Forest model on the Google Earth Engine platform. The landcover data were used to compute the following variables: proportion of forest (>70% wooded), woodland/bushland (20-70% wooded), and cropland area. Slope was derived from the Shuttle Radar Topography Mission (Farr et al., 2007) 1 arc-second (approximately 30 m) elevation data (A3.

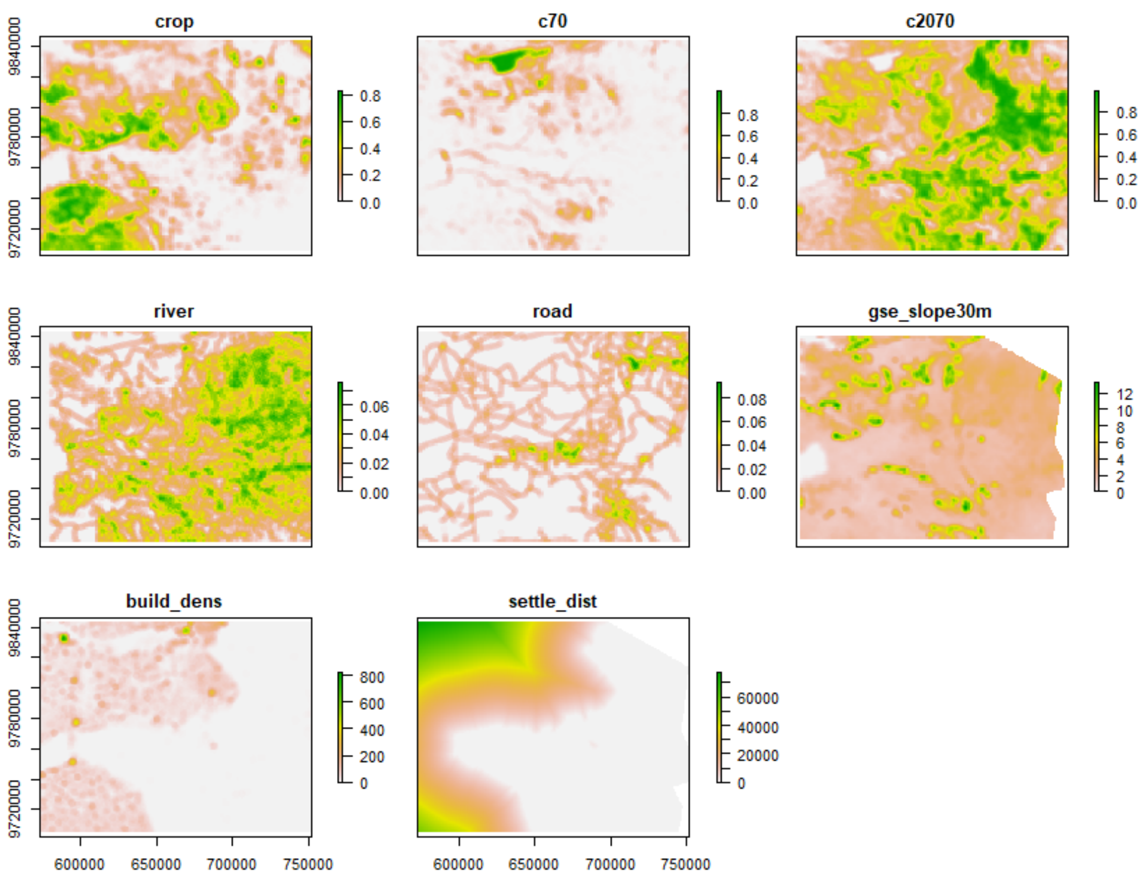


Figure A3: Landscape and human disturbance features, smoothed by a radius of 2.4 km for baboon prediction.

Table A3: Source of movement data for mean daily net displacement used to create species-specific radii

Species	Radius	Location	Source
Baboon	2.4 km	Mpala, Kenya	Crofoot M. *Papio Anubis* (olive baboon). Movebank ID: 7023252 Isbell LA, Bidner L. Leopards, baboons and vervets in Laikipia, Kenya. Movebank ID: 17629305
Elephants	5 km	Western Serengeti, Tanzania	Denninger Snyder K, Mbise N, Mjingo EE. Unpublished data, 2018-2020.
Hyena	4.3 km	Maasai Mara, Kenya	Holekamp K, Gersick A, Strandburg-Peshkin A, Jensen F, Johnson M. Hyena communication and coordination – pilot. Movebank ID: 914907848
Lion	2.1 km	Serengeti National Park, Tanzania	Craig Packer, pers. comm
Vervet	500 m	Maasai Mara, Kenya	Isbell LA, Bidner L. Leopards, baboons and vervets in Laikipia, Kenya. Movebank ID: 17629305

Table A4: Posterior mean coefficient estimates of evaluated crop conflict models. Species level effects are offsets from the corresponding population level mean effect. Model with asterisks is confounded.

	mc_bd	mc_c2070	mc_c70	mc_cd	mc_fs	mc_hh	mc_mp	mc_riv	mc_sd	mc_see	mc_slope	mc_np*	mc_landscape
a	-0.49	-0.59	-0.61	-0.62	-0.35	-0.56	-0.61	-0.62	-0.50	-0.48	-0.61	-0.44	-0.45
as_baboon	-2.52	-2.27	-2.10	-2.34	-2.50	-2.28	-2.28	-2.39	-2.35	-2.22	-2.36	-2.22	-2.59
as_elephant	2.77	2.15	2.16	2.15	1.86	2.01	1.98	2.19	2.61	2.17	2.19	2.65	2.81
as_vervet	-2.27	-1.91	-1.90	-2.12	-2.48	-2.24	-2.19	-2.20	-2.36	-2.13	-2.18	-2.11	-2.36
b_BD	-0.49	-0.60	-0.59										-0.37
b_BDs_baboon	0.02	0.03	0.25										-0.05
b_BDs_elephant	-0.42	-0.86	-1.13										-0.21
b_BDs_vervet	0.27	0.45	0.46										0.16
b_SD	-0.38								-0.41				-0.37
b_SDs_baboon	-0.21								-0.08				-0.25
b_SDs_elephant	-1.21								-1.30				-1.35
b_SDs_vervet	1.10								1.12				1.12
b_SL	-0.08	-0.08		-0.16				-0.21			-0.20		-0.01
b_SLs_baboon	0.66	0.55		0.58				0.64			0.63		0.62
b_SLs_elephant	-0.76	-0.73		-0.86				-0.88			-0.88		-0.75
b_SLs_vervet	0.19	0.21		0.28				0.35			0.35		0.17
b_C2070		-0.01											0.16
b_C2070s_baboon		-0.14											-0.24
b_C2070s_elephant		0.01											0.29
b_C2070s_vervet		0.15											-0.04
b_CR		-0.34	-0.43	-0.54									-0.10
b_CRs_baboon		0.12	0.34	0.20									0.02
b_CRs_elephant		-0.54	-0.86	-0.72									-0.17
b_CRs_vervet		0.31	0.34	0.37									0.14
b_C70			-0.13										-0.06
b_C70s_baboon			0.29										0.02
b_C70s_elephant			-0.55										-0.00
b_C70s_vervet			0.25										-0.03
b_RIV			0.03					0.09					-0.13
b_RIVs_baboon			-0.02					0.00					0.04
b_RIVs_elephant			0.04					0.02					-0.21
b_RIVs_vervet			-0.00					-0.02					0.15
b_FS					0.30							0.22	
b_FSs_baboon					-0.17							-0.14	
b_FSs_elephant					0.18							0.08	
b_FSs_vervet					0.00							0.08	
b_HH					0.27	0.35						0.27	
b_HHs_baboon					-0.10	-0.13						-0.11	
b_HHs_elephant					0.06	0.10						0.04	
b_HHs_vervet					0.05	0.06						0.07	
b_MP							-0.10						
b_MPs_baboon							0.06						
b_MPs_elephant							-0.04						
b_MPs_vervet							-0.01						
b_SEE										-0.33			
b_SEEs_baboon										0.05			
b_SEEs_elephant										-0.14			
b_SEEs_vervet										0.06			
b_NP*												0.52	
b_NPs_baboon*												-0.08	
b_NPs_elephant*												1.16	
b_NPs_vervet*												-0.71	
b_RD													-0.05
b_RDs_baboon													0.09
b_RDs_elephant													-0.08
b_RDs_vervet													-0.01

Table A5: Widely available information criteria (WAIC) scores for all evaluated crop conflict models. dWAIC is difference in WAIC scores from highest ranked model. wWAIC is weight used to model average predictions. Models with asterisks are likely confounded.

	WAIC	SE	dWAIC	wWAIC
mc_bd	736.76	41.28	0.00	0.98
mc_landscape	744.67	42.61	7.92	0.02
mc_sd	761.96	41.68	25.20	0.00
mc_np*	777.10	43.99	40.35	0.00
mc_c2070	816.55	44.03	79.79	0.00
mc_cd	821.63	43.49	84.87	0.00
mc_c70	829.96	43.95	93.20	0.00
mc_slope	838.95	43.99	102.20	0.00
mc_riv	841.81	44.31	105.05	0.00
mc_fs	859.53	44.12	122.77	0.00
mc_hh	865.41	44.02	128.66	0.00
mc_mp	874.16	44.42	137.40	0.00
mc_see	874.87	44.38	138.12	0.00

A4: Causal Inference and DAGs

One primary aim of the scientific enterprise is to infer causal effects of predictors on outcome variables of inference, to increase our understanding of how systems function. This also can help folks working in applied contexts such as mitigating human-wildlife conflict make informed interventions. Well-designed experiments are one typical approach to understand causality, but in many cases, like the study presented in this paper, experiments would be not feasible or ethical.

Many common approaches in statistical inference, such as multivariate regression, do not make any claims about causality, and statistical information flows bidirectionally between outcome variable and predictors. Researchers are often concerned about the effect of predictor, X, on an outcome variable, Y.
However, X may be correlated with another covariate(s) of interest, Z, which can confound the relationship between X and Y. To infer the relationship between X and Y, researchers will often add covariates like Z (and often times many others) to control for potential covariates. A common phrase in many ecology papers is to ''control for seasonality" or ''control for environmental effects."

Confounding factors are a real, and valid concern, but whether or not to include, or exclude, a variable in a multivariate regression depends on the directional causal relationships between measurable variables of interest, and any potential unobserved variables. In some cases, including covariate Z can reduce the precision of an estimate of the effect of X on Y or render it entirely unreliable if Z is a collider (where X and Y both cause Z).

What is a DAG

DAGs (directed acyclical graphs) and are a common tool in causal inference Pearl (2009), a topic separate from, but related to statistical inference McElreath (2020). Generalized linear models do not imply the direction of causality as information in both directions between variables of interest. DAGs imply the direction of causality. DAGs are common in field like epidemiology Textor et al. (2016), but are increasingly common in the social and biological sciences Laubach et al. (2021). By proposing a DAG about the causal relationships between predictors of importance and outcomes in our study systems DAGs can help us understand:

1. which confounding variables to include in a regression when we wish to make a claim about the causal relationship between X $\rightarrow$ Y. In causal inference, this is known as closing the *backdoor path*.
2. which covariates to exclude from our analysis, as including them will introduce a confound. A common example of this is *collider bias*.
3. whether or not reliable inferences about the causal relationship between X and Y are even possible.

Other advantages of DAGs are that they force researchers to be explicit about causal relationships and think carefully about their study system. Does X directly cause Y? Or, does X also cause Z which causes Y? Perhaps X causes Z, which is also caused by Y? The answer to these questions informs us what to include or exclude in our statistical model. Our experience is that researchers often will say X causes Y, when in reality there is a middle step that is implied or ignored. Researchers can use their knowledge of their study systems to propose a DAG or DAGs, and they should justify the thinking behind each direct causal arrow. Assuming a DAG is true, we can use it to inform which regressions we run to make the most reliable inferences about the effect of X on Y. A critic of research may also propose a different DAG, which might suggest that a different analysis should be run, or that the question may not be reliably answered at all.

Drawing a DAG

To draw a DAG, we first consider all of the variables of interest in the system (ideally those that can and cannot be measured). We typically want to know the effect of a treatment/predictor/exposure on an outcome variable. If we think X, our predictor, directly causes Y, we draw an arrow from X to Y

This arrow implies a direct causal relationship between X and Y. Something has a causal relationship if the natural process determining Y is *directly influenced* by the status of X. However, an arrow X $\rightarrow$ Y only represents the part of the causal effect that is not mediated by any of the other variables in the DAG. If one is sure X does not directly mediate Y, an arrow can be excluded. One must also ensure that causes come before effects, and X precedes Y. In instances where this is not the case, and there are bidirectional arrows between X and Y we violate this assumption and need an experiment or time series of treatments on outcomes.

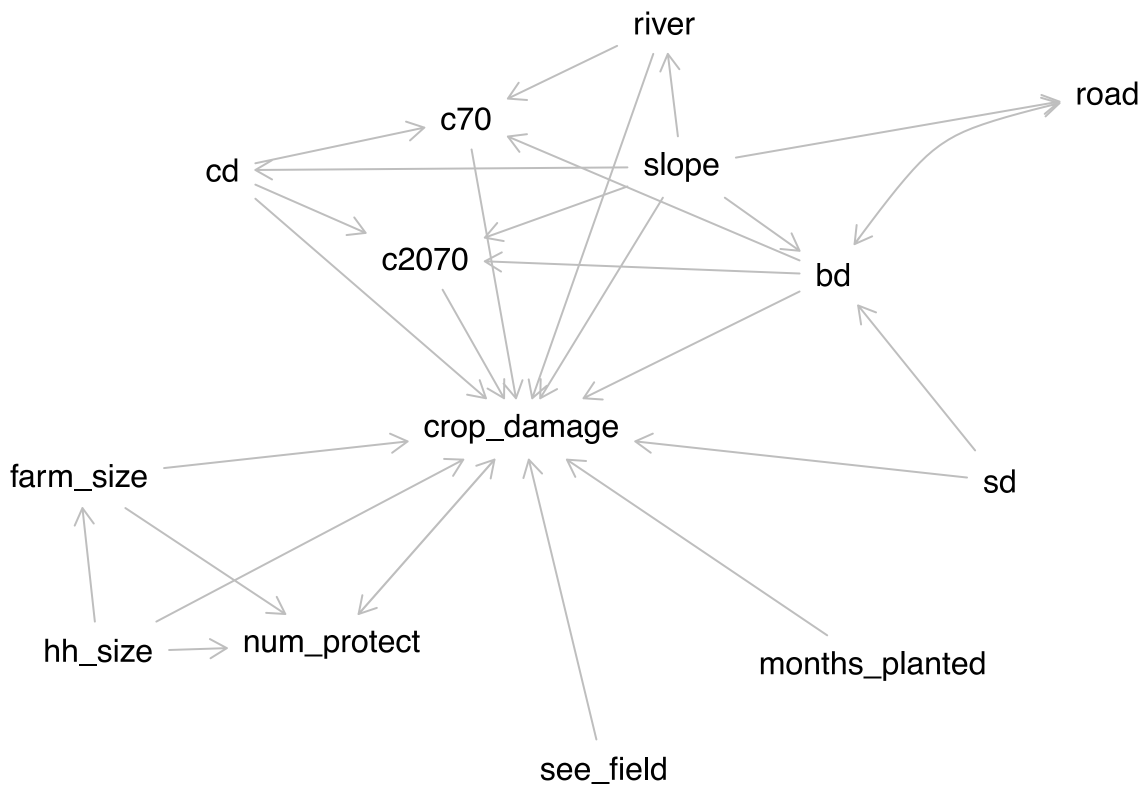
Wildlife Induced Crop Damage DAG

Below is our DAG for understanding what causes crop damage by wildlife in the GSME. This is an `.Rmd` version of Figure 2 in the main text.

```
crop_damage_dag <-
  dagitty('dag {
  c2070 -> crop_damage
  c70 -> crop_damage
  river -> c70
  river -> crop_damage
  months_planted -> crop_damage
  farm_size -> crop_damage
  farm_size -> num_protect
  num_protect -> crop_damage
  crop_damage -> num_protect
  hh_size -> num_protect
  hh_size -> farm_size
  hh_size -> crop_damage
  see_field -> crop_damage
  road <-> bd
  bd -> crop_damage
  bd -> c2070
  bd -> c70
  sd -> bd
  sd -> crop_damage
  cd -> c70
  cd -> c2070
  cd -> crop_damage
  slope -> bd
  slope -> crop_damage
  slope -> c2070
  slope -> river
  slope -> road
  slope -> cd
  }')

plot(crop_damage_dag)
```

```
## Plot coordinates for graph not supplied! Generating coordinates, see ?coordinates for how to set you
```



Reasoning for direct causal effects

1. c2070 -> crop_damage: c2070 is refuge habitat for wildlife. More habitat could mean there are more places to hide, or less habitat could mean that they are forced to utilize cropland more.
2. c70 -> crop_damage: c70 is habitat refuge for wildlife. More habitat could mean there are more places to hide, or less habitat could mean that they are forced to utilize cropland more.
3. river -> c70: The presence of water in rivers creates conditions for forest (variable c70). In this system forest is exclusively associated with riparian habitat.
4. river -> crop_damage: Animals dwell near rivers, and are likely to cause damage at places near them as a consequence.
5. months_planted -> crop_damage: The more time there are crops in the field, the more likely damage will be observed.
6. farm_size -> crop_damage: That larger the farm, the more available crops are, and the more likely they will get damaged.
7. farm_size -> num_protect: Farm size influences the type of protection strategies employed, which influences the number of strategies used. This is really an indirect pathway.
8. num_protect -> crop_damage: Using a range of strategies may reduce crop damage.
9. crop_damage -> num_protect: Farmers with crop damage may try lots of new crop strategies out of desperation.
10. hh_size -> num_protect: Larger households engage more effort in protection.
11. hh_size -> farm_size: More available people may indicate greater availability of labor, making it possible to have a larger farm.

12. hh_size -> crop_damage: Animals avoid fields with more human activity.
13. farm_size -> num_protect: Larger farms employ more protection strategies, particularly things like fences etc. that do not require person hours (i.e. guards).
14. see_field -> crop_damage: Farmers that see their field can react quickly and minimize damage or prevent wildlife from accessing their fields. Due to closer proximity, may also be more likely to spend more time protecting fields.
15. road -> bd: People will build settlements along roads due to access. It is less certain that building density also causes roads, but possible tertiary roads and smaller roads get built to connect dense places. However, the layer we used to estimate road density measure is primary roads.
16. bd -> crop_damage: Building density attracts and deters different wildlife species (i.e. vervets vs. elephants).
17. bd -> c2070: Construction of buildings causes loss in c2070 and changes classification probability.
18. bd -> c70: Construction of buildings causes loss in c70 and changes classification probability.
19. sd -> bd: Cities expand toward protected areas, settlements are less dense at edges. 500m buffer zones adjacent to PAs in Tanzania mean that settlement density is lower right next to protected area.
20. sd -> crop_damage: Different animals have different risk tolerances, some venture far from protected area, while others will avoid human settlements.
21. cd -> c70: Increased crop density and land conversion means there is less likely to be c70.
22. cd -> c2070: Increased crop density and land conversion means there is less likely to be c2070.
23. cd -> crop_damage: Crops are more accessible and it may be more beneficial to raid areas with a higher density of crops.
24. slope -> bd: More houses are built on less hilly land for ease of construction and material transport.
25. slope -> crop_damage: Elephants don't like traveling on hills, so less likely to damage farms on slopes.
26. slope -> c2070: 2070 is more likely on hillsides either due to the difficulty required in cutting trees down, lower suitability for conversion to agriculture, or ecological conditions conducive to forest growth.
27. slope -> river: Water flows down hills and rivers and water sources are likely to be in places with smaller slopes.
28. slope -> road: Slope influences where roads are built. Roads are preferentially built in easier, less hilly places and lower mountain passes.
29. slope -> cd: Crops are more densely planted in flat areas (less runoff, easier to plant things close together).

Building GLMMs from DAGs

Using the `dagitty` package in `R` we can use the `adjustmentSets` function to help us understand what are the minimal number of covariates we need to include in a model to reliably estimate the effect of a predictor on crop raiding.

Now we can look at all of the direct arrows to estimate the effect of X on Y, and determine which covariates to include in the models relevant to the predictor of interest.

For c2070 the minimal model `mc_c2070_min` includes:

```r
adjustmentSets( crop_damage_dag , exposure="c2070" , outcome="crop_damage" )
```

```
## { bd, cd, slope }
```

while the canonical model, `mc_c70_c2070_can` includes:

```r
adjustmentSets( crop_damage_dag , exposure="c2070" , outcome="crop_damage" )
```

```
## { bd, cd, slope }
```

For c70 the minimal model `mc_c70_min` includes:

```r
adjustmentSets( crop_damage_dag , exposure="c70" , outcome="crop_damage" )
```

```
## { bd, cd, river }
```

For c70 the canonical model `mc_c70_c2070_can` includes:

```r
adjustmentSets( crop_damage_dag , exposure="c70" , outcome="crop_damage" )
```

```
## { bd, cd, river }
```

For cd the minimal model `mc_cd_min` includes:

```r
adjustmentSets( crop_damage_dag , exposure="cd" , outcome="crop_damage" )
```

```
## { slope }
```

For cd the canonical model `mc_cd_can` includes:

```r
adjustmentSets( crop_damage_dag , exposure="cd" , outcome="crop_damage" )
```

```
## { slope }
```

For river the minimal model `mc_riv_min` includes:

```r
adjustmentSets( crop_damage_dag , exposure="river" , outcome="crop_damage" )
```

```
## { slope }
```

For river the minimal model `mc_riv_can` includes:

```r
adjustmentSets( crop_damage_dag , exposure="river" , outcome="crop_damage" )
```

```
## { slope }
```

For settlement distance the minimal model `mc_sd_min` includes:

```r
adjustmentSets( crop_damage_dag , exposure="sd" , outcome="crop_damage" )
```

```
##  {}
```

It requires no other covariates.

For settlement distance the canonical model `mc_sd_can` includes:

```r
adjustmentSets( crop_damage_dag , exposure="sd" , outcome="crop_damage" )
```

```
##  {}
```

It requires no other covariates.

For building density the minimal model `mc_bd_min` includes:

```r
adjustmentSets( crop_damage_dag , exposure="bd" , outcome="crop_damage" )
```

```
## { sd, slope }
```

For building density the canonical model `mc_sd_can` includes:

```r
adjustmentSets( crop_damage_dag , exposure="bd" , outcome="crop_damage" )
```

```
## { sd, slope }
```

For months planted the minimal model `mc_mp_min` includes:

```r
adjustmentSets( crop_damage_dag , exposure="months_planted" , outcome="crop_damage" )
```

```
##  {}
```

It requires no other covariates.

For months planted the canonical model `mc_fs_mp_can` includes:

```r
adjustmentSets( crop_damage_dag , exposure="months_planted" , outcome="crop_damage" )
```

```
##  {}
```

It requires no other covariates.

For see field the minimal model `mc_see_min` includes:

```r
adjustmentSets( crop_damage_dag , exposure="see_field" , outcome="crop_damage" )
```

```
##  {}
```

For see field the canonical model `mc_see_can` includes:

```
adjustmentSets( crop_damage_dag , exposure="see_field" , outcome="crop_damage" )
```

```
##  {}
```

It requires no other covariates.

For number of protection strategies, we cannot reliably make an inference conditional on this DAG being true:

```
adjustmentSets( crop_damage_dag , exposure="num_protect" , outcome="crop_damage" )
```

Note that there is no output. We discuss this at the end of this appendix.

For number of protection strategies the canonical model `m_np_can` includes:

```
adjustmentSets( crop_damage_dag , exposure="num_protect" , outcome="crop_damage" )
```

For household size the minimal model `m_hhs_min` includes:

```
adjustmentSets( crop_damage_dag , exposure="hh_size" , outcome="crop_damage" )
```

```
##  {}
```

It requires no other covariates.

For household size the canonical model `m_hhs_can` includes:

```
adjustmentSets( crop_damage_dag , exposure="hh_size" , outcome="crop_damage" )
```

```
##  {}
```

It requires no other covariates.

For farm size the minimal model `m_fs_min` includes:

```
adjustmentSets( crop_damage_dag , exposure="farm_size" , outcome="crop_damage" )
```

```
## { hh_size }
```

For farm size the canonical model `m_fs_mp_can` includes:

```
adjustmentSets( crop_damage_dag , exposure="farm_size" , outcome="crop_damage" )
```

```
## { hh_size }
```

For slope the minimal model `m_slope_min` includes:

```
adjustmentSets( crop_damage_dag , exposure="slope" , outcome="crop_damage" )
```

```
##  {}
```

It requires no other covariates.

For slope the canonical model `m_slope_can` includes:

```
adjustmentSets( crop_damage_dag , exposure="slope" , outcome="crop_damage")
```

```
## {}
```

It requires no other covariates.

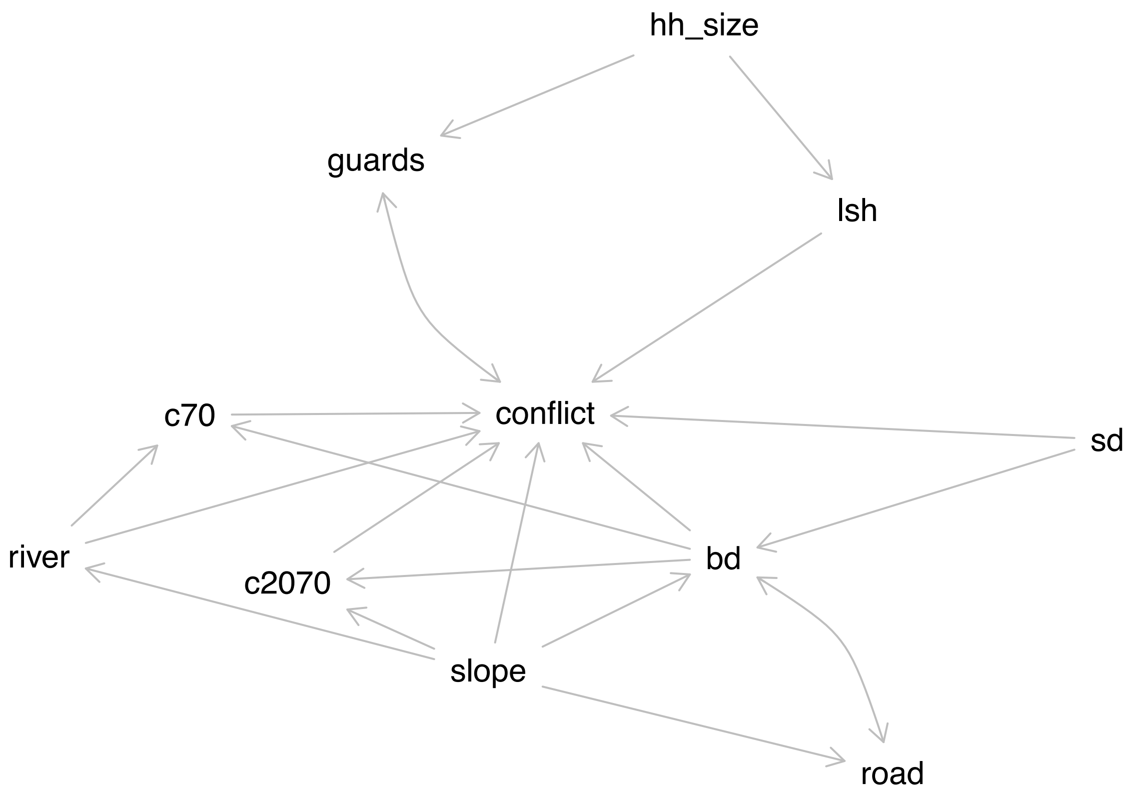
Note that c2070 and c70 have the same canonical model. Months planted and farm size have the same canonical model. Importantly, assuming the DAG is true, we cannot estimate the effectiveness of the number of protection strategies on crop damage given our current data. We need a time series or an experimental intervention to measure conflict rates before and after an intervention

Livestock Carnivore Conflict DAGs

```
ls_conf_yes_guard <-
  dagitty('dag {
  c2070 -> conflict
  bd -> conflict
  bd <-> road
  c70 -> conflict
  hh_size -> guards
  hh_size -> lsh
  lsh -> conflict
  river -> c70
  river -> conflict
  sd -> bd
  sd -> conflict
  bd -> c70
  bd -> c2070
  guards <-> conflict
  slope -> bd
  slope -> conflict
  slope -> c2070
  slope -> river
  slope -> road
}')

plot(ls_conf_yes_guard)
```

```
## Plot coordinates for graph not supplied! Generating coordinates, see ?coordinates for how to set you
```



We justify our direct causal relationships as follows:

1. c2070 -> conflict: c2070 is refuge habitat for carnivores, carnivores use c2070 as refuge to avoid detection and for shade.
2. bd -> conflict: Building density signifies human presence, and carnivores may avoid or be attracted to these areas depending on risk tolerance.
3. bd <-> road: People will build settlements along roads due to access. Roads also make it easier to build settlements and transport people and materials.
4. c70 -> conflict: c70 is refuge habitat for wildlife. More habitat could mean there are more places to hide, or less habitat could mean that wildlife are forced to utilize converted areas more often.
5. hh_size -> lsh: Larger households are often multi-generational, which means they have more capital to invest in cattle.
6. hh_size -> guards: The more people in the house, the more there are available to act as guards.
7. lsh -> conflict: The greater number of cattle that are present, the more likely that predators will encounter them / have access to livestock.
8. river -> c70: The presence of water in rivers creates conditions for forest (variable c70). In this system forest is exclusively associated with riparian habitat.
9. river -> conflict: Predators are dependent on water, depredation reported to occur near permanent water sources during the dry season.
10. sd -> bd: Cities expand toward protected areas, settlements are less dense at edges. 500m buffer zones adjacent to PAs in Tanzania mean that settlement density is lower right next to protected area.
11. sd -> conflict: Different animals have different risk tolerances, some venture far from protected area, while others will avoid human settlements

12. bd -> c70: Construction of buildings causes loss in c70 and changes classification probability
13. bd -> c2070: Construction of buildings causes loss in c2070 and changes classification probability
14. guards <-> conflict: Guards in theory reduce conflict if effective. That is their point. However, due to conflict, livestock owners may be more inclined to hire guards. To break this bidirectional arrow, one could randomly apply numbers of guards to people's herds, prevent them from changing it, and measure conflict. However, this is unethical. Instead, one would need to measure conflict levels, or number of livestock lost, as a function of the number of guards introduced, or used at each time step.
15. slope -> bd: More houses are built on less hilly land for ease of construction and material transport.
16. slope -> conflict: Predators may avoid (or not) traveling through steeper terrain.
17. slope -> rivers: Water flows down hills and is likely to be in places with decreasing slopes.
18. slope -> road: Slope influences where roads are built, the are preferentially built in easier, less hilly places and lower mountain passes.

Now we can run the adjustment sets.

For c2070 the minimal model `ml_c2070_min` includes:

```
adjustmentSets( ls_conf_yes_guard , exposure="c2070" , outcome="conflict" , type="minimal")
```

```
## { bd, slope }
```

For c70 the minimal model `ml_c70_min` includes:

```
adjustmentSets( ls_conf_yes_guard , exposure="c70" , outcome="conflict" , type="minimal")
```

```
## { bd, river }
```

For number of livestock head the minimal model `ml_lsh_min` includes:

```
adjustmentSets( ls_conf_yes_guard , exposure="lsh" , outcome="conflict" , type="minimal")
```

```
##  {}
```

It requires no other covariates.

For river density the minimal model `ml_riv_min` includes:

```
adjustmentSets( ls_conf_yes_guard , exposure="river" , outcome="conflict" , type="minimal")
```

```
## { slope }
```

For distance from settlement edge the minimal model `ml_sd_min` includes:

```
adjustmentSets( ls_conf_yes_guard , exposure="sd" , outcome="conflict" , type="minimal")
```

```
##  {}
```

It requires no other covariates.

For building density the minimal model `ml_bd_min` includes:

```r
adjustmentSets( ls_conf_yes_guard , exposure="bd" , outcome="conflict" , type="minimal")
```

```
## { sd, slope }
```

For slope the minimal model `ml_sl_min` includes:

```r
adjustmentSets( ls_conf_yes_guard , exposure="slope" , outcome="conflict" )
```

```
##  {}
```

It requires no other covariates.

For number of guards, the minimal model `ml_guards_min` includes:

```r
adjustmentSets( ls_conf_yes_guard , exposure="guards" , outcome="conflict" )
```

Note the last adjustment set. There is no output.

Measuring effectiveness of interventions using a single time point

DAGs are a useful tool to understand that we can't make reliable inferences about a protection strategy (number of guards, type of fencing, other farmer behaviors) without a measurement of conflict level before and after an intervention is implemented. Researcher need to design data collection or studies where this is a single arrow, or a different DAG is implied. Double arrows typically mean we need to break apart the timescale of measurement. Guards cause conflict in that they in theory reduce it. Conflict causes guards because people may get more guards if they experience conflict. We need data that measures conflict before and after an intervention to make any sense of their relationship.

Additional References

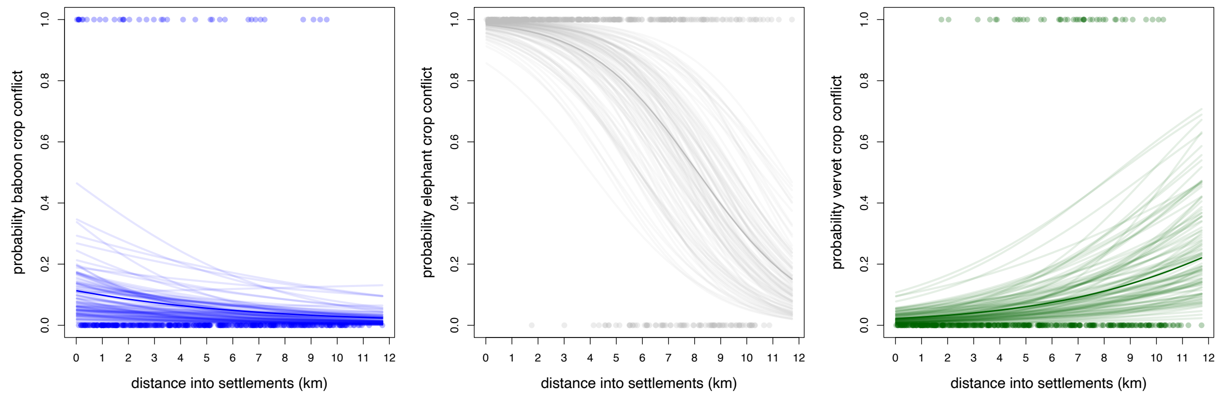
Laubach, Zachary M., Eleanor J. Murray, Kim L. Hoke, Rebecca J. Safran, and Wei Perng. 2021. "A Biologist's Guide to Model Selection and Causal Inference." *Proceedings of the Royal Society B: Biological Sciences* 288 (1943): 20202815. https://doi.org/10.1098/rspb.2020.2815.

McElreath, Richard. 2020. *Statistical Rethinking: A Bayesian Course with Examples in r and Stan*. Second. CRC press.

Pearl, Judea. 2009. *Causality*. Cambridge university press.

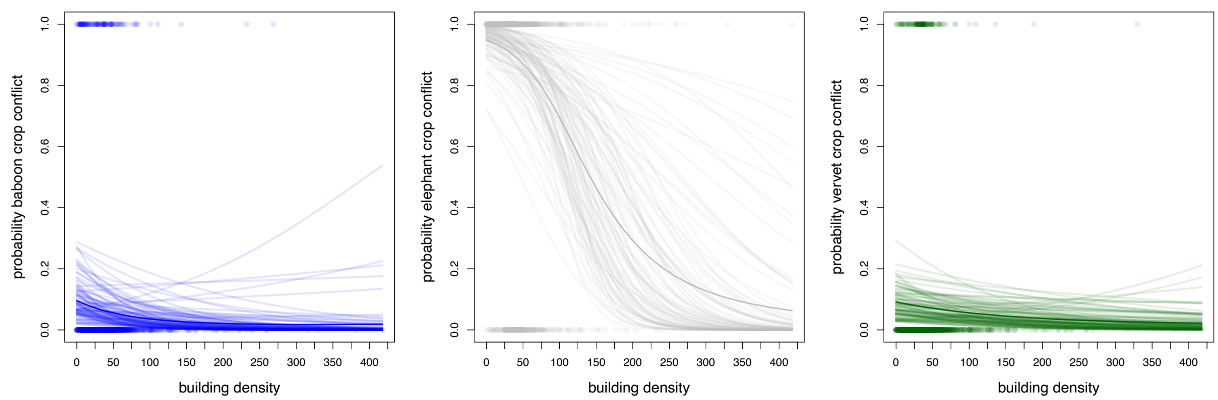
Textor, Johannes, Benito van der Zander, Mark S Gilthorpe, Maciej Liśkiewicz, and George TH Ellison. 2016. "Robust Causal Inference Using Directed Acyclic Graphs: The r Package 'Dagitty'." *International Journal of Epidemiology* 45 (6): 1887–94.

A5 Crop Damage Model Parameter Predictions



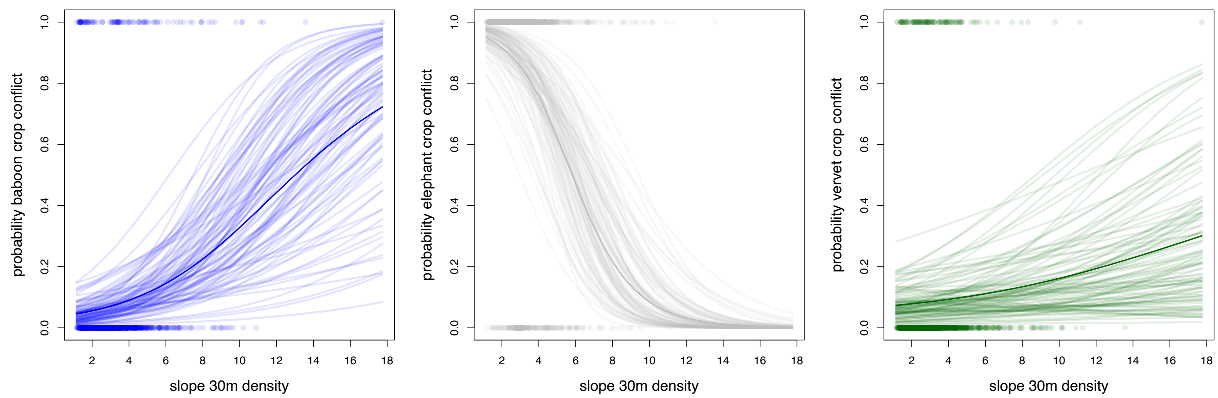
(a) baboons (b) elephants (c) vervets

Figure A4: Posterior predictions of the relationship between crop damage probability and distance to settlement edge for (a) baboons, (b) elephants and (c) vervets predicted from model mc_sd. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



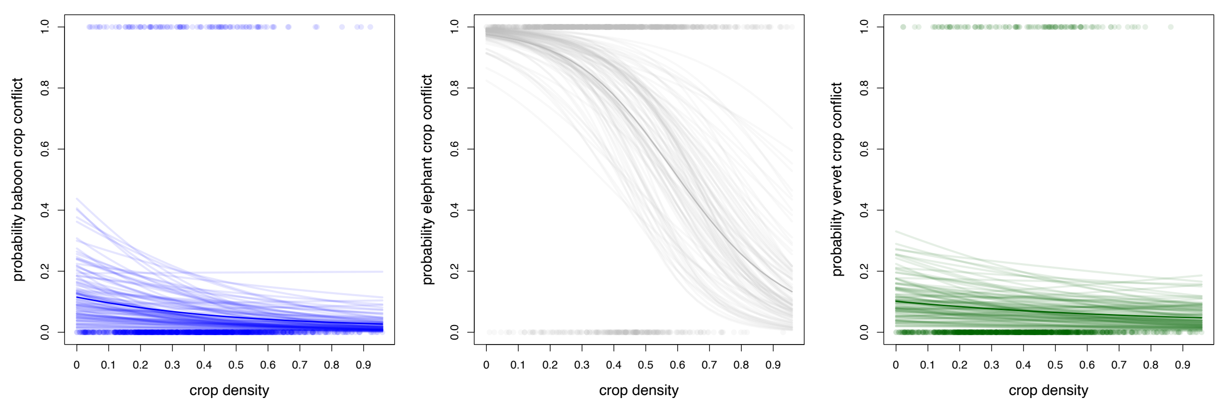
(a) baboons (b) elephants (c) vervets

Figure A5: Posterior predictions of the relationship between crop damage probability and building density for (a) baboons, (b) elephants and (c) vervets predicted from model mc_bd. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



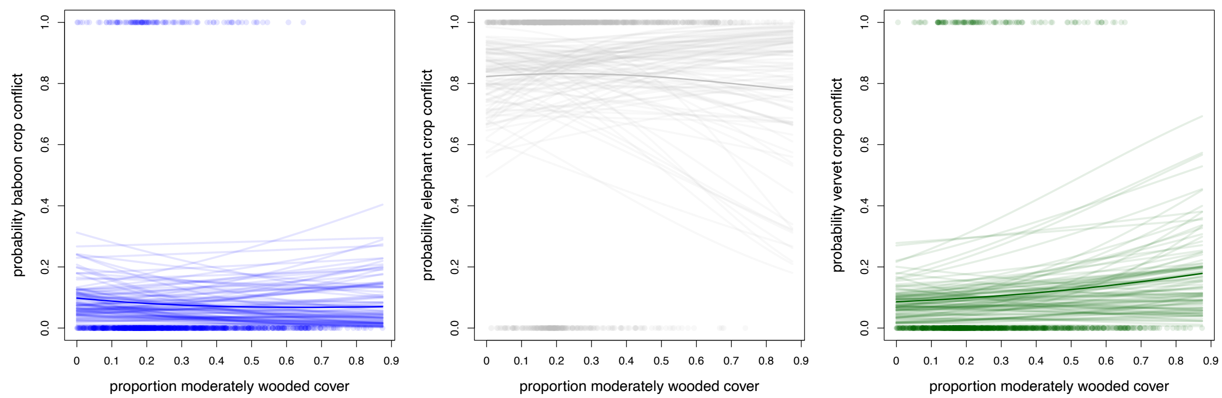
(a) baboons (b) elephants (c) vervets

Figure A6: Posterior predictions of the relationship between crop damage probability and slope for (a) baboons, (b) elephants and (c) vervets predicted from model mc_sl. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



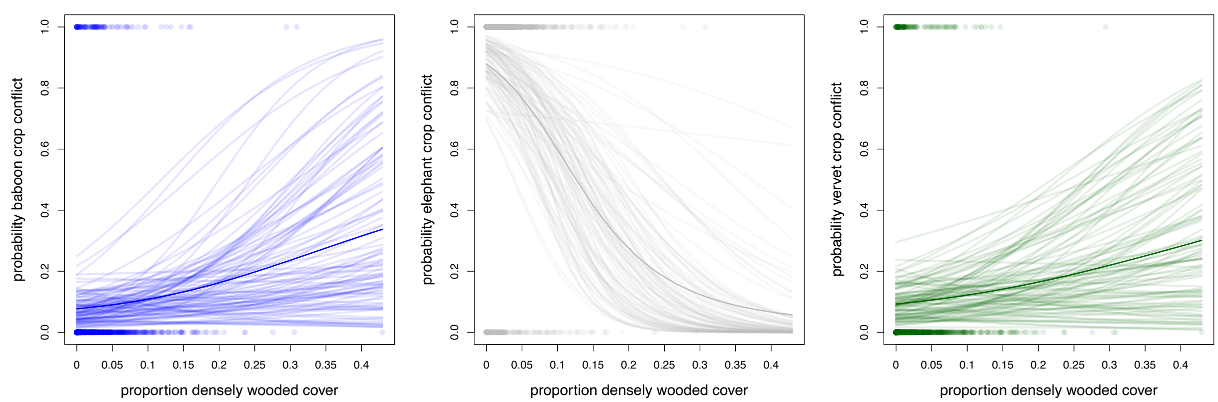
(a) baboons (b) elephants (c) vervets

Figure A7: Posterior predictions of the relationship between crop damage probability and crop density for (a) baboons, (b) elephants and (c) vervets predicted from model mc_cd. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



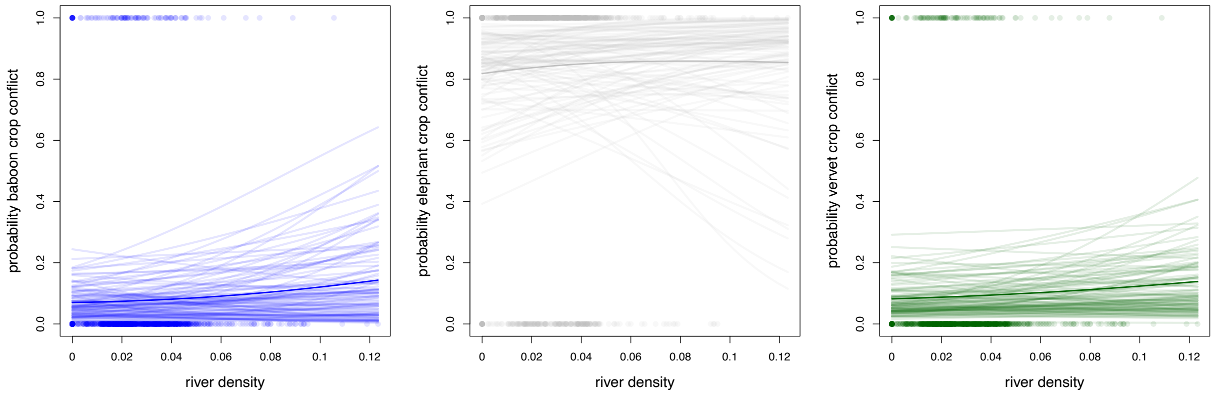
(a) baboons (b) elephants (c) vervets

Figure A8: Posterior predictions of the relationship between crop damage probability and 20- 70 % cover (woodland/open ticket/shrubland) density for (a) baboons, (b) elephants and (c) vervets predicted from model mc_c2070. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



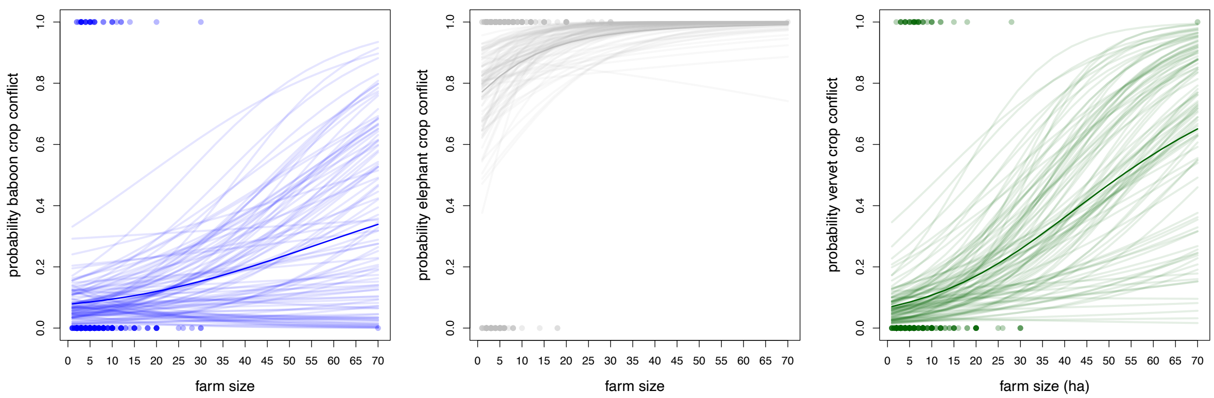
(a) baboons (b) elephants (c) vervets

Figure A9: Posterior predictions of the relationship between crop damage probability and > 70 % cover (forest/thicket) density for (a) baboons, (b) elephants and (c) vervets predicted from model mc_c70. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



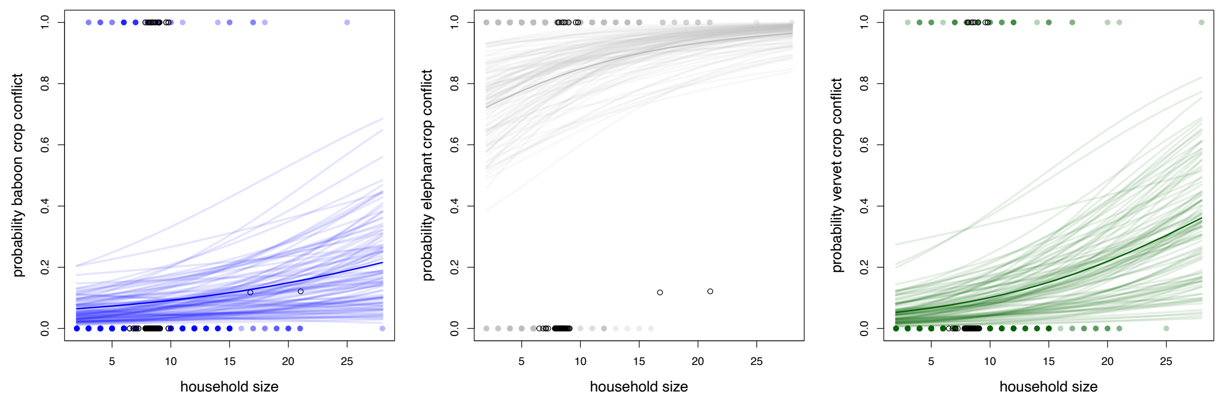
(a) baboons (b) elephants (c) vervets

Figure A10: Posterior predictions of the relationship between crop damage probability and river density for (a) baboons, (b) elephants and (c) vervets predicted from model mc_riv. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



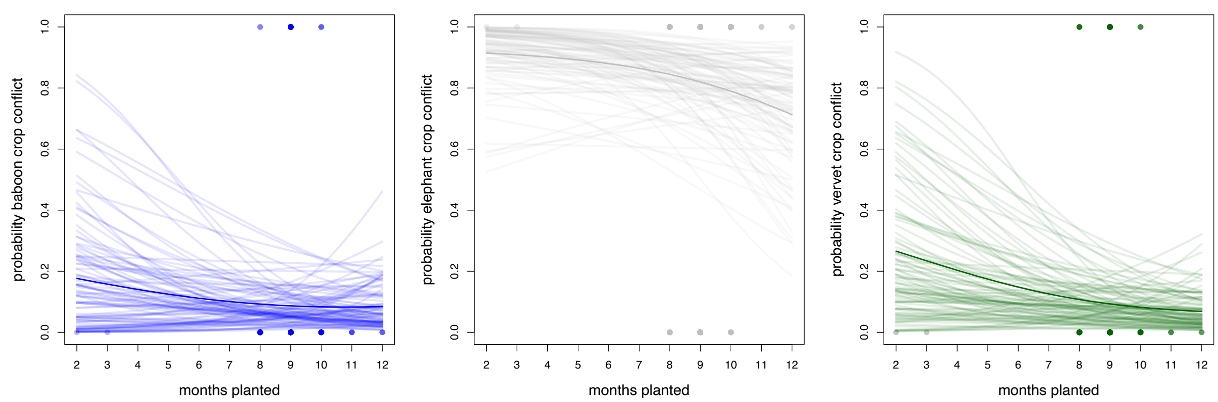
(a) baboons (b) elephants (c) vervets

Figure A11: Posterior predictions of the relationship between crop damage probability and farm size in hectares for (a) baboons, (b) elephants and (c) vervets predicted from mc_cr. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



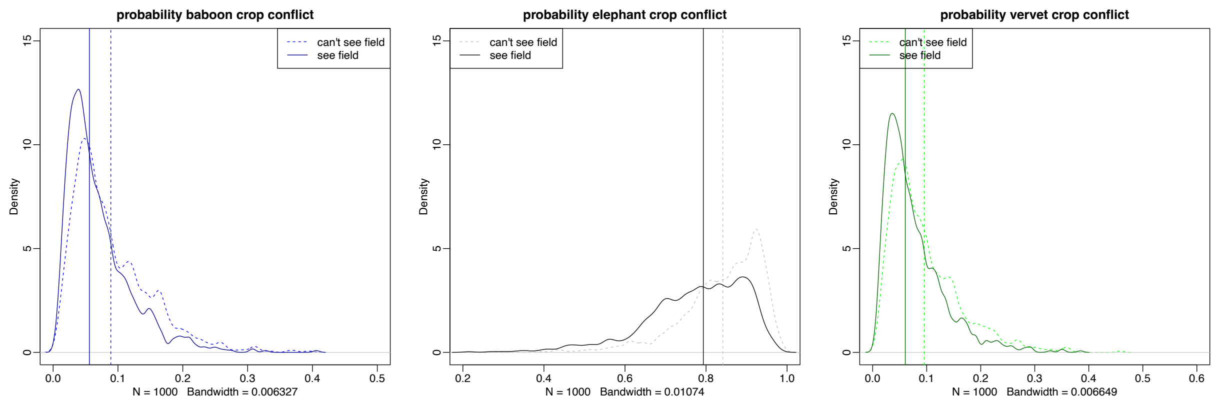
(a) baboons (b) elephants (c) vervets

Figure A12: Posterior predictions of the relationship between crop damage probability and household size for (a) baboons, (b) elephants and (c) vervets predicted from model mc_hh.Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



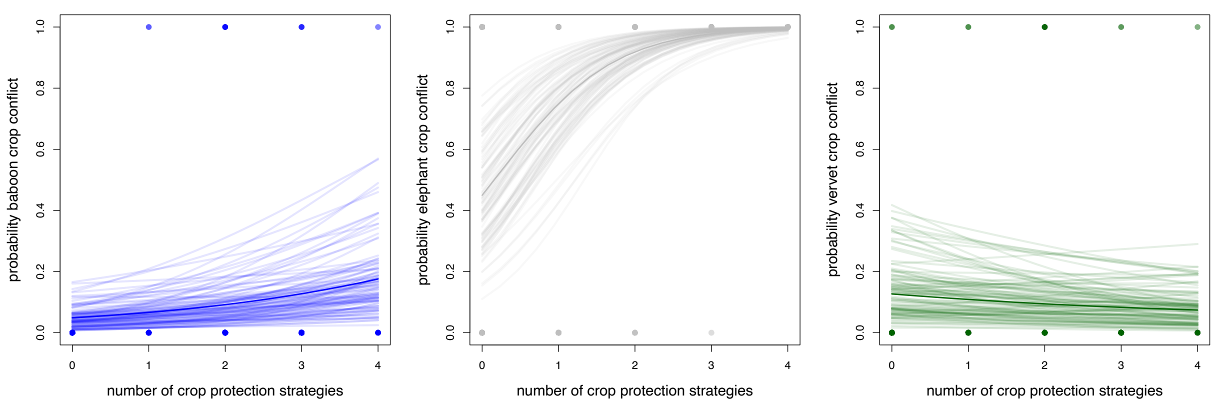
(a) baboons (b) elephants (c) vervets

Figure A13: Posterior predictions of the relationship between crop damage probability and the number of months a field was planted for (a) baboons, (b) elephants and (c) vervets predicted from model mc_mp. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



(a) baboons (b) elephants (c) vervets

Figure A14: Posterior distributions of probability of crop damage for farms where households can see and not see their fields for (a) baboons and (b) elephants. Vertical line lies at posterior mean. Dashed lines are instances where field is not visible, solid lines where fields are visible. Predictions are from mc_see.



(a) baboons (b) elephants (c) vervets

Figure A15: Posterior predictions of the relationship between crop damage probability and number of protection strategies a household implements for (a) baboons, (b) elephants and (c) vervets predicted from model mc_np. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions. Inferences from these graphs are not reliable due to confounding.

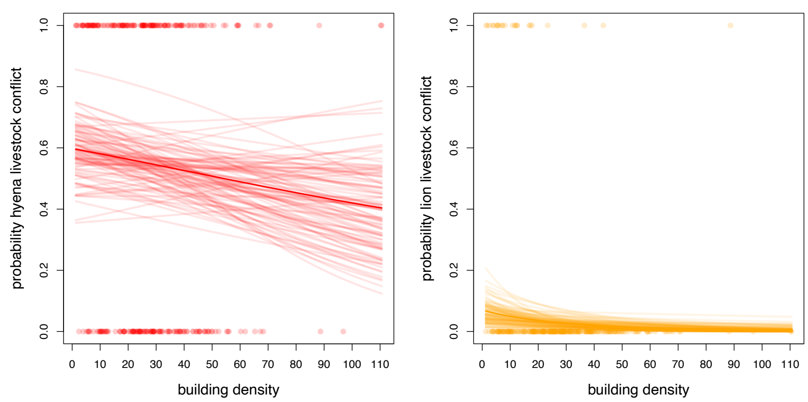
A6 Livestock Predation Model Parameter Predictions

Table A6: Posterior mean coefficient estimates of evaluated livestock damage models. Species level effects are offsets from the corresponding population level mean effect. Models with asterisks are likely confounded.

	ml_bd	ml_c2070	ml_c70	ml_riv	ml_sd	ml_sl	ml_landscape	ml_guard	ml_lsh	ml_lshXguard
a	-0.57	-0.51	-0.54	-0.56	-0.53	-0.57	-0.56	-0.55	-0.55	-0.55
as_hyena	0.72	0.65	0.68	0.66	0.66	0.67	0.73	0.73	0.71	0.77
as_lion	-3.12	-2.39	-2.37	-2.16	-2.98	-2.11	-3.76	-2.77	-2.74	-2.80
b_BD	-0.24	-0.37	-0.42				-0.27			
b_BDs_hyena	0.11	0.23	0.20				0.16			
b_BDs_lion	-0.30	-0.55	-0.63				-0.40			
b_SD	-0.47				-0.51		-0.54			
b_SDs_hyena	0.38				0.36		0.39			
b_SDs_lion	-1.20				-1.31		-1.65			
b_SL	-0.33	-0.34		-0.41		-0.44	-0.30			
b_SLs_hyena	-0.02	-0.02		0.05		0.04	-0.07			
b_SLs_lion	-0.09	-0.07		-0.18		-0.23	0.01			
b_C2070		0.03					-0.03			
b_C2070s_hyena		-0.01					0.01			
b_C2070s_lion		0.02					-0.03			
b_C70			-0.15				0.06			
b_C70s_hyena			0.06				0.09			
b_C70s_lion			-0.13				-0.11			
b_RIV			-0.23	-0.22			-0.39			
b_RIVs_hyena			-0.01	0.02			0.13			
b_RIVs_lion			-0.04	-0.06			-0.43			
b_RD							0.03			
b_RDs_hyena							-0.05			
b_RDs_lion							0.07			
b_GU*								-0.02		0.02
b_GUs_hyena*								-0.04		-0.00
b_GUs_lion*								0.05		-0.00
b_HH								0.27		0.25
b_HHs_hyena								0.21		0.24
b_HHs_lion								-0.20		-0.18
b_LSH								0.77	0.77	0.76
b_LSHs_hyena								-0.08	-0.09	-0.08
b_LSHs_lion								0.80	0.84	0.76
b_GUxLSH*										-0.04
b_GUxLSHs_hyena*										-0.08
b_GUxLSHs_lion*										0.09

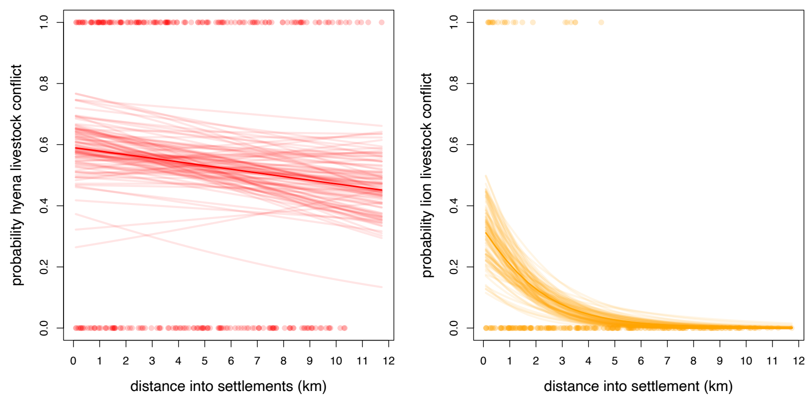
Table A7: Widely available information criteria (WAIC) scores for all evaluated livestock conflict models. dWAIC is difference in WAIC scores from highest ranked model. wWAIC is weight used to model average predictions. Models with asterisks are likely confounded.

	WAIC	SE	dWAIC	wWAIC
ml_guard*	496.92	25.44	0.00	0.73
ml_lshXguard*	499.80	25.71	2.87	0.17
ml_lsh	501.10	24.17	4.17	0.09
ml_landscape	518.13	22.90	21.21	0.00
ml_bd	520.49	22.43	23.56	0.00
ml_sd	528.82	21.14	31.89	0.00
ml_c2070	546.91	26.44	49.98	0.00
ml_c70	547.00	26.13	50.08	0.00
ml_riv	548.91	24.91	51.98	0.00
ml_sl	549.44	24.70	52.52	0.00



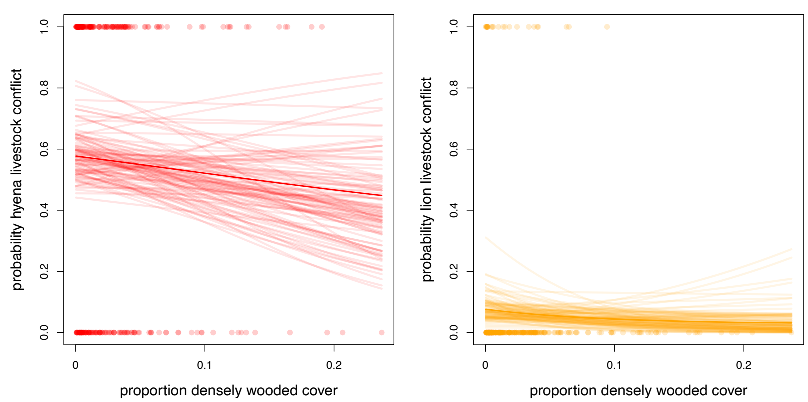
(a) hyenas (b) lions

Figure A16: Posterior predictions of the relationship between livestock damage probability and building density for (a) hyenas and (b) lions predicted from model ml_bd.



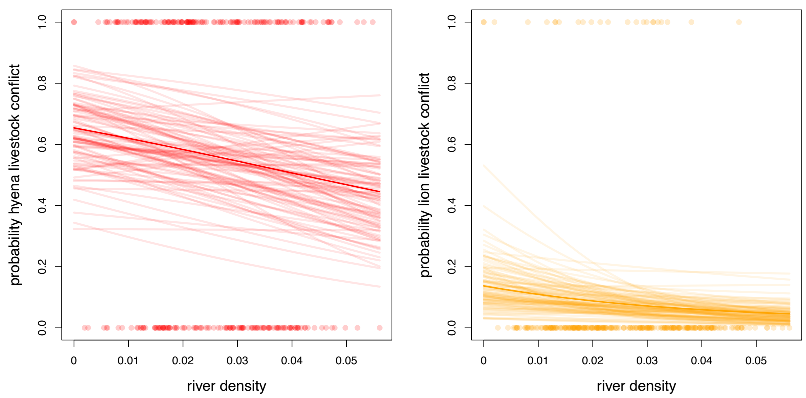
(a) hyenas (b) lions

Figure A17: Posterior predictions of the relationship between livestock damage probability and settlement distance for (a) hyenas and (b) lions predicted from ml_sd.Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



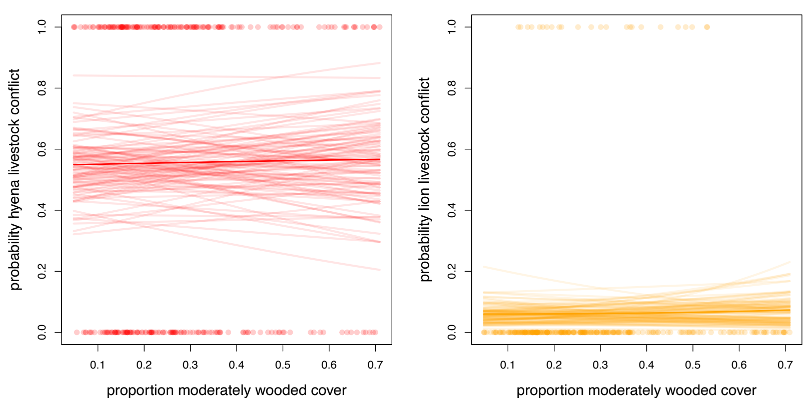
(a) hyenas (b) lions

Figure A18: Posterior predictions of the relationship between livestock damage probability and $>$ 70 % cover (forest/thicket) density for (a) hyenas and (b) lions predicted from ml_c70 model. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



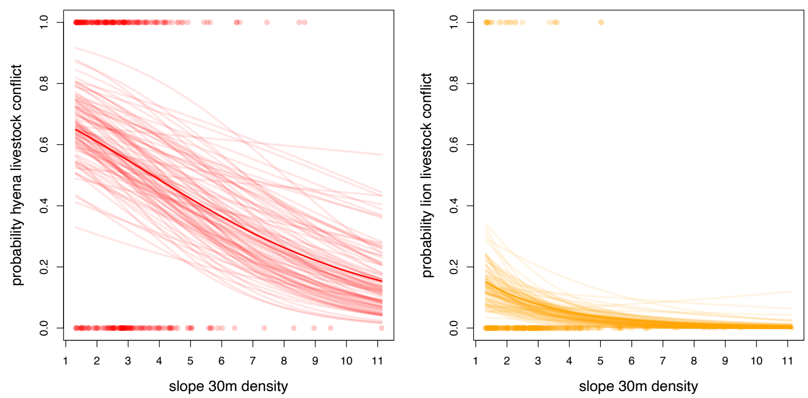
(a) hyenas (b) lions

Figure A20: Posterior predictions of the relationship between livestock damage probability and river density for (a) hyenas and (b) lions predicted from model ml_riv. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



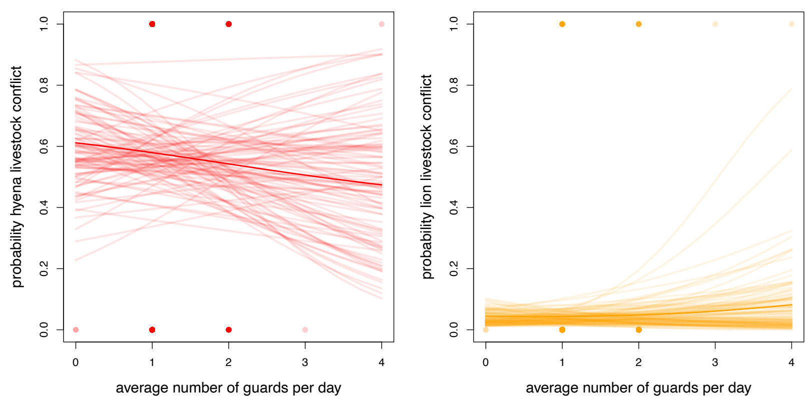
(a) hyenas (b) lions

Figure A19: Posterior predictions of the relationship between livestock damage probability and 20- 70 % cover (woodland/open ticket/shrubland) density for (a) hyenas and (b) lions predicted from model ml_c70.



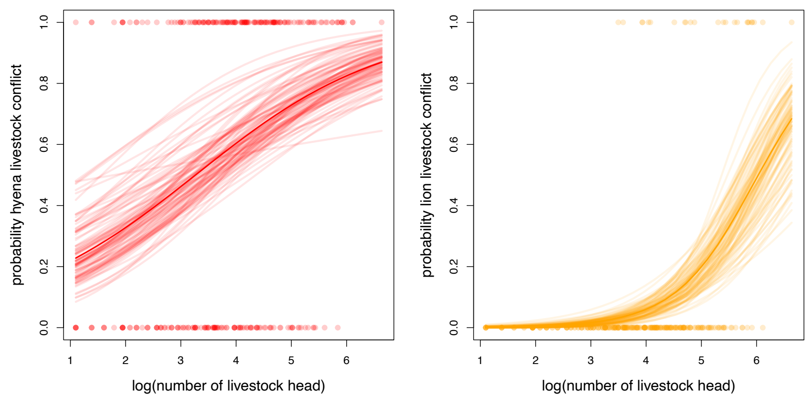
(a) hyenas (b) lions

Figure A21: Posterior predictions of the relationship between livestock damage probability and 30 meter average slope for (a) hyenas and (b) lions predicted from model ml_sl. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



(a) hyenas (b) lions

Figure A22: Posterior predictions of the relationship between livestock damage probability and number of guards during the day for (a) hyenas and (b) lions predicted from model ml_guard. Inferences from these graphs are not reliable due to confounding. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.



(a) hyenas (b) lions

Figure A23: Posterior predictions of the relationship between livestock damage probability and the number of livestock head on logarithmic scale for (a) hyenas and (b) lions predicted from ml_lsh. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions.

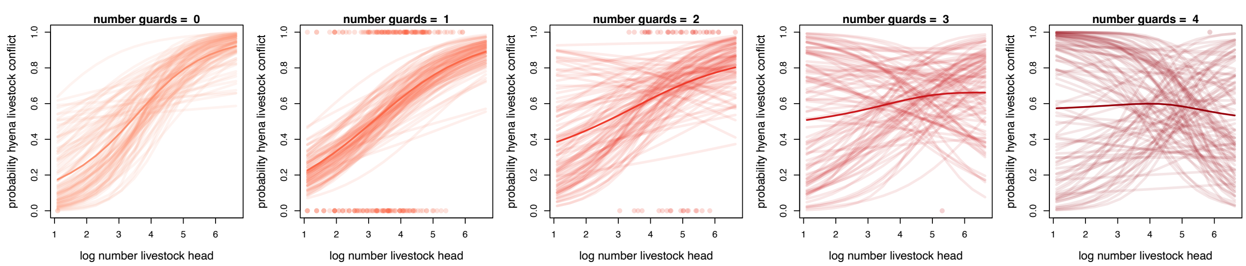


Figure A24: Posterior predictions of the interaction between number of guards and number of livestock head for livestock damage probability by hyenas predicted from ml_lshXguard. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions. Inferences from these graphs are not reliable due to confounding.

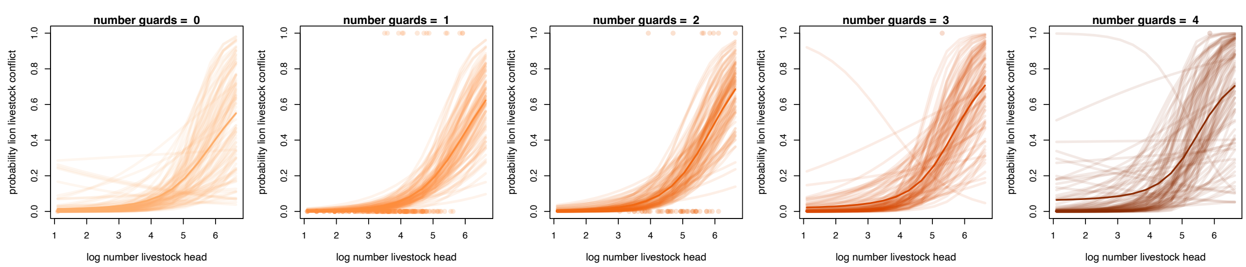


Figure A25: Posterior predictions of the interaction between number of guards and number of livestock head for livestock damage probability by lions predicted from ml_lshXguard. Dark line is posterior mean, lighter lines are 100 randomly drawn posterior predictions. Inferences from these graphs are not reliable due to confounding.