Supplementary Information

The impacts, characterisation and management of human-leopard conflict in a multi land use system in South Africa

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Online Resource 1

Table S1 Average market sale prices for livestock and game species calculated from local auctions in Vivo and auction websites in the Limpopo Province, accessed on the 2nd December 2012, covering the period from October, 2009-October, 2011. The market prices were used to determine the economic costs of livestock depredation by leopards in the Blouberg Mountain Range

Livestock Species	**Market Value (ZAR)**	**Accessed**
Nguni Bull	8000	http://www.ngunicattle.info/Sales-Results.htm
Adult Female Bonsmara	4600	http://www.proveld.co.za/results.html
Adult Female Nguni	3500	http://www.ngunicattle.info/Sales-Results.htm
Bonsmara Calf	4777	http://www.proveld.co.za/results.html
Nguni Calf	3000	http://www.ngunicattle.info/Sales-Results.htm
Sheep	800	Estimates based on local vivo auctions
Goats	700	Estimates based on local vivo auctions
Donkeys	700	Estimates based on local vivo auctions
Game Species	**Market Value (ZAR)**	**Accessed**
Bushbuck	4304	http://www.wildlifeauctions.co.za/game_info.php
Gemsbok	5167	http://www.gamefarmnet.co.za/veiling.htm
Impala	694	http://www.gamefarmnet.co.za/veiling.htm
Kudu	3405	http://www.gamefarmnet.co.za/veiling.htm
Nyala	5171	http://www.gamefarmnet.co.za/veiling.htm
Ostrich	1952	http://www.wildlifeauctions.co.za/game_info.php
Warthog	696	http://www.wildlifeauctions.co.za/game_info.php
Waterbuck	2000	http://www.gamefarmnet.co.za/veiling.htm

Online Resource 2

The locations of livestock and game attacks from October, 2009-October, 2011 were recorded using a GPS and imported into a Geographical Information System (GIS) (ArcGIS v. 10 [ESRI Inc. 2010]). Within GIS, additional data on the locations of villages, roadways, water points, inland reservoirs, river channels, nature reserve boundaries, farm boundaries, habitat type, grazing capacity was partially mapped using the assistance of local farmers knowledge and vector data acquired from the Department of Limpopo Economic Development, Environment and Tourism (LEDET) and imported into the base map. Seven environmental variables including elevation, habitat type, grazing capacity, distance to villages, distance to roadways, distance to nature reserves and distance to water were used to analyse the risk of leopard predation on game and livestock on other studies of large carnivores (Basille et al. 2009; Holmern et al. 2007; Rosas-Rosas et al. 2010; Zarco-González et al. 2012). Elevation data were extracted from a Digital Elevation Model (DEM) of the study area downloaded via the ArcGIS online capabilities in ArcMap (accessed on the 22nd May, 2012) using a 30 arc-second DEM of Africa and the extract values to points tool in ArcGIS spatial analyst tools. Distance to villages, roadways, water and nature reserves were calculated as Euclidean distances in ArcGIS, using spatial analyst tools to produce raster based distance maps with a cell size of 20x20m^2. Distance to water was estimated as the Euclidean distance to artificial water points, river channels and inland reservoirs. Distance to roadways included Euclidean distances to primary and secondary roadways. Habitat type was classified using the habitat classifications defined by Mucina and Rutherford (2006) for South Africa. Grazing capacity was a measure of the available biomass for grazing animals estimated from vegetation biomass, incorporating Normalised Difference Vegetation Index (NDVI) and tree density (Morgental et al. 2005). NDVI is a measure of photosynthetically active biomass and reflects vegetation productivity and related bioclimatic variables

(Swanepoel et al. 2012). To account for potential spatial bias arising from grid cells with varying sizes because of extended latitude range (Elith et al. 2011), the maps were projected onto an equal area projection (Africa Albers Equal Area Conic). All spatial data were converted to a cell size of $20x20m^2$ using the resample tool in ArcGIS data management tools to correspond with the resolution of the GPS occurrence data. To reduce the potential for spatial correlation between GPS points, the data were filtered in ArcGIS to obtain one point per pixel. Finally, environmental variables were assessed for multicollinearity and only pairwise correlation coefficients of < 0.5 were included in the analysis.

Maxent is an ecological niche model which uses a maximum entropy algorithm to determine the unknown distribution of a species over a geographical range, from a known sample of occurrence data and set of spatially explicit environmental conditions (Phillips et al., 2004, Phillips and Dudík, 2008). Following other studies (Abade et al. 2014; St John et al. 2011; Zarco-González et al. 2012) we used it in an alternative context to measure the risk of predation at finite scales. The set of locational GPS presence points for livestock and game attacks collected over the two year period and the set of raster maps for each environmental variable served as the input data for the Maxent Model. The default values for Maxent were used including a convergence threshold (10^{-5}), maximum iterations (500), regularisation multiplier (1) and all feature types, since these settings are found to achieve good performance in other studies (Phillips and Dudík 2008). A subsample method was used, where 10 random partitions of the occurrence localities were made (Phillips et al. 2006). In each partition, 75% of the presence localities were used for training, 10,000 random background pixels were treated as negative training data and 25% of the occurrence points were set aside for testing the final model (Livestock: $n_{training} = 42$, $n_{test} = 14$; Game: $n_{training} = 24$, $n_{test} = 7$). Low sample sizes of between 5 and 10 occurrence points perform at near maximal accuracy levels within Maxent (Hernandez et al. 2008) and so sample sizes for the game model were deemed sufficient for analysis.

Sampling bias can occur from the collection of presence points (locations of game and livestock attacks) because some areas in the landscape are sampled more intensively then others, for example, farmers may identify attacks closer to roadways or footpaths where they walk (Elith et al. 2011). To account for this sampling bias, the background data from which the negative training data sets were drawn included only the farms where livestock and game attacks were recorded which provides Maxent with a background file with the same sampling bias as the presence points. Protected areas were removed from the final prediction area to determine the distribution of predation risk outside of these areas.

The gain measures the likelihood that the model is concentrated around the occurrence sample points compared with the random background pixels if the study area (Phillips et al. 2006). Training gain is calculated first for each environmental variable alone and the drop in training gain when the variable is removed from the full model containing all predictor variables. The objective was to build models with the best set of predictor variables by starting with a full model and gradually removing the variable with the lowest decrease in the average training gain (Yost et al. 2008). The model with the fewest predictor variables and an average training gain not significantly different to the model with the highest training gain was considered the most parsimonious (Yost et al. 2008). The overlap between 95% confidence intervals for the training gain averages was used as the criterion for significance (Yost et al. 2008).

To determine which predictor variables (environmental and anthropogenic factors) most influence the spatial risk of predation by leopards we used the Maxent's Jacknife and heuristic test using the percent contribution of each predictor in the final model. This is a heuristic approach to model importance in which the contribution values (%) are determined by the increase in gain in the model provided by each variable (Phillips et al. 2006). Higher percentage values indicate a greater effect of the predictor variable influencing the risk of predation by leopards.

Finally, visual inspection of the final probability maps of leopard predation risk was assessed to see if predicted high risk areas, showed strong agreement with regions containing the highest number of attacks (Yost et al. 2008)

Model Selection

The Jacknife test of variable importance showed that elevation and distance to water produced the highest training gain for the livestock and game model respectively, indicating that these variables influence the risk of predation most greatly when modelled independently (Fig. S2a-b). Distance to water decreased the gain the most when omitted from the full model for both the livestock and game model, suggesting that distance to water contains the most information not present in other variables (Fig. S2a-b). Based on the lowest decrease in the average training gain, the order of variable removal from the livestock model was habitat, elevation, distance to nature reserves, distance to roadways, distance to water and distance to villages. For the game model, the order of variable removal was distance to roadways, habitat, distance to village, distance to nature reserves, elevation and distance to water.

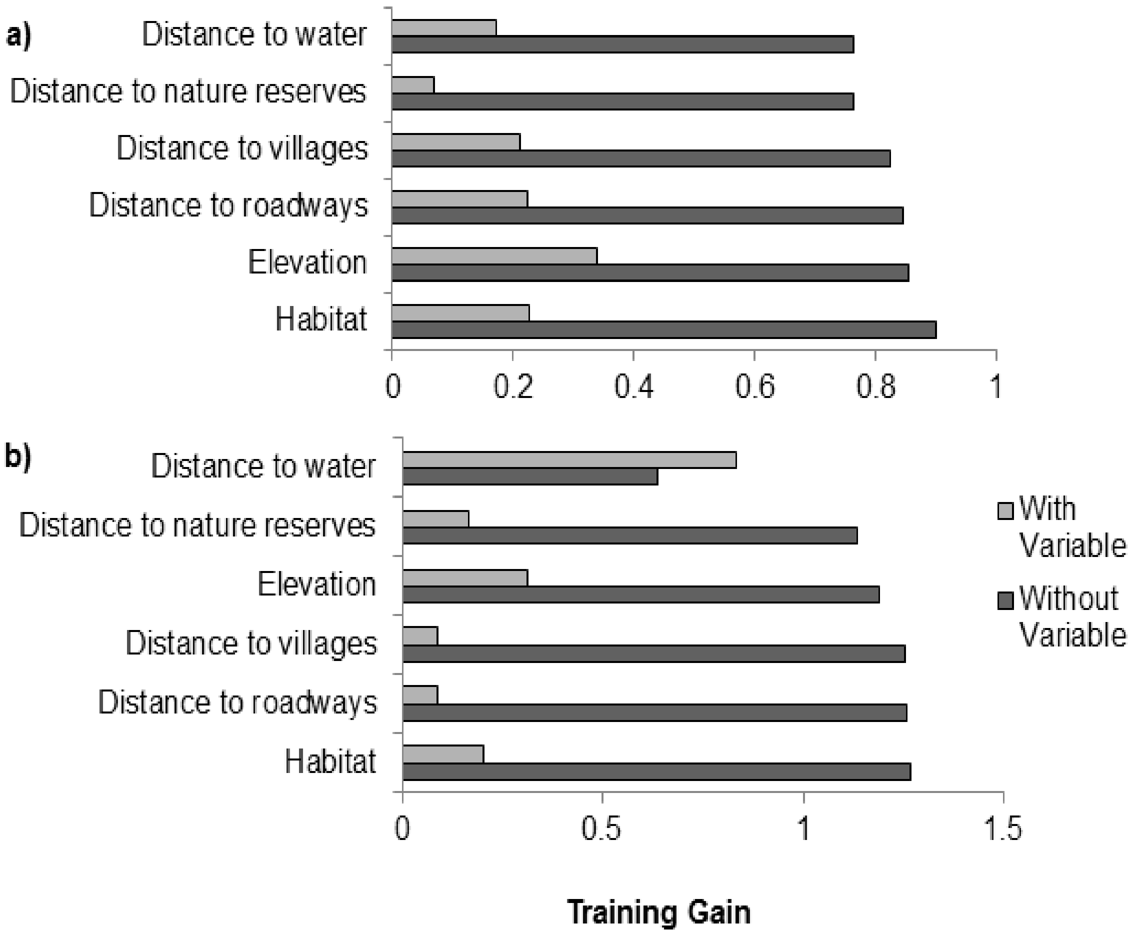

Figure S2 Jacknife results showing the training gain for each predictor variable alone and the drop in training gain when the variable is removed from the full model for **a** livestock and **b** game attacks

The average training and test AUC values were similar for the six-one variable models but decreased slightly as the number of predictor variables declined for both the livestock and game models (Fig. S3a-b). The average training gain values declined with a decreasing number of predictor variables for the livestock model and decreased after the sixth variable model, remaining consistent thereafter for the game model (Fig. S3a-b). The test gain values were similar for the six-three variable models and decreased thereafter for the livestock model and increased from the first variable model, remaining similar thereafter for the game model (Fig. S3a-b). The standard deviations of the training gain values for each partition were less variable for both livestock (0.01-0.08) and game (0.08-0.18) compared to the test gain standard deviations of 0.04-0.26 and 0.29-0.60, respectively. Considering the high sensitivity of the average training gain relative to the average AUC values, the model with the fewest predictor variables and an average training gain not significantly different to the model with the highest training gain was considered the most parsimonious (Yost et al. 2008). The overlap between 95% confidence intervals for the training gain averages was used as the criterion for significance (Yost et al, 2008). In assessing the factors accounting for spatial variation in risk, a five variable model containing elevation, distances to village, water, roadways and nature reserves was selected for the livestock model (Livestock: $n_{training} = 42$, $n_{test} = 14$) with a three variable model containing elevation, distance to nature reserves and distance to water the most parsimonious for the game model (Game: $n_{training} = 24$, $n_{test} = 7$). The average Test AUC values ($n = 10$) produced from all partitions was significant (Mann-Whitney U Test: $P < 0.001$) for both the livestock and game models, indicating a better model then predicted by chance.

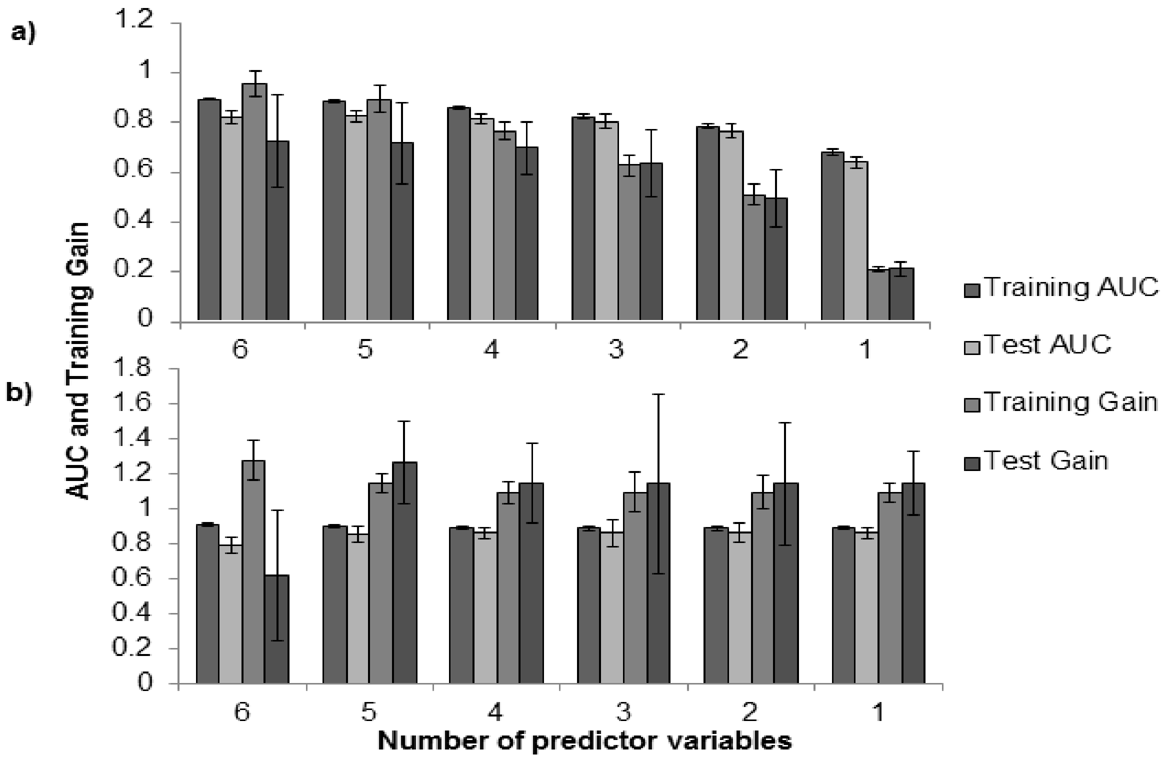

Figure S3 The Training AUC, Test AUC, Training Gain, and Test Gain averaged across 10 random partitions of the presence records with 95% confidence intervals. The x axis represents the number of predictor variables in each model for **a** livestock and **b** game attacks

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Online Resource 3

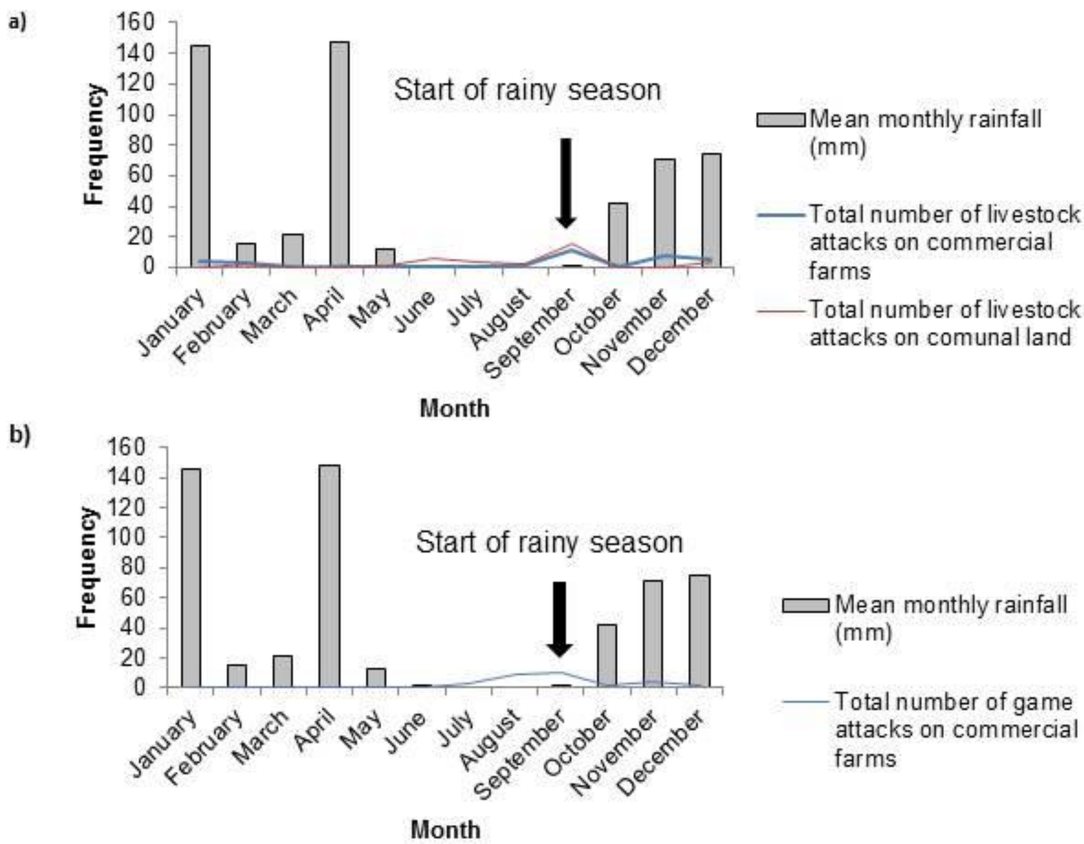

Figure S4a The total number of livestock attacks per month by leopard on commercial and communal land and **b** the total number of game attacks per month by leopard on commercial farms and mean monthly rainfall (mm) patterns from October, 2009 – October, 2011

Online Resource 4

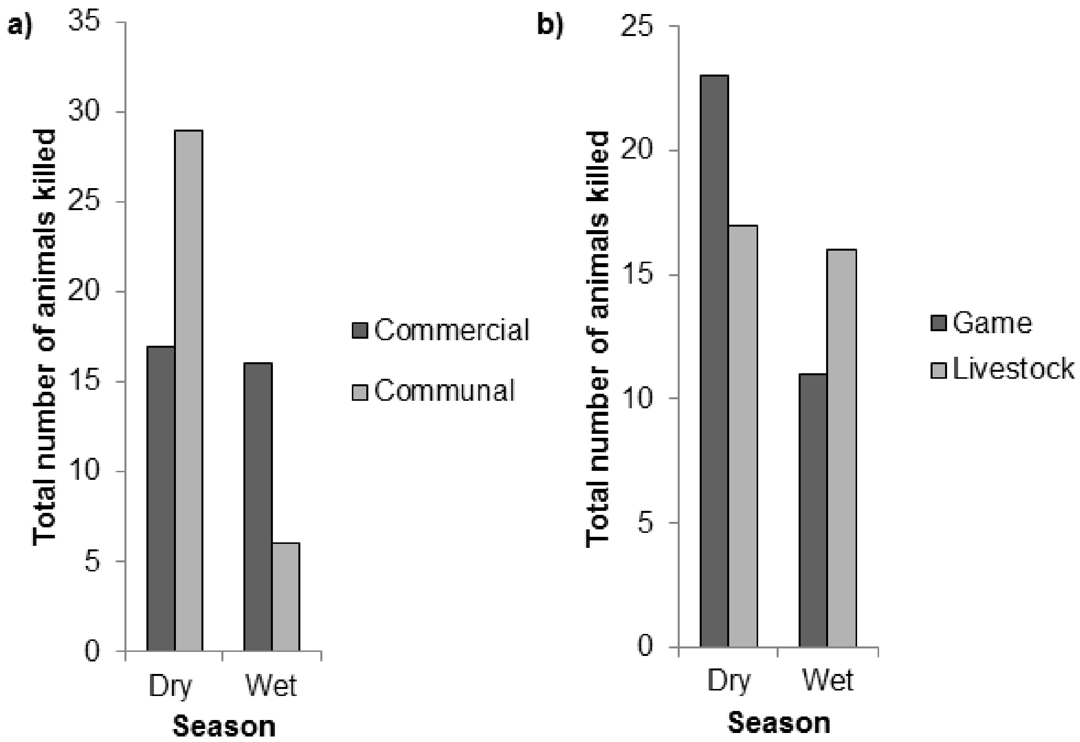

Figure S5a Total number of livestock killed by leopards during the dry (April-September) and wet season (October-March) on commercial and communal land and **b** the total number of game and livestock species killed by leopards during the dry and wet season on commercial farms from October, 2009 – October, 2011

Online Resource 5

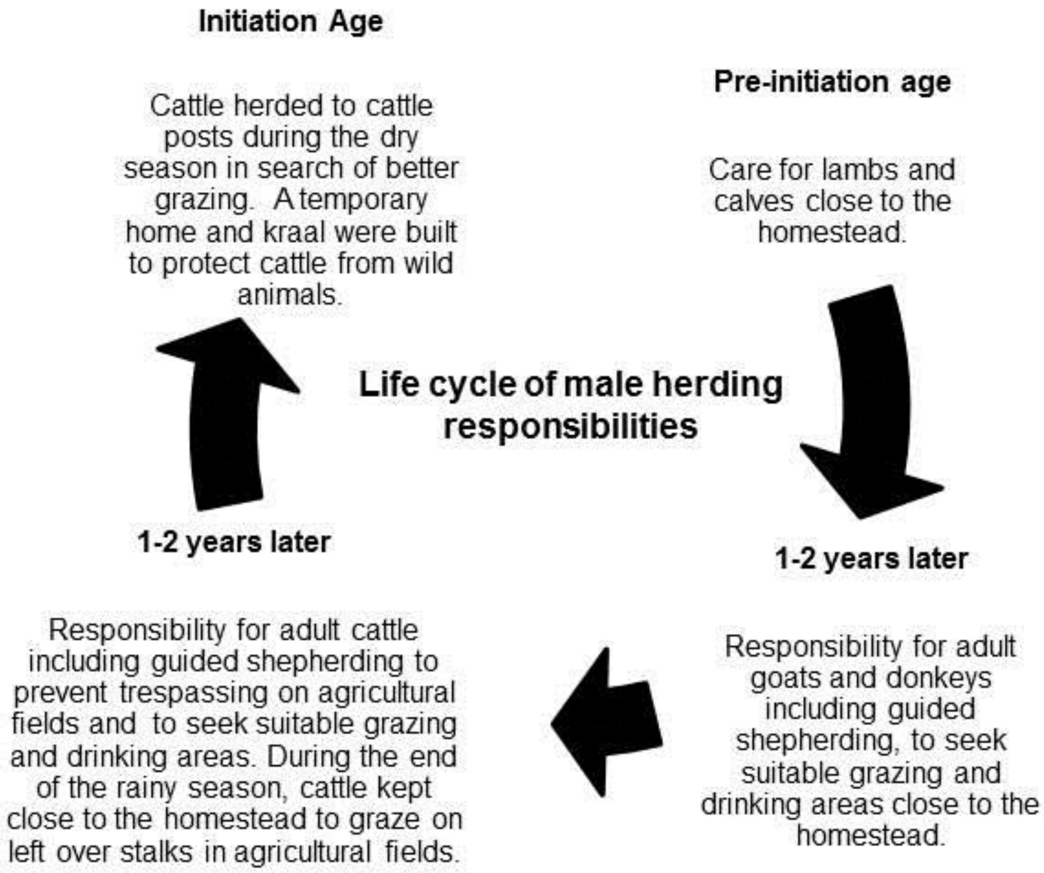

Figure S6 Traditional life cycle of male herding responsibilities amongst communal farmers