

Investigating Human-Carnivore Conflict Dynamics and Compensation Payment Processes
in a Landscape of Coexistence

by

Rupinder Kaur Bakhshi

Dr. John Poulsen, Adviser

[4/24/2020]

Masters project submitted in partial fulfillment of the
requirements for the Master of Environmental Management degree in

the Nicholas School of the Environment of

Duke University

Abstract

When large carnivores occur in proximity to humans, conflict is often manifest. The predation of livestock by carnivores imposes significant economic costs on people living near carnivore habitat, and sometimes results in human deaths and injuries. Conflict thus affects human livelihoods and well-being in various ways and can lead to retaliatory killing. The survival of large carnivores, like tigers and leopards, requires that humans and animals share space in ‘landscapes of coexistence’, within which carnivores can exploit prey and other resources without risk of injury or mortality from humans. Compensation programs are a common intervention to mitigate losses incurred by wildlife, but it is unclear whether these measures engender greater tolerance for carnivores and other wildlife.

Conflict between wildlife and humans is especially acute in and around Corbett Tiger Reserve in North India where tigers and leopards kill 700 – 1000 cattle, buffalo and horses each year and occasionally harm humans. Corbett Tiger Reserve supports among the highest densities of tigers globally and is embedded in one of the most densely populated rural regions of the world. Human injuries and fatalities, livestock depredation and crop damage are compensated by the Government. In this study, my first objective was to use a multi-year dataset (2011 – 2019) of livestock depredation events to investigate the influence of eco-geographical and anthropogenic factors on spatio-temporal variation in predation probabilities. My second objective was to assess the efficacy of the compensation process in terms of time taken to disburse payments and to identify factors that cause delays in payment. Cumulatively, these analyses will improve understanding of where livestock, carnivores and humans are most vulnerable, identify behaviors of carnivores that enable them to prey on livestock in areas used by humans, and assess how existing compensation programs can be made more effective.

I used dynamic occupancy models to estimate probabilities of livestock depredation, and colonization and extinction of conflict between quarterly seasons in 502 4 km² grid cells (sites). Specifically, I tested three hypotheses. First, tigers and leopards would avoid preying on cattle in areas with high human use unless vegetation cover provided refuges for carnivores (spatial avoidance). Second, livestock depredation hotspots would shift spatially with seasons because of changing forage availability for livestock and changing cover for carnivores. Third, I also predicted that leopard and tiger depredation events would be spatially segregated, as tigers competitively displace leopards. I used linear and linear mixed models to identify factors that caused delays in compensation payments (n=414) to test the prediction that payments would be more delayed for livestock and crop depredation in and around multi-use forests compared to human deaths and injuries and cases within Protected Areas.

A total of 3188 kills attributed to tigers and 1927 kills attributed to leopards were documented. Overall, cows and buffaloes accounted for 70% and 29% of depredation events, with horses and donkeys making up the remaining fraction. Approximately 75% of kills occurred within forests, typically close to the forest

edge, whereas the remainder of kills occurred outside forests, predominantly in farmlands. The probability of depredation was greatest in the monsoons, and approximately 50% lower in the winter and summers for tigers and marginally lower in winter and summers for leopards. For both carnivore species, depredation-colonization probabilities were notably higher in the transition from summer to monsoons (tigers: 0.11, SE=0.006; leopards: 0.069, SE=0.004), relative to transitions between other seasons. The spatial avoidance, spatial shift and spatial segregation hypotheses were all supported. Tigers and leopards avoided killing livestock in areas with extensive human presence, unless there was abundant vegetation cover or movement conduits—like forest edges, green vegetation (areas with high NDVI) and drainage features. Areas around *Van Gujjar* (a herder community) settlements were associated with higher depredation probabilities. The depredation-colonization probability peaked during summer – monsoon transition and stayed high through the monsoon, with the most significant spatial shifts in areas where vegetation increased the most, offering forage for livestock and cover for predators. Both spatial shift and spatial avoidance were more pronounced for tigers than leopards, with the latter more frequently preying on livestock in human-use areas. Leopard depredation events were concentrated along the northern boundary of the study area, likely because tigers displaced them to the lower quality habitat, with higher ruggedness and fewer wild prey. The average compensation paid by the government for loss of livestock was US \$211, approximately 30% of the value of a buffalo. Fund disbursement was greatly delayed, with claimants receiving payments 276-320 days after recording an event. Compensation was approximately two times faster for human deaths and injuries in reserve forests, but considerably slower for other forms of conflict. Compensation payments were more prompt in Protected Areas (PA) for livestock depredation, but not other forms of conflict, despite availability of more conservation funds.

These results highlight pronounced spatio-temporal variation in depredation suggesting that livestock, face high risks in relatively few hot-spots within the study area. Given the sharp decline in depredation events even 1 km away from the forest edge, the most effective way to contain conflict may be to reduce cattle numbers grazing in forests through stall feeding and through incentives such as subsidized livestock insurance packages. These schemes should be prioritized along forest edges and other densely vegetated zones where carnivores shelter to stalk or feed on livestock. Proactive risk management aside, coexistence may also be enabled by supporting tolerant attitudes of local communities. Taking steps to provide timely and adequate compensation payments may create more room for negotiations with communities to adopt practices that reduce depredation risks. In the long-term, supporting sustainable livelihoods with low impacts on wildlife habitats and more equitable benefit sharing from activities directly connected to PAs like tiger-tourism will also be important to sustain social capital for coexistence.

Introduction

Tigers (*Panthera tigris*), leopards (*Panthera pardus*) and other large carnivores commonly co-occur with humans within and beyond forest boundaries owing to their large home range requirements (Athreya et al., 2015; Carter & Linnell, 2016; Majgaonkar et al., 2019). The future of metapopulations of various large carnivores thus requires that conservation be expanded to include habitats outside protected areas (PA), including multiple use forests for logging and agricultural areas (Chanchani et al., 2016; Treves et al., 2006). The long-term persistence of these species also depends on the degree to which human and wildlife can coexist in shared landscapes. Such coexistence has been conceptualized as a dynamic but sustainable state in which humans and large carnivores co-adapt to living in shared landscapes where human interactions with carnivores are guided by effective institutions that enable long-term carnivore population persistence, garner social support for conservation, and minimize risk to tolerable levels (Carter & Linnell, 2016).

When large carnivores and humans co-occur, carnivores often prey on livestock and other domestic animals. Space-sharing, with potentially adverse impacts on people and carnivores, has both ecological and social contexts. The ecological context is broadly described by the abundance of predators and their prey, distribution of resources (forage for herbivores and prey for carnivores) and behavioral adaptations. Prey species such as deer and antelope seek to balance foraging in resource-rich areas with minimizing the risk of predation in ‘landscapes of fear’ (Brown et al., 2001; Creel & Christianson, 2008; Laundré et al., 2014; Miller & Schmitz, 2019). There is growing evidence that many predators have adapted behaviorally to exploit resources in areas of low human-caused mortality risk, which enables their persistence in human-dominated “landscapes of coexistence” (Chapron et al., 2014; Oriol-Cotterill et al., 2015).

The social context of livestock depredation, and more broadly of human – large carnivore interactions, has economic, cultural, and political dimensions. Ultimately, these factors influence human behavior – and shape attitudes such as tolerance towards carnivores, which may have significant bearing on coexistence of humans and wildlife (Carter & Linnell, 2016; Struebig et al., 2018; A. Treves & Bruskotter, 2014). Tolerance has generally been viewed to have two attributes: (a) the willingness, and (b) the ability of people to behaviorally adapt to presence of carnivores (Carter & Linnell, 2016). When one or both of these elements are deficient, carnivores may be targeted resulting in population declines (Ripple et al., 2014).

Studies from various systems have shown that people and large carnivores can co-exist, but the tolerance of carnivores by humans is neither static nor guaranteed. Tolerance may wear thin for a variety of reasons – most notably the inability of communities to withstand unmitigated economic losses, perceived or real fear of death or injury, and opportunity costs arising from conflict with large carnivores (Kansky & Knight, 2014; Lischka et al., 2019; Packer et al., 2019). Therefore, the future of large carnivores in increasingly

congested and fragmented landscapes may depend on measures, actions, and policies that help engender tolerant attitudes. The existence and efficacy of institutions and mitigation mechanisms can greatly influence norms and behavior, or redress actual and perceived threat to human lives and livelihoods from conflict, and may critically determine whether, where and to what extent carnivores are accommodated in human-dominated landscapes (Treves & Bruskotter, 2014).

A widely used mitigation mechanism is payment through compensation schemes. The intent of compensation is to ameliorate losses and build tolerance for wildlife, though its efficacy may depend on whether it is accessible and expedient. The reality is that compensation payments often fall short of this lofty goal (Dickman, Macdonald and Macdonald 2011) because they are undermined by corruption, lack transparency, have convoluted procedures, fail to account for transaction costs, and provide meagre support (MacLennan et al., 2009; Nyhus, 2016; Watve et al., 2016).

Realizing species persistence in landscapes of coexistence – where large carnivores are able to meet their life history needs, find adequate refuge areas and be supported by accommodating human behaviors – is especially relevant in nations where protected areas are small, boundaries between wildlife habitats and human-use areas are porous, and anthropogenic pressures on wildlife habitats are pervasive (Chanchani et al., 2016). India typifies these conditions, perhaps more so than any other nation, and herein lies a paradox. India supports the greatest diversity of wild felids (15 species) and approximately 70% of the world's wild tigers (Jhala et al. 2015), despite having high human densities and livestock populations, and scoring poorly on various governance and economic indices that influence conservation (Dickman et al., 2015; Inskip et al., 2016). Insights about how humans and carnivores coexist in densely populated nations like India can be gained from understanding how a suite of ecological and social factors influence the prevalence, trends and outcomes of conflict (Hazzah et al., 2009; Suryawanshi et al., 2014; Miller et al., 2015).

At least, three key components of coupled socio-ecological systems need to be investigated to understand the causes and consequences of human carnivore conflict. First, developing a robust understanding of the spatial and temporal dynamics of depredation is necessary to determine how landscape-geography, grazing systems and carnivore space use intersect and give rise to conflict. An extension of this would be to also understand risks for carnivores and the vulnerability of interacting human communities. Second, understanding of human use of shared landscapes – by assessing socio-economic attributes, attitudes and perceptions that define and shape the contours of landscapes of coexistence for carnivores—and being informative of the willingness and ability of people to tolerate risk and of mechanisms for communities to cope with their losses. Finally, while a variety of mitigation measures – including compensation—may exist

in conflict-hotspots, their efficacy is seldom evaluated. An objective assessment of the mechanisms and processes of mitigation measures can help increase their efficiency and potentially reduce losses while engendering greater tolerance towards wildlife (Karanth et al., 2018).

The first component requires understanding heterogeneity in spatial and temporal patterns of livestock depredation as a function of relevant ecological and geographic attributes including land-use, vegetation cover, topography, drainage, extent and location of habitat edges, and human footprint. Studies over the past decade in India have advanced our understanding of some of these aspects, including both similarities and differences between carnivore species. Large carnivore species in a system may exhibit similar traits, such as hunting tactic (e.g., ambush or active) and habitat domain (i.e., use of space and habitat within an animal's home range), and generally rely on similar landscape attributes to ambush and kill prey (Miller et al., 2015). However, tigers and leopards often segregate temporally or spatially to minimize interference competition (Harihar et al., 2011; Miller et al., 2016). Thus, livestock depredation by leopards and tigers may vary considerably, with tigers generally preying on larger livestock like buffaloes and cows, and leopards preying more frequently on calves, sheep and goats (Bargali & Ahmed, 2018; Sekhar, 1998). In central India, livestock were most at risk from tigers near dense forests and at moderate distances from human activity, while leopards posed most risk near open vegetation (Karanth et al., 2012; Miller et al., 2016). Large cat predation on livestock can be influenced by human infrastructure and activities such as the locations of human settlements, extent, and ways that humans use the landscape, as well as grazing systems in and around forests and natural grasslands. Close proximity between livestock grazing sites and high-quality carnivore habitat is one of the strongest indicators of attacks by nearly all carnivores (Miller, 2015). Other studies in central India and Mexico found that the risk of attacks by tigers and other carnivores like jaguar and puma is considerably higher for livestock grazed within parks or unguarded than stall-fed in shelters (Karanth et al., 2012, 2013; Miller, 2015; Zarco-González et al., 2013). The risk of depredation was found to peak at approximately 1 kilometer from roads and villages and is lower at closer and greater distances from infrastructure in a study in central India (Miller, 2015; Miller et al., 2015). One key limitation of these studies is that they did not explicitly consider long term data or seasonal dynamics in livestock depredation, even though seasonal changes in cover and forage availability influence wildlife habitat use, with corresponding shifts in conflict hotspots (Goswami et al., 2015; Warriar 2019).

The second component, variations in the layered interactions between social and economic conditions, culture, norms and behavior that shape human attitudes towards wildlife, may explain why large carnivores have persisted in some habitat-areas in India even as they have declined in others. Socio-economic-cultural and political interactions that shape behavior towards carnivores need to be understood at multiple

interconnected levels. The economic status of local communities, their financial dependence on livestock, and the costs they bear (economic, transactional and psychological) from depredation shape their response to such events (Dickman, 2010; Kansky et al., 2016; Kansky & Knight, 2014). Responses may be tempered by social norms and social capital, that either condone actions such as retaliatory killing, or mobilize other actions such as regulation on grazing, raising money to build fences or petitioning the government for redressal (Rastogi et al., 2014; Steinmetz et al., 2014). Additionally, existence and enforcement of government rules and laws will influence the behaviors and actions of local communities. Finally, religious beliefs can shape human attitude towards carnivores. Some religions revere tigers and lions and other wildlife as deities or spirits and have taboos against harming them (Dhee et al., 2019). There have been few rigorous investigations of human attitudes towards large carnivores in India, and even less is known about how attitudes and behaviors influence reactions such as tolerance or retaliatory killing.

The third component of landscapes of coexistence is the creation of effective mitigation measures of human-carnivore conflict. Preventing conflict, especially livestock depredation, is often impractical because livestock are grazed in and around forests across India. Mitigation comes principally in the form of compensation payments made by the government, and sometimes by non-governmental organizations, to address economic losses caused by livestock depredation, crop damage and human death and injuries. However, there is considerable variation in implementation among states (Karanth et al., 2018). On average, livestock owners receive just \$74 as compensation – a small proportion of the \$400 - 800 cost of productive livestock (Karanth et al., 2018). These payments are often insufficient to offset monetary losses, let alone address consequences such as psychosocial well-being, disruption of livelihoods and food insecurity (Barua et al., 2013). Moreover, rural communities seeking compensation incur opportunity costs through time lost from work and transaction costs associated with bureaucratic processes (Madhusudan 2003; Barua et al., 2013). The loss of livestock and costs of seeking compensation lead to feelings that that authorities are apathetic towards their well-being, and such perceptions may be reinforced by exclusionary forest management practices, protracted negotiations over compensation, and long delays in issuing compensation payments (Madhusudan 2003; Karanth et al., 2013; Margulies & Karanth, 2018; Watve et al., 2016). These factors affect both the ability and willingness of communities to tolerate wildlife in their surroundings (Barua et al., 2013; Carter & Linnell, 2016). Even though compensation payments for human-wildlife conflict are widespread in India, the efficacy of payment mechanisms have rarely been investigated and it remains unknown if these payments help engender greater tolerance for large carnivores.

Investigating Conflict and Coexistence in a Global Conflict Hotspot

There are possibly few places in the world where large carnivores exact as high of a toll on livestock as the periphery of Corbett Tiger Reserve (CTR) in north India. Tigers and leopards cumulatively kill more than 800 livestock including cows, buffaloes, horses, mules, and donkeys along a portion of the boundary of CTR and adjacent multiple use forests each year (Bargali and Ahmed, 2018). Still, CTR supports some of the highest tiger densities in the world. My research has two objectives: (i) to model the spatio-temporal dynamics of conflict using a long-term data set on livestock depredation by tigers and leopards, and (ii) to assess the efficacy of compensation payments in this landscape.

To mitigate livestock depredation, we must understand the elements of the Corbett landscape of coexistence that carnivores exploit to prey on livestock and identify where communities are most likely to incur losses from carnivore depredation. This information can contribute to refining and prioritizing existing conflict mitigation strategies to enable coexistence of people, livestock, and large carnivores in landscapes.

There are two tiers of compensation payments in the Corbett landscape to address livestock depredation by tigers and leopards. The first tier is called the Interim Relief Scheme (IRS) and has been implemented since 2006 by the World-Wide Fund for Nature, India (WWF-India) and the Corbett Foundation (TCF). Between 2006-19 more than 10000 incidents of livestock depredation from 356 villages were compensated. The IRS pays a small sum of money (equivalent of US \$40) within 72 hours of a livestock killing after field verification. The scheme disburses this ‘interim relief’ payment rapidly as motivation against carcass poisoning and other forms of retaliatory killing (Bargali and Ahmed 2018). The second tier is a compensation payment made by the state government, which is supposed to provide US \$ 200 to livestock owners within two months of the depredation event. In addition to livestock depredation, compensation is made for human deaths and injuries attributed to carnivores and crop depredation by herbivores. The payment process is widely reported to be fraught with delays, despite improvements in policies and procedures by the government. However, an evidence-based evaluation of the government compensation across management areas and categories of conflict has not yet been carried out. The goal of this study is to determine the extent of delays in the government payment processes, identify factors that cause delays, and make recommendations for increasing the efficacy of this program.

Predictions and Hypotheses

To develop a comprehensive account of the dynamics of livestock depredation by tigers and leopards, I focus on carnivore behavior. I was particularly interested in investigating how tigers and leopards optimize resource selection (killing large-bodied livestock) while lowering risk of death or injury through encounters with humans. I explored two aspects of the ‘landscape of coexistence’ expected to influence heterogeneity in livestock predation: spatial avoidance and habitat shifts.

I evoke the *spatial avoidance (of humans) hypothesis* to explain how tigers and leopards exploit resources (livestock) in human dominated areas while lowering risks by sheltering in refuges (Chanchani et al., 2016). Evidence in support of this hypothesis includes use of areas by carnivores across an increasing gradient of human activities being influenced by availability of vegetation cover (Sunarto et al., 2012), and by the extent of drainage features that provide easy access for livestock into forests and tigers into human-use areas.

For the *habitat shift hypothesis*, I expect seasonal spatial shifts in depredation events by tigers and leopards, as they adapt behaviorally to exploit variation in cover to access areas of livestock grazing. The pronounced monsoon, which follows the dry hot summers of similar length across South Asia, drastically changes vegetation biomass, both within forests and the agricultural matrix (Fig. 1). The seasonal variation in vegetation cover is important on two accounts. The cyclical drying of vegetation in summer months in forest understory alters the extent of cover and food availability for both wild and domestic ungulates that carnivores prey upon. And in monsoon, there is more grass growth and browse availability in the forests, and increased opportunities for grazing along village and forest edges because of increased productivity. Evidence for this hypothesis will be the shift (colonization) of depredation hotspots to areas with the greatest variation in vegetation cover across seasons, including in areas with high human use.

Additionally, I hypothesize that that the risk of intraguild predation on leopards by tigers – an artefact of resource competition – will be manifested in *spatial segregation* of livestock depredation by the two species. My expectation is that leopards depredation events will consistently be concentrated more in sub-optimal habitats (with greater fragmentation and disturbance) relative to tiger depredation hot-spots (Harihar et al., 2011).

Finally, I have three predictions about duration of time taken by government agencies to settle claim applications: 1) the government compensation payment processes faces delays even after procedural reforms; 2) the payment processes are affected by both procedural delays and lack of fund availability; 3)

while human death and injuries would be speedily compensated both in and around protected areas and reserve forests, there are significant delays in compensating livestock losses and crop depredation. This is relevant because while carnivore attacks on humans are fortunately a rare occurrence, these later two forms of conflict are widely prevalent in the landscapes.

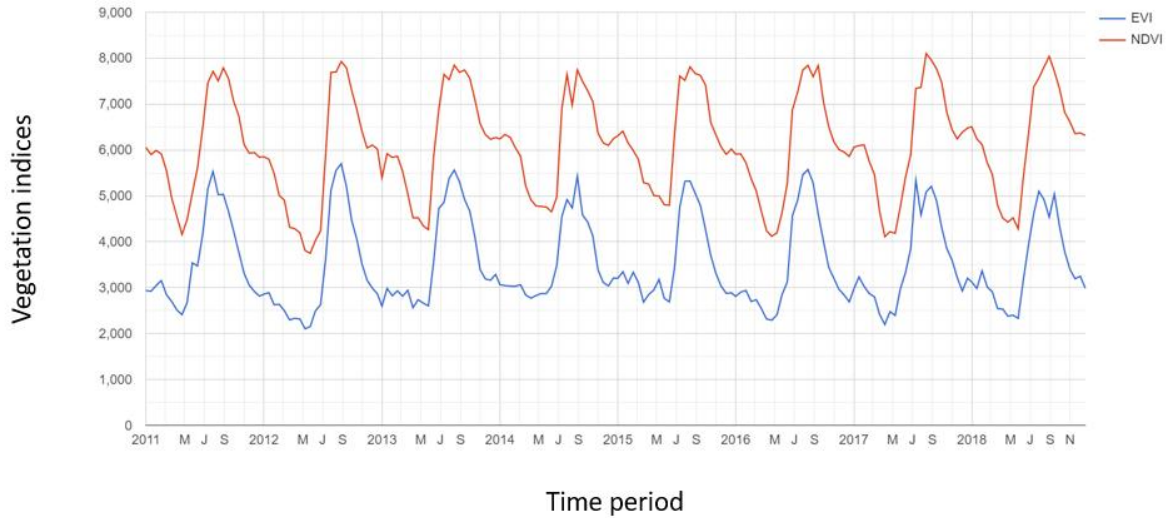


Figure 1 Seasonal trends in NDVI and EVI values in the study area including the core areas of Corbett Tiger Reserve. The indices values are scaled here as multiples of 10000 and the values on y-axis are mean NDVI and EVI for the entire region for every 16-day interval from March 2011 to Feb 2019. The ticks on the x-axis are labelled for the months of May(M), July(J) and September (S).

Study Area

The study encompasses the northern and southern Boundaries of Corbett Tiger Reserve (CTR) and portions of Ramnagar and Terai West Forest Divisions (multiple use forests), which lie to the east of Corbett Tiger Reserve in the state of Uttarakhand, India (Fig.1). Corbett National Park supports about 15 tigers/100 km² among the highest densities of the species globally, and the surrounding forest divisions also have high tiger densities (Bisht et al., 2019, Jhala et al., 2015). CTR and its surrounding areas support some of the highest densities of wild prey across the tiger’s range (Harihar et al., 2014, Jhala et al., 2015). While there is no specific information on the status of leopards in CTR, the species occurs prolifically in the Terai Arc landscape and in nearby Himalayan ranges (Harihar et al., 2011; Naha et al., 2018). In addition, the area supports a rich faunal diversity, with about 50 species of mammals, over 500 species of birds, varied amphibians and reptiles and significant elephant populations (Chape et al. 2003).

The geography in and around CTR is rugged and ranges in elevation from 200 to 2500 m. The dominant vegetation type is northern Indian moist-deciduous forest (Champion & Seth, 1968; Harihar et al., 2014). Major tree species include *Shorea robusta* (Sal), *Anogeissus latifolia* (Dhaura), *Mallotus philippinensis* (Rohini) and *Acacia catechu* (Khair). The area also has extensive tracts of scrub savannah and alluvial grasslands (Hussain et al., 2016). Grasslands are restricted to riverine areas, such as the banks of the Ramganga river and reservoir, and hill slopes (Johnsingh & Joshua, 1994). The average annual rainfall is 1925 mm, which occurs mostly during the southwest monsoon (June-September) (Bargali & Ahmed, 2018). The forests are surrounded by extensive agriculture, hundreds of villages and towns, and a network of roads and railway lines.

The Terai Arc Landscape, which spans the fertile Gangetic plains and adjacent lower Himalaya, is one of the most densely populated rural landscapes globally, with densities of over 400 people km⁻² (Census 2011). The hills to the north are less densely populated, but the landscape is a mosaic of fragmented forests and settlements with terraced fields. In contrast, the southern boundary between forests and human-use areas is more pronounced, and areas beyond the forest boundaries are associated with more intensive agriculture and rapid land use change (Harihar et al., 2014). Animal husbandry is also a major form of livelihood in the area, with livestock occurring at densities of around 50 animals km⁻² (Gilbert, et.al 2018). Livestock are extensively grazed in the buffer zones of Protected Areas and areas of Reserve Forests where grazing is sanctioned, and communities depend on forests for fuelwood and a variety of non-timber forest products. The communities living in the area are a mix of different ethnicities including groups from the *Kumaon* Himalayas, migrant communities from the plains of assorted of castes and religions, and *Van gujjars*, a Muslim semi nomadic pastoralist community.

The *Van gujjars* are the major livestock-herding community in the region. They live in encampments (*deras*), predominantly within the buffer zone of forests. The *Van gujjars* graze their livestock, primarily buffaloes, in the forests, and lop foliage off trees to source supplementary fodder (Harihar & Pandav, 2012; Harihar et al., 2014). While the *Van gujjars* were largely migratory in the past, moving between winter pastures in the terai forests and summers in the upper ranges of the Himalayas (Hussain et al., 2016), they now largely reside in the terai forests year-round due to various socio-political changes over the past century and reduced access to grazing commons in the mountains (Gooch, 2009). A single *Van gujjar* settlement composed of multiple families may own 37 to 500 livestock (Hussain et al., 2016). The community is socially and economically marginalized owing to its semi-nomadic mode of living. With the breakdown of the annual migration to the mountains, it is difficult to sustain large herds of livestock. Because of the remoteness of their forest-settlements, they also lacks access to basic civic infrastructure and government

aid, and many households now favor relocation out of forests to nearby agricultural areas (Harihar et al., 2015; Hussain et al., 2016). In addition to the *Van gujjars*, *Taungya* villages are also located in forests where they are largely disconnected from government welfare schemes, and therefore disenfranchised and vulnerable (Kothari et al. 2009).

While CTR is widely viewed as an area of successful tiger conservation, other tracts of tiger and leopard habitat within the Terai Arc Landscape have had varying conservation outcomes. For example, tigers are nearly extinct in a large section of Rajaji Tiger Reserve, to the west of Corbett, because of poaching and habitat fragmentation (Harihar et al., 2014), and tigers are similarly depleted in Nandhaur Wildlife Sanctuary to the east of Corbett (Mann et al., 2013). The extent to which large carnivores are poached by way of retaliatory killing is unknown, and such events are only rarely recorded (Musavi et al 2006).

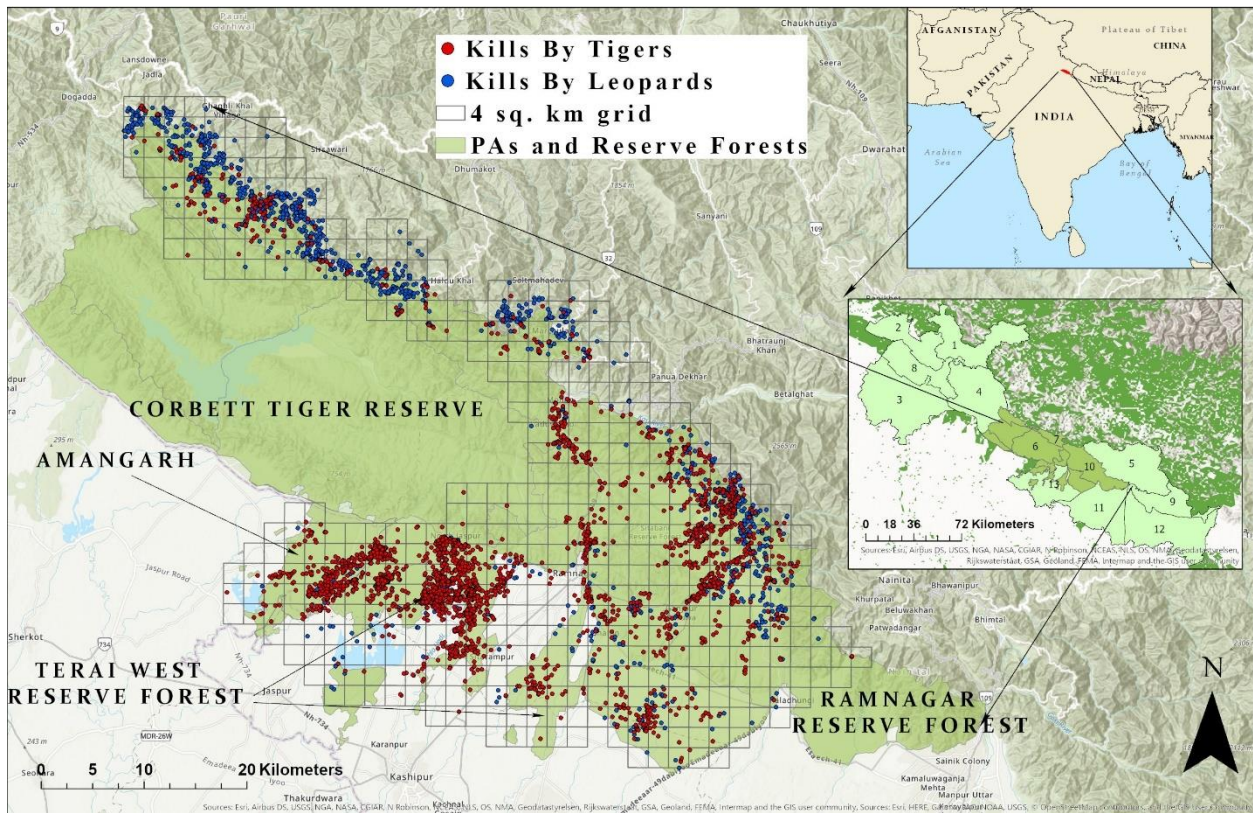


Figure 2. Study area comprised of the Corbett Tiger Reserve and the surrounding reserve forests. Locations of livestock depredation incidents between 2011-18 are depicted as red (Tigers) and blue (Leopards) points. Top inset shows the location of the study area within India in the state of Uttarakhand in Himalayan foothills. The second inset shows Terai arc landscape Uttarakhand with 12 PAs and Reserve forests (RF) where compensation evaluation data were sampled, including 1- Narendranagar RF, 2-Dehradun RF, 3- Haridwar RF, 4- Lansdowne RF, 5-Nainital RF, 6- 7 Corbett Tiger Reserve, 8- Rajaji National Park, 9- Haldwani RF, 10-Ramnagar RF, 11-Terai Central RF, 12-Terai-East RF, 13-Terai West RF. The dark green section is the Corbett Landscape.

Methods

Data collection

To assess spatial and temporal dynamics of livestock depredation in the landscape, I used a combination of livestock kill locations and geospatial covariates. The livestock kill locations were recorded as part of the 'Interim Relief Scheme' compensation program implemented by WWF and TCF from March 2011 to Feb 2019. Data prior to 2011 were not used because GPS locations of depredation sites were not collected. For each conflict event reported from across 356 villages within the study area, field officers would visit depredation sites within 72 hours of being notified by livestock owners. The field officers collected detailed information on the location (GPS coordinates) and date of the event, livestock species, sex, age, and predator species. Identification of the predator was based on direct sightings at the carcass, observations of villagers, and multiple forms of indirect evidence including prints, canine puncture marks, and patterns of carcass consumption (Bargali & Ahmed, 2018).

To evaluate the government compensation program, I used forest department records for the state of Uttarakhand from Jan 2013 to Dec 2015. People affected by conflict incidents including livestock depredation, crop damage and human deaths/injury report cases to the nearest forest range office to claim payments of compensation. The reported incidents go through several stages of approvals before payments are disbursed. WWF-India collated claim data from 78 range offices from 12 Reserve Forest Divisions and PAs in the Terai Arc Landscape including CTR. I removed range offices with < 20 to sample areas where conflict was more frequent, and randomly sampled 18 range offices (33%) from the remaining 53 range offices, to get a representative sample. I then categorized the reported cases from these offices into crop depredation, livestock depredation and human death/injury. Finally, I randomly selected 20 cases for each category within a range office and compiled information on incident date, details of incidents, village name, forest range, forest management status (PA or Reserve or Reserve Forest), status of payment (whether paid or pending at the time of data collection) and payment date (where applicable) from government records. These records were only maintained in register or files dispersed across multiple range offices and information had to be manually gleaned from them in a limited time span. Hence the sample sizes were small. Data on distance of the village of claimants to the range office were collected through interviews with clerical staff at the range offices. In all, information from 648 depredation cases were collated for analyses.

Delineating sites, seasons, and occasions for dynamic occupancy models

I delineated the study area boundaries using a concave hull, setting the k-nearest neighbor value as 3 (Moreira & Santos 2007), to include all villages and *Van gujjar deras* covered under the IRS compensation program, while excluding other settlements. Within the study area, I overlaid a 4 km² grid comprising 502

2 km × 2 km cells to which livestock depredation events were assigned. Preliminary analysis suggested that this cell size had >10% probability of capturing a depredation event but was small enough to describe spatio-temporal heterogeneity in depredation events at the local village scale (MacKenzie et al., 2006).

Because the study area included both forests and agricultural areas, and vegetation cover strongly influences risk of livestock predation (Karanth et al., 2012; Miller et al., 2015), I defined three primary seasons based on seasonal variation in vegetation cover in forests and farmlands. Forests, and particularly forest fringe areas, serve as the grazing commons for much of the year. In agricultural areas, crop growth and harvest can be divided three main seasons: summer or lean season (March-June), when vegetables, maize or soybean are the primary crops; monsoon season (July- October), which is the rice cultivation season; and winter season (November-February), when wheat is cultivated. Forest vegetation also shows variation across these seasons, with prolific growth in the monsoons and desiccation of vegetation during the summer. Livestock are expected to be more vulnerable to predation during the monsoons because the dense forest understory conceals predators. Crop cycles cause variation in land cover providing large expanses of standing crops seasonally. Crop seasons may affect livestock depredation by carnivores in two ways: first, during the monsoons, there is greater growth of grass along farmland boundaries where livestock may be grazed, and mature crops provide concealment to carnivores near human settlements (Warrier 2019). Secondly, the availability of crops draws wild prey species near villages, where carnivores pursuing deer, antelopes and pigs are also more likely to encounter livestock.

Dynamic occupancy modeling: model description

I used yearly livestock depredation data collected over eight years and multi-season occupancy models (MacKenzie et al., 2003) to estimate the probability of livestock depredation at a site and seasonal dynamics of these probabilities for both tigers and leopards. These data were compiled in a matrix with 502-sites (columns) × 96-months (rows) separately for tigers and leopards. There were 24 primary seasons (each with four months). I assigned a value of 1 to sites and months where one or more depredation events were recorded and 0 (no depredation or non-detection) to all cells which there was no recorded depredation event. The data consist of detection or non-detection of livestock depredation, so use of a site is defined as the occurrence of one or more livestock depredation events at a site (Goswami et al., 2015). Multi-season occupancy models explicitly model potential changes in the occupancy (depredation) status of a site over time with colonization (γ) and local extinction (ϵ) occurring between primary seasons. The probability of depredation (Ψ) is estimated within a season (MacKenzie et al., 2017). Spatial and temporal variation in the parameters was modeled as a function of measured covariates via a logit link function (MacKenzie, 2006).

Given pronounced seasonality in livestock depredation events around CTR (Bargali and Ahmed 2018), I used the $\Psi, \gamma, \varepsilon$ parameterization of the model where occupancy was estimated for the first primary period (Ψ_1) in addition to colonization probability (γ) – site with no livestock depredation in primary period t had livestock depredation in $t+1$, and the extinction probability (ε) – site with livestock depredation in primary period t , had no livestock depredation in primary period $t+1$, (MacKenzie et al., 2003)

The likelihood of the data and model for occurrence of livestock depredation in the first primary period is estimated as:

$$\mathcal{L}(\psi, p | data) = \left[\psi^{N_d} \prod_{j=1}^J p_j^{s_j} (1 - p_j)^{N_d - s_j} \right] \left[\psi \prod_{j=1}^J (1 - p_j) + (1 - \psi) \right]^{N - N_d}, \quad (1)$$

where N_d is the number of sites where livestock depredation was detected at least once, N is the total number of sites, and s_j is the number of sites where the livestock depredation was detected during month j (secondary sampling period) of the total J monthly occasions, p is the detection probability, which is the probability that a depredation event occurring at a site will get detected (MacKenzie et al., 2003). The occupancy in subsequent seasons was derived using:

$$\psi_{t+1} = \psi_t(1 - \varepsilon_t) + (1 - \psi_t)\gamma_t, \quad (2)$$

Occupancy analysis assumes that the state of livestock depredation of cells remains unchanged (or changes randomly) across months within a primary sampling period, but may change at sites between seasons due to colonization and extinction – i.e. a cell without depredation in season t but with depredation in season $t+1$ and the opposite, respectively (Davis et al., 2019; Goswami et al., 2015). Given the small grid size, detections are interpreted as ‘habitat use’, given that 4-km² cells within which data were collated are considerably smaller than the home ranges of tigers and leopards (MacKenzie, 2006). I assumed that changes in depredation status of cells within a season are random (probability of a tiger preying on livestock at a point in time is independent of use at a previous point in time (Goswami et al., 2015).

Dynamic occupancy modeling: Covariates and predicted relationships with livestock depredation, colonization, and extinction

Using the 4-km² grid cells as the units of analysis, I derived 13 geospatial covariates from a combination of open source remotely sensed data and NGO datasets (Table 1). Vegetation cover is important for the spatial avoidance and spatial risk hypotheses, therefore I defined five covariates related to vegetation. I predicted that cells with higher Normalized Difference Vegetation Index (NDVI) (*sumMedNDVI*) would be associated with a higher probability of livestock depredation (Ψ_1) because green vegetation (foliage) provides cover for predators. Further, I predicted that colonization of sites with respect to depredation (γ) would be highest where there was the greatest increase in NDVI values (increased vegetation cover) between seasons (represented by the covariates *MoSuDiff*, *WiMoDiff* and *SuWiDiff*), while I expected the inverse for extinction (ϵ). Additionally, I quantified the area of forest in each cell, positing that cells with more forest area (and conversely less area under agriculture and other human land-use types) will be associated with higher colonization probability (γ). I expected that these vegetation characteristics would similarly influence tiger and leopard-related depredation (and the related dynamic parameters), except that more leopard-related events were expected in areas with low forest cover.

Given that both livestock and carnivores frequently use drainage features, I computed two drainage covariates: proximity to drainage features (*Dist2Strea*) and extent of drainage features within a cell (*StreaLen*), expecting that that cells close to or with greater drainage would be associated with higher probabilities of depredation and colonization. Similarly, I computed two edge covariates – forest edge extent (*EdgeLen*) and distance to forest edge (*Dis2Edge*) – and predicted that depredation and colonization probabilities would both be greater in cells close to or with more edge because livestock extensively graze along forest edges,. I expected that tigers and leopards would exploit edges and drainage features which provide cover for carnivores to ambush prey.

I derived a terrain ruggedness index to potentially explain observed differences in intensity of depredation by tigers and leopards (Bargali & Ahmed, 2018). I predicted that leopards would use northern habitats that are more fragmented and less suitable for wild prey like Chital, while tigers would use the prey-rich habitats to the south. Thus, terrain was a proxy for habitat quality and resource (wild prey availability), for which we did not have spatially explicit data.

Finally, I collated three human-disturbance and livestock-related covariates: intensity of night-lights (*NightLit*), human population density (*PopDens*) and presence of *Gujjar deras* (or encampments) within 500 m (*GujBuff*). I predicted that more populated cells and those with higher values of night-lights would be associated with lower colonization and higher extinction probabilities. However, I expected leopard-

related depredation would be higher in these areas than tiger-related depredation because leopards are adept at using habitats in proximity to human settlements (Braczkowski et al., 2018). I included *Gujjars* because they build their settlements and graze their livestock (primarily buffaloes) in forests. I predicted that depredation events and colonization probabilities would be high in the vicinity of *deras*, because of the concentration of large herds of livestock.

Length of forest edge in each grid cell, distance to forest edge from grid cell centroids, and proportion of forest in a grid cell were calculated using by digitizing forest boundaries of topographic maps in ArcGis Pro and a land-use land cover (LULC) layer obtained from WWF-India. I obtained NDVI from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Earth Observing System-Terra platform available as a 16-day composite at 250 m resolution. The product (image collection id *MODIS/006/MOD13Q1*) was accessed in Google Earth Engine (GEE) . I extracted median NDVI for each of 24 seasons (summer, winter, and monsoon for 2011-18) and estimated seasonal medians for all eight summers, monsoon seasons, and winters for the duration of the study. I then calculated seasonal differences between overall median NDVIs. Finally, I estimated mean percent tree cover for each grid using the MOD44B.006 Terra Vegetation Continuous Fields Yearly Global 250m dataset available on GEE with image collection id *MODIS/006/MOD44B*.

To estimate the length and proximity of streams to kills sites, I built a hydrological model using a 90 m Digital Elevation model (DEM) from SRTM data (Jarvis et al., 2008) (Table1). To do so, I filled DEM sinks and estimated flow direction and accumulation using *D8 neighbors* as the flow direction type and thresholding the flow accumulation in each pixel to be greater than 100 in ArcGIS Pro. I delineated streams using *Strahler* stream order to assign degree of flow to each stream. From the hydrological model, I calculated the length of streams in each grid cell and distance of grid cell centroid to the nearest stream. The higher order streams in the landscape tend to have a much larger width than the lower order streams. To account for variation in width while creating the length of stream covariate, I rescaled the length of streams in each grid cell by multiplying it by the corresponding stream order attribute values, such that I multiplied the lengths of streams with highest width by 6 and those with lowest widths by 1. The topographic ruggedness index (TRI) was calculated from the SRTM DEM 90 to express the elevation difference between adjacent cells of a digital elevation grid (Riley et al 1999).

The night lights data were obtained from the National Oceanic and Atmospheric Administration (NOAA)'s Global Radiance-Calibrated Nighttime Lights Version 4 dataset available on GEE (image id: *NOAA/DMSP-OLS/CALIBRATED_LIGHTS_V4*). Human population density was estimated using the SEDAC (CIESIN 2016) and SHRUG datasets ((Asher et al., n.d.), that enabled combining spatial information of SEDAC

datasets available for 2001 with the latest population census data available in the SHRUG (2011) as both had unique SEDAC village IDs as a common attribute. Areas around *Van Gujjar* settlements were delineated by creating a 500 m buffer around the settlements, and a binary (1/0) covariate was assigned to each cell to delineate whether it included a *Van Gujjar deras* or not.

I checked for multicollinearity between landscape variables to screen out redundant variables. Percent tree cover and TRI were highly correlated ($r > 0.7$) (Dormann et al. 2013); therefore, I removed percent tree cover because TRI was the only variable describing terrain. All geo-spatial covariates were extracted using Google Earth Engine (Gorelick, et al., 2017), R v. 3.5.1 (R Development Core Team 2015) and ArcGIS Pro (v.2.4.2, ESRI, CA,USA).

Table 1 The final list of covariates retained after checking for multicollinearity, with a description of method/source, the mean, minimum and maximum values, and the predicted relationship with the modelled parameters – probability of livestock depredation (Ψ), colonization of depredation, (γ) and extinction of depredation (ϵ), represented by +/-. The two covariates, length of edge (km) and population density were excluded from global model structures for γ and ϵ .

Covariate	Description	Mean and range of covariate values	Parameter and expected influence
Extent of drainage features (km) (<i>StreaLen</i>)	Estimated from SRTM DEM 90m (Jarvis <i>et al</i> , 2008) using hydrological modelling.	7.12 km (0-28 km)	$\Psi (+), \gamma (+), \epsilon (-)$
Distance to drainage features (km) (<i>Dist2Stre</i>)	Estimated as the distance of the grid cell centroid to the nearest stream feature in km	0.384 km (0.00022-1.54 km)	$\Psi (-), \gamma (-), \epsilon (+)$
Intensity of night lights (<i>NightLit</i>)	Estimated from the NOAA Global Radiance-Calibrated Nighttime Lights Version 4, for the year 2010-2011 by taking median of the Avg_vis band that represents the average digital band numbers from observations with cloud-free light detection. The raster layer obtained was then used to estimate mean values for each grid cell.	2.91 (0-22.49)	$\Psi (+), \gamma (+), \epsilon (-)$

Human population density (persons/ha) (<i>popDen</i>)	Derived by combining information from SEDAC (2001) and SHRUG (2011) datasets (Asher et al., n.d.). and mean population densities were extracted for settlements in each grid cell. (Not used in γ , ϵ models)	4.8 (0-772)	$\Psi (+)$
Topographic ruggedness index (<i>TRI</i>)	Estimated from the SRTM DEM 90m (Riley et al 1999) and extracted as a mean for each grid	46.196 (1.64-137.17)	$\Psi (+)$, $\gamma (+)$, $\epsilon (-)$ (Leopards >Tigers)
Vegetation Cover (-1 to 1) (<i>sumMedNDVI</i>)	Estimated as single median of eight median NDVI layers , one for each summer (March-June) for every year from 2011-18	0.500 (0.246-0.676)	$\Psi (+)$, $\gamma (+)$, $\epsilon (-)$
Proximity to <i>Gujjar</i> camps (<i>GujjBuf500</i>)	Binary covariate based on whether <i>Van Gujjar deras</i> or areas within 500 m of <i>deras</i> were within a cell.	0/1	$\Psi (+)$, $\gamma (+)$, $\epsilon (-)$
Distance to forest edge (km) (<i>Dist2Edge</i>)	Distance in km of the grid centroid to the edge of the forest, represented as a negative value for the grid centroids lying inside the forest, and positive value for areas outside the forest	-3.852 (-15.896 to 2.597)	$\Psi (-)$, $\gamma (-)$, $\epsilon (+)$
Extent of forest edge (km) (<i>EdgeLen</i>)	Extent of edge in km of the forest edge in each grid. (Not used in γ , ϵ models)	5.09(km) (0-34.74 km)/	$\Psi (+)$
Proportion of Forest (<i>PropFor</i>)	Proportion of area of the grid cell covered by forest	0.715 (0-1)	$\Psi (+)$ $\gamma (+)$, $\epsilon (-)$
Difference between monsoon and summer NDVI (<i>MoSuDiff</i>)	Difference between NDVI values for the seasonal transition between summer to monsoon	0.274 (0.0164-0.409)	$\gamma (+)$, $\epsilon (-)$

Difference between winter and monsoon NDVI (<i>wiMoDiff</i>)	Difference between NDVI values for the seasonal transition between Monsoon to Winter	- 0.1136 (-0.262- -.0199)	$\gamma (-), \epsilon(+)$
Difference between summer and winter NDVI (<i>SuWiDiff</i>)	Difference between NDVI values for the seasonal transition between Winter to Summer	- 0.1599 (-0.3209-0.054)	$\gamma (-), \epsilon(+)$

Analysis

Dynamic occupancy modeling

I adopted a multi-step analysis process (e.g. Warrier 2019) to test my *a-priori* predictions pertaining to depredation occurrence and related colonization and extinction separately for tigers and leopards. In the first step, I built 88 models to test the relative influence of vegetation, habitat edges, drainage features and anthropogenic disturbance on Ψ_1 , γ and ϵ . I retained a global covariate structure for γ and ϵ , while the detection probability, p was held constant at 0.9 in these models and all subsequent analytical steps. I assessed model support using AIC weights (ω) to ascertain the best supported covariate structure for the probability of livestock depredation of 1st season (summer 2001) Ψ_1 , without any seasonal variation, indicated by the model with highest AIC weight (ω) and carried the model forward to the next step.

In the second step, I retained the Ψ_1 to the best supported model structure from step 1, retained a global structure for ϵ and built 64 alternate models to assess which covariates best explained spatiotemporal heterogeneity in γ . In the third step, I held Ψ_1 and γ to their best supported model structures (from steps 1 and 2) and ran 54 models to identify models that explained heterogeneity in ϵ . The steps were executed for both tiger and leopard depredation events separately. I used model averaged estimates as the final probabilities of Ψ_1 , γ and ϵ . A derived estimate of Ψ for all 24 primary seasons was calculated using the three modelled parameters Ψ_1 , γ and ϵ . The effect of individual covariates was assessed using beta coefficients and relationships between probabilities and individual covariate estimates.

In the above steps, to assess spatial avoidance, I modeled $\Psi_{1,\gamma}$ and ϵ as functions of additive combinations of vegetation, drainage, and edges, with and without anthropogenic covariates. The spatial avoidance hypothesis would be supported (separately for each of the model parameters) if models that contained additive and especially interactive combinations of the human disturbance covariates with vegetation, drainage or edges were (a) better supported than models without these combinations; and (b) if there was a distinguishable (or statistically) significant shift in the intercept or slope of the relationship between covariates that were indicative of human disturbance and $\Psi_{1,\gamma}$ or ϵ , at varying levels of the vegetation, edge or drainage covariates. Similarly, I assessed support for the habitat shift hypothesis by testing if changing vegetation cover across seasons resulted in a shift of depredation to cells with the greatest increase in cover, including in areas with greater human influence. Finally, to assess the spatial segregation of depredation between tigers and leopards due to interspecific competition, I compared the significance and direction of slopes of coefficients for covariates from the final tiger and leopard models. Spatial segregation would be inferred if depredation, colonization, and extinction probabilities showed marked spatial variation between tigers and leopards and be explained by differences in relative influence of covariates, and opposite or significantly different slopes for coefficients. For clarity and brevity, I present these hypotheses in results for parameter γ .

Occupancy models allow for modelling of detection probability (p) to account for false negatives in case of non-detections at a site (i.e., animals may use a site, but not be detected). I, however, used a fixed value of $p = 0.9$ for these analyses because only information on livestock depredation events was collected in this study without additional information on habitat use by these cryptic carnivores. True absence of depredation at any given site/time does not imply that the species was absent from the site (Warrier., 2019). Fixing p for these analyses is reasonable for three reasons. First, people are likely to report conflicts so they can receive two separate compensations. Second, the WWF compensation program has been in place for roughly 15 years, thus communities are familiar with the reporting process. Third, field offices for the IRS program are located along the northern and southern boundaries of CTR, enabling personnel to reach depredation sites within 72 hours of a reported kill (Bargali and Ahmed, 2018). I adopted a conservative approach and set the probability of detection of depredation events at 0.9 rather than 1 to account for occasional unreported or unverified events due to extenuating circumstances, such as the temporary break down of an interior-road during the monsoons.

Occupancy analyses was carried out in program MARK (White & Burnham 1999), using *Robust Design Occupancy with* $\Psi_{1,\gamma}$ and ϵ parameterization of dynamic occupancy models.

Evaluating compensation Scheme

I evaluated three elements of the government compensation program: the extent of delays in fund disbursement, variations in delays for paid or pending cases and factors affecting time taken to disburse payments. Out of the 648 collated cases, I used 414 complete cases in the analysis after removing missing data. To assess the extent of delays in total time taken to settle cases, I summarized the duration (in days) between date of incident and the date of payment, for a total of 414 cases of three forms of conflict, human deaths/injuries, livestock depredation and crop depredation by herbivores, and computed the associated variation.

Second, to compare delays in paid and pending cases, I tested the premise that the duration of time taken to make payments after the divisional forest officer or DFO (final approval authority in the process) sanctions the compensation would be different for paid and pending cases. I surmised that long delays post-approval in pending cases compared to paid cases would reflect budgetary constraints as most of the procedural steps have been completed. To understand whether paid and pending cases differed in *post DFO approval time*, I compared group means of post approval times between paid and pending cases using an ANOVA. I applied a square root transformation to the data to decrease heteroscedasticity (Fig. 16 and 17 in Appendix). This transformation also retained meaningful zeros in the response variable, representing cases paid on the same day as DFO approval.

Third, I used a linear mixed model to explore the effect of conflict type, PA status and distance of villages from range offices that processed and disbursed payments on the duration of time to make payments. Although the response variable, number of days until payment, was count data, the high mean of the data meant that it was approximately normally distributed. The response variable was positively skewed, and a log transformation improved the fit to the normal distribution line (Fig. 18 in Appendix). The data also met the assumption of homoscedasticity for linear regression (Fig. 20). Because the time taken for the government to process compensation applications depends on factors associated with each individual range office such as personnel, number of total cases, and efficiency, I included range office as a random effect in the model. Type of conflict, PA classification of the forest and distance of the village from range office were included as fixed effects. I included both two- and three-way interactions for the fixed effects in the full model as a PA may have better resources and funds to— disburse payments faster, or carry out verifications visits to remote villages quicker and may prioritize a different type of conflict than a reserve forest. I reduced the full model using backwards model selection and AIC scores to discriminate among models. All analyses were carried out in R v. 3.5.1 (R Development Core Team 2015).

Results

The livestock data consisted of 5115 depredation records from March 2011 to Feb. 2019 of which 38% were attributed to leopards and 62% to tigers. Of the 3188 livestock kills by tigers, 18% were outside forest boundaries; for leopards, 36% of 1927 livestock kills were beyond forest boundaries. Domestic animals preyed upon by tigers included female and bulls of cattle (70%), buffaloes (29%) and horses (2%). Of these, 85-96% were adults, or sub-adult animals and only a small percentage were juveniles. Leopard prey included 95% cattle, 5% buffaloes and 0.6% horses. Of leopard prey, 28% of buffaloes were adults or sub-adults, 77% of cattle, and 77% of horses were adults or sub-adults.

Spatio-temporal dynamics of livestock depredation

The locations of tiger and leopard kills were ascribed to the site \times month (occasion) matrices, resulting in 1472 unique leopard depredation events and 2133 unique tiger depredation events. Here I present summaries of results from the final modeling step for the tiger and leopard datasets (modeling variation in ϵ , having determined optimal covariate combinations for the other parameter models). No single model was highly supported, and the support (AIC weights) were instead distributed across multiple models (Tables 6-11 in Appendix) and thus I used model averaging to make multi-model inference for parameter estimates (Burnham and Anderson, 2002). The model averaged estimates of Ψ_1 , probability of livestock depredation in the first season (summer 2011), was 0.06 (SE=0.014) for tigers and 0.49 (SE=0.012) for leopards (Table 2). Derived estimates of Ψ for all 24 seasons indicated strong seasonality in depredation events for tigers and leopards (Fig. 3 and 4). For tigers, the probability of depredation was approximately two times higher in the monsoons (~14%) than the other two seasons (~7%) and the summer and winter were not significantly different. For leopards, depredation in the monsoon was ~8% which was marginally, but not significantly higher than summer depredation (<7%) and significantly higher than winter (<6%). The best supported models from the third modeling step had 34% and 75% of the overall support, respectively. For the parameter Ψ_1 , or occurrence of depredation in the first primary season (summer 2011), the significant covariates in the best-supported model for tigers included TRI, presence of *Van Gujjar* settlements, distance to forest-farm edge, extent of edge and cover related covariates like median summer NDVI and proportion of forests in the grid cells (Table 6, Appendix; Fig. 5).

Proportion of forest and proximity to pastoral community had significant positive effects, while NDVI had a significant negative effect on depredation (Ψ_1). However, the uncertainty associated with the NDVI estimates was high (Fig. 5). The best supported model for Ψ_1 for leopards also included variables associated with cover (NDVI and proportion of forests), extent and proximity to streams, both edge related covariates, three human settlement covariates and TRI (Table 9, Appendix). But effect was significant only for two

variables – extent of edge at a site, which had a positive effect and distance to edge from the sites which had a negative effect (Fig.6).

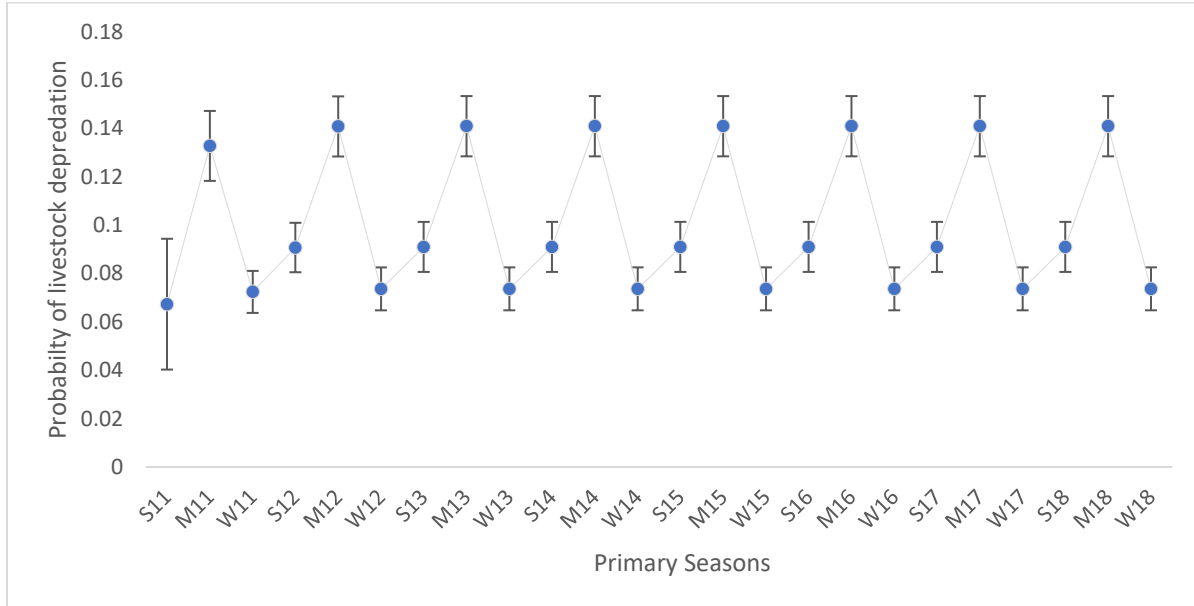


Figure 3 Probability of occurrence of livestock depredation for tigers across primary seasons Ψ , derived from modeled estimates Ψ_1 , γ and ϵ , where S, M and W represent Summer, Monsoon and Winter and the suffixed numbers represent years from 2011-2018. The error bars represent 95% CI.

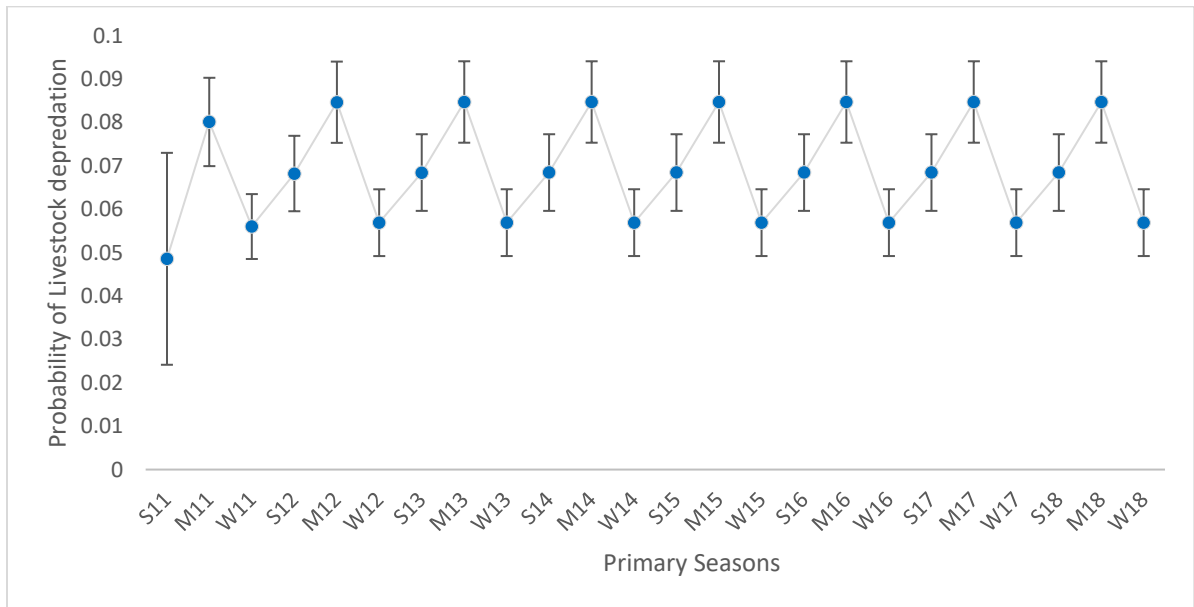


Figure 4. Probability of occurrence of livestock depredation for leopards across primary seasons Ψ , derived from modeled estimates Ψ_1 , γ and ϵ , where S, M and W represent Summer, Monsoon and Winter and the suffixed numbers represent years from 2011-2018. The error bars represent 95% CI.

Colonization probabilities of depredation (γ) for tigers were marginally higher in the transition from summer to monsoon (0.11 (SE=0.006)) than colonization from the monsoon to winter (0.05 (SE=0.004)) and from winter to summer (0.07 (SE=0.005)) (Table 2). The corresponding probabilities for extinction (ϵ) of depredation events between seasons were 0.54 (SE=0.028) (summer - monsoon), 0.78 (SE = 0.018) (monsoon – winter) and 0.72 (SE=0.027) (winter to summer) (Table 2).

For leopards, there was a 0.69 (SE=0.032) probability that sites with depredation in the summer would not have predation events in the monsoon season (ϵ), and a 0.76 (SE = 0.025) probability that sites with livestock kills in the monsoon season would not have kills in winter. Sites with livestock depredation in winter have a 0.69 (SE=0.034) chance of depredation extinction in the summer. In terms of colonization (γ), during the summer to monsoon transition, the probability of new sites experiencing depredation was 0.069 (SE=0.004), whereas the probability of colonization between the monsoon and winter was 0.04 (SE=0.003); and between winter and summer was 0.054 (SE=0.004) (Table 2).

Table 1 Model averaged estimates (Estimate), their standard error (SE) and confidence intervals (CI) calculated by averaging all tiger and leopard models with non-zero AIC weights in step 3, i.e. the best supported models for probability of depredation (Ψ_1), colonization (γ) and extinction (ϵ). Season transitions are represented by S-M (summer to monsoon), M-W (monsoon to winter), W-S (winter to summer).

	Parameter	Estimate	SE	CI's
Tiger	Ψ_1	0.067	0.014	0.045 - 0.1
	ϵ (S-M)	0.543	0.028	0.487 - 0.597
	ϵ (M-W)	0.789	0.018	0.751 - 0.823
	ϵ (W-S)	0.72	0.027	0.664 - 0.77
	γ (S-M)	0.11	0.006	0.099 - 0.121
	γ (M-W)	0.052	0.004	0.044 - 0.06
	γ (W-S)	0.076	0.005	0.067 - 0.087
Leopard	Ψ_1	0.049	0.012	0.029 - 0.08
	ϵ S-M)	0.696	0.032	0.63 - 0.756
	ϵ (M-W)	0.762	0.025	0.709 - 0.808
	ϵ (W-S)	0.694	0.034	0.624 - 0.757
	γ (S-M)	0.069	0.004	0.061 - 0.078
	γ (M-W)	0.04	0.003	0.034 - 0.047
	γ (W-S)	0.054	0.004	0.047 - 0.063

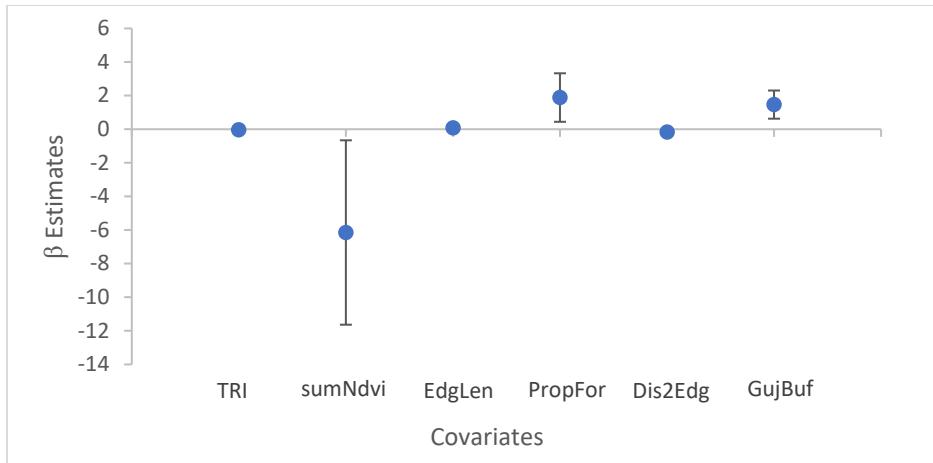


Figure 4. The β estimates for significant covariate effects on probability of depredation in first primary season (or Ψ_1) from the best supported model structure for tiger. The covariates include- TRI- Terrain ruggedness index, sumNdvi- summer median NDVI, EdgLen- extent of edge in a grid cell, PropFor- Proportion of forest, Dis2Edg- Distance to edge, GujBuf- Presence of Gujjar deras within 500 m of the cell centroids. The error bars represent 95% CI. Covariates like TRI, Edglen and Dis2Edg had lower CIs that were marginally greater than 0. The best supported models for depredation probability in season 1, with 90% of overall AIC weight are provided in Table 6 in Appendix.

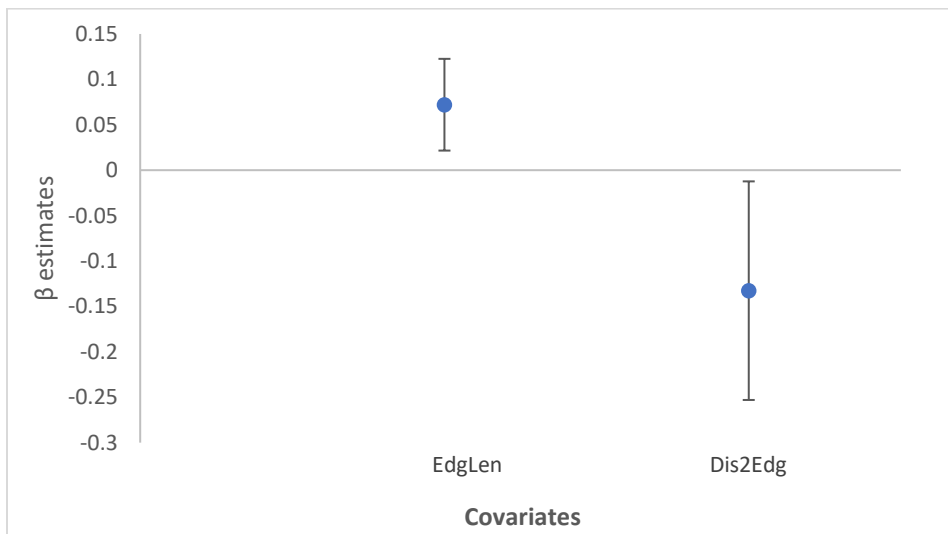


Figure 5 Beta estimates for the significant variables from the top Ψ_1 model for leopards. The covariate Edglen- Extent of edge (km), Dis2Edg- Distance of the grid cell centers to edges. The error bars represent 95% CI. The best supported models for depredation probability in season 1, with 90% of overall AIC weight are provided in Table 9 in Appendix.

The presence of the *Van Gujjar* inhabitations (with large livestock holdings) had significant positive influence on colonization (i.e. occurrence of depredation where previously it was absent) of sites with conflict occurrence by both tigers and leopards, whereas distance to streams had a negative effect (Fig. 7 and 8). The colonization probability for tiger depredation events decreased with increasing topographic complexity but increased with greater topographical complexity for leopards. Similarly, with increasing proportion of forest within a site, depredation colonization probabilities increased for tigers, but decreased for leopards. The best supported model for probability of colonization for tigers also included significant positive effects extent of streams), NDVI change between seasons and presence of pastoral community .The interaction between variables representing the spatial avoidance of human presence while accessing resources –intensity of night lights and proportion of forests also had a significant positive effect on colonization (Fig. 7).

The best supported model of γ for leopards also included significant positive effect of extent of streams and night lights — and negative effect of distance to edges, interactive effect of extent of streams and intensity of night lights (Fig. 8).

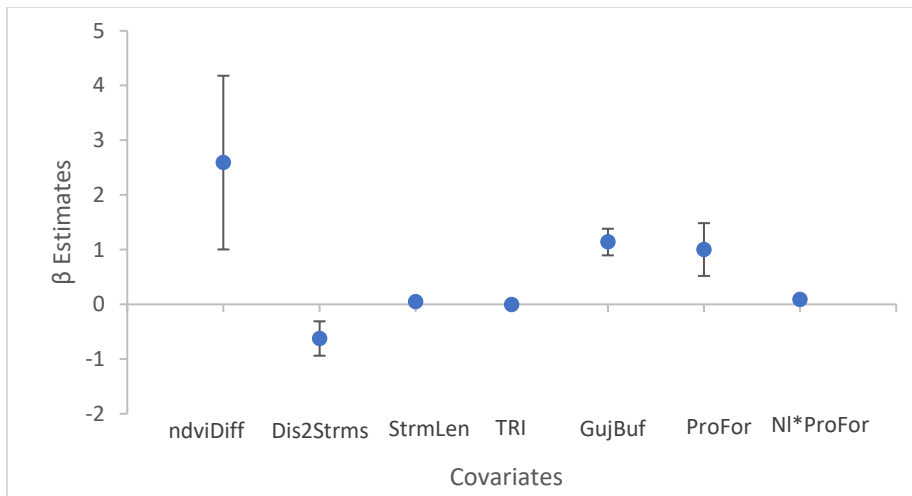


Figure 6. The beta estimates for significant covariates from best supported model for probability of colonization for tigers. The covariates include ndvi Diff- Seasonal NDVI change for each seasonal transition, Dis2Strms- Distance to Streams, StrmLen- Extent of streams within site, GujBuf- Presence of gujjar or pastoral community settlements within 500 m of sites, ProFor- Proportion of forests at sites, NL*ProFor- interactive effect between night lights and proportion of forests. The error bars represent 95% CI. Covariates like TRI, Strmlen and NLx PropFor had lower CIs that were marginally greater than 0. The best supported models for colonization with 90% of overall AIC weight are provided in Table 7 in Appendix.

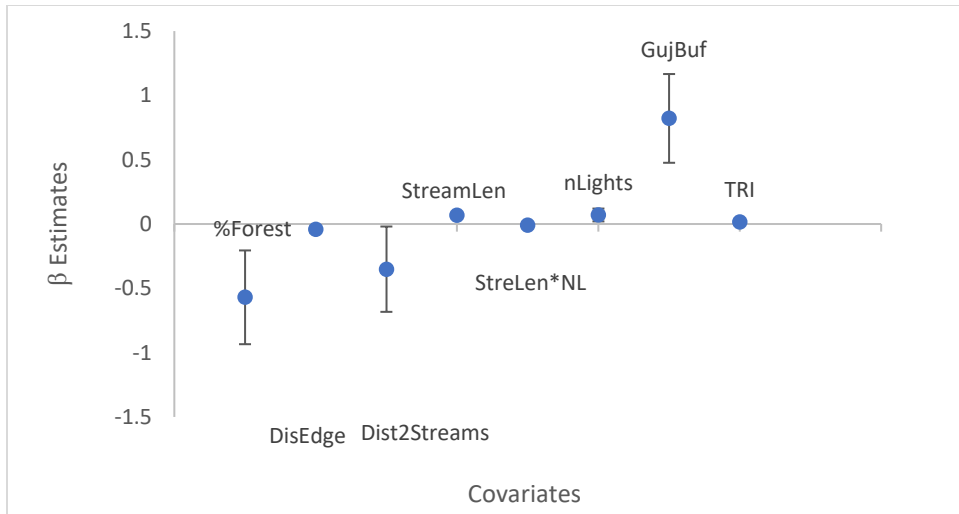


Figure 7 Beta estimates for the significant variables from the top γ model for leopards. The covariates include %Forest- Proportion of forest, DisEdge- Distance of sites to forest-farm edge, Dist2Streams- Distance of sites to streams, StreamLen- Extent of streams(km), StreLen*NL- interaction of extent of streams with intensity of night lights, nLights- intensity of night lights, GujBuf- Presence of gujjar deras within 500 m of sites, TRI- Terrain ruggedness Index. The error bars represent 95% CI. Covariates like TRI, Strelen xNL and Dis2Edg had lower CIs that were marginally greater than 0. The best supported models for colonization with 90% AIC weight are provided in Table 10 in Appendix.

The best supported model for probability of extinction of livestock depredation for tigers included positive effects of TRI and negative effects of proportion of forests and proximity to pastoral settlements (Fig. 9). The best supported model for probability of extinction for leopards had significant positive effect of proportion of forests, and significant negative effect of seasonal NDVI Change (Fig. 10).

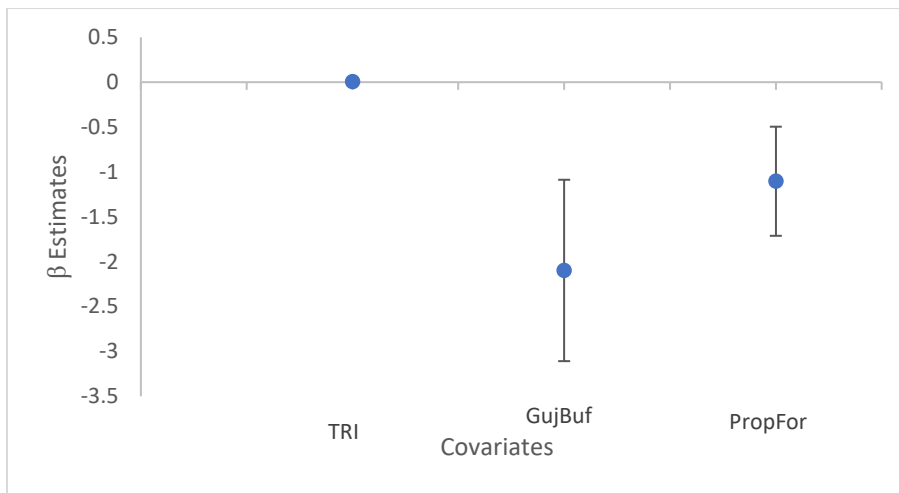


Figure 8. Beta estimates for significant covariate effects on probability of extinctions plotted from the best supported model for tigers. The covariates include, TRI- Terrain ruggedness index, GujBuf- Presence of gujjar deras within 500 m, PropFor- Proportion of Forest. The error bars represent 95% CI. Covariates like TRI, had lower CIs that were marginally greater than 0. The best supported models for extinction with 90% of overall AIC weight are provided in Table 8 in Appendix.

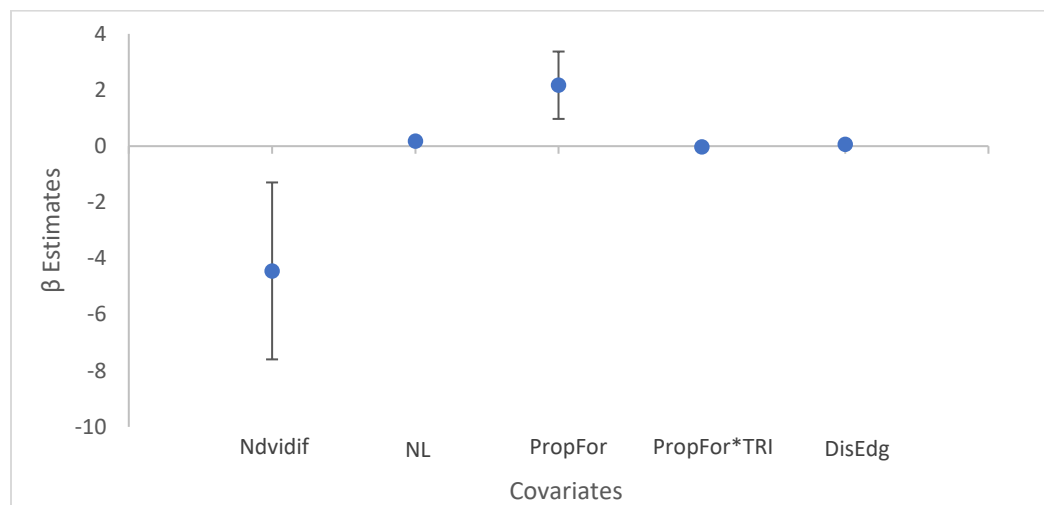


Figure 9 Beta estimates for significant covariates from top ϵ model for leopards. The covariates include Nvidif- seasonal ndvi change, NL- intensity of night lights, PropFor- Proportion of Forest, PropFor*TRI- interactive effect of proportion of forest and terrain ruggedness index and DisEdg- Distance of sites to forest-farm edge. The error bars represent 95% CI. Covariates like NL, PropFor x TRI and Dis2Edg had lower CIs that were marginally greater than 0. The best supported models for extinction with 90% overall AIC weight are provided in Table 11 in Appendix.

Spatial avoidance hypothesis: For tigers, depredation probabilities (and associated colonization probabilities) were markedly lower in areas outside forests and at greater distances from edges than within forests. These probabilities decreased as human disturbance increased, with tigers spatially avoiding killing livestock in areas with high human disturbance. However, in areas with moderate human presence, where livestock are grazed extensively, colonization probabilities around settlements were a function of vegetation cover, with sites with more cover being exploited both by tigers across all seasons. This is evident from the interaction between γ and night light intensity from the best supported tiger models. In sites with low forest cover, tiger depredation events decrease as night light increases; however, in sites with high forest cover, probability of depredation increases with the intensity of night lights (Fig.12). Similarly, the sites near *Van Gujjar* settlements inside the forest demonstrated high colonization probability for all three seasonal transitions consistently (Fig. 13).

Leopards show similar effects in general, but are more adept at exploiting livestock in areas with greater levels of human use indicated by the negative influence of proportion of forests, double the proportion of depredation incidents outside forests (36%) than tigers (18%), and positive relationship between extent of edges on depredation and colonization probabilities, and negative relationship between extinction of depredation and increasing NDVI (Fig. 6 and 8).

Carnivores adopt varying strategies to prey on livestock while remaining concealed from humans by actively selecting areas with greater vegetation cover across all seasons. The spatial avoidance hypothesis was more prominently supported for tigers through positive effect of interaction between proportion of forests and night lights, and presence of pastoral community. Leopards demonstrated spatial avoidance of humans while accessing prey, differently than tigers. The negative effect of proportion of forests on colonization and decline in extinction of depredation with increasing seasonal ndvi change, indicates that areas of vegetation cover outside the forest boundary e.g. farmlands, that have higher human risk, are utilized by leopards more. The effect of extent of streams and night lights on leopard colonization also provides evidence for spatial avoidance as the colonization of leopard depredation increased with increase in stream lengths but decreased when stream lengths interacted with high night lights.

Spatial shift hypothesis: For any given seasonal transition, colonization by tigers increased in areas with the greatest gains in NDVI (green vegetation cover) between seasons (Fig. 11). The effect was especially pronounced for the transition from summer to monsoon when there is a spurt in vegetation growth.

Notably, the number of sites with a relatively large change in colonization probabilities was higher in the summer-monsoon transition than in the other seasonal transitions (Fig. 13). The relationships of γ with covariates demonstrate how the spatial shift and spatial avoidance strategies for livestock depredation operate in tandem, and how factors other than vegetation influence depredation probabilities within and between seasons (Fig. 11 and 12). Tigers were more likely to shift to preying on livestock in areas where the vegetation became dense across seasonal transitions, and these effects were more pronounced near drainage features, which provide safe conduits into human use areas, than farther from drainage features (Fig. 11). For leopards, the relationships of parameters with vegetation covariates (NDVI and Forest Cover) were weaker, or even contrary to those for tigers.

Spatial segregation: Tiger and leopard depredation and seasonal shifts in depredation sites were markedly divergent. Leopard depredation events were concentrated along the northern boundary of the study area, whereas tiger depredation events were distributed more uniformly, but more thinly in the northern zone (Fig. 16). Tiger and leopard depredation and colonization probabilities diverged according to proportion of forests, extent of edge and TRI. Of these covariates, species colonization probabilities were particularly different with respect to TRI (Fig. 14 and 15). The northern boundary of the study area is associated with higher ruggedness and higher probability of colonization by leopards than tigers (Fig. 16).

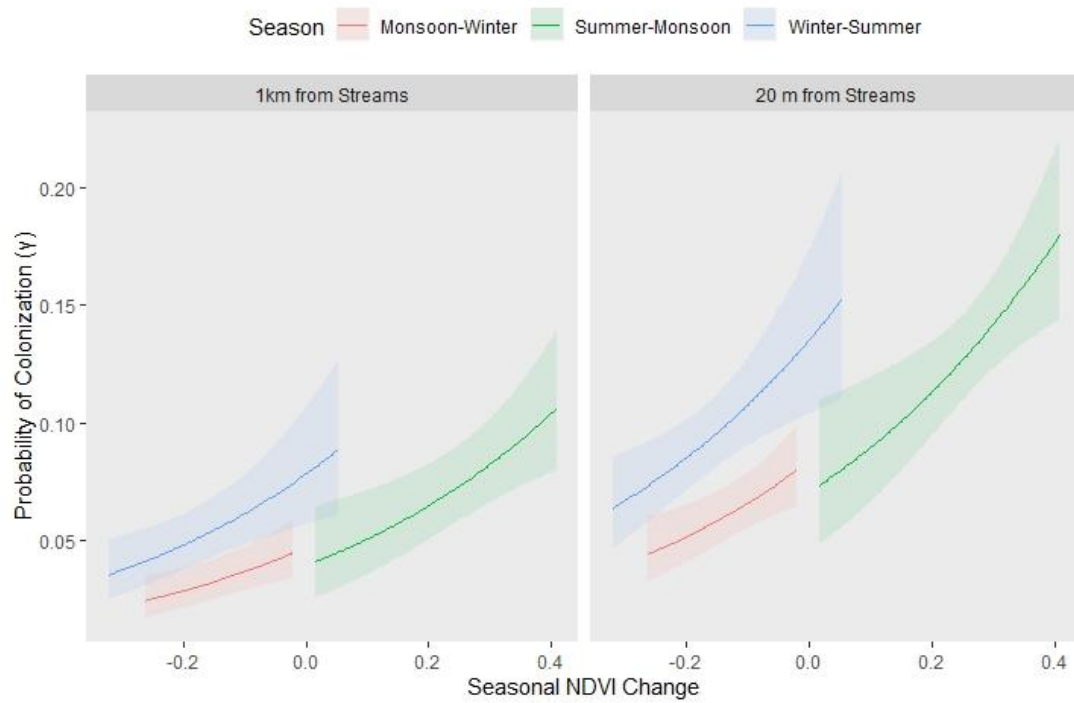


Figure 10. Temporal dynamics in livestock depredation by tigers depicted by probability of colonization for transitions between the three aggregate primary seasons and the effect of change in NDVI during those seasonal transitions.

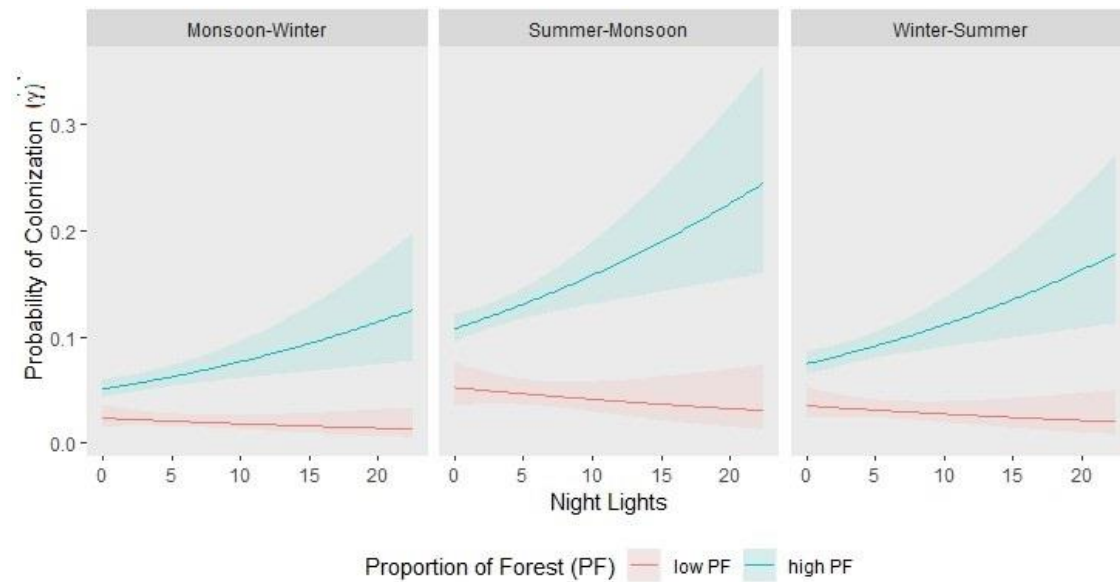


Figure 11. Relationship between probability of colonization of depredation by tigers and intensity of night lights at two different values of proportion of forests at sites. For all seasonal transitions, the probability of colonization is higher when high night light sites are in proximity to forested sites (high proportion of forest cover).

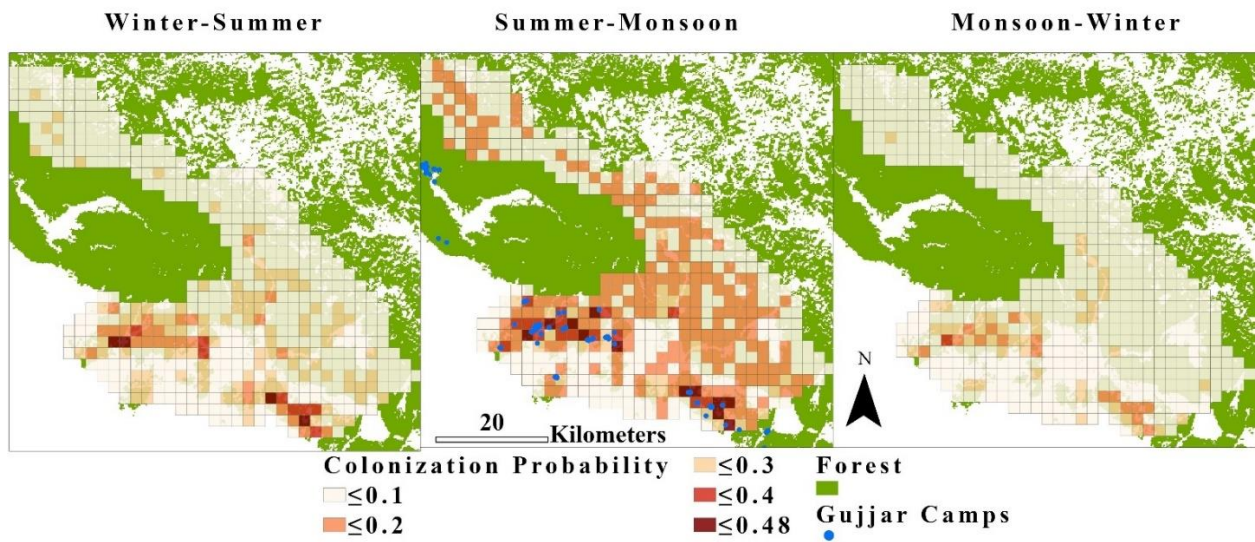


Figure 12. Colonization probabilities for tigers for the three seasonal transitions.

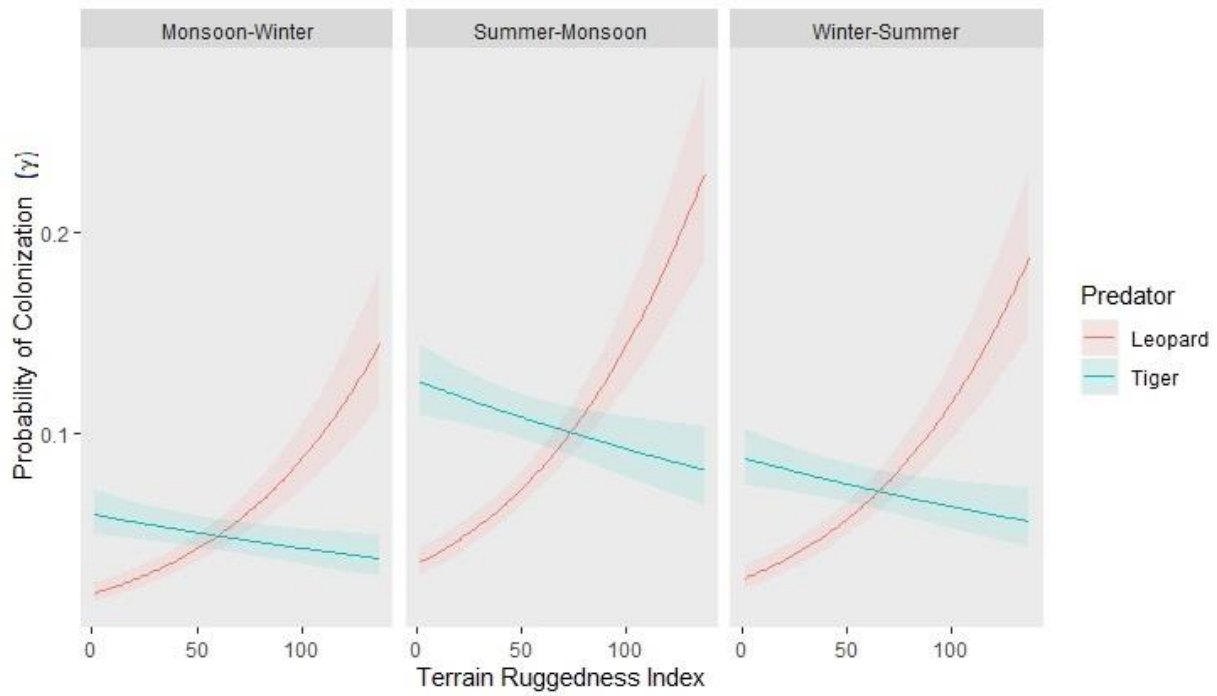


Figure 13. Relationship between colonization and terrain ruggedness index for tigers and leopards.

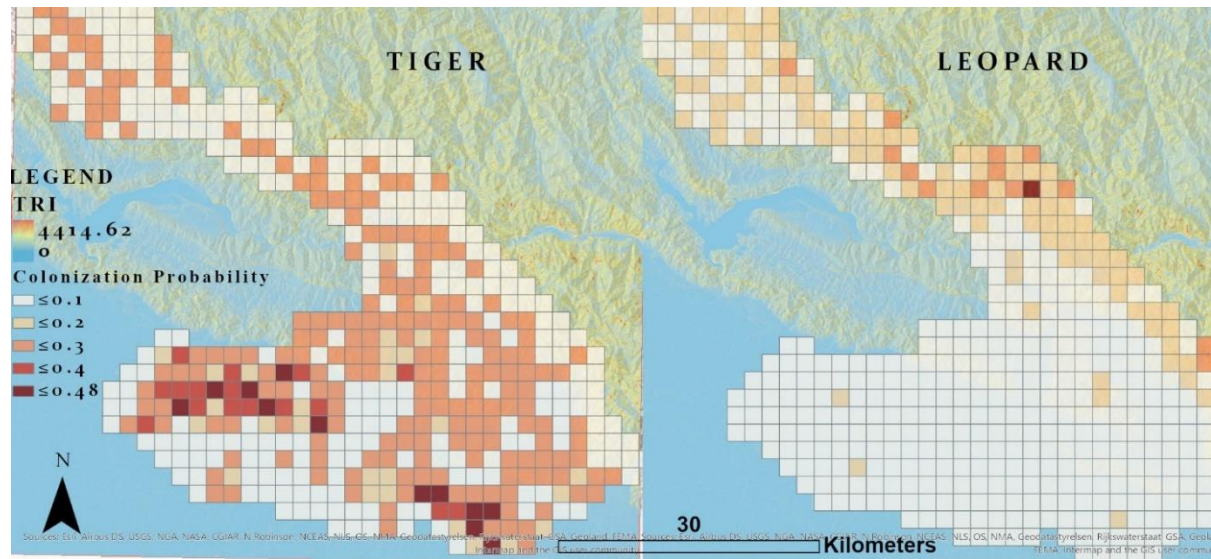


Figure 14. Comparison of relationship between colonization probabilities and terrain ruggedness for tigers and leopards.

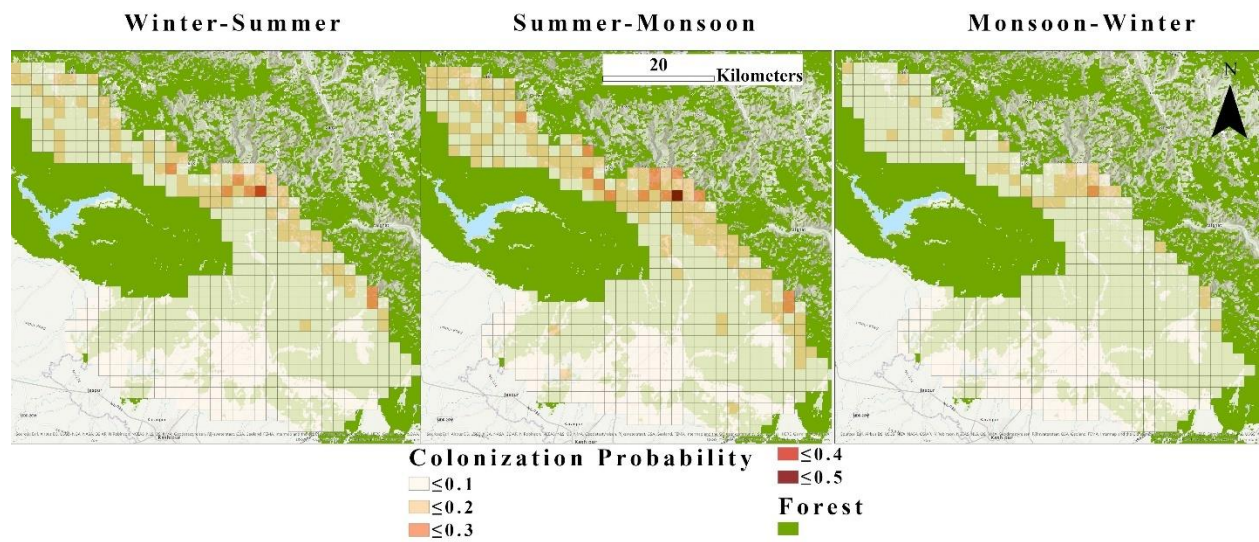


Figure 15. Colonization probabilities for three seasonal transitional for leopards.

Evaluation of Compensation Payments

The 18 sampled forest ranges from 12 PAs and Reserve Forests were expected to vary in the number of HWC compensation applications and time to settle them due to variation in the number of villages in each range, intensity of HWC, and even reporting of incidents by villages that do not have additional non-government compensation schemes. Livestock depredation was the most commonly reported conflict, followed by crop damage and human death/injury.

The average time between reporting of an incident and compensation was 504 days (min = 19, max = 1274, SD = 256). For human death/injury, the average time to compensation was 392 days (min = 19, max = 971, SD = 306). Average time to compensation was 498 days (min = 33, max = 1274, SD = 280) for livestock depredation and 532 days (min = 91, max = 1242, SD = 199) for crop loss. The average time to compensation was 439 days in PAs (min = 19, max = 971) and 525 days in reserve forests (min = 33, max = 1274). The average distance between incident villages and the nearest range office was 14 km (min = 0, max = 100). Out of the 414 cases, compensation was paid for 47% and still pending for 53% at the time of data collection. The mean time taken to settle paid cases was 409 days (min = 19, max = 1242, SD = 276) and to settle pending cases was 589 days (min = 281, max = 1274, SD = 202).

Table 3. Samples sizes for each category of HWC and the proportion of cases paid at the time of data collection.

Predictor variable	Level	Sample size (N)	Paid (N)
Conflict category	Human Death/Injury (HDI)	28 (6.8%)	26 (92.9 %)
	Livestock Depredation (LD)	230 (55.5%)	103 (44.8%)
	Crop Damage (CD)	156 (37.7%)	67 (43.0 %)
Protected area status	Protected Area	102 (24.6%)	73 (71.6 %)
	Non-Protected Area	312 (75.4%)	123 (39.4%)

Among paid cases, crop depredation had the highest mean compensation time followed by livestock depredation and human death/injury (Fig. 17). The mean time taken for payment of cases was higher for reserve forests than for PAs. Human death/injury was excluded from analysis for pending cases due to a very small sample size ($N = 2$). Crop damage and livestock depredation cases were pending for similar amounts of time. Fewer cases were pending with range offices in PAs ($N = 29$) compared to non-PAs ($N = 189$). On average, cases in PAs and reserve forests were pending for similar number of days.

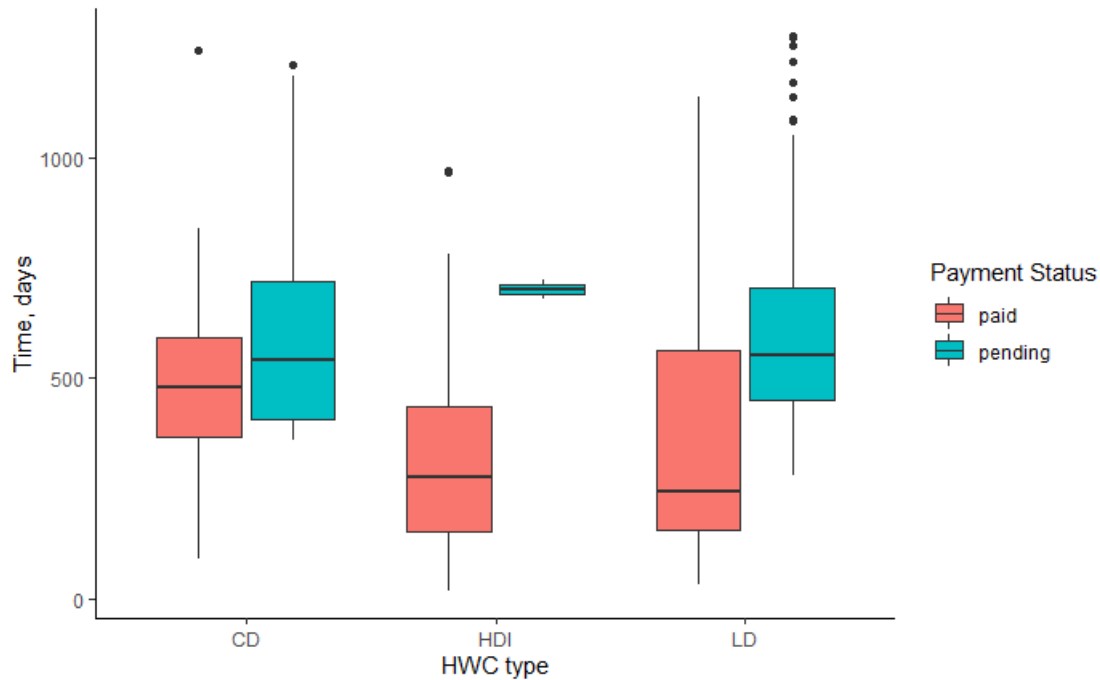


Figure 16. Depiction of total time taken, in days, across categories of HWC and status of payment: CD is crop damage, HDI is human death/injury and LD is livestock depredation.

Post DFO approval delays for paid vs. pending cases

There was a significant difference in the square root of mean *post DFO approval time* between paid and pending cases ($F_{1,241} = 178.9, p < 0.001$). Mean post approval delay for paid cases was significantly less than that of the pending cases (Tukey HSD: $\text{diff}(\text{paid-pending}) = -9.5, p < 0.001$). Post approval delay times for pending cases were 90 days higher than for paid cases.

Factors influencing compensation times in paid cases

The time of compensation in a reserve forest for a human death/injury incident was 165 days (Table 4). By comparison, time to compensate livestock predation was 320 days ($t = 3.243, df = 181, p < 0.01$) and to compensate crop damage was 333 days ($t = 3.656, df = 188, p < 0.001$). The effect of the PA classification on time for compensation differed significantly by type of conflict. Time taken to compensate for human

injury/death was greater by 194 days in PAs than in reserve forests ($t = 1.895$, $df = 23$, $p < 0.1$). Similarly, time taken to compensate for crop damage was also higher by 189 days in PAs than in reserve forests ($t = -1.13$, $df = 188$, $p < 1$). By contrast, time taken to compensate livestock predation was lower by 46 days in PAs than in reserve forests ($t = -3.166$, $df = 190$, $p < 0.001$). Time to compensate livestock predation and crop damage was significantly greater than human death and injury in reserve forests. Livestock predation incidents were significantly lower in PA's than other forests.

Table 4. The results from the most parsimonious model, includes type of human wildlife conflict(Livestock depredation, Crop damage and Human death & injury and whether the case is in a PA or non-PA. The estimates in bold are significant.

Variable	Estimate (Standard Error)
Livestock depredation	0.662 (0.204)
Crop damage	0.700 (0.191)
PA	0.776 (0.409)
Livestock Depredation x PA	-0.925 (0.292)
Crop damage: PA	-0.327 (0.289)
Intercept (Human death Injury x not PA)	5.108 (0.233)

Time to compensation varied greatly among forest ranges (random effect: $\sigma = 0.56$). The fixed effects explained just 9% of the variance in the data, whereas the fixed and random effects together explained 56.5%.

Table5. Predicted mean total time taken to settle paid cases.

PA vs Not PA	Type of conflict	Number of days
Reserve Forest	Human Death/Injury	165
	Livestock Predation	320
	Crop Loss	333
Protected Area	Human Death/Injury	359
	Livestock Predation	276
	Crop Loss	522

Discussion

This study advances our understanding of the ecological drivers of conflict and efficacy of mitigation measures in four key ways that are informative for strategies to sustain large carnivores and reduce conflict with humans in landscapes of coexistence. First, vegetation cover has a profound influence on depredation, especially for tigers. While the associations between cover and predation risk for livestock have been established (Karanth et al., 2012; Miller, 2015), this study contributes to an emerging understanding of how large carnivores, particularly tigers, adopt spatial avoidance as a key behavioral response to balance risk with securing food resources in landscapes of coexistence. Cover, or the existence of ‘refuges’ close to human areas where prey resources such as livestock are available, enable this behavior. While areas with high human presence outside forests were avoided, agricultural areas and other spaces with high human use along forest edges, adjacent to drainage features, areas in the vicinity of *Van Gujjar* camps and even farmlands were all sites of depredation – despite being close to human settlements. This establishes the extent to which carnivore and humans share space in human dominated landscapes – leading to the persistence of large carnivores in working landscapes (Chanchani et al., 2016). Tigers and leopards are not animals of the dense forest alone as some studies have suggested (Kanagaraj et al., 2011); rather, they are also ‘culture followers’, extensively exploiting edges where foraging opportunities may abound (Boomgaard 2001). This might be especially true in areas with high densities of big cats, like Corbett National Park, where tiger home ranges are considerably smaller than reported elsewhere (Bisht et al., 2019). Tigers and leopards use edge habitats where livestock are grazed, and which are adjacent to one of the world’s most densely populated landscapes. Livestock of pastoralists within the forests or at its edge will intrinsically be at risk.

Second, this research also casts light on how large carnivores adapt to intrinsically dynamic habitats, in which cover changes seasonally, to maximize opportunities to predate on livestock. The grazing patterns of livestock too, are driven by such changes in vegetation, as animals are herded to areas with abundant grass. It has recently been documented that even relatively minor increases in vegetation productivity/ cover drive variation in the habitat use by carnivores and herbivores in forest-farmland mosaics (Warrier 2019). My results demonstrate how such spatial shifts in habitat use as a function of changing cover across seasons fundamentally affects the locations and probabilities of livestock depredation.

Third, the spatial avoidance and spatial shift strategies of carnivores are concurrently adopted by species such as tigers and leopards. Notably, neither tigers, nor leopards preyed on many livestock beyond one or two kilometers from the forest’s edge, especially in the hot dry months or seasons with low crop cover. The area south of CTR is densely populated and generally hostile to large carnivores with relatively few refuges

with adequate cover. By contrast, the northern boundary is fringed by a mosaic of forests and settlements and contains ample refuges amidst human-use areas, and the results suggest that these spaces were associated with greater conflict in the immediate vicinity of human settlements. This is in contrast to the areas around Pilibhit and Dudhwa tiger reserves, two PAs a few hundred kilometers away from CTR with relatively lower tiger densities, where matrix of land use around the forests is dominated by sugarcane cultivation, and tiger and other wildlife occur commonly in these farmlands (Warrier, 2019). The lack of extensive tiger or leopard presence (or evidence for depredation) in the agricultural areas even a few kilometers away from the boundaries of CTR despite the species' high densities, indicates how agricultural areas may be less permeable for big cats here than other regions of India, possibly because of high human densities with relatively smaller agricultural farms and land use change. Unless the mosaic surrounding primary big-cat habitats has ideal refuge habitats like sugarcane plantations, the occurrence of tigers and leopards in rural landscapes may rapidly decline at increasing distances from forest edges. The extent of landscapes of coexistence beyond the primary forest habitats of big cats may, therefore, vary in different geographical contexts, and as the matrix outside forests become more hostile carnivores will increasingly be restricted to forests. Notably, the boundaries of landscapes of coexistence may not be static and instead vary seasonally as cover changes and predators adapt to these changes to maximize their opportunities to exploit prey while still remaining concealed from humans. A direct implication on this for people, such as the approximately 700,000 human inhabitants living in area where the depredation data was collected, is that they face very different risks from predators: for some livestock depredation is an imminent reality, for others only a few kilometers away, it may only be a remote possibility.

Fourth, there are species-specific differences in patterns of livestock predation. While leopards show seasonal peaks in predation, the relationship between leopard predation and vegetation are more complex than tigers, with a high probability of livestock predation occurring outside forests in agricultural areas and other human land-use types. These results demonstrate that leopards are behaviorally more plastic and can adapt to human use areas. The spatial segregation in tiger and leopard predation sites is likely best explained by hostile interactions between tigers and leopards, with leopards occupying areas where tigers occur at relatively low densities (Harihar et al., 2011). Past studies from Corbett Tiger Reserve indicate that densities of spotted deer or chital, a preferred wild prey, are associated with low elevations and decreased ruggedness and were generally higher in the south or inside inviolate PA areas than along the northern boundaries (Harihar et al., 2014). Additionally, the forest-farm boundary along the northern boundary of Corbett is a lot more fragmented by small hill villages with relatively low human population densities embedded within high vegetation cover. In the north, the boundaries between forests and farms are blurred as farms with fodder and fruit trees are often found surrounded with forests. In contrast, the southern forest-farm boundary

has a clearer demarcation with most of the human settlements, except for the pastoral community settlements and few forest villages, being outside the forests. For leopards, the habitats along the northern fringes may still be good quality habitat. Areas within the PA support higher wild prey densities than the surrounding landscape. Rugged terrain provides more opportunities for leopards to conceal themselves from tigers, and people in these northern areas also stock more cows than buffaloes and as therefore cows are more prominent in leopard diets than buffaloes. While there is lack of information on diet compositions of leopards and tigers in and around Corbett, an earlier study in Rajaji National Park, a PA connected to Corbett Tiger Reserve via Reserve forests or multiple use forests in the west, found that as tiger populations recovered in the area, leopard diets showed increased occurrence of domestic prey from 7% to 32 % in 4 years while wild prey species (sambar and chital) decreased in leopard diets from 83% to 40.5% (Harihar et al., 2011). Such interactions between apex predators can have several cascading impacts, such as shifts in the intensity of crop depredation by wild herbivores, when leopards and other carnivores that are displaced by tigers intensively use areas along the margins of human settlements, and prey upon wild herbivores that enter farmlands (Thinley et al., 2018).

Fifth, the immense delays in compensation payments by State agencies, especially in the case of conflict, suggests that in its current form this scheme may largely be uncoupled from its positive conservation impacts – and may be ineffective in deterring actions such as retaliatory killing (Madhusudan 2003). While most people who lose livestock to these carnivores typically received some compensation payments, they are so greatly delayed that their efficacy in building any tolerance for carnivores may be undermined. Nonetheless, the scheme likely has some utility by reducing the economic burden on affected people, who expect that they will eventually receive a claim. Notably, Uttarakhand is one of the few Indian states to have invested resources and efforts on improving compensation mechanisms, and the average payments livestock depredation incidents (\$211) are much higher than the national average of \$74 (Karanth et al., 2018). Clearly, there are still critical deficiencies in the processes for settling cases, with an inordinate amount of delay affecting most payments. Informal interviews with authorities in the State Forest Department indicate that post-approval compensation payments are often delayed by lack of funding and budgetary constraints. These are systemic problems across many parts of India (Karanth et al. 2018). Under these circumstances the Interim Relief Scheme which provided compensation rapidly may be relevant from a conservation standpoint, given that payment is made quickly, however small the amount.

This study has a few limitations. First is fixing the value of detection probability (p) at 0.9, rather than estimating it. This was done because undoubtedly, the use forest and agricultural areas within the study system by big cats is manifold higher than is manifest in reported events of livestock depredation. However, we did not have additional information on the occurrence of tigers and leopards within the grids that would

have allowed the decomposition of the detection probability to discriminate between species (tiger or leopard) occurrence without conflict, and detection of conflict, as might have been enabled by collecting additional data (e.g. using camera traps or sign survey data) (Warrier 2019). Because of the lack of data on species occurrence (other than related to depredation events), I was also not able to ascribe different occupancy states for habitat use and conflict (Athreya et al., 2015; Srivathsa et al., 2018). While Goswami et al. (2015) also used a multi-season occupancy model to estimate crop depredation by elephants, they modeled variation in p . Tigers and leopards are lot more furtive and considerably harder to detect while elephants were easily detected in crop fields. While my inferences would have been richer if we had been able to discriminate between habitat use and depredation probabilities to model variation in p , I note that studies that have previously modeled predation risk using data of livestock depredation events have typically not accounted for heterogeneity in detection probability and still provided useful conservation insights (Abade et al., 2014; Kaartinen et al., 2009; Miller, 2015; Adrian Treves et al., 2004). Second, because fine-scale data of habitat attributes at depredation sites were not collated, I did not explicitly account for environmental factors that influence depredation probabilities at multiple spatial scales (Miller et al., 2015; Rostro-García et al., 2016). Finally, I would have been able to more fully explore various hypotheses, especially around spatial segregation of tigers and leopards if spatially explicit data, at a sufficiently fine scale, on the density or occurrence of these carnivores and their wild prey and livestock densities and grazing patterns had been available.

Conservation and Management Implications

Sustaining human-carnivore coexistence: supporting vulnerable communities

Given the evidence that livestock are most vulnerable to depredation by tigers and leopards when they are resident within forests or in settlements near the forest's edge, and that conflict peaks in the monsoons, targeted interventions may lower conflict rates for the most vulnerable communities. Vulnerable groups include: (a) small and marginal farmers that depend on agriculture and/or livestock rearing for livelihood; (b) *Van gujjars* who lack tenurial security, live inside forests, and own large herds of livestock; and, (c) other agriculture-based communities living in forest villages like the *Taungya* who depend on forests and have low tenurial security. Given that all three groups have access to forests, their livestock spend long hours grazing. Thus, promoting stall-feeding could reduce losses from predation, but will require construction of predator-proof corrals, feeding and watering troughs, and securing fodder access. It is equally important to grant these communities greater access to financial instruments to cope with economic losses caused by conflict, for example through expedited compensation and by facilitating enrollment in livestock insurance schemes. The provisioning of these benefits must be a negotiated process to ensure that rules are developed and enforced to reduce grazing in forests. Furthermore, it is essential to understand

community attitudes and dynamics to strengthen social capital and channel it in support of conservation (Rastogi et al., 2014)

Alternative fodder access to reduce grazing

A transition from pastoralism to a more sedentary lifestyle has been documented among communities living around carnivore populations and affected by shrinking traditional grazing areas with land conversion into PA systems (McCabe, 2003; Harihar et al., 2015; Margulies & Karanth, 2018). Stall feeding does not completely replace grazing in these systems due to lack of economically viable alternatives to replace grazing which has negligible direct economic costs. A suite of options instead of a single approach is needed in this system. These options should include promotion of stall feeding and improving access to fodder alternatives like cut and carry or rotational grazing in community commons and at restored multiple use forest patches adjacent to settlements. Innovative linkages with non-forest fodder sources like food processing factories that discard green vegetable waste is also promising. Often, forest patches near settlements are infested with invasive species and could be earmarked for restoration and community use to use for regulated and rotational grazing.

Financial instruments to offset economic losses

Devising a combination of financial instruments with sustainable funding instead of relying on just compensation schemes is important (Dickman et al. 2011; Harihar et al., 2015). One idea is livestock insurance to both incentivize stall feeding and provide access to expedited compensation by leveraging revenue and livelihood development schemes. The WWF-India's livestock insurance initiative (a pilot intervention) at one village leveraged a livestock insurance scheme by the animal husbandry department to subsidize insurance premiums for five livestock units per farmer. The compensation schemes run by the forest department should continue to be part of the financial mitigation measures but need to be streamlined by technological upgrades in record keeping. The Interim Relief Scheme should be maintained until the government compensation is provided more rapidly. Additionally, mobile apps could be developed to ensure flow of information between the forest department and communities to keep them informed about the status of their application. As monsoons pose higher risk for depredation, the government could plan budgets according to incident reporting rates.

Improved access to sustainable livelihoods and development

Multiple studies around CTR found that communities affected by livestock depredation, especially, the pastoral *Van gujjars*, consider lack of access to development programs like education, health care and government financial support schemes, as their primary concern instead of depredation by carnivores

(Harihar et al., 2015; Rastogi et al., 2014). Studies have also documented their inclination to accept government relocation packages to shift to a mainstream sedentary lifestyle outside the forest as was done in other PAs like Rajaji National Park, an idea that was not widely popular among the community around Corbett, in the past (Harihar et al., 2015). Several families elicited interest in livestock buyback arrangements to move away from grazing large numbers of livestock as grazing areas become increasingly scarce (Harihar et al., 2015).

Voluntary relocation with settlement of rights is often a protracted process, but community members who do not accept voluntary relocation packages should still be engaged through access to schemes like more productive dairy-based livelihoods that enable and encourage a shift to fewer hybrid stall-fed livestock. In addition, improved access to education would enable them to move on to better livestock management practices that are more efficient in terms of returns and environmentally sustainable.

Sustaining social capital for large carnivore conservation

Areas like Corbett Tiger Reserve, where communities co-occur with carnivores widely and face conflict incidents like livestock depredation averaging 800 annually, the persistence of carnivore population hinges on ability and willingness of communities to tolerate risks and losses from carnivores (Carter & Linnell, 2016). One of the reasons Corbett Tiger reserve is touted as a success in PA management is that the communities view interactions with wildlife, even negative ones, as a part of life (Rastogi et al., 2014). Many interventions to prevent negative effects of conservation and increase the benefits, therefore, need collective action through community-based institutions. Social capital characterized by solidarity, reciprocity and cooperation and networks of mutual support are crucial for facilitating collective community action (Rastogi et al., 2014)₂. Therefore, any intervention plan needs to pay special attention to socio-economic dynamics within the community and find ways to channel it to support conservation. Adequate time and effort should be invested to ensure that costs and benefits of interventions are distributed equitably. Similar outcome from wildlife tourism have been documented around Corbett, where an elite capture of benefits from tourism resorts have eroded social capital (Rastogi et al. 2014). Therefore, community engagement needs to embed a dimension of cultivating the social capital among communities most affected by conflict.

Securing the future for large carnivores

The strong protection regime in CTR has helped sustain one of the largest tiger populations globally within the Reserve and its surrounding areas. Yet, survival probabilities for tigers, found to be only around 60% for males and marginally higher for females, in these areas are considerably lower than other prominent PAs in central India (Bisht et al., 2019). With such high densities of carnivores and large livestock populations in the area measures to deter retaliatory killing are especially relevant in the surrounding reserve forests where lesser sums are sanctioned by the Government for wildlife conservation, and where compensation payments for livestock depredation may be especially delayed. There have been some positive developments that have helped strengthen management in some forest divisions around Corbett – like accreditation of two neighboring reserve forests as Conservation Assured Tiger Standards(CA|TS) sites. CA|TS are a set of standards to benchmark if essential management conditions have been met in Forest Divisions beyond PAs, and ensure that deficiencies are addressed and high standards be maintained (<http://www.conservationassured.org/>). Other forest divisions in the study area such as Amangarh and Terai West Forest Division and the hill divisions to the North of CTR need considerably higher investment for conservation and protection. Another cause for concern is that areas on the Nepal border east of CTR have been identified as poaching and wildlife trade hotspots within India (Sharma et al., 2014).

There is very scant information on the prevalence of retaliatory killing – but better monitoring can perhaps help safeguard animals. For example, if camera traps are deployed at kill locations, valuable information will be gained on the individual tigers and leopards involved, and such data will help refine survival analyses for the species in the future, as well as better document the fate of individual animals. There have also been recent advances that have used genetic data to identify individual tigers and leopards from swabs taken from livestock carcasses. A combination of these methods, linked to rapid data processing and early warning systems may help reduce conflict, and its associated risks for tigers and leopards.

Ultimately conflict arising from livestock depredation may be reduced if fewer cattle enter tiger and leopard habitats. Even if this is not a possibility in the near future, compensation instruments and mechanisms need to be urgently reformed, so they provide a strong incentive for conservation. Finally, the success of tiger conservation in this crowded part of the planet is a testimony to the forbearance of communities that share space with tigers: this needs to be recognized, investigated further and supported. Undoubtedly, this system will offer many lessons that may be adapted to enable the conservation of large carnivores in human dominated landscapes.

Acknowledgements

It is my pleasure to thank everyone who has been part of this journey. This project would not have been possible without support from WWF-India. Dr. Pranav Chanchani, Lead- Tiger Conservation Programme, WWF-India, was an integral part of this project and analysis. Dr. Dipankar Ghose, Director, Species & Landscapes, Mr. Yash Magan Shethia, Associate Director, Species & Landscape and Dr. Anil Kumar Singh, Team Leader, Terai Arc Landscape, WWF-India, mentored me and facilitated my work on human-wildlife conflict in various ways over the years. I also want to thank, the field team at the WWF landscape program office in Haldwani and external field help including, Mr. Joy Dasgupta, Mr. Chandra Singh Negi, Mr. Gopal Dutt Papne, Mr. Umed Kandari and Ms. Neha Negi for supporting me in the field. I would also like to thank Harshad Karandikar, former Lead for Human Wildlife Conflict at WWF-India and Ankita Sardana, former Senior Program Officer at WWF-India, who were involved in conceptualizing the compensation evaluation study and data collection. A special thanks to Dr. Advait Edgaonkar, Assistant Professor, Indian Institute of Forest Management, Bhopal, India, who also helped with designing the compensation evaluation study. Dr. Abhishek Harihar kindly shared locations of *Van gujjar* settlements in the study area.

The Interim Relief Scheme is co-implemented by WWF-India and The Corbett Foundation (TCF). I am grateful to Dr Harendra Bargali and the TCF field team for their many contributions to fieldwork and data compilation over the years.

At Duke University, I want to thank my advisor, Professor John Poulsen for being immensely supportive every step of the way. I would also like to acknowledge Professors, Dean Urban and Jennifer Swenson, and John Fay for their exceptional teaching of landscape ecology and spatial analysis. I am thankful to Professor Stuart Pimm who greatly encouraged me to join this program. Shivangi Jain, MEM '20, assisted with the compensation evaluation study.

I am grateful for the Fulbright-Nehru Masters fellowship and the Nicholas Scholars award that enabled me to study at Duke University. The KLN Fund at Duke enabled my summer field travel to India. I also want to acknowledge the administrative support from USIEF in New Delhi and the Nicholas School. Finally, I want to thank my family for always supporting my dreams.

References

- Abade, L., Macdonald, D. W., & Dickman, A. J. (2014). Assessing the relative importance of landscape and husbandry factors in determining large carnivore depredation risk in Tanzania's Ruaha landscape. *Biological Conservation*, *180*, 241–248. <https://doi.org/10.1016/j.biocon.2014.10.005>
- Asher, Sam and Lunt, Tobias and Matsuura, Ryu and Novosad, Paul (2019). The Socio-economic High-resolution Rural-Urban Geographic Dataset on India (SHRUG) (<http://www.devdatalab.org/shrug>).
- Athreya, V., Srivathsa, A., Puri, M., Karanth, K. K., Kumar, N. S., & Karanth, K. U. (2015). Spotted in the News: Using Media Reports to Examine Leopard Distribution, Depredation, and Management Practices outside Protected Areas in Southern India. *PLOS ONE*, *10*(11), e0142647. <https://doi.org/10.1371/journal.pone.0142647>
- Bargali, H. S., & Ahmed, T. (2018). Patterns of livestock depredation by tiger (*Panthera tigris*) and leopard (*Panthera pardus*) in and around Corbett Tiger Reserve, Uttarakhand, India. *PLOS ONE*, *13*(5), e0195612. <https://doi.org/10.1371/journal.pone.0195612>
- Barua, M., Bhagwat, S. A., & Jadhav, S. (2013). The hidden dimensions of human–wildlife conflict: Health impacts, opportunity and transaction costs. *Biological Conservation*, *157*, 309–316. <https://doi.org/10.1016/j.biocon.2012.07.014>
- Bisht, S., Banerjee, S., Qureshi, Q. and Jhala, Y., 2019. Demography of a high-density tiger population and its implications for tiger recovery. *Journal of Applied Ecology*, *56*(7), pp.1725-1740.
- Braczkowski, A. R., O'Bryan, C. J., Stringer, M. J., Watson, J. E., Possingham, H. P., & Beyer, H. L. (2018). Leopards provide public health benefits in Mumbai, India. *Frontiers in Ecology and the Environment*, *16*(3), 176–182. <https://doi.org/10.1002/fee.1776>
- Brown, J. S., Kotler, B. P., & Bouskila, A. (n.d.). *Ecology of fear: Foraging games between predators and prey with pulsed resources*. *38*, 17.
- Carter, N. H., & Linnell, J. D. C. (2016). Co-Adaptation Is Key to Coexisting with Large Carnivores. *Trends in Ecology & Evolution*, *31*(8), 575–578. <https://doi.org/10.1016/j.tree.2016.05.006>
- Chanchani, P., Noon, B. R., Bailey, L., & Warrier, R. A. (2015). Conserving tigers in working landscapes. *Conservation Biology*, *0*(0), 1–12. <https://doi.org/10.1111/cobi.12633>
- Chapron, G., Kaczensky, P., Linnell, J. D. C., von Arx, M., Huber, D., André, H., López-Bao, J. V., Adamec, M., Álvares, F., Anders, O., Balčiauskas, L., Balys, V., Bedő, P., Bego, F., Blanco, J. C., Breitenmoser, U., Brøseth, H., Bufka, L., Bunikyte, R., ... Boitani, L. (2014). Recovery of large carnivores in Europe's modern human-dominated landscapes. *Science*, *346*(6216), 1517–1519. <https://doi.org/10.1126/science.1257553>

- CIESIN (Center for International Earth Science Information Network, Columbia University). 2016. Gridded Population of the World, Version 3 (GPWv3): Population Count. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). [Available online at: <http://sedac.ciesin.columbia.edu/data/collection/gpw-v3>. Accessed 01 March 2019].
- Creel, S., & Christianson, D. (2008). Relationships between direct predation and risk effects. *Trends in Ecology & Evolution*, 23(4), 194–201. <https://doi.org/10.1016/j.tree.2007.12.004>
- Davis, A. J., Kirby, J. D., Chipman, R. B., Nelson, K. M., Xifara, T., Webb, C. T., Wallace, R., Gilbert, A. T., & Pepin, K. M. (2019). Not all surveillance data are created equal—A multi-method dynamic occupancy approach to determine rabies elimination from wildlife. *Journal of Applied Ecology*, 56(11), 2551–2561. <https://doi.org/10.1111/1365-2664.13477>
- Dhee, Athreya, V., Linnell, J. D. C., Shivakumar, S., & Dhiman, S. P. (2019). The leopard that learnt from the cat and other narratives of carnivore–human coexistence in northern India. *People and Nature*, 1(3), 376–386. <https://doi.org/10.1002/pan3.10039>
- Dickman, A. J. (2010). Complexities of conflict: The importance of considering social factors for effectively resolving human-wildlife conflict: Social factors affecting human-wildlife conflict resolution. *Animal Conservation*, 13(5), 458–466. <https://doi.org/10.1111/j.1469-1795.2010.00368.x>
- Dickman, Amy J., Hinks, A. E., Macdonald, E. A., Burnham, D., & Macdonald, D. W. (2015). Priorities for global felid conservation: Global Felid Conservation. *Conservation Biology*, 29(3), 854–864. <https://doi.org/10.1111/cobi.12494>
- Dormann, C.F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J.R. García Marquéz, B. Gruber, B. Lafourcade, P.J. Leitão, T. Münkemüller, C. McClean, P.E. Osborne, B. Reineking, B. Schröder, A.K. Skidmore, D. Zurell, and S. Lautenbach. 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography* 36: 027–046
- Boomgaard, P. 2001. *Frontiers of fear: tigers and people in the malay world, 1600–1950*. Yale University Press, New Haven, Connecticut, 308 pp. ISBN 0-300-08539-7,
- ESRI 2018. ArcGIS Pro 2.4.2: Release 10. Redlands, CA: Environmental Systems Research Institute.
- Gooch, P. (2009). Victims of conservation or rights as forest dwellers: Van gujjar pastoralists between contesting codes of law. *Conservation and Society*, 7(4), 239. <https://doi.org/10.4103/0972-4923.65171>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*.

- Goswami, V. R., Medhi, K., Nichols, J. D., & Oli, M. K. (2015). Mechanistic understanding of human-wildlife conflict through a novel application of dynamic occupancy models: Dynamics of Human-Wildlife Conflict. *Conservation Biology*, 29(4), 1100–1110. <https://doi.org/10.1111/cobi.12475>
- Harihar, A., Pandav, B., & Goyal, S. P. (2011). Responses of leopard *Panthera pardus* to the recovery of a tiger *Panthera tigris* population: Response of leopard to recovery of tiger. *Journal of Applied Ecology*, 48(3), 806–814. <https://doi.org/10.1111/j.1365-2664.2011.01981.x>
- Harihar, A., Pandav, B., & MacMillan, D. C. (2014). Identifying realistic recovery targets and conservation actions for tigers in a human-dominated landscape using spatially explicit densities of wild prey and their determinants. *Diversity and Distributions*, 20(5), 567–578. <https://doi.org/10.1111/ddi.12174>
- Harihar, A., Veríssimo, D., & MacMillan, D. C. (2015). Beyond compensation: Integrating local communities' livelihood choices in large carnivore conservation. *Global Environmental Change*, 33, 122–130. <https://doi.org/10.1016/j.gloenvcha.2015.05.004>
- Hazzah, L., Borgerhoff Mulder, M., & Frank, L. (2009). Lions and Warriors: Social factors underlying declining African lion populations and the effect of incentive-based management in Kenya. *Biological Conservation*, 142(11), 2428–2437. <https://doi.org/10.1016/j.biocon.2009.06.006>
- Hussain, A., Dasgupta, S., & Bargali, H. S. (2016). Conservation perceptions and attitudes of semi-nomadic pastoralist towards relocation and biodiversity management: A case study of Van Gujjars residing in and around Corbett Tiger Reserve, India. *Environment, Development and Sustainability*, 18(1), 57–72. <https://doi.org/10.1007/s10668-015-9621-6>
- Inskip, C., Carter, N., Riley, S., Roberts, T., & MacMillan, D. (2016). Toward Human-Carnivore Coexistence: Understanding Tolerance for Tigers in Bangladesh. *PLOS ONE*, 11(1), e0145913. <https://doi.org/10.1371/journal.pone.0145913>
- Jarvis, A., Reuter, H.I., Nelson, A. & Guevara, E. (2008) Hole-filled SRTM for the globe Version 4. Available from the CGIAR-SXI SRTM 90 m database: <http://srtm.csi.cgiar.org> (accessed 25 July 2011).
- Jhala, Yadvendra & Qureshi, Qamar (eds.). (2015). Status of Tigers, co-predators and prey in India, 2014. Wildlife Institute of India and National Tiger Conservation Authority, New Delhi.
- Johnsingh, A. J. T., & Joshua, J. (1994). Conserving Rajaji and Corbett National Parks – the elephant as a flagship species. *Oryx*, 28(2), 135–140. <https://doi.org/10.1017/S0030605300028453>
- Kaartinen, S., Luoto, M., & Kojola, I. (2009). Carnivore-livestock conflicts: Determinants of wolf (*Canis lupus*) depredation on sheep farms in Finland. *Biodiversity and Conservation*, 18(13), 3503–3517. <https://doi.org/10.1007/s10531-009-9657-8>

- Kanagaraj, R., Wiegand, T., Kramer-Schadt, S., Anwar, M., & Goyal, S. P. (2011). Assessing habitat suitability for tiger in the fragmented Terai Arc Landscape of India and Nepal. *Ecography*, *34*(6), 970–981. <https://doi.org/10.1111/j.1600-0587.2010.06482.x>
- Kansky, R., Kidd, M., & Knight, A. T. (2016). A wildlife tolerance model and case study for understanding human wildlife conflicts. *Biological Conservation*, *201*, 137–145. <https://doi.org/10.1016/j.biocon.2016.07.002>
- Kansky, R., & Knight, A. T. (2014). Key factors driving attitudes towards large mammals in conflict with humans. *Biological Conservation*, *179*, 93–105. <https://doi.org/10.1016/j.biocon.2014.09.008>
- Karanth, K. K., Gopaldaswamy, A. M., DeFries, R., & Ballal, N. (2012). Assessing Patterns of Human-Wildlife Conflicts and Compensation around a Central Indian Protected Area. *PLoS ONE*, *7*(12). <https://doi.org/10.1371/journal.pone.0050433>
- Karanth, K. K., Gopaldaswamy, A. M., Prasad, P., & Dasgupta, S. (2013). Patterns of human–wildlife conflicts and compensation: Insights from Western Ghats protected areas. *Biol Conserv*, *166*, 175–185. doi:[10.1016/j.biocon.2013.06.027](https://doi.org/10.1016/j.biocon.2013.06.027)
- Karanth, K. K., Gupta, S., & Vanamamalai, A. (2018). Compensation payments, procedures and policies towards human-wildlife conflict management: Insights from India. *Biological Conservation*, *227*, 383–389. <https://doi.org/10.1016/j.biocon.2018.07.006>
- Lasgorceix, Antoine and Kothari , Ashish (2009). Displacement and Relocation of Protected Areas: A Synthesis and Analysis of Case Studies. *Economic and Political Weekly*, Vol. 44, No. 49, pp. 37-47
- Moreira, Adriano & Santos, Maribel. (2007). Concave hull: A k-nearest neighbours approach for the computation of the region occupied by a set of points. 61-68.
- Laundré, J. W., Hernández, L., Medina, P. L., Campanella, A., López-Portillo, J., González-Romero, A., Grajales-Tam, K. M., Burke, A. M., Gronemeyer, P., & Browning, D. M. (2014). The landscape of fear: The missing link to understand top-down and bottom-up controls of prey abundance? *Ecology*, *95*(5), 1141–1152. <https://doi.org/10.1890/13-1083.1>
- Lischka, S. A., Teel, T. L., Johnson, H. E., & Crooks, K. R. (2019). Understanding and managing human tolerance for a large carnivore in a residential system. *Biological Conservation*, *238*, 108189. <https://doi.org/10.1016/j.biocon.2019.07.034>
- MacKenzie, D. I. (1st Ed.). (2006). Occupancy estimation and modeling: Inferring patterns and dynamics of species. Academic Press, Burlington
- MacKenzie, D. I. (2nd Ed.). (2017). Occupancy estimation and modeling: Inferring patterns and dynamics of species. *Academic Press*, Burlington.

- MacKenzie, D. I., Nichols, J. D., Hines, J. E., Knutson, M. G., & Franklin, A. B. (2003). Estimating site occupancy, colonization, and local extinction when a species is detected imperfectly. *Ecology*, 84(8), 2200–2207. <https://doi.org/10.1890/02-3090>
- MacLennan, S. D., Groom, R. J., Macdonald, D. W., & Frank, L. G. (2009). Evaluation of a compensation scheme to bring about pastoralist tolerance of lions. *Biological Conservation*, 142(11), 2419–2427. <https://doi.org/10.1016/j.biocon.2008.12.003>
- Madhusudan, M. 2003. Living amidst large wildlife: livestock and crop depredation by large mammals in the interior villages of Bhadra Tiger Reserve, South India. *Environmental Management*, 31: 0466. <https://doi.org/10.1007/s00267-002-2790-8>.
- Majgaonkar, I., Vaidyanathan, S., Srivathsa, A., Shivakumar, S., Limaye, S., & Athreya, V. (2019). Land-sharing potential of large carnivores in human-modified landscapes of western India. *Conservation Science and Practice*, 1(5), e34. <https://doi.org/10.1111/csp2.34>
- Margulies, J. D., & Karanth, K. K. (2018). The production of human-wildlife conflict: A political animal geography of encounter. *Geoforum*, 95, 153–164. <https://doi.org/10.1016/j.geoforum.2018.06.011>
- McCabe, J. T. (2003). Sustainability and Livelihood Diversification among the Maasai of Northern Tanzania. *Human Organization*, 62(2), 100–111. <https://doi.org/10.17730/humo.62.2.4rwr1n3xptg29b8>
- Miller, J. R. B. (2015). Mapping attack hotspots to mitigate human–carnivore conflict: Approaches and applications of spatial predation risk modeling. *Biodiversity Conserv.* <https://doi.org/10.1007/s10531-015-0993-6>
- Miller, J. R. B., Jhala, Y. V., & Jena, J. (2016). Livestock losses and hotspots of attack from tigers and leopards in Kanha Tiger Reserve, Central India. *Regional Environmental Change*, 16(S1), 17–29. <https://doi.org/10.1007/s10113-015-0871-5>
- Miller, J. R. B., Jhala, Y. V., Jena, J., & Schmitz, O. J. (2015). Landscape-scale accessibility of livestock to tigers: Implications of spatial grain for modeling predation risk to mitigate human–carnivore conflict. *Ecology and Evolution*, 5(6), 1354–1367. <https://doi.org/10.1002/ece3.1440>
- Miller, J. R. B., & Schmitz, O. J. (2019). Landscape of fear and human-predator coexistence: Applying spatial predator-prey interaction theory to understand and reduce carnivore-livestock conflict. *Biological Conservation*, 236, 464–473. <https://doi.org/10.1016/j.biocon.2019.06.009>
- Musavi, A. & Khan, J.A. & Kumar, S. & Khan, A. & Malik, P.K. & Kushwaha, Satya & Khati, D.S. & Sarin, G.D.. (2006). A study of Tiger human conflict in buffer zone of the Corbett Tiger Reserve: Protected area-people relationship. *International Journal of Ecology and Environmental Sciences*. 32. 241-257.

- Naha, D., Sathyakumar, S., & Rawat, G. S. (2018). Understanding drivers of human-leopard conflicts in the Indian Himalayan region: Spatio-temporal patterns of conflicts and perception of local communities towards conserving large carnivores. *PLOS ONE*, 13(10), e0204528. <https://doi.org/10.1371/journal.pone.0204528>
- Nyhus, P. J. (2016). Human–Wildlife Conflict and Coexistence. *Annual Review of Environment and Resources*, 41(1), 143–171. <https://doi.org/10.1146/annurev-environ-110615-085634>
- Oriol-Cotterill, A., Valeix, M., Frank, L. G., Riginos, C., & Macdonald, D. W. (2015). Landscapes of Coexistence for terrestrial carnivores: The ecological consequences of being downgraded from ultimate to penultimate predator by humans. *Oikos*, 124(10), 1263–1273. <https://doi.org/10.1111/oik.02224>
- Packer, C., Shivakumar, S., Athreya, V., Craft, M. E., Dhanwatey, H., Dhanwatey, P., Gurung, B., Joshi, A., Kushnir, H., Linnell, J. D. C., & Fountain-Jones, N. M. (2019). Species-specific spatiotemporal patterns of leopard, lion and tiger attacks on humans. *Journal of Applied Ecology*, 56(3), 585–593. <https://doi.org/10.1111/1365-2664.13311>
- R Core Team. 2018. R: A Language and Environment for Statistical Computing. url: <https://www.R-project.org/>.
- Rastogi, A., Hickey, G. M., Badola, R., & Hussain, S. A. (2014). Understanding the Local Socio-political Processes Affecting Conservation Management Outcomes in Corbett Tiger Reserve, India. *Environmental Management*, 53(5), 913–929. <https://doi.org/10.1007/s00267-014-0248-4>
- Riley, S.J., DeGloria, S.D. & Elliot, R. (1999) A terrain ruggedness index that quantifies topographic heterogeneity. *Intermountain Journal of Sciences*, 5, 23–27.
- Ripple, W. J., Estes, J. A., Beschta, R. L., Wilmers, C. C., Ritchie, E. G., Hebblewhite, M., Berger, J., Elmhagen, B., Letnic, M., Nelson, M. P., Schmitz, O. J., Smith, D. W., Wallach, A. D., & Wirsing, A. J. (2014). Status and Ecological Effects of the World’s Largest Carnivores. *Science*, 343(6167), 1241484–1241484. <https://doi.org/10.1126/science.1241484>
- Rostro-García, S., Tharchen, L., Abade, L., Astaras, C., Cushman, S. A., & Macdonald, D. W. (2016). Scale dependence of felid predation risk: Identifying predictors of livestock kills by tiger and leopard in Bhutan. *Landscape Ecology*, 31(6), 1277–1298. <https://doi.org/10.1007/s10980-015-0335-9>
- Sekhar, N. U. (1998). Crop and livestock depredation caused by wild animals in protected areas: The case of Sariska Tiger Reserve, Rajasthan, India. *Environmental Conservation*, 25(2), 160–171. <https://doi.org/10.1017/S0376892998000204>

- Sharma, K., Wright, B., Joseph, T., & Desai, N. (2014). Tiger poaching and trafficking in India: Estimating rates of occurrence and detection over four decades. *Biological Conservation*, *179*, 33–39. <https://doi.org/10.1016/j.biocon.2014.08.016>
- Srivathsa, A., Puri, M., Kumar, N. S., Jathanna, D., & Karanth, K. U. (2018). Substituting space for time: Empirical evaluation of spatial replication as a surrogate for temporal replication in occupancy modelling. *Journal of Applied Ecology*, *55*(2), 754–765. <https://doi.org/10.1111/1365-2664.13005>
- Steinmetz, R., Srirattaporn, S., Mor-Tip, J., & Seuaturien, N. (2014). Can community outreach alleviate poaching pressure and recover wildlife in South-East Asian protected areas? *Journal of Applied Ecology*, *51*(6), 1469–1478. <https://doi.org/10.1111/1365-2664.12239>
- Struebig, M. J., Linkie, M., Deere, N. J., Martyr, D. J., Millyanawati, B., Faulkner, S. C., Le Comber, S. C., Mangunjaya, F. M., Leader-Williams, N., McKay, J. E., & St. John, F. A. V. (2018). Addressing human-tiger conflict using socio-ecological information on tolerance and risk. *Nature Communications*, *9*(1), 3455. <https://doi.org/10.1038/s41467-018-05983-y>
- Sunarto, S., Kelly, M. J., Parakkasi, K., Klenzendorf, S., Septayuda, E., & Kurniawan, H. (2012). Tigers Need Cover: Multi-Scale Occupancy Study of the Big Cat in Sumatran Forest and Plantation Landscapes. *PLoS ONE*, *7*(1), e30859. <https://doi.org/10.1371/journal.pone.0030859>
- Suryawanshi, K. R., Bhatia, S., Bhatnagar, Y. V., Redpath, S., & Mishra, C. (2014). Multiscale Factors Affecting Human Attitudes toward Snow Leopards and Wolves: Attitudes toward Snow Leopards and Wolves. *Conservation Biology*, *28*(6), 1657–1666. <https://doi.org/10.1111/cobi.12320>
- Thinley, P., Rajaratnam, R., Lassoie, J. P., Morreale, S. J., Curtis, P. D., Vernes, K., Leki, L., Phuntsho, S., Dorji, T., & Dorji, P. (2018). The ecological benefit of tigers (*Panthera tigris*) to farmers in reducing crop and livestock losses in the eastern Himalayas: Implications for conservation of large apex predators. *Biological Conservation*, *219*, 119–125. <https://doi.org/10.1016/j.biocon.2018.01.015>
- Treves, A., & Bruskotter, J. (2014). Tolerance for Predatory Wildlife. *Science*, *344*(6183), 476–477. <https://doi.org/10.1126/science.1252690>
- Treves, Adrian, Naughton-Treves, L., Harper, E. K., Mladenoff, D. J., Rose, R. A., Sickley, T. A., & Wydeven, A. P. (2004). Predicting Human-Carnivore Conflict: A Spatial Model Derived from 25 Years of Data on Wolf Predation on Livestock. *Conservation Biology*, *18*(1), 114–125. <https://doi.org/10.1111/j.1523-1739.2004.00189.x>
- Treves, Adrian, Wallace, R. B., Naughton-Treves, L., & Morales, A. (2006). Co-Managing Human–Wildlife Conflicts: A Review. *Human Dimensions of Wildlife*, *11*(6), 383–396. <https://doi.org/10.1080/10871200600984265>

- Warrier, Rekha.(2019).Conserving tigers beyond protected area boundaries: the spatial ecology of tigers and their prey in farmlands in north India. *PhD Dissertation*. Colorado state University.
- Watve, M., Patel, K., Bayani, A., & Patil, P. (2016). A theoretical model of community operated compensation scheme for crop damage by wild herbivores. *Global Ecology and Conservation*, 5, 58–70. <https://doi.org/10.1016/j.gecco.2015.11.012>
- White GC, Burnham KP. 1999. ProgramMARK: survival estimation from populations of marked animals. *Bird Study* 46:S120–S139.
- Zarco-González, M. M., Monroy-Vilchis, O., & Alaníz, J. (2013). Spatial model of livestock predation by jaguar and puma in Mexico: Conservation planning. *Biological Conservation*, 159, 80–87. <https://doi.org/10.1016/j.biocon.2012.11.007>

Appendix

Table 6 The model results for the best supported models with 90% of AIC weights for tigers from step 1 which includes the global models for γ and ε and different model structures for Ψ_1 . The global models for γ and ε were the same -- γ , ε (season * seasonal NDVI+ StreaLen+ Dis2Stre+NL+TRI+GujBuf+PropFor+Dis2Edg)

Model	Δ AICc	AICc Weights	Model Likelihood	Num. Parameters
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + ExtentDrain + Gujjar + TRI) γ (global) ε (global)	0.00	0.21	1.00	31
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + Gujjar + TRI) γ (global) ε (global)	0.55	0.16	0.76	31
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + Gujjar + TRI) γ (global) ε (global)	1.08	0.12	0.58	30
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain + Gujjar + TRI) γ (global) ε (global)	1.17	0.12	0.56	32
Ψ_1 (Dist2Edge + PropFor + sumNDVI + ExtentDrain + Gujjar + TRI) γ (global) ε (global)	1.68	0.09	0.43	30
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain+ PopDens + Gujjar + TRI) γ (global) ε (global)	2.57	0.06	0.28	33
Ψ_1 (Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain + Gujjar + TRI) γ (global) ε (global)	2.69	0.05	0.26	31
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + ExtentDrain + Gujjar + TRI) γ (global) ε (global)	2.83	0.05	0.24	30
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain+ NL/sett + Gujjar + TRI) γ (global) ε (global)	3.15	0.04	0.21	33

Table 7 The model results for the best supported models with 90% of AIC weights for tigers from step 2 which includes the best supported model for Ψ_1 , global model for ϵ and different model structures for γ . The top model for Ψ_1 was Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + ExtentDrain + Gujjar + TRI) and global models for ϵ was ϵ (season * seasonal NDVI+ StreaLen+ Dis2Stre+NL+TRI+GujBuf+PropFor+Dis2Edg)

Model	Δ AICc	AICc Weights	Model Likelihood	No. Parameters
$\Psi_1(Top)\gamma$ (season x Dis2Edge+SeasonalNDVI+StreamLen+Dis2Stre+ NL+xPropFor+TRI+Gujjar) ϵ (Global)	0.00	0.56	1.00	32
$\Psi_1(Top)\gamma$ (season x Dist2Stream +SeasonalNDVI+Dis2Edge^2+ StrLen +NL/Settle + PropFor + TRI + Gujjar) ϵ (Global)	2.86	0.13	0.24	31
$\Psi_1(Top)\gamma$ (season x Dis2Strm + StrLen + NL/sett + PropFor + SeasonalNDVI + TRI + Gujjar) ϵ (Global)	3.48	0.10	0.18	30
$\Psi_1(Top)\gamma$ (season x Dist2Stream +SeasonalNDVI+Dis2Edge^2+ StrLen +x NL/Settle + PropFor + TRI + Gujjar) ϵ (Global)	4.62	0.06	0.10	32
$\Psi_1(Top)\gamma$ (season x Dis2Edge+ PropFo+SeasonalNDVI+ NL/Settle + StrLen+Dist2Stream + TRI + Gujjar) ϵ (Global)	5.11	0.04	0.08	31
$\Psi_1(Top)\gamma$ (season x Dis2Edge+SeasonalNDVI+NL+TRI+ xPropFor+gujjar+StrLen+Dis2Stream) ϵ (Global)	6.10	0.03	0.05	32

Table 8 The model results for the best supported models with 90% of AIC weights for tigers from step 3 which includes the top models for Ψ_1 and γ and different model structures for ε . The top models for Ψ_1 and γ were -- Ψ_1 (Strmlen+ TRI+ NDVI+ EdgeLen+ Prop For+ Dist2Edge+ GujBuf), γ (NDVIchange+ Dist2Edge+ Dist2Strea+ StrmLen+ NL+ TRI+ GujBuf+ PropFor+ NL x PropFor)

Model	Δ AICc	AICc Weights	Model Likelihood	No. Parameters
Ψ_1 (Best), γ (Best) ε (TRI+GujBuf+PropFor+GujBuf x PropFor)	0	0.34	1	28
Ψ_1 (Best), γ (Best) ε (TRI+GujBuf+PropFor)	1.87	0.13	0.39	27
Ψ_1 (Best), γ (Best) ε (NDVI change+ TRI+GujBuf+PropFor)	2.63	0.092	0.27	28
Ψ_1 (Best), γ (Best) ε (TRI+GujBuf+ PropFor+PropFor xTRI)	3.75	0.05	0.15	28
Ψ_1 (Best), γ (Best) ε (NDVI change+StrmLen+NL+TRI+GujBuf+PropFor+GujBuf x PropFor+Dis2Edg)	4.52	0.04	0.10	32
Ψ_1 (Best), γ (Best) ε (NDVI change+TRI+GujBu+PropFor+Dis2Edg)	4.61	0.03	0.10	29
Ψ_1 (Best), γ (Best) ε (NDVI change+StrmLen+Dis2Str+NL+TRI+GujBu+PropFor+GujBufx PropFor+Dis2Edg)	4.81	0.03	0.09	33
Ψ_1 (Best), γ (Best) ε (NDVI change+NL+TRI+GujBuf+PropFor+Dis2Edg)	5.07	0.03	0.08	30
Ψ_1 (Best), γ (Best) ε (NDVI change+StrmLen+Dist2Stre+NL+TRI+GujBuf+PropFor+GujBuf x StreLen+Dis2Edg)	5.12	0.03	0.08	33
Ψ_1 (Best), γ (Best) ε (NDVI change+Dis2Stre+NL+TRI+GujBu+PropFor+NL x NDVI change+Dis2Edg)	5.38	0.02	0.06	32
Ψ_1 (Best), γ (Best) ε (NDVI change+StrmLen+Dis2Stre+NL+TRI+GujBu+PropFor+TRI x NDVI change+Dis2Edg)	5.47	0.02	0.07	33

$\Psi I(Best), \gamma(Best) \varepsilon(\text{season} \times NDVI \text{ change} + StrmLen + Dis2Stre + NL + TRI + GujBuf + PropFor + PropFor \times Dist2Edg \times Dis2Stre + Dis2Edg)$	6.47	0.01	0.04	33
$\Psi I(Best), \gamma(Best) \varepsilon(\text{season} \times NDVI \text{ change} + TRI + GujBuf + PropFor + TRI \times PropFor + Dis2Edg)$	6.48	0.01	0.04	30
$\Psi I(Best), \gamma(Best) \varepsilon(\text{season} \times NDVI \text{ change} + TRI + GujBu + PropFor + Dis2Edg \times PropFor + Dis2Edg)$	6.53	0.01	0.04	30
$\Psi I(Best), \gamma(Best) \varepsilon(\text{season} \times NDVI \text{ change} + StrmLen + Dis2Stre + NL + TRI + GujBuf + PropFor + Dis2Edge ^2)$	6.58	0.01272	0.04	32
$\Psi I(Best), \gamma(Best) \varepsilon(\text{season} \times NDVI \text{ change} + NL + TRI + GujBu + PropFor + NDVI \text{ change} \times PropFor + Dis2Edg)$	6.79	0.01	0.03	31
$\Psi I(Best), \gamma(Best) \varepsilon(\text{season} \times NDVI \text{ change} + Dis2Stre + NL + TRI + GujBu + PropFor + NDVI \text{ change} \times PropFor + Dis2Edg)$	6.80	0.01	0.03	32
$\Psi I(Best), \gamma(Best) \varepsilon(\text{season} \times NDVI \text{ change} + NL + TRI + GujBuf + PropFor + GujBuf \times PropFor + Dis2Edg)$	6.96	0.01	0.03	31

Table 9 The model results for the best supported models with 90% of AIC weights for leopards from step 1 which includes the global models for γ and ϵ and different model structures for Ψ_1 . The global models for γ and ϵ were the same -- γ , ϵ (season * seasonal NDVI+ StreaLen+ Dis2Stre+NL+TRI+GujBuf+PropFor+Dis2Edg)

Model	Δ AICc	AICc Weights	Model Likelihood	Num. Par
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + Gujjar + TRI) γ (global) ϵ (global)	0.00	0.37	1.00	31
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain + Gujjar + TRI) γ (global) ϵ (global)	1.86	0.15	0.40	32
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain+ PopDens + Gujjar + TRI) γ (global) ϵ (global)	3.49	0.06	0.17	33
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + ExtentDrain + Gujjar + TRI) γ (global) ϵ (global)	3.57	0.06	0.17	31
Ψ_1 (Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain + Gujjar + TRI) γ (global) ϵ (global)	3.74	0.06	0.15	31
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain+ NL/sett + Gujjar + TRI) γ (global) ϵ (global)	3.87	0.05	0.14	33
Ψ_1 (EdgeExtent + PropFor + sumNDVI + DistantDrain + ExtentDrain + Gujjar + TRI) γ (global) ϵ (global)	3.91	0.05	0.14	31
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + DistantDrain + ExtentDrain + Gujjar + TRI) γ (global) ϵ (global)	3.96	0.05	0.14	31
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + ExtentDrain + Gujjar + TRI) γ (global) ϵ (global)	4.87	0.03	0.09	30
Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + DistantDrain + ExtentDrain+ PopDens + Gujjar + TRI+NL) γ (global) ϵ (global)	5.47	0.02	0.06	34

Table 10. The model results for the best supported models with 90% of AIC weights for leopards from step 2 which includes the best supported model for Ψ_1 , global model for ϵ and different model structures for γ . The top model for Ψ_1 was Ψ_1 (EdgeExtent + Dist2Edge + PropFor + sumNDVI + ExtentDrain + Gujjar + TRI) and global model for ϵ was ϵ (season * seasonal NDVI+ StreaLen+ Dis2Stre+NL+TRI+GujBuf+PropFor+Dis2Edg)

Model	Δ AICc	AICc Weights	Model Likelihood	Num. Par
Ψ_1 (Top) γ (season * Dist2Stream + Dis2Edge StrLen +x NL/Settle + PropFor + TRI + Gujjar) ϵ (global)	0.00	0.51	1.00	0.00
Ψ_1 (Top) γ (season * Dis2Edge + StrLen +x NL/Settle + PropFor + TRI + Gujjar) ϵ (global)	2.36	0.16	0.31	2.36
Ψ_1 (Top) γ (season * Dist2Stream + Dis2Edge StrLen + + PropFor + * NL/Settle + TRI + Gujjar) ϵ (global)	3.67	0.08	0.16	3.67
Ψ_1 (Top) γ (season * Dis2Edge + StrLen +x NL/Settle + Seasonal_NDVI + TRI + Gujjar+propFor) ϵ (global)	3.69	0.08	0.16	3.69
Ψ_1 (Top) γ (season * Dis2Edge+x PropFo+SeasonalNDVI + Gujjar) ϵ (global)	3.99	0.07	0.14	3.99
Ψ_1 (Top) γ (season* Dis2Edge+SeasonalNDVI+StreamLen+Dis2Stre+NL+ xPropFor+TRI+Gujjar) ϵ (global)	5.15	0.04	0.08	5.15

Table 11. The model results for the well supported models with 90% of AIC weights for leopards from step 3 which includes the top models for Ψ_1 and γ and different model structures for ε . The top models for Ψ_1 and γ -- were Ψ_1 (StreaLen+ TRI+ NDVI+ EdgeLen+ PropForest+ Dist2Edge+ Dist2Strea+ NL+ popDen+ GujBuff), γ (Dist2Edge + Dist2Strea + StreaLen + NL+ StreaLen x NL+ TRI+ GujBuff+ PropFor)

Model	Δ AICc	AICc Weights	Model Likelihood	Num. Par
$\Psi_1(\text{Best}), \gamma(\text{Best}), \varepsilon(\text{NDVI change} + \text{NL} + \text{TRI} + \text{PropFor} + \text{PropFor} \times \text{TRI} + \text{Dis2Edg})$	0	0.75	1	32
$\Psi_1(\text{Best}), \gamma(\text{Best}), \varepsilon(\text{NDVI change} + \text{StremLen} + \text{Dis2Stre} + \text{NL} + \text{TRI} + \text{GujBuf} + \text{PropFor} + \text{PropFor} \times \text{TRI} + \text{Dis2Edg})$	4.79	0.07	0.09	35
$\Psi_1(\text{Best}), \gamma(\text{Best}), \varepsilon(\text{NDVI change} + \text{StremLen} + \text{Dis2Stre} + \text{NL} + \text{TRI} + \text{GujBuf} + \text{PropFor} + \text{GujBuf} \times \text{StremLen} + \text{Dis2Edg})$	5.22	0.06	0.07	35
$\Psi_1(\text{Best}), \gamma(\text{Best}), \varepsilon(\text{NDVI change} + \text{StremLen} + \text{NL} + \text{TRI} + \text{PropFor} + \text{PropFor} \times \text{TRI})$	5.78	0.04	0.06	32

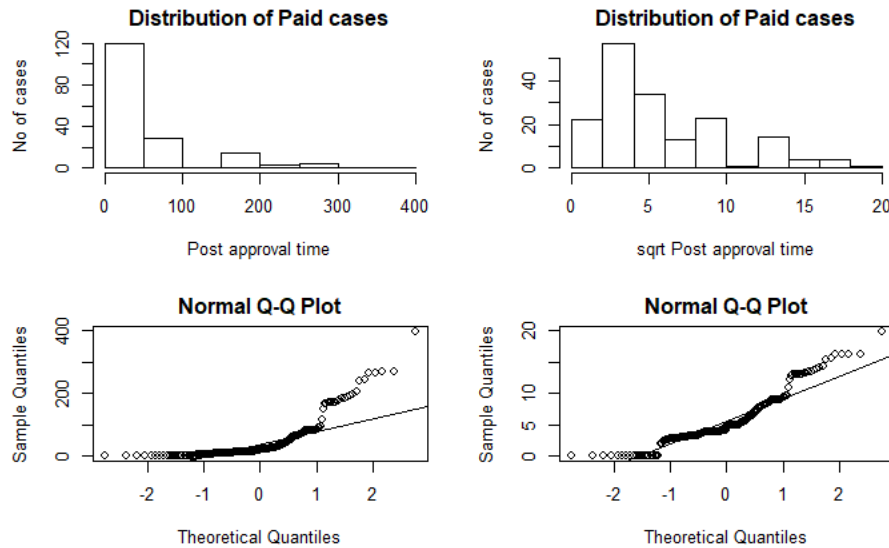


Figure 17 Distributions of raw and square root transformed post approval times for paid case

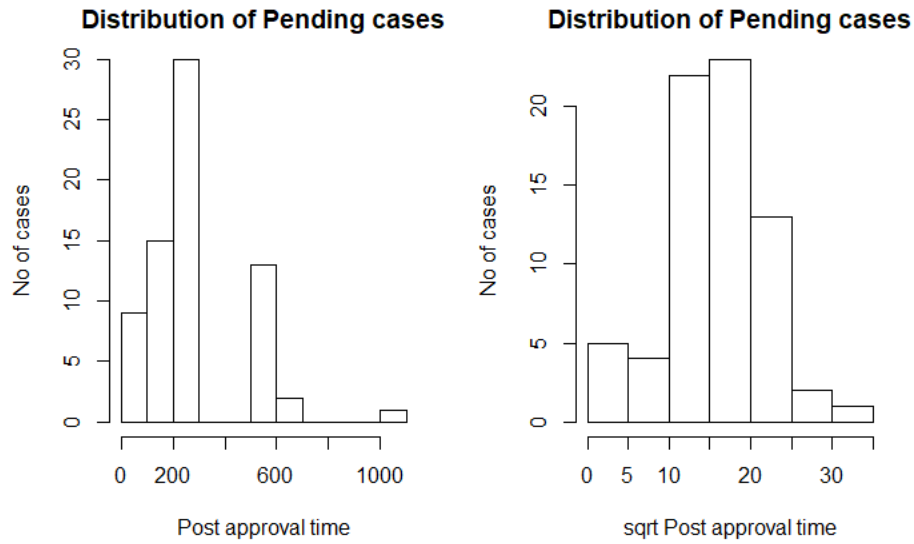


Figure 18 Distributions of raw and square root transformed post approval times for pending cases

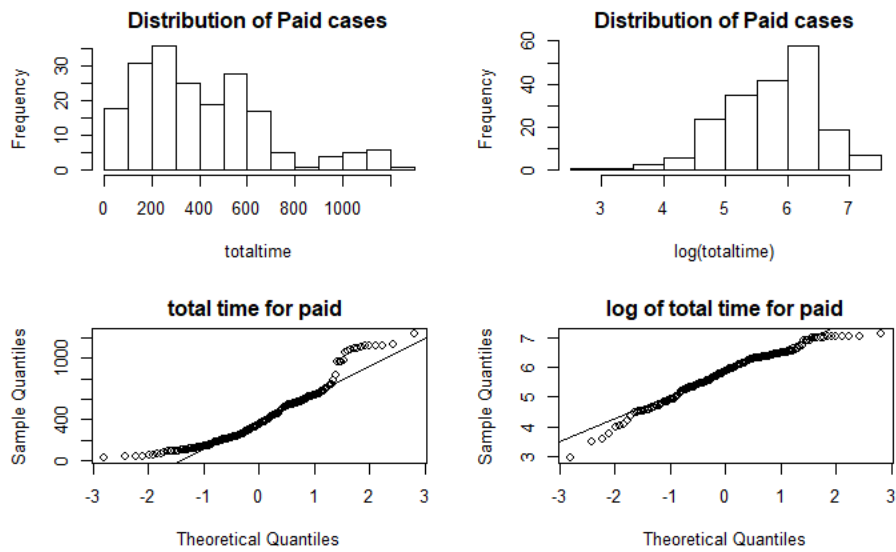


Figure 19 Distribution of raw and log transformed totaltime for paid cases

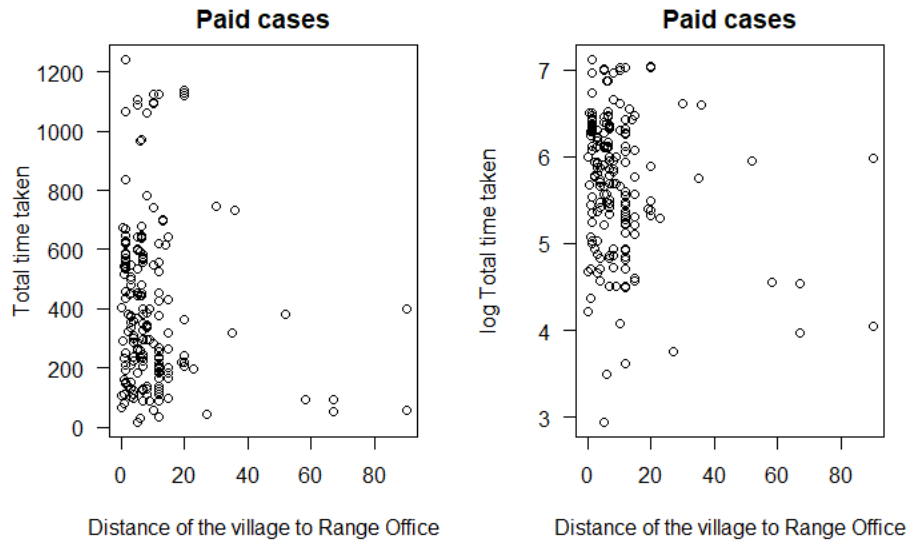


Figure 20 Relationship of raw and log transformed totaltime for paid cases to distance

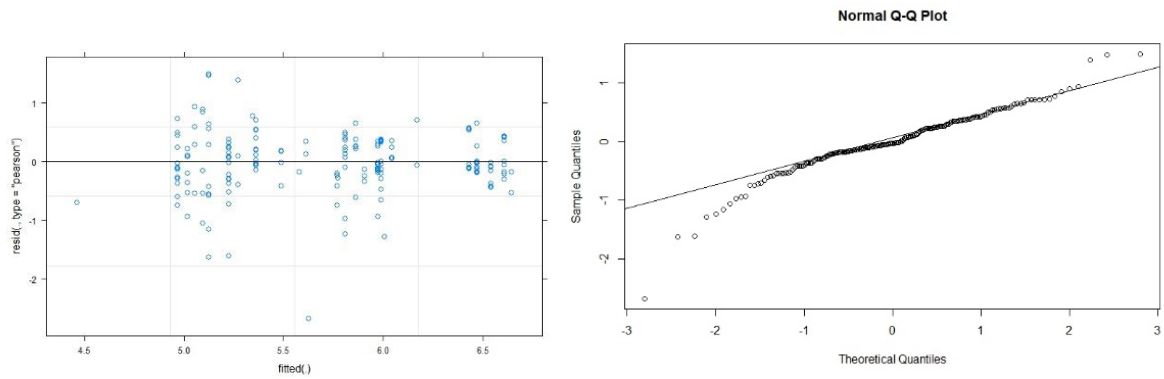


Figure 21 Residuals against fitted values; Q-Q plot of residuals to confirm normality and homoscedasticity of model residuals for the final model