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Predictive spatial modeling of wildfire occurrence and poaching events related to Siberian tiger conservation in Southwest Primorye, Russian Far East

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PREDICTIVE SPATIAL MODELING OF WILDFIRE OCCURRENCE AND POACHING EVENTS RELATED TO SIBERIAN TIGER CONSERVATION IN SOUTHWEST PRIMORYE, RUSSIAN FAR EAST

By

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Siberian tiger (*Panthera tigris altaica*) populations worldwide have been drastically reduced in number over the past several decades. The Primorye region of the Russian Far East remains one of the final strongholds for the estimated 400 Siberian tigers remaining in the wild. As a flagship species, Siberian tigers play a crucial socio-economic role in helping agencies and non-profits to motivate, fund, and implement broader conservation efforts. Even while defended by organizations such as the Wildlife Conservation Society (WCS), Siberian tigers in Primorye face an onslaught of threats to their continued existence. Profound land use changes due to the proliferation of wildfire (habitat loss), and the effects of wildlife poaching (loss of prey and individual tigers) represent the greatest threats to Siberian tigers in this region. Understanding where wildfire and poaching are most likely to occur can help inform fire management strategies, and anti-poaching ranger patrols led by WCS and the Russian National Park Service. I used a spatial statistics approach to model predictions of wildfire occurrence, and the likelihood of poaching violations across a 7,440 km^2 portion of Southwest Primorye, which includes the 2,620 km^2 Land of the Leopard National Park.

I found that wildfires are tied to the presence of humans on the landscape. Proximity to settlements and roadways were highly correlated with an increased likelihood of burning. Additionally, terrain characterized by low slopes, and drier, south aspects were also at an increased risk of burning. Predictive mapping of wildfire indicated that coastal areas in the central portion of the study area, and much of the northern extent of the study area are the most likely to experience burning. My occupancy model-based investigation of poaching violations found that proximity to human development, and topographical features both affect the probability of rangers detecting a direct or indirect poaching violation on the landscape. In particular, my findings indicate that poaching is most likely to occur outside of protected areas in lower slope valleys where people are more easily able to traverse the landscape on foot or by vehicle. The northern terminus of the study area, and a northwest central pocket of the study area both indicated relatively high (~30%) probabilities of poaching violations occurring. By modeling and spatially mapping both wildfire and poaching violation likelihood, my work can help inform WCS and Russian Park Service management strategies to help maintain intact Siberian tiger habitat, and reduce the loss of tigers as a consequence of direct and indirect poaching.

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BACKGROUND

The Primorye region in the southern reaches of the Russian Far East is one of the more densely forested regions of Russia. These lush forests support a wide variety of flora and fauna, many of which are endemic (Newell 2004). Since the late 1800s when the Russian government commenced a more vigorous effort to develop this region, there has been widespread natural resource extraction (Newell 2004). Despite the international attention from organizations such as Wildlife Conservation Society (WCS) focused on conserving biodiversity in this area, as Newell (2004) states, "little progress has been made to develop sustainable communities living within these ecosystems. This deficiency needs to be resolved if people are to be permanently dissuaded from poaching endangered species and illegally harvesting…natural resources." WCS, and their branch in Russia, focus on protecting some of the world's rarest and most unique species as a means to achieve biodiversity conservation, and promote the protection of critical wildlife habitats (WCS Russia 2017). One of the most iconic and endangered species WCS focuses on is the Siberian (or Amur) tiger (*Panthera tigris altaica*).

The Siberian tiger is one of eight traditional subspecies, three of which have gone extinct within the past 80 years (Luo *et al.* 2004). Historically, tiger populations totaled over 100,000 in number, and inhabited much of Asia; however, all remaining subspecies continue to face a variety of pressures in the form of habitat loss, fragmentation, human persecution in response to the loss of human life or livelihood, and the combined effects of direct and indirect (tiger prey) poaching (Luo *et al.* 2004, Goodrich *et al.* 2011, Nowell & Jackson 1996). As recently as the 1890s Siberian tigers numbered as many as 3,000 individuals, and ranged from eastern Mongolia to the Russian Far East, northeastern China, and the Korean Peninsula (Tian *et al.* 2011). Today, their populations extend across a far smaller geography, restricted to dwindling habitats primarily in the Russian Far East (Nowell & Jackson, 1996).

Siberian tigers are the largest, and northernmost of the remaining tiger subspecies, with males often weighing over 250kg (550lbs) (Tian *et al.* 2011, Nowell & Jackson 1996). Siberian tigers are restricted to forest-covered landscapes throughout the Russian Far East, typically Korean pine forests (Carrol & Miquelle 2006). Southwest Primorye offers a relative abundance of forested land that provide the three key habitat requirements for Siberian tiger survival; adequate prey, cover, and water (Nowell & Jackson 1996).

Tigers have long been considered flagship species due to their general popularity, cultural importance, and charismatic nature (Bowen-Jones & Entwistle 2002). Unlike keystone species which are critical components of an ecosystem's health, flagship species are known for performing a socio-economic role, and are most often used for raising public awareness and garnering funds for conservation (Walpole & Leader-Williams, 2002, Bowen-Jones & Entwistle, 2002) Given the extensive exploitation of Amur tiger habitat, furthering the protection of this subspecies can aid in the stimulation of conservation awareness and action locally in the Russian Far East and globally (Miquelle *et al.* 2005, Bowen-Jones & Entwistle 2002).

Relatively low genetic diversity, combined with increased human-tiger interactions both inside and outside protected areas levy serious threats to the already strained Siberian tiger population (Luo *et al.* 2004, Woodroffe & Ginsberg 1998). The primary pressures that Siberian tigers face in Russia's Primorye region are habitat loss and fragmentation, the reduction of key prey species, and the direct killing of tigers for traditional Chinese medicine (Miller *et al.* 2013). The loss of critical tiger prey species (mainly wild boar, red deer, and roe deer) from both legal and illegal hunting, and the actual poaching of individual tigers present the most pressing short-term threats to Siberian tigers, while the destruction of habitat (mostly as a result of fire) is a growing threat to the long-term stability of the Siberian tiger population in Russia (Miller *et al.*

2013). In the end, the success of Siberian tiger conservation hinges on reducing human effects across the landscape (Kerley *et al.* 2002).

This thesis will address two of the major pressures on Amur tiger survival: the loss of forested tiger habitat due to fire, and loss of tigers due to direct (killing of tigers) and indirect (killing of tiger prey species) poaching (Kerley *et al.* 2002). Specifically, I sought to determine if spatial statistics would allow for the predictive mapping of these two issues. Following this introductory chapter, Chapter 1 presents my work focused on predicting the spatial distribution of wildfire across the Southwest Primorye landscape. I examined how human features and activities across Southwest Primorye such as settlements, roads, and railways, and the varying terrain of the region are linked to the likelihood of wildfires occurring on the landscape. Understanding where wildfire is most likely to happen can aid WCS and the Russian Park Service in designating where limited firefighting resources should be directed. Reducing the prevalence of wildfire would play a critical role in maintaining the last remaining large tracts of high quality Siberian tiger habitat found in Southwest Primorye.

In Chapter 2 I turn my attention to an investigation centered on the direct and indirect poaching of Siberian tigers and their prey base. I examined the vast amount of ranger patrol data compiled in WCS Russia's SMART (Spatial Monitoring and Reporting Tool) program and analyzed the spatial relationships between recorded poaching events, and various geospatial covariates related to the locations at which poaching events were encountered. Understanding which variables influence the spatial distribution of poaching violations informs predictive mapping of where poaching is likely occurring. As poaching remains one of the most pressing short-term threats to the survival of Siberian tigers, increasing the effectiveness of anti-poaching patrols could go a long ways towards increasing tiger population numbers.

Fewer than 400 Siberian tigers are estimated to remain in the wild, the vast majority of them in Russia's Primorye region (Kerley *et al.* 2002). Despite the relatively small population of existing Amur tigers, WCS has good reasons to remain optimistic about their Siberian Tiger Project as, "the Amur tiger may have a greater chance of survival than other subspecies [of tiger] because it inhabits a large block of relatively unfragmented and undisturbed habitat in the Russian Far East with low human population density" (Kerley *et al.* 2002). This current state of affairs is tenuous, however, as increasing pressures on several fronts threaten to destabilize Amur tiger populations.

I completed this work as a student enrolled in the International Conservation & Development (ICD) degree option of the Resource Conservation degree program. At the core of the ICD program is the goal of providing graduate students the opportunity to engage with international conservation and social justice organizations focused on implementing real environmental change. In a serendipitous moment, my advisor Dr. Chris Servheen connected me with Dr. Dale Miquelle (WCS Russia) while I was in the middle of reading the thrilling book *The Tiger: A True Story of Vengeance and Survival*, by John Valliant. Dr. Miquelle is mentioned on several occasions throughout the book, and I was immediately hooked on the idea of being able to contribute in whatever small way possible to WCS' Siberian tiger conservation efforts. My academic and professional background provided a strong foundation for pursuing a spatial and statistical investigation related to Siberian tiger conservation. The biggest downside to this computationally heavy project was that I could conduct my work in its entirety sitting at a computer over 5,000 miles from my study site. Perhaps in the future I will set foot amongst the Korean pine forests where the last Siberian tigers still roam wild.

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CHAPTER I: SIBERIAN TIGER CONSERVATION: MODELING A PREDICTIVE LAYER OF THE LIKELIHOOD OF WILDFIRE OCCURRENCE IN SOUTHWEST PRIMORYE, RUSSIA

INTRODUCTION

The mission of the Wildlife Conservation Society (WCS) is, broadly, to "conserve the world's largest wild places…home to more than 50% of the planet's biodiversity" (www.wcs.org). WCS studies and leverages charismatic megafauna, such as great cats and elephants, to drive their global effort of protecting terrestrial and marine areas. WCS focuses on these large, iconic wildlife in order to best protect vast landscapes. In doing so, WCS helps maintain ecosystem health, and biodiversity found within these conserved areas. WCS also employs wildlife experts to study and implement strategic conservation plans for these species of concern. In the Southwest Primorye region of the Russian Far East, the WCS concentrates much of its work on defending what remains of the Siberian (Amur) tiger population. A core component of their tiger conservation effort is the protection and maintenance of high quality habitat. In Southwest Primorye, wildfires – most often ignited by humans – present one of the greatest threats to the continued long-term health of Siberian tiger populations.

Unlike many places around the world (areas of the western United States for example), the landscape in Southwest Primorye is not composed of flora and fauna that co-evolved alongside a regular fire regime. To the contrary, "primary aboriginal tribes as a whole have tried to protect their areas from fire damage" (Sheingauz 2000). The Russian Far East was largely unsettled by any outside 'modernized' civilization until the 1800s when Slavic migrants arrived who, "were not habitual to forests…were afraid of it and very often they burnt it as their enemy, seeing it as a source of wild animals that destroyed their fields and mosquitos that bit them and their cattle" (Sheingauz 2000). These migrants arrived in large part as a result of Russia's burgeoning interest in the North American fur trade (Bassin 1999). A concerted push from the central Russian government recognized the value in developing the Primorye region as a base from which fur-related commercial activities could be funneled and supported (Bassin 1999).

Well over a century has now passed since the rapid settlement of the Primorye region by Slavic peoples occurred, and the past several decades have seen a major increase in the presence of fire on the landscape. While low severity burns offer the potential for renewed understory growth, the forests of Southwest Primorye have been, for the most part, experiencing stand-replacement fires which pose an ever increasing threat to traditional Siberian tiger habitat and populations (Cushman and Wallin 2000, Loboda 2008). Mature Korean pine (*Pinus koraiensis*) forests, prime Siberian tiger habitat, have been nearly eliminated at lower elevations, and are being steadily reduced at higher elevations as well (Cushman and Wallin 2000). It is estimated, from remotely sensed satellite data that, over half of Southwest Primorye burns at least once every decade, with the outcome that today, less than 57% of the region remains forested (WCS Russia 2012).

Starting fires due to a general fear of the unknown, has since become somewhat of a "spring tradition" for residents in the Primorye area as they seek to gain more highly productive hayfields, or sometimes simply in order to burn their fields before neighbors set their fires (Sheingauz 2000, D. Matikhina*). In addition, out in the forests, a wide variety of flame sources such as campfires, and cigarettes are often responsible for fires (Sheingauz 2000). On rare occasions, poachers commit arson in order to divert the efforts of local fire and ranger brigades away from the poacher's desired hunting grounds (D. Matikhina*). Lastly, the rapid expansion of the logging road network brought with it many people with minimal knowledge of the value of forests to ecosystem function. Many of these newcomers held the belief that the Russian Far East was so vast and abundant with forests that forest fires didn't represent a significant threat to the landscape (Sheingauz 2000). In addition to fire, the hyper-proliferation of logging roads throughout Southwest Primorye is also a threat to tigers and has accelerated since the early 1990s. Timber harvest and road building have been damaging due to weakened forestry governance caused by political disorder and an ongoing economic crisis in the Russian Far East (Inoue & Isozaki 2003).

The catastrophic intensity and increasing frequency with which many fires burn results in the reversion of significant amounts of tiger habitat to early successional forests (Cushman and Wallin 2000, Cushman and Wallin 2002). These fires fragment and degrade tiger habitat. Once a mature stand of forest is burned by a high-intensity wildfire, areas dominated by Korean pine – traditionally high-quality tiger habitat – will not return to dominance for 90-100 years (Chen, Li, and Lin 2003).

In response to the burgeoning pressures of wildfire on large cat habitat in Southwest Primorye, the Wildlife Conservation Society (WCS) developed a collaborative Fire Management Program to help coordinate local and international NGOs, regional and local governments, and protected area managers to develop a “comprehensive response to seasonal ground fires” (WCS Russia 2012). My work assists in the goals of this program by providing predictions of where wildfire is most likely to occur moving forward. Understanding the spatial proliferation of fire across the region is critical to increasing our understanding of the future of wildfire in Southwest Primorsky Krai. This work can help inform wildfire management to better protect intact Siberian tiger forested habitat.

Hypotheses

This investigation focused on studying the relationship between different socio-spatial variables and wildfire prevalence in order to; 1) describe the current geographic distribution of wildfire on the landscape; 2) produce a statistical model to identify areas where wildfire is likely to occur in the future; and, 3) create a predictive layer of future wildfire likelihood (probability) for the study area.

I predicted that close proximity (short distance) from human development and travel corridor variables (settlements, roadways, rivers, railways) would increase the likelihood of wildfire occurring, and that areas with steep slopes, southern aspects, and high mean climatic water deficit would also experience a higher probability of burning (Albini 1976, Abatzoglou & Williams 2016). I hypothesized that with increasing percent protected there would be a decrease in the likelihood of fire. Lastly, I predicted that as elevations increased further from coastal regions the likelihood of fire would decrease due to increased precipitation, and insulation from human development (Mermoz *et al*. 2005).

Study Area

My investigation focused on the Southwest portion of Primorsky Krai (Primorye) in the Russian Far East. This region is defined geographically by the Pacific Coast for much of the eastern border, following the Razdolnaya River north to the border with China. The border with China defines almost the entirety of the western and southern boundaries of the study area, with the exception of an approximately 11 mile border shared between Russia and North Korea (Figure 1). My study area stretches from approximately 42 ^{o} to 45^{o} north latitude, and between 130^{o} to 132^{o} longitude. Vladivostok, the largest city in the region is just outside the study area and overlooks Golden Horn Bay at the eastern terminus of the Trans-Siberian Railway. The local economy has a rich history of resource extraction (timber, metals, and coal) which has continued through the modern era primarily in the form of food production, fish processing, and logging (Lieberman & Nellis 1995). Southwest Primorye is sparsely populated, with the majority of citizens residing in a few of the larger settlements such as Slavyanka, Barabash, and Andreyevka (Goodrich *et al.* 2010).

The forests of Southwest Primorye consists predominantly of Korean pine (*Pinus koraiensis*) at higher elevations, and a wide variety of deciduous trees such as oak (*Quercus mongolica*) at lower elevations (Goodrich *et* al. 2010, Newell 2004). The Sea of Japan to the east moderates the local climate, which is known for dry, cold winters, and hot, wet summers (Goodrich *et* al. 2010). The Primorye region is home to the most sizeable intact tract of Siberian tiger habitat in Russia (Miquelle *et al.* 2015). The majority of prime Siberian tiger habitat in Southwest Primorye lies within the recently established Land of the Leopard National Park, a 262,000 hectare mosaic of protected and unprotected land that constitutes almost 50% of the Southwest Primorye study area.

METHODS AND PROCEDURES

Data Acquisition

Geospatial datasets such as settlements, roadways, rivers, and railroads were provided by the WCS Russia office for use in this investigation. Annual data of area burned by wildfire was also provided by the WCS Russia office across a 21 year period of time spanning from 1996-2016 with the exception of 1999 and 2000 (Figure 2). This data was generated by manual digitization of burned areas using satellite imagery. Digital elevation models (DEM) for the study area were downloaded at 1-arc second (~30m) resolution from the USGS EarthExplorer portal (http://earthexplorer.usgs.gov). This data was collected by NASA's Shuttle Radar Topography Mission (SRTM) which was flown aboard the space shuttle *Endeavour* over an 11 day period in February, 2000 (https://lta.cr.usgs.gov/SRTM1Arc). These DEMs were used to generate slope, elevation, and aspect datasets. Annual climate water deficit data was procured for the same 21 year study period – excluding 1999 and 2000 – from TerraClimate, a product of the Climatology Lab at the University of Idaho (Abatzoglou *et al.* 2018).

Analysis Design

The analysis focused on the spatial relationships between fire prevalence, and various human and natural features on the landscape (roads, railways, elevation, slope, etc.) that potentially influence the presence or absence of wildfire. I adopted a resource selection function approach to draw inferences about the likelihood of wildland fire on the landscape. The study area within Southwest Primorye outlined above was divided into a grid with cells 1-km^2 in area. A cell size of 1-km^2 was chosen as it attained a balance between a large enough area for efficient spatial data processing, and small enough to incorporate the predictive layer into a fire management strategy context. I hypothesized that a host of 9 biophysical (land cover, slope, elevation, etc.) and human (distance to road, distance to settlement, etc.) spatial covariates would best predict the presence of wildfire on the landscape (Table 1). Each grid cell was given either a value of 1 (presence) if any portion of it had burned at least once over the 21 year study period or a value of 0 (absence) if no portion of the cell had burned at all (Figure 2). In addition, each grid cell was given the mean values for each of the 9 specified covariates.

For this investigation, I assumed perfect detection wherever wildfire was recorded as having burned. I used a generalized linear model with a logit link to model the presence/absence of wildfire based on the mean grid values. I then projected my predictive model across the entire study area where the probability of a fire occurring (B) is given by the equation

$$B = \frac{\exp(\beta + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p)}{1 + \exp(\beta + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p)} \qquad \text{(Manly } et\ al. \text{ 2002)}$$

All data curation and necessary generation was completed using ArcGIS 10.4.1. All statistical analysis was conducted using the statistical environment R (R Core Team 2017).

Model Selection & Covariate Development

All covariates were extracted at the sampling unit level. For each 1-km^2 covariate values were determined as the mean of all pixel values within that grid cell. Exceptions were all covariates related to distance between human development objects and grid cells. Distances were computed from the centroid of each cell to the nearest object of concern. In such cases where a sampling cell overlaid a human development object, a value of 0 was given. I determined correlation values between all initial covariates, and where necessary removed covariates so that all remaining variables had correlation values below ±0.5. I defined a global logistic regression model with all remaining non-correlated covariates, and used the *dredge* function from R package MuMIn to perform an automated model selection which outputs all possible combinations of model variables (Barton 2018, Burnham & Anderson 2010). Using the final selected model from the *dredge* function ($\Delta AIC < 2$), I computed fitted values for each cell, and then generated a map of predicted wildfire probability across the study area in ArcMap 10.4.1.

Model Validation

I performed a model assessment test on the top-ranked model discussed above. I withheld a random 20% subset (n = 1,604) of the overall dataset for testing, and trained the model based on the remaining 80% (n = 6,418). For each grid cell in the test dataset, a value of 0 for unburned or 1 for burned was predicted based off the results of the trained model. I determined a cell to have burned if the predicted probability was greater than the overall mean number of cells burned (0.506). Lastly, I compared predicted burn presence to actual burn presence in the test dataset to determine model accuracy.

RESULTS

Model Selection

I dropped both covariates elevation and distance to nearest railway from potential inclusion in the final model due to correlation values > ±0.5. The top-ranked model for probability of burning (weight =1) from the dredge results included all of the remaining 7 covariates (Table 2). The most influential predictors of wildland fire were slope, mean climatic water deficit, and percent of the grid cell protected (Table 3). With the two exceptions of the effect of increasing slope, and increasing distance from nearest river on the likelihood of wildfire occurring, model results supported my theoretical hypotheses (Table 1). My model predicts that wildfires are more likely to occur on lower angled slopes and southern aspects with higher annual climate water deficit (Table 3). In addition, fires are more likely to burn in proximity to human development and infrastructure such as roads and settlements (Table 3). Model validation resulted in an 81.3% accuracy assessment of withheld data.

Predictive Model Layer Mapping

My top-ranked model suggests that wildfire is most likely to burn along eastern coastal areas, the northern portion of the study region, and much of the southern tip of Southwest Primorye (Figure 3). There is a lower estimated probability of wildland fire occurrence in central, and western portions of the study area (Figure 3).

DISCUSSION

My results demonstrate that the distribution of wildfire throughout Southwest Primorye can be tied to both human development on the landscape, as well as biophysical features of the local terrain. As I hypothesized, areas in close proximity to towns and roadways are much more likely to experience fires (Table 3, Figures 3). As discussed earlier, fires in Southwest Primorye are most often caused directly by humans either intentionally (springtime burns, field clearing, poaching distractions, etc.) or unintentionally (discarded cigarettes, neglected campfires, etc.); therefore, it comes as no surprise that the covariates distance to nearest town and distance to nearest road are negatively related – further away, less vulnerable – to probability of burning (Sheingauz 2000).

My model indicates that there are biophysical conditions that are more likely to facilitate a wildfire burning than the human factors. Contrary to my original hypothesis, areas of high slope are less likely to burn (Table 3). The strong effect of terrain features relative to human features may be the result of most settlements and roads existing in low-lying, coastal regions where slopes are on average less steep than the interior. So, steeper slopes simply exist further from ignition sources than gradual slopes, which contributes to the negative relationship between slope and likelihood of burning. The results support my hypothesis that mean climatic water deficit (mm H_2O) positively influences the likelihood of fire occurrence. Considering that increasing climatic water deficit indicates increasing aridity, it makes sense that drier areas where there is a greater difference between potential and actual evapotranspiration are more susceptible to burning (Abatzoglou & Williams 2016). The positive influence of southern aspects on increasing aridity is widely known, and my model supports this understanding as drier, southerly facing terrain features are more likely to burn than steep, shaded northern slopes (Dobrowski 2011). The relationship between distance to nearest river and probability of burning is a less obvious conclusion. The high density, and universal distribution of rivers makes it difficult to establish why as distance from nearest river increases, the probability of burning increases. I had hypothesized the opposite effect as I had thought that waterways would be used in a similar fashion as roadways for transportation and the movement of peoples in general which would bring with it an increase in potential ignition sources. The positive relationship may be due to the vegetative landscape being less fire prone adjacent to waterways than in more arid, higher areas.

Although hypothesized correctly, the effect of protected land on the likelihood of fire is particularly interesting. While thoroughly dissected by roads, most of the protected lands across the region lie among the furthest reaches from human settlements (Figure 1). Logically, roadways nearest to settlements should experience greater traveler rates (potential fire ignition sources) than those further from settlements. While distance from human fire sources is partly responsible for the negative relationship between percent protected land and likelihood of burning, the on the ground efforts of Russian firefighters could also be linked to the low probability of fires taking off in protected lands (WCS Russia 2012). This finding aligns with the results from WCS Russia’s on-the-ground efforts to curb wildfire in Siberian tiger habitat, which have had a demonstrably positive effect (WCS Russia 2012). However, the results of my model suggest that large portions of protected land in the north, and central portions of Southwest Primorye remain at high-risk to wildfires, and it is recommended that WCS Russia rekindles their Fire Management Program in these regions in order to minimize the loss of tiger habitat and safeguard the future for a healthy Siberian tiger population (Figure 3).

LIMITATIONS & FUTURE RESEARCH

In this particular region of the world, geospatial data availability limitations make it difficult to develop robust models. Future efforts could focus on generating better quality datasets such as higher-resolution land cover data across the entire study area, and for multiple year chronological sequences. By including land cover data future models could better take into account the varying frequencies and intensities of wildfire across Southwest Primorye’s diverse topography. As an example, low vegetation or grasslands are more likely to burn faster and more frequently, and as a result forested tiger habitat on the periphery of such grasslands would be in greater danger of burning than areas deep in the forest core.

Another limitation of my investigation was my assumption of perfect detection of wildfire. Any cell that intersected with the fire boundaries provided by WCS was considered as having burned over the 20 year study period. The hand-digitized fire boundaries could contain errors where technicians either failed to delineate areas that had burned, or had included areas that had not actually burned. Future research could turn to further investigating the quality, and precision of the fire data. Modeling techniques – such as occupancy modeling – could be used to take into account the imperfect fire data generation process.

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*D. Matikhina is a local resident of Southwest Primorye, employee of the Russian National Park Service, and a past graduate exchange student at the University of Montana. Reference was used with permission.

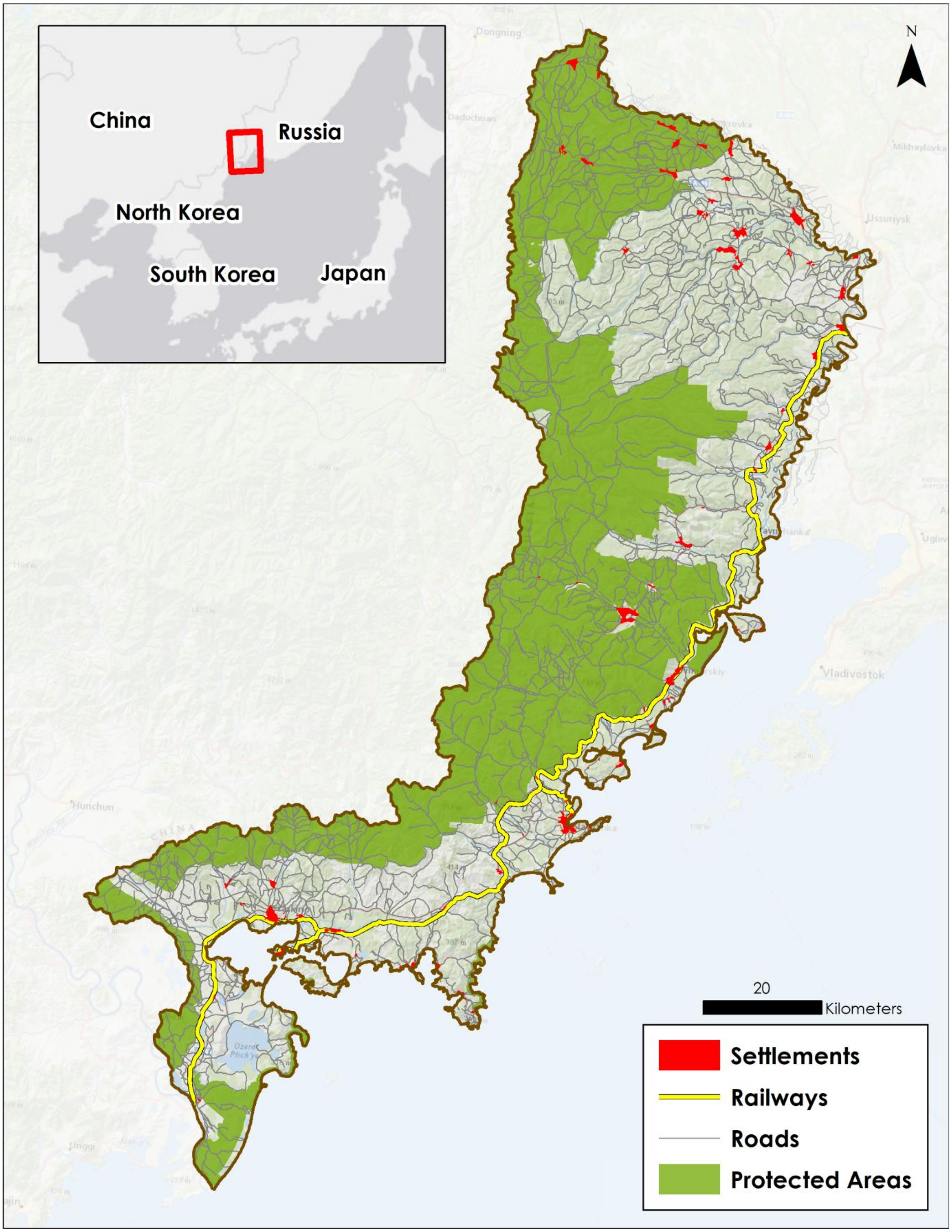

Figure 1. Map of project extent and notable model covariates, Southwest Primorye, Russian Far East.

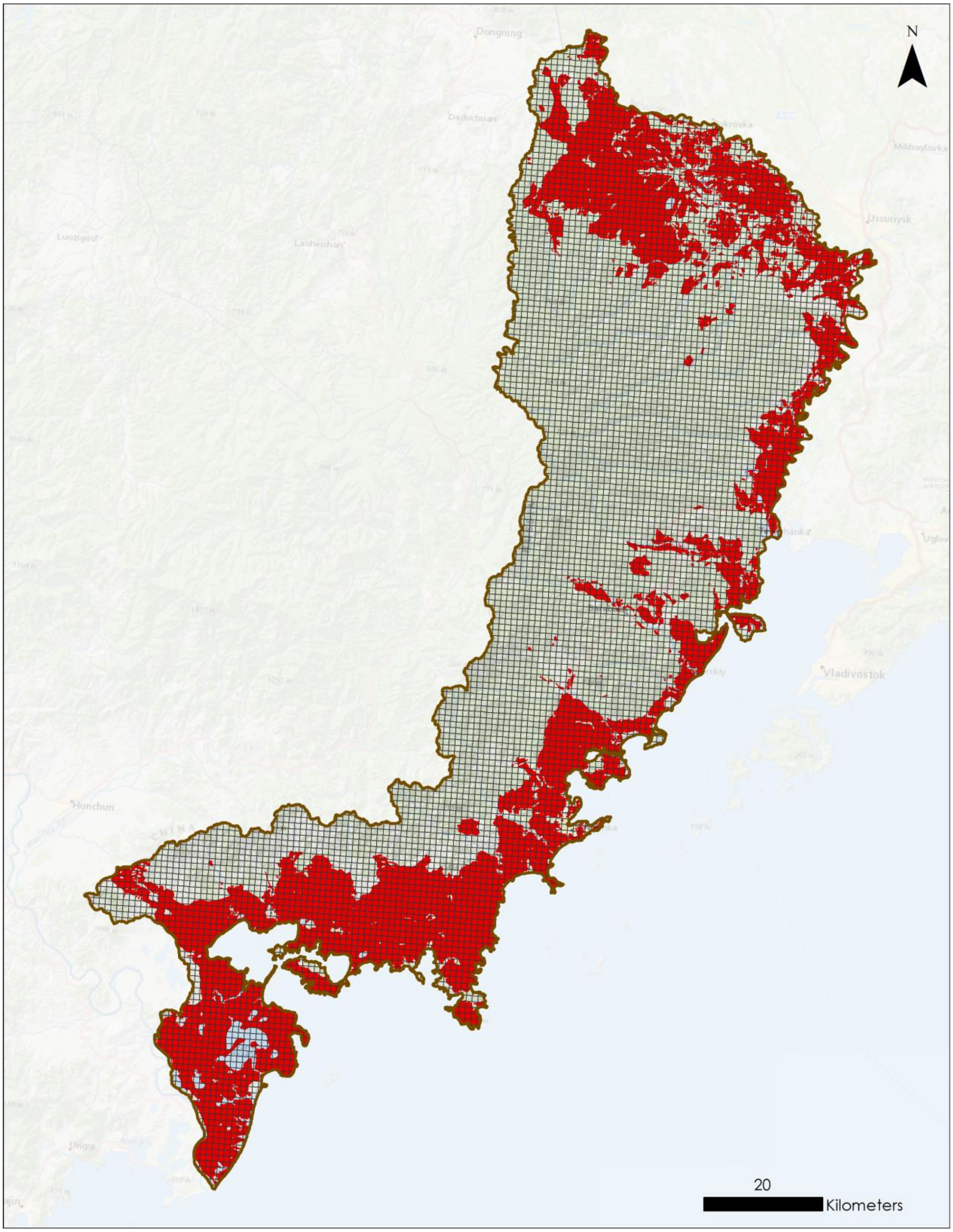

Figure 2. Map of all areas burned over the 21 year study period (red), and the grid cells used for the resource selection function analysis unit.

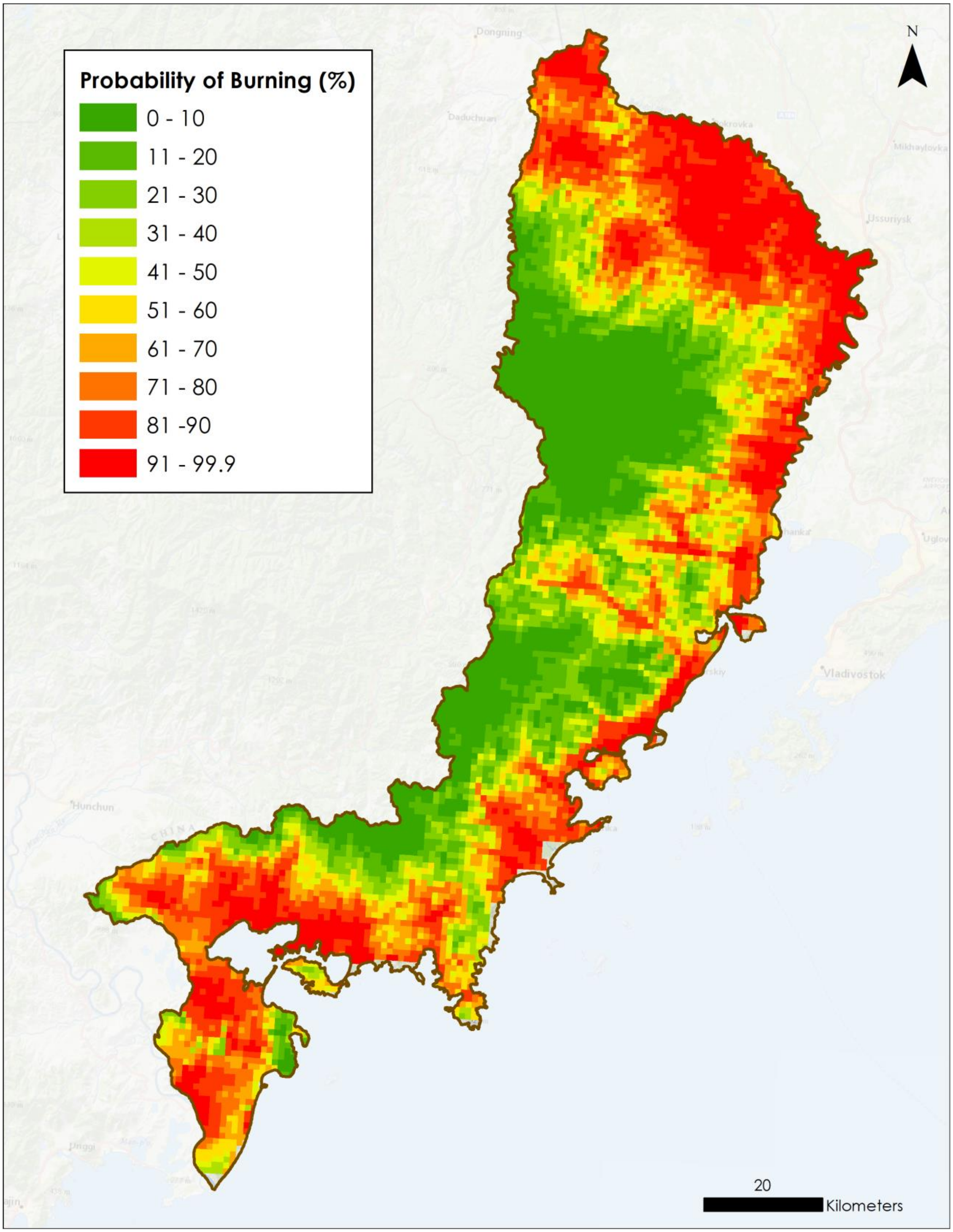

Figure 3. Map of predicted likelihood of wildfire occurrence across Southwest Primorye, Russian Far East.

Table 1. List of all covariates to be incorporated in model selection process for predicting likelihood of wildfire presence throughout Southwest Primorsky Krai.

Covariate	Data Source	Hypothesized Effect	Published evidence of the effect
Slope (Slp)	USGS – EarthExplorer	+	Albini, 1976
Aspect (Asp)	USGS – EarthExplorer	+	Oliveras et al., 2009
Elevation (Elev)	USGS – EarthExplorer	-	Mermoz et al., 2005
Dist. Nearest Town (Town)	WCS Russia/Conor Phelan	-	Loboda, 2008, Sheingauz, 2000
Dist. Nearest Rail (Rail)	WCS Russia/Conor Phelan	-	Loboda, 2008, Sheingauz, 2000
Dist. Nearest Road (Road)	WCS Russia/Conor Phelan	-	Loboda, 2008, Sheingauz, 2000
Dist. Nearest River (River)	WCS Russia/Conor Phelan	-	Loboda, 2008, Sheingauz, 2000
Percent Protected Land (Prot)	Russian National Park Service	-	Sheingauz, 2000
Annual Climate Water Deficit (Def)	Climatology Lab – TerraClimate	+	Abatzoglou & Williams, 2016

Table 2. Top five models outputted from MuMIn dredge function, and ranked by AIC. Top model, with weight =1, contains all 7 covariates. No model averaging was necessary.

Top Models	**AIC**	**ΔAIC**	**AIC weight**	**Number of Parameters**
logit(*B*)= Slp+Asp+Town+Road+River+Prot+Def	6677.8	0.00	1	7
logit(*B*)= Slp+Town+Road+River+Prot+Def	6699.0	21.11	0	6
logit(*B*)= Slp+Asp+Town+River+Prot+Def	6716.3	38.50	0	6
logit(*B*)= Slp+Town+River+Prot+Def	6738.2	60.34	0	5
logit(*B*)= Slp+Asp+Town+Road+River+Prot	6742.3	64.44	0	6

Table 3. Model coefficients for top-ranked model outputted from multi-model inference analysis. Estimates were back-transformed from logit scale to be presented in probabilities. Parameters with estimates >0.5 have a positive relationship with occurrence of wildfire.

Covariate	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.7989351	2.008e-01	6.870	6.44e-12
Slp	0.4511601	8.401e-03	-23.328	<2e-16
Asp	0.5007948	6.626e-04	4.798	1.60e-06
Town	0.4999367	8.235e-06	-30.722	<2e-16
Road	0.4998518	9.560e-05	-6.202	5.57e-10
River	0.5002389	1.278e-04	7.479	7.46e-14
Prot	0.4984389	6.607e-04	-9.452	<2e-16
Def	0.5033174	1.658e-03	8.002	1.23e-15

CHAPTER II: SIBERIAN TIGER CONSERVATION: ANALYSIS OF RANGER PATROL DATA TO INFER SPATIAL PATTERNS OF POACHING-RELATED VIOLATIONS ACROSS SOUTHWEST PRIMORYE, RUSSIA

INTRODUCTION

The mission of the Wildlife Conservation Society (WCS) is, broadly, to "conserve the world's largest wild places…home to more than 50% of the planet's biodiversity" (www.wcs.org). WCS studies and leverages charismatic megafauna, such as great cats and elephants, to drive their global effort of protecting terrestrial and marine areas. WCS focuses on these large, iconic wildlife in order to best protect vast landscapes. In doing so, WCS helps maintain ecosystem health, and biodiversity found within these conserved areas. WCS also employs wildlife experts to study and implement strategic conservation plans for these species of concern. In the Southwest Primorye region of the Russian Far East, the WCS concentrates much of its work on defending what remains of the Siberian (Amur) tiger population. Core components of their tiger conservation effort are to monitor threats to tigers, and reduce human-tiger conflict. Direct (killing of tigers) and indirect (killing of tigers' prey) poaching is the most pressing short-term threat Siberian tigers face across their range.

In a prey-depleted environment such as Southwest Primorye a relatively small, and seemingly benign increase in tiger poaching can trigger extinction (Damania *et al.* 2003). The immediacy of the poaching issue, and the socioeconomic factors that add complexity to the issue make poaching a daunting and difficult task for those involved in tiger conservation. Adding to research difficulties, despite a fenced boundary between Russia and China, Siberian tigers in Russia have been found to make use of habitat across the border in the Changbaishan Mountains (Miquelle *et al.* 2015).

WCS and the Russian Park Service face a spectrum of both long-term and short-term threats to the remaining Siberian tiger populations. The proliferation of fires throughout the

Russian Far East, especially over the past few decades, has consistently been one of the leading long-term issues confronting the WCS Siberian Tiger Project. The flora and fauna of Southwest Primorye did not co-evolve alongside a wildfire regime, so recent fires lit by humans devastate the landscape and effectively eliminate high quality forested tiger habitat wherever they burn (Loboda 2008). On the other hand, poaching, driven largely by the demand for tiger parts in traditional Asian medicines, remains the most persistent short-term threat to tigers (Chapron *et al.* 2008). Wildlife poaching in the Russian Far East is highly detrimental to tiger populations as it reduces tiger population numbers on two fronts. The direct poaching of tigers for the chance to sell the bones and skin on the international black market for quick financial gain is clearly, and measurably detrimental to Amur tiger populations. Robinson *et al.* (2015) found poaching (and suspected poaching) to be the primary causes of Amur tiger mortality, leading to an estimated 10% annual loss of population, making it difficult for the current tiger population to grow any larger than the 400 or so remaining individuals (Matyushkin 1996). Less quantifiable, but no less detrimental to the Siberian tiger population, is the impact of poaching of tiger prey species. Chapron *et al.* (2008) stated that despite the large swaths of existing suitable habitat, tigers are absent or at exceedingly low numbers, most likely due to a lack of prey.

Efforts to curb tiger poaching remain a top priority for tiger conservation; however, the social and economic realities of tiger poaching in the Russian Far East make this a daunting task. Where other tiger subspecies exist in countries such as India, it is understood that there is, “a level of organization and confidence among trafficking networks…[to move] large consignments of skins to satisfy a growing market” (Banks & Newman 2004). In the Russian Far East the complex and rapid changes that swept the region over the past few decades have led to more unique politically and economically founded reasons for the sudden increase in Amur tiger poaching. For the majority of the twentieth century the border between the Soviet Union and China was closed and well-manned so that access to the Asian black-market demand for tiger products was virtually impossible (Miquelle *et al.* 2005).

The collapse of the Soviet Union in 1991 set off a turbulent period of time in the Russian Far East as the dominant communist economic ideology gave way to a market economy after a few years of transition (Åslund 2009). The advent of capitalism throughout the region saw an immediate easing on border restrictions and gun laws, making it much easier to smuggle wildlife products into China (Miquelle *et al.* 2005). Local residents in the Primorye region had always relied on their surrounding natural resources to provide a subsistence lifestyle, but the sudden arrival of capitalism brought with it the privatization of many of the lands upon which locals had depended (Miquelle *et al.* 2005). Now, as the Soviet domain crumbled, villagers were suddenly forced to earn some form of income in a defunct economy suffering from massive inflation (Miquelle *et al.* 2005). The Siberian tiger population has continued to suffer as a result of this economic upheaval as tigers became a highly profitable resource almost overnight (Miquelle *et al.* 2005).

One of the reasons that Amur tiger poachers have been an elusive target for WCS and government rangers is that tigers are rarely the target of a focused poaching effort, with most poached tigers falling victim to an opportunistic shot (Miquelle *et al.* 2005). Additionally, tigers can fall victim to being caught in snares set to illegally hunt other animals (Goodrich *et al.* 2011, Goodrich 2010). Unlike their counterparts in India deliberately heading into the forest to hunt tigers, hunters in the Primorye region are most often seeking to poach a deer or boar for immediate consumption to fulfill their subsistence needs. Provided the right circumstances some of these individuals may choose to cross the threshold to become a tiger poacher. Coming across a tiger, or its tracks, in the forest presents the hunter with, “not only the prospect of commercial gain, but a complex mixture of emotions” (Miquelle *et al.* 2005). At this point, the hunter takes into account several different considerations including: perceived ability to kill the tiger; likelihood of being caught; current economic circumstances; personal values held regarding Amur tigers; and the prospect of finding a buyer (D. Miquelle[†], personal communication, April 18, 2017).

Without such a clear-cut enemy to face in the field, WCS has focused its anti-poaching efforts on using modern law enforcement tactics such as the spatial monitoring and reporting tool (SMART) approach (WCS Russia 2017). At the core of the SMART program is a special software package built specifically for organizations combatting poaching, and is in use at more than 600 conservation sites in 55 countries worldwide (WCS Russia 2017, SMART Annual Report 2017). The SMART program was developed through a global partnership of nine conservation organizations, three governance councils, and eleven task forces. The software takes geospatial and categorical data inputs from ranger patrol efforts to continuously compare the results of patrols over time (WCS Russia 2017). As part of the project, greater communication is cultivated between staff from WCS, park inspectors, and government managers to constantly reassess patrol effectiveness, and to determine priority areas for future ranger efforts (WCS Russia 2017). By applying the SMART program, WCS hopes to provide the local ranger teams with a more rigorous and data-driven decision-making process regarding where, when, and how to patrol. My work leveraged the power of this accumulated geospatial data to generate poaching predictions across the study area.

Hypotheses

I investigated the relationship between different socio-spatial variables and ranger-recorded violations in order to; 1) identify general patterns of poaching, and the geography of these patterns, at present; 2) identify variables on the landscape that influence where poaching is likely to occur in the future; and, 3) create a predictive layer of these patterns to help inform future ranger patrol efforts.

As opposed to a random distribution of poaching violations across the study area, I hypothesized that cells closer in proximity to human infrastructure (settlements) and travel corridors (roads, rivers, and railways) would be more likely to contain poaching violations as people present the greatest source of fire ignitions (Table 1). Similarly, I predicted that terrain features more difficult to traverse by vehicle or on foot (steep slopes, high elevations) would have a lower probability of poaching presences (Table 1). Lastly, I anticipated that poachers would be most likely found in unburned, forested habitats found on wetter more northerly aspects as such environments provide better habitat for their quarry (Cushman and Wallin 2000, Table 1).

Study Area

My investigation focused on the Southwest portion of Primorsky Krai (Primorye) in the Russian Far East. This region is defined geographically by the Pacific Coast for much of the eastern border, following the Razdolnaya River north to the border with China. The border with China defines almost the entirety of the western and southern boundaries of the study area, with the exception of an approximately 11 mile border shared between Russia and North Korea (Figure 1). My study area stretches from approximately 42^{o} to 45^{o} north latitude, and between 130^{o} to 132^{o} longitude. Vladivostok, the largest city in the region is just outside the study area and overlooks Golden Horn Bay at the eastern terminus of the Trans-Siberian Railway. The local economy has a rich history of resource extraction (timber, metals, and coal) which has continued through the modern era primarily in the form of food production, fish processing, and logging (Lieberman & Nellis 1995). Southwest Primorye is sparsely populated, with the majority of citizens residing in a few of the larger settlements such as Slavyanka, Barabash, and Andreyevka (Goodrich *et al.* 2010).

The forests of Southwest Primorye consists predominantly of Korean pine (*Pinus koraiensis*) at higher elevations, and a wide variety of deciduous trees such as oak (*Quercus mongolica*) at lower elevations (Goodrich *et* al. 2010, Newell 2004). The Sea of Japan to the east moderates the local climate, which is known for dry, cold winters, and hot, wet summers (Goodrich *et* al. 2010). The Primorye region is home to the most sizeable intact tract of Siberian tiger habitat in Russia (Miquelle *et al.* 2015). The majority of prime Siberian tiger habitat in Southwest Primorye lies within the recently established Land of the Leopard National Park, a 262,000 hectare mosaic of protected and unprotected land that constitutes almost 50% of the Southwest Primorye study area.

METHODS & PROCEDURES

Data Acquisition

Geospatial datasets such as settlements, roadways, rivers, and railroads were provided by the WCS Russia office for use in this investigation. Digital elevation models (DEM) for the study area were downloaded at 1-arc second (~30m) resolution from the USGS EarthExplorer portal (http://earthexplorer.usgs.gov). This data was collected by NASA's Shuttle Radar Topography Mission (SRTM) which was flown aboard the space shuttle *Endeavour* over an 11 day period in February, 2000. I used these DEMs to generate slope, elevation, and aspect datasets. Annual climate water deficit data was procured for the same 21 year study period from TerraClimate, a product of the Climatology Lab (Abatzoglou *et al.* 2018).

I was permitted access to the Russian Park Service's SMART database. The SMART software is an open source, non-proprietary program that is used by the Russian Park Service to facilitate the storing and curation of GPS data collected by rangers. Rangers in Southwest Primorye use handheld GPS units to collect geospatial data on their patrol locations, times, and activities. Patrollers also use SMART to record all locations of direct or indirect poaching events.

Analysis Design

My investigation focused on the spatial relationships between poaching and poaching related events, and a variety of human and biophysical features on the landscape that potentially influence the distribution and likelihood of poaching activities on the ground. I used an occupancy modelling approach, borrowed from wildlife biology and ecology fields where it was developed, and is most frequently used to draw inferences about species' population numbers and distribution across an area (MacKenzie *et al.* 2006, Hines *et al.* 2011, Long *et al.* 2011).

The field of occupancy modeling leverages the power of modern computing to estimate the likelihood of a species occupying a specific spatial locale as opposed to attempts at summarizing general species abundance across the landscape (MacKenzie *et al.* 2006). Biologists and ecologists employ a number of different monitoring approaches – from remote cameras to hair snares – in order to determine species presence or absence/pseudo-absence at a given point or within a given area (Long *et al*. 2011).

Instead of using occupancy modeling to estimate a particular species presence, I applied occupancy modeling to GPS data collected by ranger patrols over a 49 month period from January 2012 to January 2016. This GPS data was curated and accessed from the SMART database maintained by the Russian Park Service and WCS Russia. Similar work has been done in areas such as Nyungwe National Park in Rwanda where Moore *et al.* (2017) developed occupancy models with the objective of increasing ranger efficiency with the potential to reduce threats in a more cost-effective and logistically feasible manner.

I divided the study area within Southwest Primorye outlined above into a grid of cells 1-km^2 in area. I chose a cell size of 1-km^2 as it attained a balance between large enough area for efficient spatial data processing, yet small enough to provide rangers with practical areas to patrol and assess for poaching. I used a host of 11 biophysical (land cover, slope, elevation, etc.) and human (distance to road, distance to settlement, etc.) spatial covariates that I hypothesized would best predict the distribution of poaching events across the landscape (Table 1).

My occupancy modelling relied upon three linked datasets in order to properly estimate which geospatial covariates influence poaching violation distribution (MacKenzie *et al*. 2006). I adapted my occupancy model to address spatial replication as the data had a high number of spatially indexed counts with a scarcity detected poaching violations. These indicates a large number of absences or zeros, and a small number of presences or ones. These datasets are site-specific covariates (spatial variability), likelihood of detecting the event of interest (detection), and the recorded presence or pseudo-absence of the event of interest (occupancy) (MacKenzie *et al.* 2006). For my investigation, occupancy was the presence of a single or multiple poaching violation(s) for a given time series of patrol visits. Detection was determined by the extent to which each grid cell was visited by a ranger patrol. The spatial covariates inform the model as to which site specific variables influenced the presence or pseudo-absence of poaching violations. I composed a spatial variability dataset using the mean values with each 1-km^2 cell for the 10 region wide covariates (Table 1). I accounted for variation in the probability of detection by calculating the number of times per month that ranger patrols visited any given cell. Detection is described by the following equation wherein p is the detection probability (probability that a poaching violation *N* appears in the count statistic C of times visited).

$$\hat{p} = \frac{C}{\hat{N}} \quad \text{(MacKenzie } et\ al. \text{ 2006)}$$

To quantify the amount of time ranger patrols spent in any give cell (detection), I divvyed up all ranger patrol routes into 250m segments. For each cell, by month, I summed the number of 250m segments. I calculated occupancy for each grid cell based on whether or not the cell contained a poaching violation during each of the 49 months studied. My analysis sought to predict occupancy as the probability that a randomly selected site or sampling unit (grid cell) within the study area had the presence of a poaching violation. Occupancy (ψ) is described by the following equation wherein *x* is the number of occupied sites, and *s* is the number of total sites.

$$\hat{\psi} = \frac{\hat{x}}{s} \quad \text{(MacKenzie } et\ al. \text{ 2006)}$$

I completed all data curation and final predictive mapping using ArcGIS 10.4.1. I conducted all statistical analysis using the package Unmarked in the statistical environment R (Fiske & Chandler, 2011, R Core Team, 2017).

Model Selection & Covariate Development

All covariates were extracted at the sampling unit level. So, for each 1-km^2 covariate values were determined as the mean of all pixel values within that grid cell. Exceptions were all covariates related to distance between human development objects and grid cells. Distances were computed from the centroid of each cell to the nearest object of concern. In such cases where a sampling cell overlaid a human development object, a value of 0 was given. I determined correlation values between all initial covariates, and where necessary removed covariates so that all remaining variables had correlation values below ±0.5. I compiled an unmarked framework from the three datasets (spatial variability, detection, and occupancy) to link data values from each respective dataset to the same cell. I tested for a relationship between visitation (detection) and occupancy. I defined a global occupancy model with all remaining non-correlated covariates, and used the *dredge* function from R package MuMIn to perform an automated model selection which outputs all possible combinations of model variables (Barton 2018, Burnham & Anderson 2010). I averaged all models with the lowest AIC values within a ΔAIC < 2 of each other (Burnham & Anderson 2010). Using the final selected model, I computed fitted values for each cell, and then generated a map of predicted wildfire probability across the study area in ArcMap 10.4.1.

RESULTS

Patrol Assessment

Over the course of the 49 month study period, Russian rangers patrolled along a total of over 356,977 km of roadways, trails, and waterways (Figure 2). The rangers recorded a total of 955 poaching and poaching related events. The majority of these encounters (n = 868) were illegal trespassing violations, considered a meaningful proxy of intent to poach[†], and the remaining events (n = 87) were either direct poaching violations or possession of an illegal firearm (Figure 2). The vast majority of poaching violations were recorded in the central portions of the Southwest Primorye region where rangers logged the most kilometers of patrolling as well (Figure 2).

Model Selection

I developed an occupancy model to predict the probability of poaching violation occupancy ($\hat{\psi}$) as a function of various biophysical and human infrastructure variables. I removed elevation, aspect, and wildfire probability from potential inclusion in the final model due to correlation values > ±0.5. The automated model selection analysis indicated eight top-ranked models for subsequent model averaging. Top-ranked models were chosen by lowest AIC values where $\Delta AIC < 2$ (Burnham & Anderson 2010). The eight models included to some extent, all 7 remaining possible covariates (Table 2).

The result of the modeling predicts that poaching, and poaching related activities, are more likely to occur gradual terrain in close proximity to human infrastructure and transportation routes (Table 3). In addition, there is a higher probability of poaching violations being found in wetter parts of the region (Table 3). Lastly, grid cells with a higher percentage of protected land are more likely to contain poaching events (Table 3).

Given the results of the averaged best model candidates, the most influential predictors of poaching occurrences are slope, and proximity to roads, rivers, and settlements, while the parameters slope and percent protected land were the most commonly applicable as they were found in all eight models used in the average (Table 2). With the single exception of the effect of protected lands on poaching likelihood, final averaged model results supported my theoretical hypotheses (Table 1).

Predictive Model Layer Mapping

My top-ranked averaged model suggests that poaching is most likely to occur throughout the central portion of the study area, and to a certain degree at the southern tip of Southwest Primorye (Figure 3). There is a very low estimated probability of poaching occurrence in the core northern and southern regions of the study area (Figure 3).

DISCUSSION

For anti-poaching applications, this is a powerful tool as it allows for meaningful assessment of entire landscapes to highlight regions or areas where poaching may be occurring undetected. The power of occupancy modelling lies in its ability to decouple relationships which would otherwise drive the outcome of a modelling exercise. In this case, being able to account for the number of time each grid cell was visited addresses the difference in detection probability between cells. It comes as no surprise that proximity to human features throughout the region is a major driver of poaching likelihood (Table 3). Individual poachers in this study area are most likely beginning their forays from their homes, or after piloting a vehicle a short distance away (Miquelle *et al.* 2005). Although predicted as such, the effect of proximity to waterways and rivers was more significant than expected (Table 3). I surmise that waterways are heavily used as movement corridors for individuals seeking to engage in poaching behaviors, and could perhaps benefit from increased patrolling. The effect of slope on poaching events was also more influential than initially expected, but aligns with my prediction. My hypothesis, supported by analysis results, assumes that individuals traversing a landscape in search of an animal to harvest are most likely to try and move as efficiently as possible to conserve energy, which would involve avoiding steep slopes unless necessary (Table 3).

Worthy of note is the positive effect of protected land status on the probability of poaching presences (Table 3). I had predicted that more stringent monitoring of protected areas would decrease the likelihood of poachers venturing into such regions; however, model results indicate that poaching is actually more likely to occur in grid cells with higher percentages of protected land (Table 3). This relationship may be the consequence of better habitat, easier to access solitude, and increased quarry numbers – all variables sought by a hunter or poacher – inside protected areas.

When compared to the location of poaching events recorded throughout the study period (Figure 2), the predictive map (Figure 3) does indicate a few areas of interest where patrollers spent little time or did not detect poaching occurrences, but my model specifies a moderate to high likelihood of poaching taking place. In the far northern portion of the study area there is a large reach where not a single patrol took place, and analysis results indicate poaching probabilities as high as 30% (Figures 2 & 3). Although well patrolled, there is a pocket of land in the northwest central region which also has probabilities in the range of 30-40% where not a single direct or indirect poaching event has been recorded (Figures 2 & 3). Finally, the southern tip of the study area contains likelihood values as high as 50%, yet has seen limited patrolling, and not a single poaching event documented (Figures 2 & 3). Integrating occupancy modelling into conservation action to curb Siberian tiger poaching has the potential to guide ranger patrol strategy development to insure that areas at potentially high risk of poaching are receiving the law enforcement attention necessary.

LIMITATIONS & FUTURE RESEARCH

In this particular region of the world, geospatial data availability limitations make it difficult to develop robust models. Future efforts could focus on generating higher quality datasets such as land use, and habitat layers that are currently lacking in either resolution or spatial coverage. Specifically, incorporating the distribution of Siberian tigers on the landscape into the anti-poaching model could enhance the model's predictive power. This research directive would first require the development of a separate occupancy model would be required in order to determine the probability of tigers' presence at any given point across the study area. This is due to the sparsity of population-level tiger locational data in Southwest Primorye.

My analysis only scratched the surface of what could be done with the SMART program database. Time and statistical expertise limitations kept my investigation relatively simple, but future work could focus on teasing apart how different patrol types (foot versus vehicle versus boat), different patrol teams (who and how many), and different temporal factors (time of day, seasons, etc.) factor into the efficacy of anti-poaching efforts. The SMART software itself could also be enhanced moving forward to ingrain predictive modeling into the workflow. With modern advances in spatial statistics and machine learning algorithms, predictive models could be continually augmented with the addition of every piece of patrol and violation data to constantly improve the model's effectiveness .

Further developments in this regard were also limited by my cursory knowledge of the inner workings of the SMART software, and my lack of familiarity with the Russian language. I remain optimistic that despite these obstacles, I was able to develop a predictive anti-poaching model. I have demonstrated that conservation organizations and government agencies could apply this approach and methodology to other areas around the globe where ranger patrols routinely collect data on their efforts.

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[†]D. Miquelle is an American wildlife biologist and employee of the Wildlife Conservation Society who has been living 10 months each year in the Primorye region of the Russian Far East for the past ~25 years. Reference was used with permission.

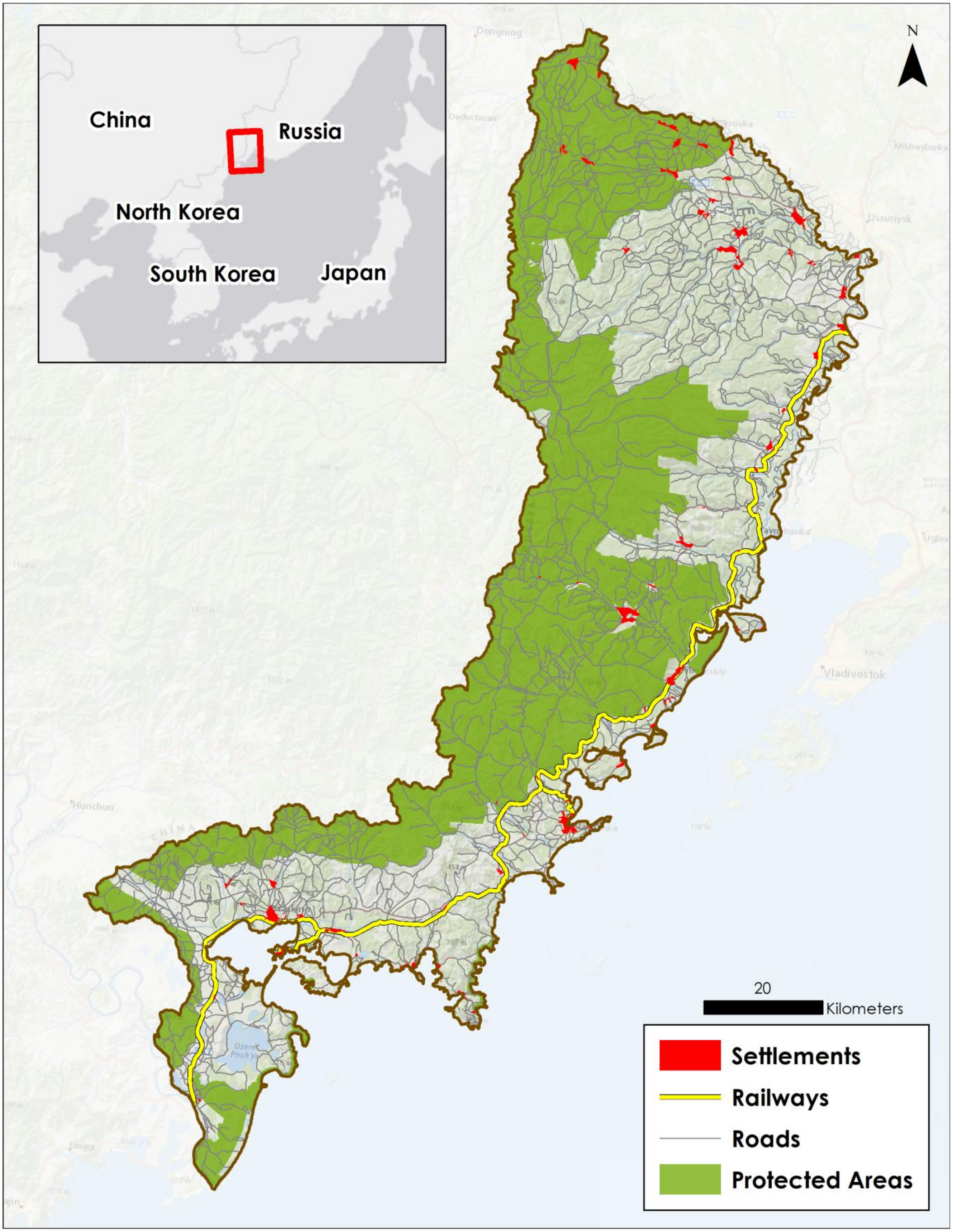

Figure 1. Map of project extent and notable model covariates, Southwest Primorye, Russian Far East.

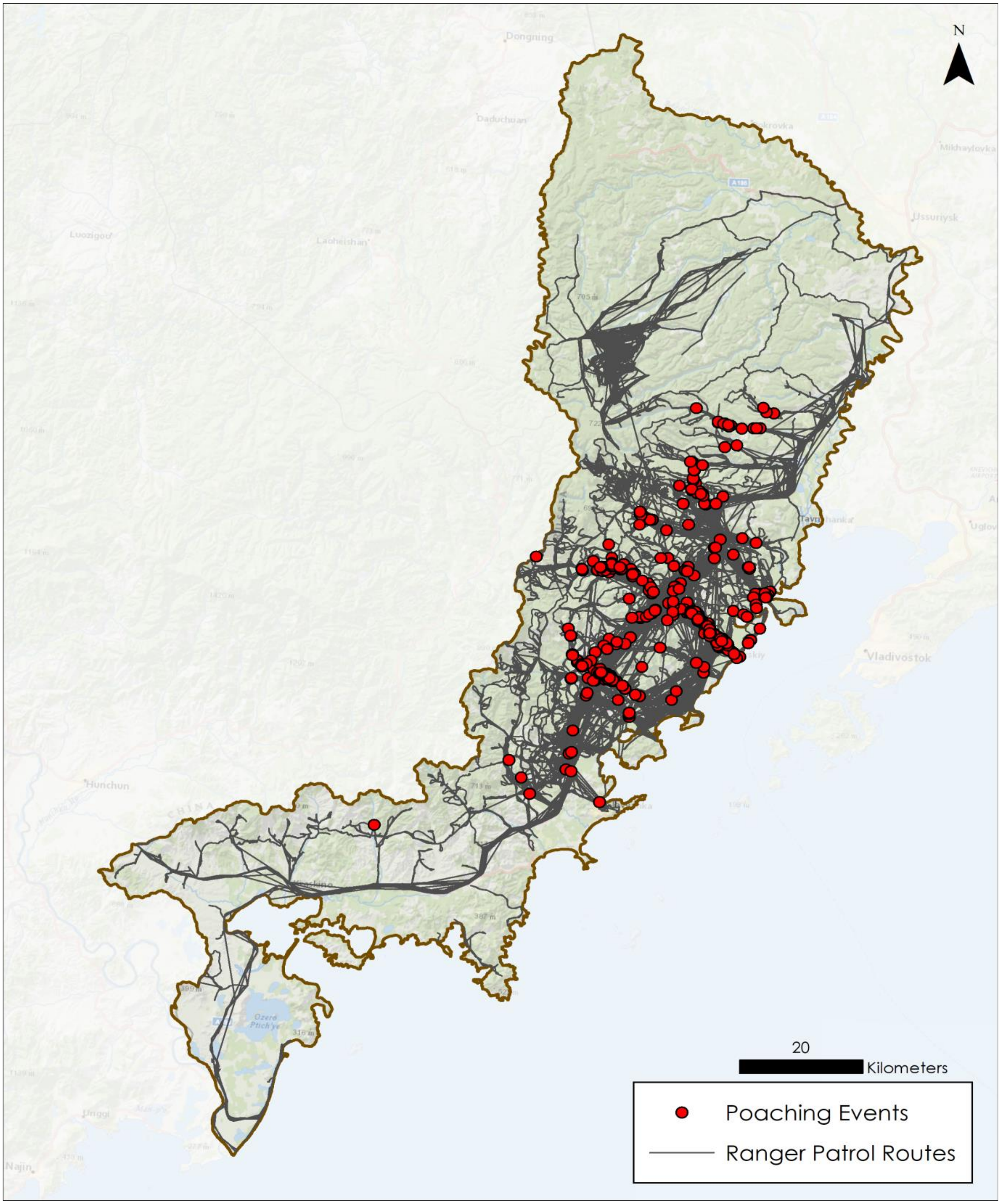

Figure 2. Map of all GPS recorded routes patrolled over the course of the 49 month study period (January 2012 – January 2016, and all direct and indirect poaching violations.

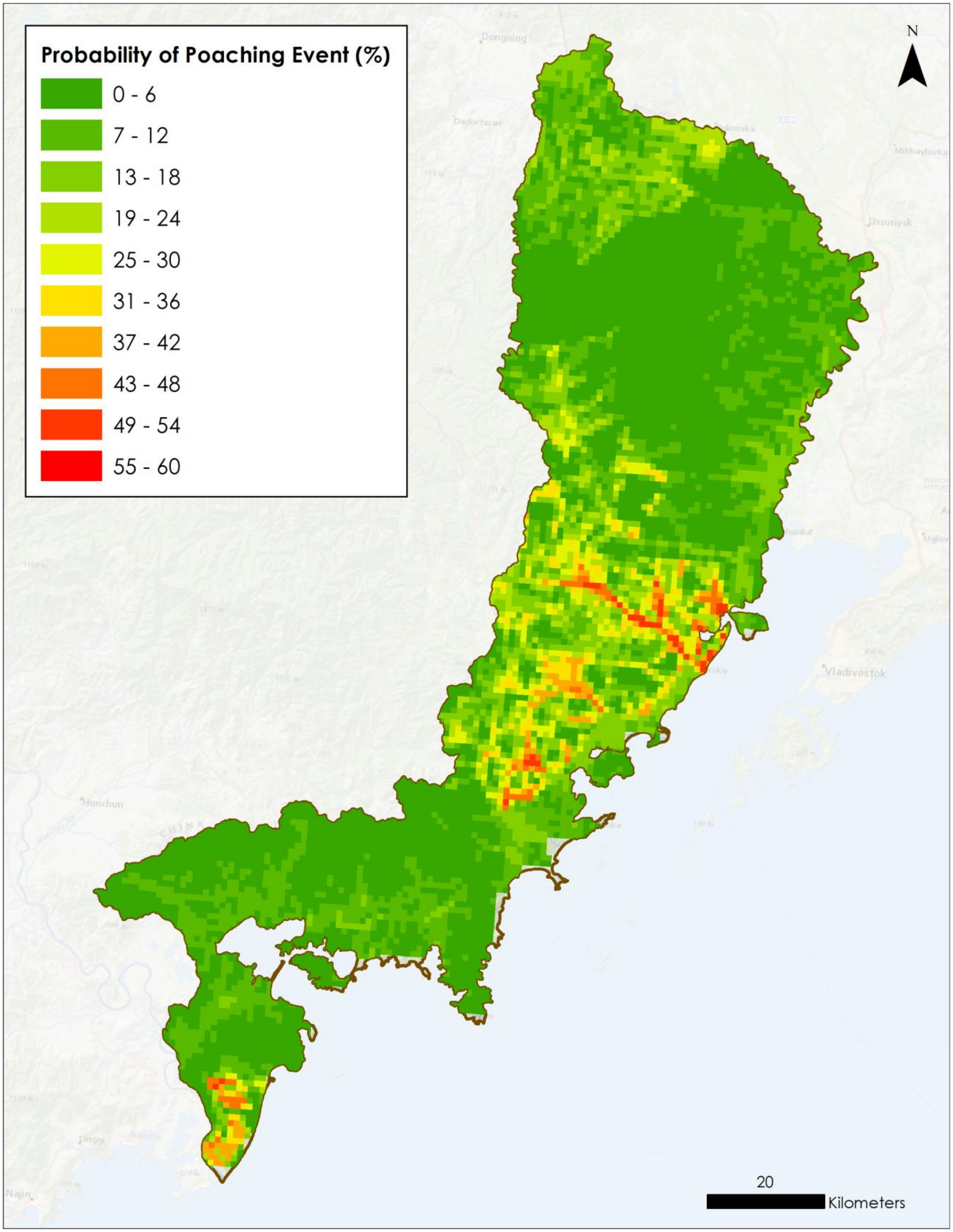

Figure 4. Map of predicted likelihood of poaching and poaching related events across Southwest Primorye, Russian Far East.

Table 1. List of all covariates to be incorporated in model selection process for predicting likelihood of poaching violation presence (occupancy) across the Southwest Primorsky Krai focus area.

Covariate	**Data Source**	**Hypothesized Effect**
Slope (Slp)	USGS – EarthExplorer	-
Aspect (Asp)	USGS – EarthExplorer	-
Elevation (Elev)	USGS – EarthExplorer	-
Dist. Nearest Town (Town)	WCS Russia/Conor Phelan	-
Dist. Nearest Rail (Rail)	WCS Russia/Conor Phelan	-
Dist. Nearest Road (Road)	WCS Russia/Conor Phelan	-
Dist. Nearest River (River)	WCS Russia/Conor Phelan	-
Percent Protected (Prot)	Russian National Park Service	-
Annual Climate Water Deficit (Def)	Climatology Lab - TerraClimate	-
Wildfire Probability (Fire)	Conor Phelan	-

Table 2. Top ten models outputted from MuMIn dredge function, and ranked by AIC. Top eight models (ΔAIC **< 2)** *were used in subsequent model averaging for the best predictive performance.*

Top Models	**AIC**	**ΔAIC**	**AIC weight**	**Number of Parameters**
ψ = (Slp+Town+Road+River+Prot+Def), p = visits	3734.9	0.00	0.396	6
ψ = (Slp+Town+Road+River+Rail+Prot+Def), p = visits	3736.3	1.38	0.198	7
ψ = (Slp+Town+Road+River+Prot), p = visits	3737.5	2.62	0.107	5
ψ = (Slp+Town+Road+River+Rail+Prot), p = visits	3738.0	3.08	0.085	6
ψ = (Slp+Town+Road+Prot+Def), p = visits	3738.4	3.44	0.071	5
ψ = (Slp+ Road+River+Rail+Prot+Def), p = visits	3739.9	4.98	0.033	6
ψ = (Slp+ Road+River+Rail+Prot), p = visits	3739.9	5.00	0.032	5
ψ = (Slp+Town+Road+Rail+Prot+Def), p = visits	3740.0	5.04	0.032	6
ψ = (Slp+Town+Road+Prot), p = visits	3742.7	7.77	0.008	4
ψ = (Slp+ Road+River+Prot+Def), p = visits	3742.8	7.91	0.008	5

Table 3. Model coefficients for average of eight top-ranked models outputted from multi-model inference analysis. Estimates were back-transformed from logit scale to be presented in probabilities. Parameters with estimates >0.5 have a positive relationship with the occurrence of poaching and poaching related events.

Covariate	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.743488	-5.456880	0.06020	0.000000
Slp	0.344659	0.119246	-5.38638	1.73E-07
Town	0.420262	0.124093	-2.61100	0.015698
Road	0.305334	0.330970	-2.48463	0.013199
River	0.250960	0.593785	-1.83800	0.067017
Rail	0.431636	0.197156	-1.44180	0.244400
Prot	0.504553	0.002551	7.15075	1.21E-11
Def	0.488987	0.024166	-1.82060	0.084860