THE UNIVERSITY OF EDINBURGH

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EVALUATING FOREST LOSS IN
RED PANDA (*AILURUS FULGENS*) HABITAT
BETWEEN 2000 & 2018

BY

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Abstract

Habitat loss has consistently been identified as the largest threat facing the endangered red panda (*Ailurus fulgens*) (Glatston *et al.*, 2015). Deforestation is driving red panda habitat loss and has contributed to the species rapid decline, yet the state of red panda habitat is unknown across its entire range. This gap in knowledge is a barrier for effective conservation of panda populations (Thapa *et al.*, 2018a). Using the Global Forest Change (GFC) dataset, this dissertation quantifies the extent of forest loss across the red panda habitat, and maps the areas of low and high forest disturbance. My results show that 1753 km^2 (>1.3%) of forest has been lost between 2000-2018, with roughly equal amounts of forest being lost each year. Hotspots of forest loss were identified in India, Burma, and China, with lower elevations more likely to lose forest than higher elevations. The forest network in red panda habitat appears connected in each sub population; however, two narrow forest corridors showed substantial deforestation. These results suggest that the red panda is at risk of further reproductive isolation due to the loss of critical forest corridors. Conservation action should be targeted at maintaining high elevation forest corridors, ensuring red panda populations maintain genetic viability. This dissertation highlights that a range wide view of red panda populations is needed to inform effective conservation decision making. In addition to localised ground based surveys, remote sensing tools such as GFC should be used to monitor the condition of red panda habitat over large areas.

Table of Contents

Acknowledgements

List of abbreviations

CITES - Convention on International Trade in Endangered Species of Wild Fauna and Flora

GEE – The Google Earth Engine

GFC – Global Forest Change dataset

H0 – Null hypothesis

Ha – Alternate hypothesis

IUCN - The International Union for Conservation

MaxEnt – Maximum entropy species distribution model

NASA JPL - The National Aeronautics and Space Administration Jet Propulsion Laboratory

RQ1 – Research Question 1

RQ2 – Research Question 2

UAV – Unmanned Aerial Vehicle

WDPA – World Database of Protected Areas

1. Introduction

Many vertebrate species are experiencing severe declines in their ranges and populations around the world. Over 300 vertebrates have become extinct since 1500, and the abundance of persisting species has decreased by 25% on average (Dirzo *et al.*, 2014). These declines are predominantly driven by anthropogenic land use change and habitat fragmentation (Acharya *et al.*, 2018). In mammals, different traits predict how a species will respond to habitat modification. Large arboreal mammals with narrowly defined niches and low dispersal capabilities are the most susceptible to population declines following habitat disturbance, and face the greatest risk of extinction following such changes (Gallagher *et al.*, 2015; Lino *et al.*, 2018). The red panda (*Ailurus fulgens*) (Figure 1) meets all of these criteria, and is thought to be declining rapidly across its range (Glatston *et al.*, 2015).

Significant attention is given to reversing mammal population declines and finding evidence-based solutions for mammal conservation, particularly with regards to preventing species extinction. Whether conservation action is driven by an ethical desire or an economic justification, data are always needed to inform effective management plans (Gauthier *et al.*, 2013). For species like the red panda, where data are unavailable due to the remoteness and extensiveness of range, remote sensing tools can be employed to measure and monitor relevant ecosystem variables. Pre-processed satellite imagery (Box 1, page 5) can be used to quantify land use changes (particularly deforestation) in red panda habitat (Buchanan *et al.*, 2018). Due to the predicted susceptibility of red pandas to habitat disturbance, knowing how their forests are changing is key to understanding the state of the population and informing conservation plans.

Figure 1: The red panda (Ailurus fulgens styani) in natural habitat, Ya'an, China (left) and its remote habitat in Annapurna, Nepal (right). Left photo credit: pfaucher, iNaturalist (CC BY-NC 4.0). Right photo credit: Cameron Cosgrove.

1.1 The red panda

The red panda is an endangered mammal that composes its own unique taxonomic family *Ailuridae*. They are endemic to Nepal, Bhutan, Burma (Myanmar), and China (Figure 2). Two genetically distinct populations of red pandas exist (*A. f. fulgens* and *A. f. styani*), separated by the Nujiang River Valley in China. *A. f. styani* is the most easterly population, found in the mountains of Sichuan (Thapa *et al.*, 2018b). The Sichuan subspecies tends to be larger than the western populations and has more defined facial markings. Whether these two subspecies actually represent two distinct species is unclear due to the lack of genetic information from wild populations. The Meghalaya population in India (Figure 2) is genetically and morphologically similar to *A. fulgens* but can occupy more tropical forest at lower elevations (Thapa *et al.*, 2018a).
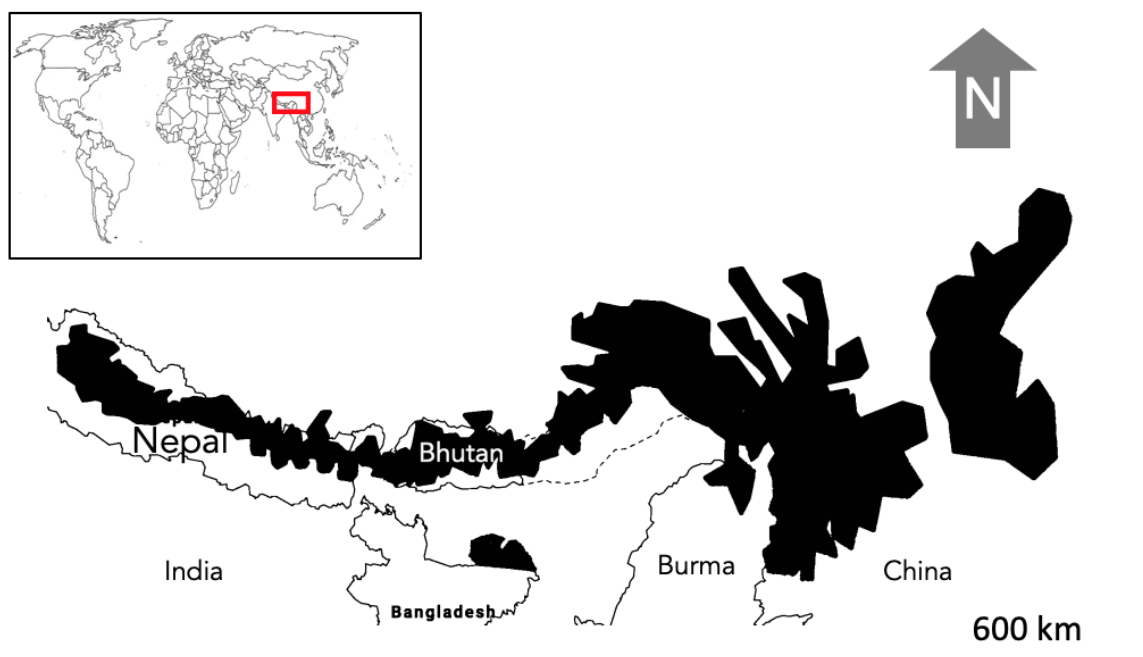
Figure 2: Red panda range. Distribution of the red panda is represented by the filled solid black area. The red box on the world map shows the area represented by the larger map. Countries are represented by the black polygons. Three isolated sub-populations exist; the southern slopes population that stretches from Nepal to western China, the Meghalaya population in India (just north of Bangladesh), and the eastern Chinese population inhabited by the subspecies *A. f. styani.* Original figure by author, distribution adapted from Thapa *et al* 2018b.

Red pandas are found in hillside forests with bamboo understory located between 1,000 and 5,000 m elevation. Red pandas are exacting in their habitat requirements, and prefer undisturbed forests with over 30% forest and bamboo cover (Bista *et al.*, 2017). While they are considered omnivores, red pandas subsist almost exclusively on bamboo, with it making up 98% of their diet (Thapa *et al.*, 2018a). Red pandas are crepuscular, predominantly solitary, and exist at low densities (roughly 1 panda per 4 km^2). With a particularly low dispersal capability for a mammal

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of its size, red pandas have been recorded moving a maximum of 30 km away from their place of birth (Bista *et al.*, 2017). They have an expected lifespan of 8-10 years in the wild, with female red pandas typically giving birth to two cubs every year.
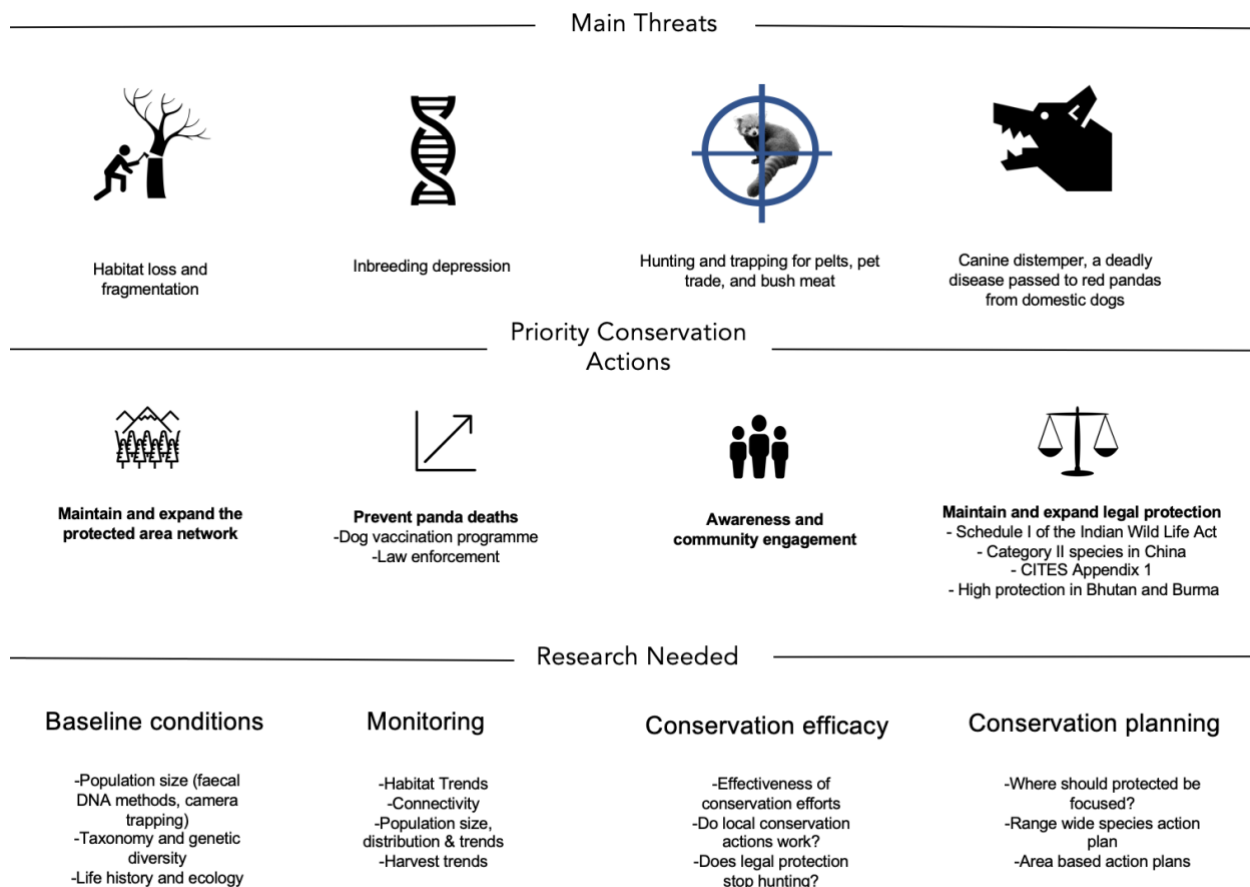
Figure 3: A summary of red panda conservation efforts and the research still needed. All information from the recent review of red panda conservation and the IUCN Red List assessment (Glatston *et al.*, 2015; Thapa *et al.*, 2018a). Icons from the Noun project (CC BY-NC 4.0).

Even though this charismatic mammal is now receiving more public attention, conservation efforts for the species lag significantly behind the more famous giant panda (*Ailuropoda melanoleuca*) and other high-altitude species such as the Himalayan musk deer (*Moschus leucogaster*). Red pandas would be expected to receive more funding due to their cute appearance and prevalence in many zoos around the world. Despite their potential as a flagship species for conservation in the Himalayas, this species remains severely understudied (Bennett *et al.*, 2015). Many aspects of red panda ecology and distribution are still unknown, and research is urgently needed to inform conservation action (Thapa *et al.*, 2018a). It is suspected that the population of red pandas has declined by >50% over the past three generations, raising extinction concerns (Glatston *et al.*, 2015). Precise population trends are unknown due the sparse number of red panda records

across its range. Red pandas are elusive and most occurrence information comes from indirect signs such as scat and pug marks in Nepal and China. The difficulty of this species to survey in the wild may explain the lack of research.

Economic opportunities for people in red panda habitat are limited, and are often based around harvesting natural resources, which tends to damage red panda habitat. Forest loss has been ranked as the largest threat that red pandas face in two independent threat assessments (Glatston *et al.*, 2015; Thapa *et al.*, 2018a). Small-scale timber harvesting and clearing for agriculture are the dominant mechanisms for forest loss in red panda habitat (Panthi *et al.*, 2017). Large-scale commercial forestry is very uncommon within red panda habitat (Curtis *et al.*, 2018), likely due to the slow growth-rate of timber at high altitudes and the steep terrain. Previously effective conservation actions have involved the establishment of community woodlands and local rangers, plus providing locals with more efficient cooking stoves to reduce wood consumption (McNamara, 2009). However, these conservation efforts are very localised, and are currently insufficient to protect the species (Thapa *et al.*, 2018a).

1.2 Project rationale

A range-wide conservation plan is needed to effectively protect red pandas (Thapa *et al.*, 2018a); however, very little information exists on the red panda population as a whole. As a result, we don't know where the forest is being lost in red panda habitat or how widespread deforestation is across its range. This could lead to the protection of wrong areas and the inefficient investment of conservation resources. Given the concern about the rate of red panda population decline, there is a particular urgency in evaluating how forests are changing in red panda habitat.

The tight arboreal niche of red pandas and their predicted susceptibility to habitat disturbance makes evaluating forest change across the range particularly useful for conservation planning (Joshi *et al.*, 2016). Indeed, the IUCN Red List assessment has identified habitat monitoring as the highest priority research topic for red pandas (Glatston *et al.*, 2015). It is not possible to directly evaluate habitat change with satellite imagery, because habitats are complex and are composed of many features that are too small to be detected. However, looking at how forest cover is changing is a reasonable proxy for inferring where major habitat change is happening. If forest is lost in red panda habitat, it represents a loss of habitat for that area. Identifying how forest cover is changing can help inform where the key areas that need protecting are and if panda habitat is being fragmented and isolated.

In this dissertation, I have used a publically available forest cover change dataset (Box 1) to assess how forests across the red pandas' range have changed from 2000 to 2018. This is a timely analysis, as both the data on the distribution of red pandas and the tools required to analyse large forest change data are only recently available. A MaxEnt distribution model for red pandas was created in 2018 to accurately define the range of red pandas (Appendix 1) and since 2013, the Google Earth Engine (GEE) - a Cloud-based spatial analysis platform - has been available to process large datasets such as Global Forest Change (GFC). The computing power required to create and analyses the GFC dataset was not available to the public before the GEE. By analysing GFC data within the red panda range, I can assess how the forest is changing and draw conservation implications. There is precedent for this approach too, as a similar technique using GFC data was used to evaluate change in key tiger habitat in 2016 (Joshi *et al.*, 2016).

I address two main research questions in this dissertation: i) how much forest has been lost in red panda habitat, and ii) where has this loss occurred? I have done this by analysing the amount of forest lost from 2000 to 2018 over the entire predicted range of the red panda and comparing how the amount of loss differs between countries, elevation, protected areas, and habitat quality classes. I have also created a forest loss map to qualitatively explore finer-scale patterns of forest loss.

Box 1. The Global Forest Change Dataset V1.6 (Hansen *et al.*, 2013)

The Global Forest Change (GFC) dataset, created in 2013 and updated regularly, is the highest resolution, publically available dataset available for measuring forest loss around the world. The data is derived from Landast imagery and has a resolution of 30 m^2. GFC contains three types of measurements. **Treecover2000** shows the % canopy cover at the year 2000, and records any vegetation taller than 5 m. **Forest Loss** shows any pixel that has transitioned from forest to no forest each year between 2000 and 2018. **Forest Gain** shows all the pixels that have shown a transition from no forest cover to forest cover between 2000 and 2013.

GFC has a very high classification accuracy (>90%), but when compared to on-the-ground measurements, can omit areas of forest and loss due to its resolution. Omission is the dominant GFC error in areas dominated by small-scale timber extraction. This underestimates the total loss, but still shows the broad spatial arrangement of loss. Version 1.6 of GFC has improved detection of small-scale timber loss, but this has only been applied to the years 2013-2018 so far.

1.3 Research questions and hypotheses

RQ1: How much forest has been lost in red panda habitat?

Due to the stated significance of this threat from the IUCN Red List and other conservation scientists, I expect a sizable amount of forest (around 10%) to have been lost across this entire range. I also expect the amount of forest lost per year to increase over time. This is because the human population is increasing in red panda habitat, increasing the pressure on timber resources (Shehzad *et al.*, 2014; Wardrop *et al.*, 2018). If my predicted amount and rate of forest loss is found, it will provide evidence for the urgency of conservation efforts surrounding red pandas. Habitat trends are a key component of species extinction risk assessments, and these findings could inform updated IUCN Red List assessments.

H1a: The area of forest in red panda habitat has decreased by >10% from 2000 to 2018 across the entire range.
H10: The area of forest in red panda habitat has decreased by <10% from 2000 to 2018 across the entire range.

H2a: The amount of forest lost each year has increased in red panda habitat from 2000 to 2018 across the entire range.
H20: The amount of forest lost each year has remained the same or decreased in red panda habitat from 2000 to 2018 across the entire range.

RQ2: Where has forest been lost in red panda habitat?

It is predicted that the proportion of forest loss will differ across red panda range. Different countries have varying land management strategies and intensity of resource use. For example, I expect Bhutan to show the lowest proportion of forest loss due to its relatively low population; whereas I expect China to show the highest forest loss due to its relatively high population (Wardrop *et al.*, 2018). Across the entire range, forest loss is expected to be higher at lower elevations due to easier human access. Areas of high habitat suitability are expected to lose the most forest out of every habitat class, due to the fact that these areas tend to have the highest quality timber and bamboo resources, and thus would be targeted more for resource extraction (Acharya *et al.*, 2018). I expect protected areas to show less forest loss than unprotected areas because of the stronger legal protection in these areas. I have used IUCN protected area classifications to distinguish between different levels of protection within protected areas (Appendix 4). If these predictions are supported, they will broadly indicate the most impacted and threatened areas, and can help identify possible drivers of forest loss.

H3a: Different countries have lost different proportions of forest cover in red panda habitat.
H30: Different countries have lost the same proportion of forest cover in red panda habitat.

H4a: Lower elevations were correlated with more forest loss.
H40: There was no correlation between lower elevations and more forest loss, or the correlation was negative.

H5a: Areas of high habitat suitability have seen the highest proportion of forest loss.
H50: Areas of high habitat suitability have seen the lowest proportion of forest loss or showed no difference.

H6a: Protected areas have lost the least proportion of forest compared to unprotected areas.
H60: Protected areas have lost the highest proportion of forest compared to unprotected areas or show no difference in the proportion of lost forest.

2. Methods
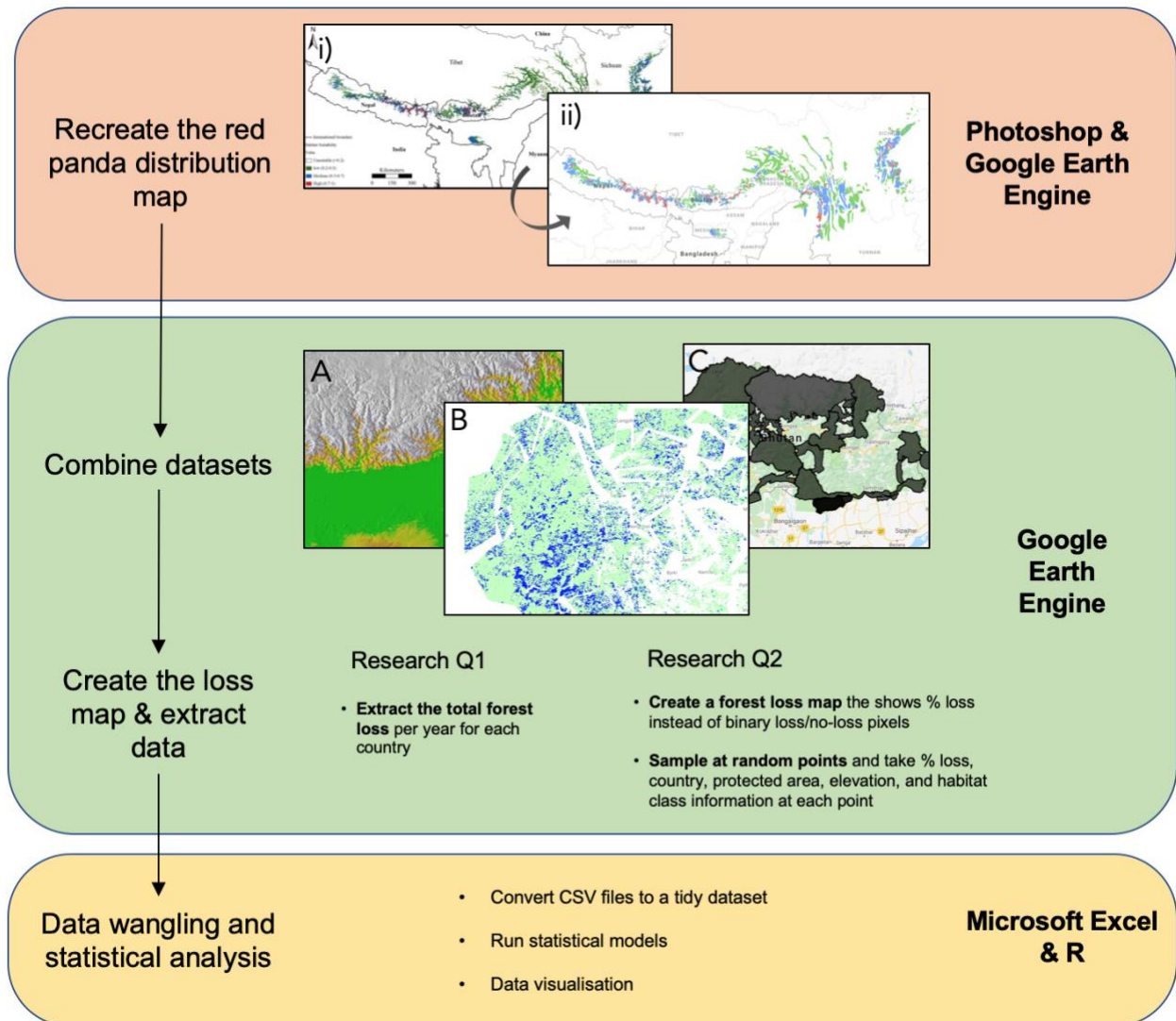
Figure 4: Overview of my methods showing the main steps (left), the process (middle) and the computer programs used (right). Image (i) shows the original MaxEnt distribution map from Thapa *et al* and image (ii) shows my own recreation. Image A shows a visualisation of the elevation data, B a GFC loss visualisation, and C the protected planet polygons (shaded area) for Bhutan.

2.1 Defining the study area

All geospatial analysis was conducted within red panda habitat. Red panda habitat was defined as any GFC pixel within the Thapa *et al* distribution, with over 20% canopy cover in the year 2000. Canopy cover was specified to better reflect red panda habitat requirements, as they are predominantly found in areas with > 30% canopy cover (Bista *et al.*, 2017; Thapa *et al.*, 2018b).

The Thapa *et al* distribution was chosen because it is the most accurate and up-to-date distribution model available for red pandas. GFC data is only available from 2000 to 2018, which has defined the temporal scope of this study.

The distribution map created by Thapa *et al* was unavailable as an electronic shapefile, so I recreated the map myself to use in my analysis. This was a two-stage process. I used Photoshop to help add the distribution map (Appendix 1) onto an image of the base layer of GEE. The aim of this was to geo-reference the image by hand using country borders as control points. Shapes were then copied from the photoshopped map onto the GEE base map, using different geometries to represent the different habitat classes (Low 20-50%, Moderate 50-70%, and High suitability 70-100%) (Appendix 2). Great care was taken to accurately recreate the map in the GEE.

2.2 Analysis in the Google Earth Engine

(Example scripts for the GEE analysis can be found in Appendix 6 and 7)

Table 1: A description of the datasets used in my GEE

Dataset	Data Provider	Description
GFC V1.6	(Hansen *et al.*, 2013)	A Landsat derived image collection of forest cover change around the world. (See Box 1 for more details)
SRTM	NASA JPL (Farr *et al.*, 2007)	Shuttle Radar Topography Mission data. Global digital elevation model.
WDPA	UN Environment World Conservation Monitoring Centre / Protected Planet	World Database on Protected Areas (polygons). The type of protected area, and other associated aspects are recoded.
LSIB	United States Department of State, Office of the Geographer	Large Scale International Boundary Polygons, Simplified. The polygon shape files of every country in the world as of 2016.

All data used in this dissertation came from pre-existing and publicly available datasets (Table 1). Each dataset was imported into the GEE and had been pre-georeferenced and processed. In

order to use the WDPA and Country Polygon datasets in my forest loss map analysis, I converted these shapefiles to an image. This was done so I could add this data as an image band to the loss map and easily extract their values after analysis. The conversion was done by cropping a binary land mask (an image where land = 1 and water = 0) to each shape, then creating a new image variable for each country and protected area category. All analyses were conducted using the native scale of the GFC dataset (the highest image detail possible) which was around 30 m^2.

Calculating total yearly forest loss (RQ1)

The area of forest lost was calculated by using the pixel area function on the loss pixels within each yearly loss band. A reducer function was then used to sum the loss pixels for each year in each country. The total tree cover at the year 2000 and the amount of gain at 2013 were also extracted in order to calculate the percent loss and associated forest regrowth. The loss data was exported as a CSV file and imported into Rstudio version 3.5.2.

The forest loss map (RQ2)

I transformed the binary GFC forest loss data into an image where each pixel represents the average forest loss within a 1 km^2 buffer. I did this for two reasons: i) It is easier to visualise the data and see areas of high and low forest disturbance and ii) It provides more information on the magnitude of loss at a sample site. A mean neighbourhood circular kernel was used to convolve the image and convert loss/no-loss pixels to a % loss measure. The image was then cropped to the bounds of the study area and visualised using a custom colour pallet that highlights both areas of low and high forest loss.

To extract data for statistical analysis, I created my own image collection - merging the forest loss image, country data, elevation, protected area coverage, and habitat class. This gave each pixel information about the amount of loss in the surrounding 1 km^2 and the value of each independent variable. In order to gauge the variation in forest loss within areas of interest, I used a sample-based approach. Using GEE's random point generator, I sampled 5000 random pixels from my loss map image collection. A visual assessment showed that 5000 was deemed to be the maximum number of samples possible without significant overlapping of sample points. Any more than this would increase double-counting of points and make my sample less independent. A table listing the % forest loss and associated independent variables was exported as a CSV file and imported into Microsoft Excel, where it was manipulated into a 'tidy dataset'. Data was then filtered in Rstudio to exclude samples in areas with less than 20% forest and in any overlapping habitat classes caused by error in the recreation of the distribution map.

2.3 Statistical analysis

Each hypothesis was tested separately and all models were planned *a priori*. As such, no model comparisons have been made. Rstudio version 3.5.2 was used to run all statistical analysis and sample scripts can be found in Appendix 8 and 9. Data distributions and residual fits were visually assessed using QQ plots and histograms for all research questions to check the data met the model assumptions (Whitlock & Schluter, 2015b). The threshold for statistical significance was set to alpha = 0.05 for every analysis.

RQ1

The data was assessed and did not reveal obvious heteroscedasticity or deviations from normality. A linear model with a Gaussian distribution was chosen to test if the amount of forest loss was increasing over time in red panda habitat. The data represented the total % of forest lost each year and this was tested against the year of measurement (percent_loss ~ Year).

RQ2

The structure of the data extracted from the loss map was severely zero-inflated and non-normal. Linear mixed models were intended to be used but non-parametric methods had to be used instead to test hypothesis 3, 5, and 6 (Whitlock & Schluter, 2015a). Kruskal-Wails tests were used to compare the median value of % forest loss of the different groups. This non-parametric test was deemed appropriate because the distribution of forest loss values was the same shape in every group (visually assessed with a histogram) (Whitlock & Schluter, 2015b). A post-hoc analysis using the kruskalmc function in the R package "pgirmess" (Giraudoux, 2018) was run to identify significantly different medians while also accounting for the multiple comparisons being made. This process is analogous to the parametric Tukey HSD test used on ANOVA model outputs.

The data used to test H4 (percent_loss ~ elevation) was transformed into a binary response, with every non-zero % loss value transformed into a 1. The transformed data sufficiently met the assumptions of a linear model (Whitlock & Schluter, 2015b). A logistic regression model was then used to test if elevation significantly predicted the probability of finding a forest loss pixel (loss/no-loss ~ elevation).

3. Results

3.1 RQ1: How much forest has been lost in red panda habitat?

The rate of forest loss in red panda habitat has not significantly increased across the entire range from 2000-2018 (linear model, slope = 0.0014 $\pm$ SE 0.0013, $F_{statistic}$ = 1.204, df = 16, adjusted R^2= 0.012, P = 0.288). A total forest loss of 1.3% (1753 km^2) was found across the entire range from 2000-2018 (Figure 5). The amount of regrowth measured between 2000 – 2013 in red panda habitat was 227 km^2.
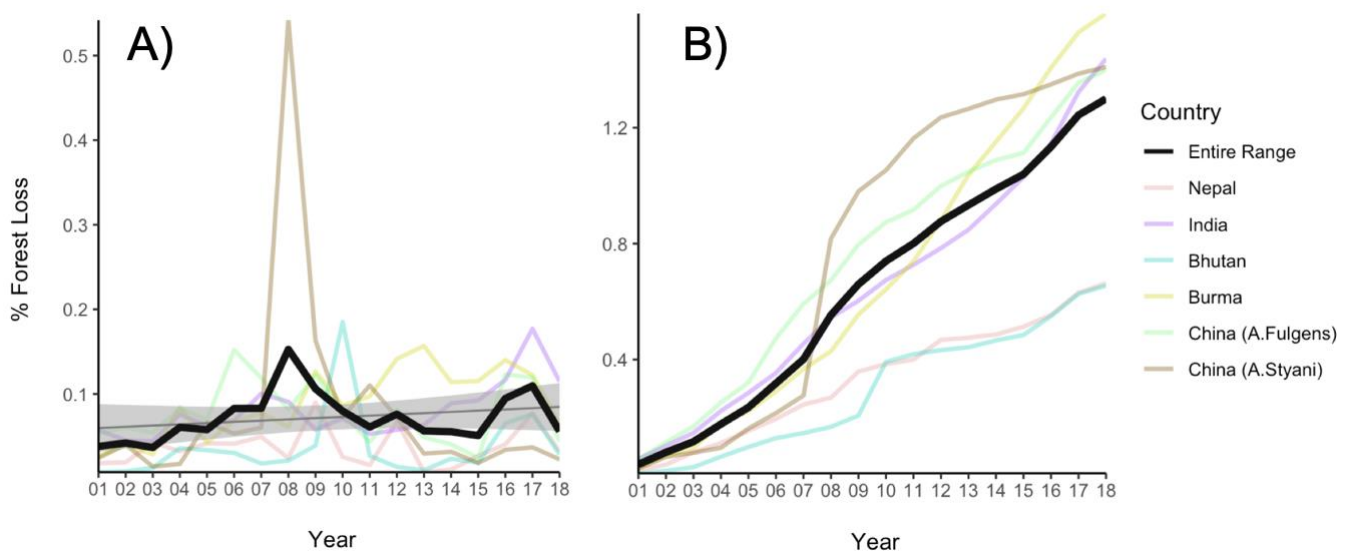
Figure 5: Total forest cover has decreased in red panda habitat from 2000 – 2018. Figure A shows the yearly % forest loss over the study period for the entire range of the red panda, and each country. The linear model is shown as the smaller black line with the SE shown in grey. Figure B shows the same data as figure A but represented as a cumulative total, no model fit is shown. The final point at 2018 in graph B represents the total loss over the study period. The total area of red panda habitat measured was 134880 km^2.

3.2 RQ2: Where has forest been lost in red panda habitat?

Habitat loss in red panda habitat is clustered and not uniform across the range (Figure 6). A visual assessment of the location of loss showed that forest loss was usually found close to roads and human settlements. Two particularly narrow habitat corridors were found along the southern slopes population (A and B in Figure 6). These narrow regions both show high amounts of forest loss. Three hotspots of forest loss were also identified (i, ii, iii in Figure 6).
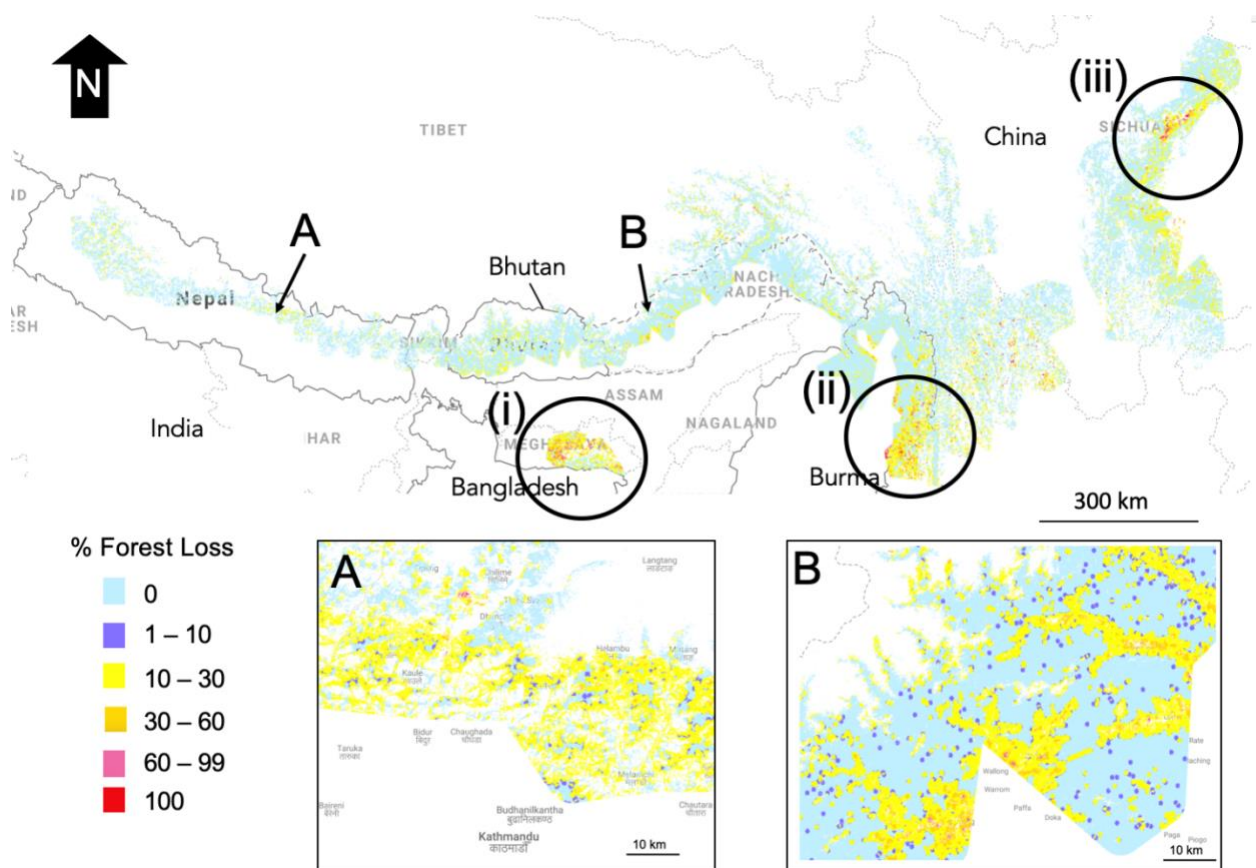
Figure 6: Map of forest loss in red panda habitat, with two narrow habitat corridors (A and B) identified, and hotspots of forest loss circled in black. Each point on the map represents the average forest loss within the surrounding 1 km^2 circular area. Range wide map created with a scale of 100 m in the GEE, zoom in maps A and B created at the native scale of GFC dataset (~30m). **A full page and unlabelled version of this map is found in Appendix 3.**

Significantly different proportions of forest were lost in different countries (Kruskal-Wallis, $\chi2$ = 69.256, df = 5, p-value 1.463e-13). China (both subspecies) showed the highest average loss and Bhutan, Burma, and Nepal showed the lowest average loss (Figure 7).

Figure 7: The average forest loss sampled in each country. Points show the mean loss and the error bars represent the standard error of each mean. The 'Significant Differences' section show the significantly different medians calculated in the post-hoc test. Sample sizes for each group are represented by n.

The probability of sampling a pixel with forest loss was three times higher at lower elevations compared to higher elevations (Logistic regression, $F_{statistic} = 80.532$, df = 3071, Adjusted $R^2 = 0.025$, p-value = $<2e^{-16}$) (Figure 8).
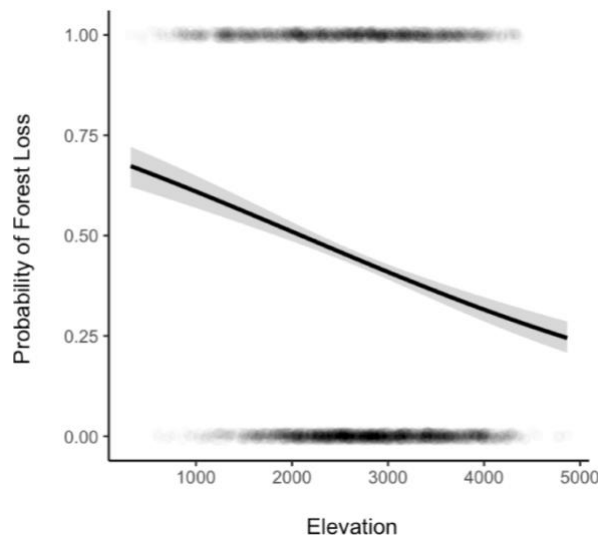
Figure 8: Lower elevations are more likely to experience forest loss. The data smudges at 0 and 1 on the X axis represent the distribution of data points used in the model (n=3071). The output of logistic regression model is represented as the black line with the SE of predicted values shown in grey.

High suitability habitat lost about half the amount of forest than moderate and low suability habitat (Kruskal-Wallis, χ2 = 13.753, df = 2, p-value 0.001).
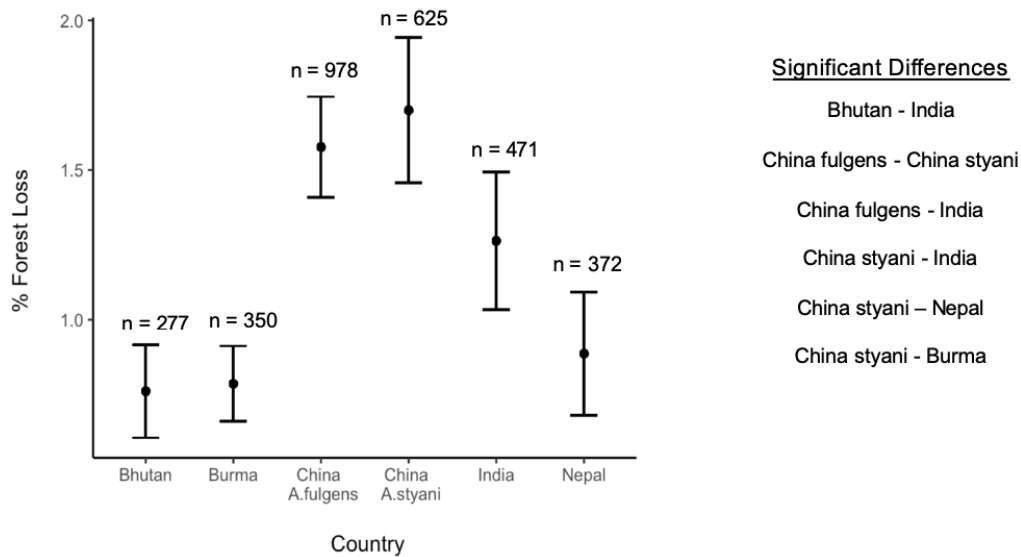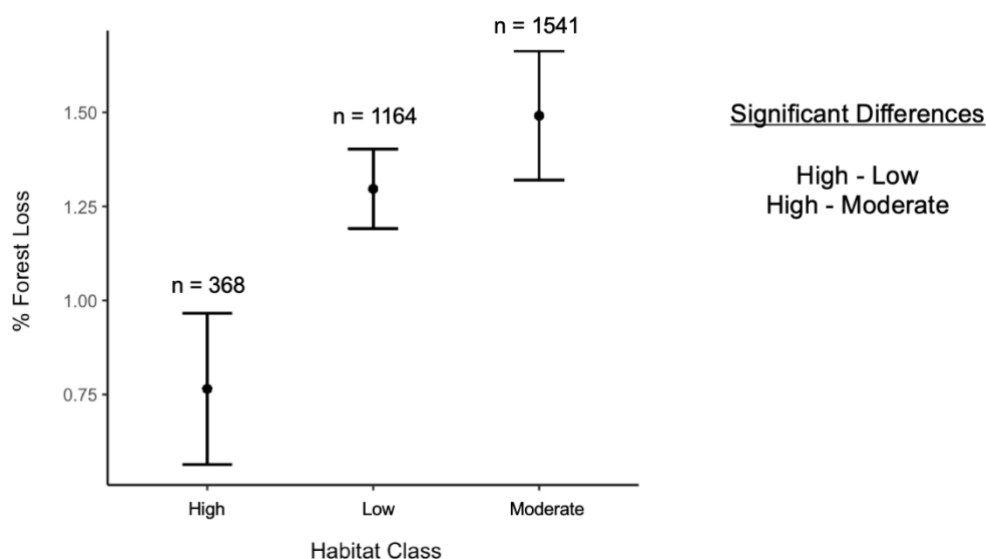

Figure 9: The average forest loss sampled in each habitat class. Points show the mean loss and the error bars represent the standard error of each mean. The 'Significant Differences' section show the significantly different medians calculated in the post-hoc test. Sample sizes for each group are represented by n.

Unprotected area showed the highest average amount of forest loss but only category IV areas were significantly lower. (Kruskal-Wallis, χ2 = 16.108, df = 3, p-value = 0.001).

Figure 10: The average forest loss sampled in each protected area category. Only three categories had sufficient (> 20) samples to be included in the analysis. Points show the mean loss and the error bars represent the standard error of each mean. The 'Significant Differences' section show the significantly different medians calculated in the post-hoc test. Sample sizes for each group are represented by n.

4. Discussion

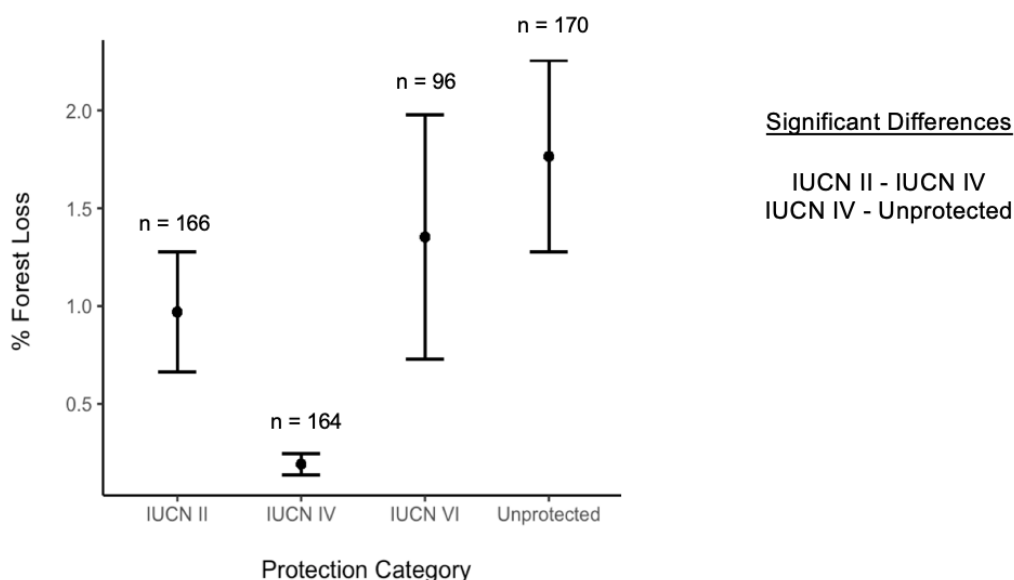Red panda habitat has lost significantly less forest cover than expected, with only 1.3% of forest cover lost between 2000 and 2018 (opposed to the expected 10%). Taking into account the relatively low level of observed regrowth, red panda habitat has likely seen a net decrease in forest cover. The rate of forest loss was not found to be positive across the entire range either, resulting in the rejection of both alternate hypotheses for RQ1. However, visual assessment of the forest loss map shows substantial deforestation in narrow forest corridors, suggesting that it is not the quantity of loss we should be concerned with, but rather where that loss is occurring.

As expected, the highest proportion of forest loss was observed in China, at lower elevations, and in unprotected areas. Contrary to my predictions, low suitability habitats showed the most loss, as opposed to high suitability habitats. Three main hotspots of loss were identified: i) Meghalaya, India; ii) southern panda habitat along the Burma and China border; and iii) 50 Km NW of Chengdu, China. My findings reveal that forest loss is clustered and not homogenous across the red panda habitat range, and that forest loss along the southern slopes of the Himalayas may lead to isolated red panda populations due to disturbance within narrow forest corridors. My results also support the suggestion that the Meghalaya area of India is becoming highly degraded and unsuitable for red pandas.

4.1 How is red panda habitat changing?

RQ1: How much forest has been lost in red panda habitat?
The low level of calculated total forest loss was unexpected, but not unreasonable. Within a similar GFC study conducted across Asia, core tiger key habitat lost 7% of forest cover, with 1.5% loss specifically in Nepalese tiger habitats (Joshi *et al.*, 2016). This was vastly less than was expected, with the authors' initial predictions around 30% forest loss from 2000 to 2014. The large discrepancy between predicted and observed values was suspected to be caused by the GFC dataset's failure to capture the full extent of forest loss, omitting large areas of deforestation. Validating their results with high resolution ($< 5 \text{ m}^2$) imagery and in-person on-the-ground studies, Joshi *et al* found that the Hansen Dataset omitted $31\% \pm 28\%$ (95% confidence intervals) of actual loss; however, GFC accurately captured the spatial pattern of loss. Much higher levels of omission were observed in another GFC study in Ghana (Mitchard *et al.*, 2015), with >80% of forest loss detected by high-resolution imagery not detected by GFC. Both of these studies looked at remote regions where small-scale deforestation is the dominant mechanism for forest loss – a factor that is shared throughout red panda habitat as well (Panthi *et al.*, 2017). The total 1.3% loss I have recorded here is likely an underestimation of actual deforestation levels.

The amount of forest loss per year is not increasing across the entire range. This is unexpected due to the fact that the human population across this region is increasing overall (Wardrop *et al.*, 2018). The linear model used did not account for the potential temporal correlation in the data, as a growing population should cause later years to show more similar amounts of forest loss. However, even if this correlation was accounted for, it would only serve to decrease the predicted forest loss over time and would be unlikely to change the inference made about the trend of forest loss. Additionally, accounting for the GFC methods updated in 2013 (Box 1) would also serve to decrease the predicted forest loss over time, as more loss was likely detected from 2013 - 2018. Therefore, I am confident that forest loss is not increasing across the entire range. This result is makes more sense when compared to other studies, that show a slight decrease in deforestation in Bhutan (Lim *et al.*, 2017) and nearby mountainous regions of Pakistan (Shehzad *et al.*, 2014). Deforestation rates across South East Asia as a whole are increasing by 5% more every year (Miettinen *et al.*, 2011). However, the inclusion of countries like Indonesia and the Philippines, places that are experiencing the most rapid deforestation in the world, are likely skewing these large-scale results. It is important to note that even though the amount of forest loss per year is not increasing over time, a steady of amount of loss can still lead to the fragmentation of red panda habitat.

RQ2. Where has forest loss occurred?

Red panda habitat has experienced the largest amount of forest loss in China compared to other countries. This is evident through the average forest loss of both Chinese samples being almost double the amount of loss than that observed in Bhutan and Nepal. Interestingly, there appears to be a big difference in the sample loss estimate for Burma (0.75%, Figure 7) and the total loss estimate (1.4%, Figure 5B). This is likely due to the highly clustered pattern of forest loss in Burma, resulting in the sample base estimates underestimation of total loss. I suspect the pattern of loss across elevation is due to higher accessibility and proximity to human populations. Additionally, I would theorise that the unexpected habitat class result can be explained by this elevation pattern too, with lower elevation containing the most low-suitability habitat (ideal panda habitat is between 3000-4000m (Bista *et al.*, 2017)). Concerning country and elevation, the results support the link between higher human populations and forest loss, with the highest loss being in China as well as the more populated and accessible lower elevations.

As expected, unprotected areas showed the highest average forest loss, but, surprisingly, only category IV areas showed significantly less forest loss. While IUCN II should, in theory, have higher protection than category IV areas, the location of a protected area can have a large impact on its management (Chettri *et al.*, 2008). For example, class II protected areas in Bhutan have

been criticised for the lack of legal enforcement of hunting and timber extraction (Jamtsho & Wangchuk, 2016; Dendup *et al.*, 2017). Protected areas are also often disproportionately assigned to high and remote regions (Joppa & Pfaff, 2009). This spatial bias in location could result in a neutral explanation of my results, with protected areas losing less forest because they are located away from population centres, rather than as the result of active management. In short, it is reassuring that some protected areas show less loss in red panda habitat than unprotected areas, as it suggests active management and stronger legal protection may be working. However, my reliance on non-parametric tests prevented covariates such as elevation and country from being statistically accounted for, so I cannot reasonably attribute a cause to lower observed forest loss in category IV areas.

4.2 What needs to be considered when interpreting my results?

Due to the nature of my data, I had to rely on some non-parametric tests in RQ2, and due to the large number of 0 values (no forest loss) across every group, there were many tied ranks in the Kruskal-Wallis calculation. The standard process of averaging tied ranks was preformed, which prevented an exact p-value from being calculated (Giraudoux, 2018). This resulted in a conservative estimate of significance (lowering the power) and reduced the type 1 error rate (Whitlock & Schluter, 2015b). Kruskal-Wallis tests compare the differences in the median value of groups, opposed to the average that Figures 5, 7, 9, and 10 show. If different groups have a large difference in the number of tied ranks, the median values can be offset, further lowering the power of the test. A combination of these factors likely resulted in the unusual significant differences, with forest loss measurements of China *A.fulgens* and China *A.styani* showing a significant difference, but the visually distinct groups of Bhutan and China *A.fulgens* showing no significant difference (Figure 7). A further approach to overcome this would include models that explicitly deal with non-integer zero-inflated data - potentially a quasi-Poisson mixed effect model or a two-part hurdle model that would model the 0 values separately (Zeileis *et al.*, 2008). By adding longitude and latitude grouping factors to these models, I could also partially account for the spatial autocorrelation in my data.

The only aspect of my methods that makes this analysis specific to red pandas is exploring GFC data within the species' range. This makes my red panda specific conclusions dependent on the validity of the distribution map. An accuracy evaluation of the distribution map by Thapa *et al* showed that over 75% of red panda occurrence records fell within moderate and core suitability areas, with the remaining records falling within low suitability areas. In the absence of another specific red panda distribution, the Thapa *et al* distribution was the best available. My recreation

of the distribution map will have introduced some errors and will have resulted in the incorrect mapping of some panda habitat. However, a visual assessment of my map showed a close correspondence with the original. By limiting the study area to pixels with > 20% forest cover in 2000, I further refined the MaxEnt distribution, making it more specific to red panda ecology.

While forest loss in red panda habitat represents absolute habitat loss, habitat degradation that occurs without forest loss was not measured. It is likely that far more than 1.3% of red panda habitat is being lost through human activities such as the clearing of understory vegetation or the pollution of water sources. Habitat degradation was identified as large threat to red pandas in central Nepal, where livestock were causing significant erosion and trampling understory vegetation (Acharya *et al.*, 2018). My method only considered forest loss and did not account for any other form of habitat loss. Also, by defining the study site as any pixel within the potential distribution with >20% tree cover, I prevented any new forest gain from being measured. It is possible that forest lost prior to 2000 is now recovering and may become suitable red panda habitat; however, this was not considered in this research. Red pandas prefer primary old-growth forest, so any new forest regrowth from 2000 would likely still be unsuitable habitat for the species (Bista *et al.*, 2017). It is due to this fact that I did not pursue this line of inquiry. However, if the study was conducted over a longer time period, the forest gain would be an important factor to consider, as old deforested areas may be regenerating in red panda habitat.

4.3 Conservation implications

Effective species conservation plans need to consider the arrangement of habitat and how that habitat is changing. These results add to the knowledge of red panda habitat connectivity by showing that each of the three sub-populations has forest connectivity throughout each range, suggesting that habitat may be connected too. However, this connectivity might be threatened by forest loss within narrow corridors. The amount of forest disturbance that red pandas can tolerate is unknown, but observation in the wild suggest that red pandas require intact undisturbed forest patches (Acharya *et al.*, 2018). In addition, their low dispersal capabilities may prevent red pandas from crossing large areas of unsuitable habitat. If red pandas cannot move through a corridor because of the extent of forest loss, genetic flow will be reduced. I think this is a particularly significant concern in the southern slopes population and Meghalaya. The reproductive isolation of red pandas may make some populations genetically unviable (Ramalho *et al.*, 2018). Conservation efforts should consider this potential isolation and confirm that a population is genetically viable before investing conservation resources. Translocation of pandas between parts of the range might be required in the future to maintain genetic diversity. The specific narrow corridors identified in Figure 6 might be good places to establish protected areas for red pandas.

Considering the potential threat of reproductive isolation, I would conclude that maintaining the connection of high-elevation red panda habitat should be an aim for red panda conservation. Higher elevations are less likely to experience forest loss and should be the easiest to places to maintain forest cover (Figure 8), due to lower human populations and reduced conservation conflicts. Other high-altitude species in the region, such the Tibetan black bear (*Ursus thibetanus*), the Mishmi Takin (*Budorcas taxicolor*), and the golden sub-nose monkey (*Rhinopithecus roxellana*), share the same habitat as red pandas (Bista *et al.*, 2018). All of these species would also be likely to benefit from the targeted protection of high-altitude forest corridors. Pooling resources and maximising the benefits for as many species as possible could be an effective way to achieve red panda conservation goals (Thapa *et al.*, 2018a).

4.4 Future work

The conservation of red pandas suffers from a lack of data and the spatial bias of study sites (Glatston *et al.*, 2015). Surveys should be expanded to confirm the species distribution across Bhutan, Burma, and the eastern part of Tibetan China (Appendix 5). Remote sensing tools, such as camera trapping, would be an effective method to confirm occurrence, and could also indicate the density of red pandas (Burton *et al.*, 2015). On-the-ground habitat monitoring should be expanded and opportunities for remote sensing explored, such as the use of active remote sensing to measure changes in forest structure or using UAVs and machine learning algorithms to quickly survey the food plants in a region. Monitoring the change in forests or habitats is useful for conservation planning, but is even more effective when used in conjunction with population data (Hone *et al.*, 2018).

In furthering my studies, I would explore how forest gain has changed in addition to change in forest loss. This was not possible with the GFC V1.6 data due to the fact that forest gain is only given as a total from 2000-2013. The next data release (GFC V2) is stated to have more gain data at a yearly resolution (Hansen *et al.*, 2013). Re-conducting the analysis with this data would show forest cover dynamics in red panda habitat more thoroughly. I suspect that a lot of forest was lost prior to 2000, and it would be interesting to see how those cleared areas are changing over time in red panda habitat. I would then statistically analyse this data with models that more fully account for zero-inflated, non-normal distributions, and covariates. A more statistically powerful analysis would help unpick the drivers of forest change, and compare the relative importance of factors such as elevation, area management, and habitat suitability.

5. Conclusion

This study provides the first assessment of the magnitude of forest loss and the location of that loss in red panda habitat. I found that across the entire range, the total area of deforestation is lower than expected (1.3%), and that there was no increasing trend of forest loss from 2000-2018. It is suspected that the location of forest loss - rather than the total amount of loss - is likely more significant to red panda populations. Two narrow corridors were identified as being threatened by deforestation, potentially causing reproductive isolation in the future. Forest loss hotspots were identified in India, along the Burma and China border, and in Sichuan province. These findings are the only assessment of change within red panda habitat that considers the entire population as a whole, and have implications for red panda conservation.

Conservation implications:

- There appears to be forest connectivity throughout the range of each red panda sub-population. However, localised loss in narrow forest corridors could potentially reduce this connectivity, leading to genetic isolation, particularly in the southern slopes population.

- The genetic viability of a red panda population should be considered before conservation resources are spent. Monitoring the connectivity of red panda forests using GFC data, or other remote sensing tools, would indicate if genetic isolation is likely.

- The pattern of lower forest loss at higher elevations suggests that high-altitude forests may be valuable places to focus protection to ensure connectivity throughout the red panda's range.

Concern about deforestation within red panda habitat appears to be justified. In order to maintain forest connectivity throughout red panda habitat, further research on the distribution and dispersal capabilities of this enigmatic species is urgently needed.

6. References

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7. Appendices
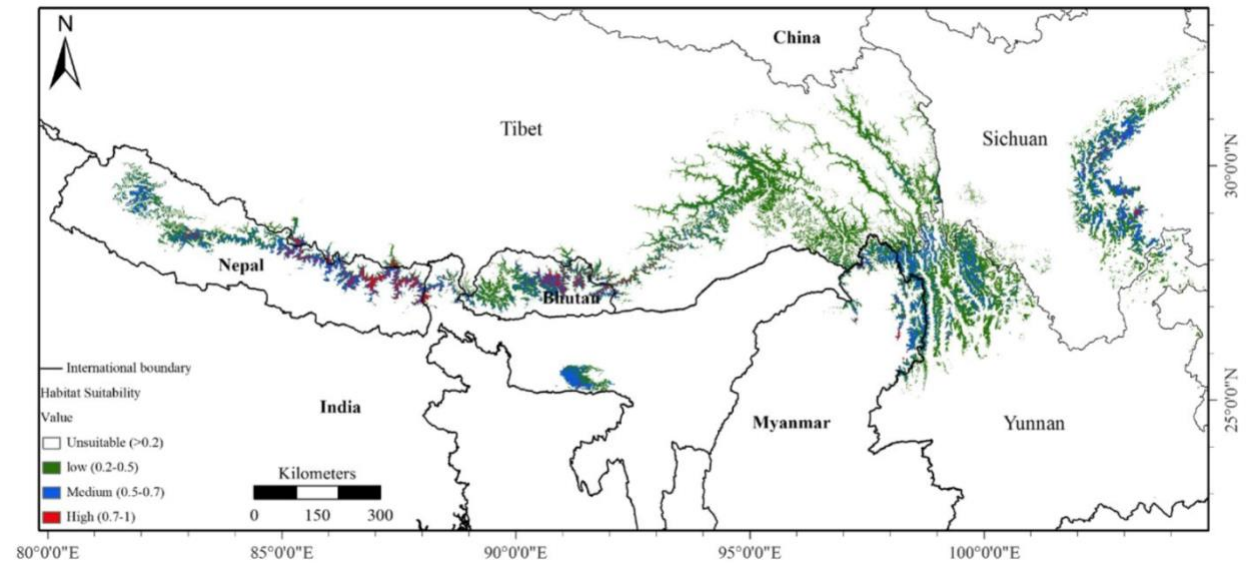
*Appendix 1: The MaxEnt distribution map created by Thapa et al 20*18b. (CC BY-NC 4.0)
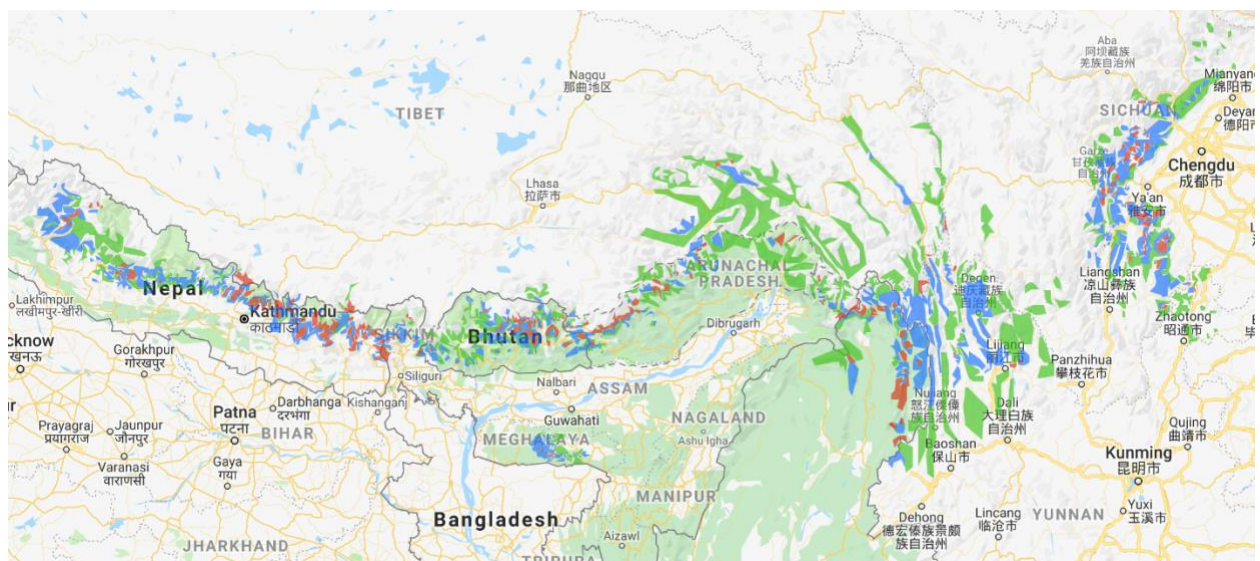
Appendix 2: My recreation of the MaxEnt distribution map created by Thapa et al 2018b. (CC BY-NC 4.0). Coloured polygons represent the habitat classes detailed in Appendix 1.
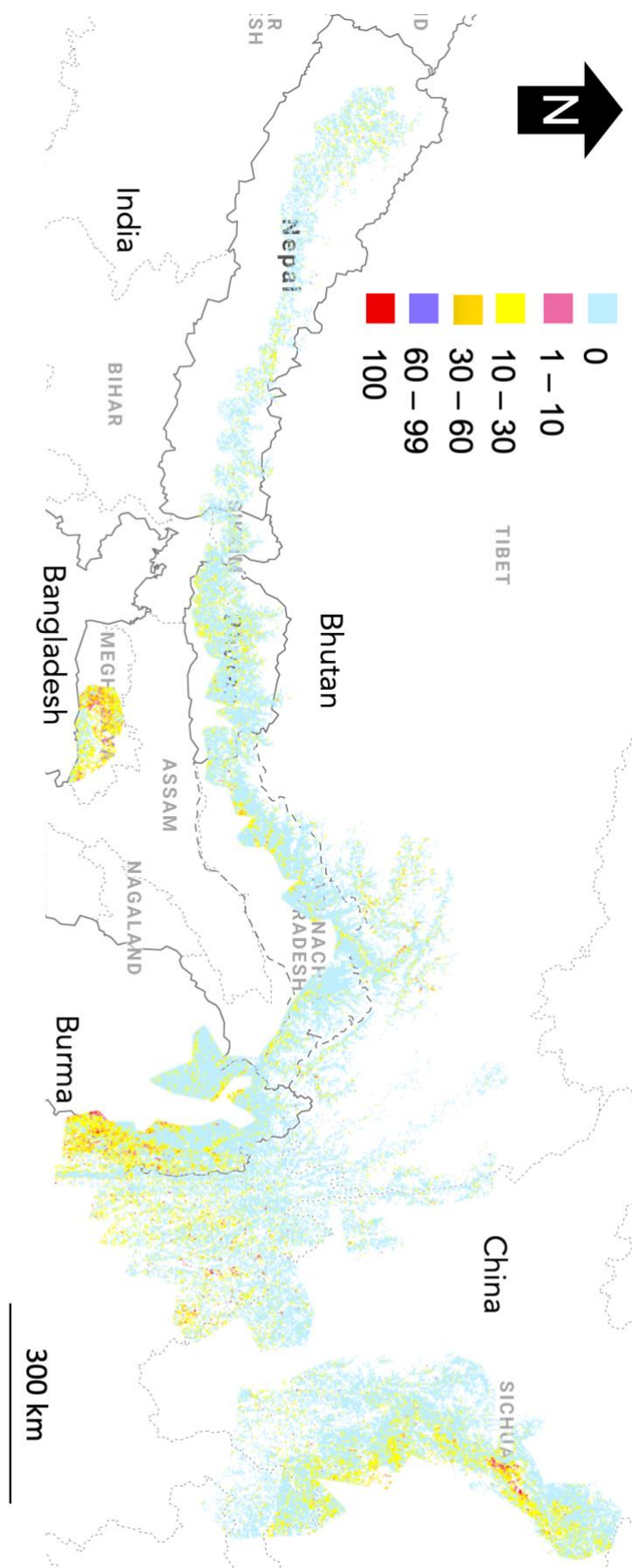
Appendix 3: Map of forest loss in red panda habitat. Each point on the map represents the average forest loss within the surrounding 1 km^2 circular area. Range wide map created with a scale of 100 m in the GEE.

Appendix 4. Explanation of IUCN Protected Area Categories measured in this dissertation.

Category	Description
II	**National Park:** Large natural parks set aside to protect big ecological processes and local species.
IV	**Habitat/Species Management Area:** Designed to protect specific species. Often actively managed for a specific cause.
VI	**Protected area with sustainable use of natural resources:** Wildlife protected but allowances are made for people to use the land sustainably.
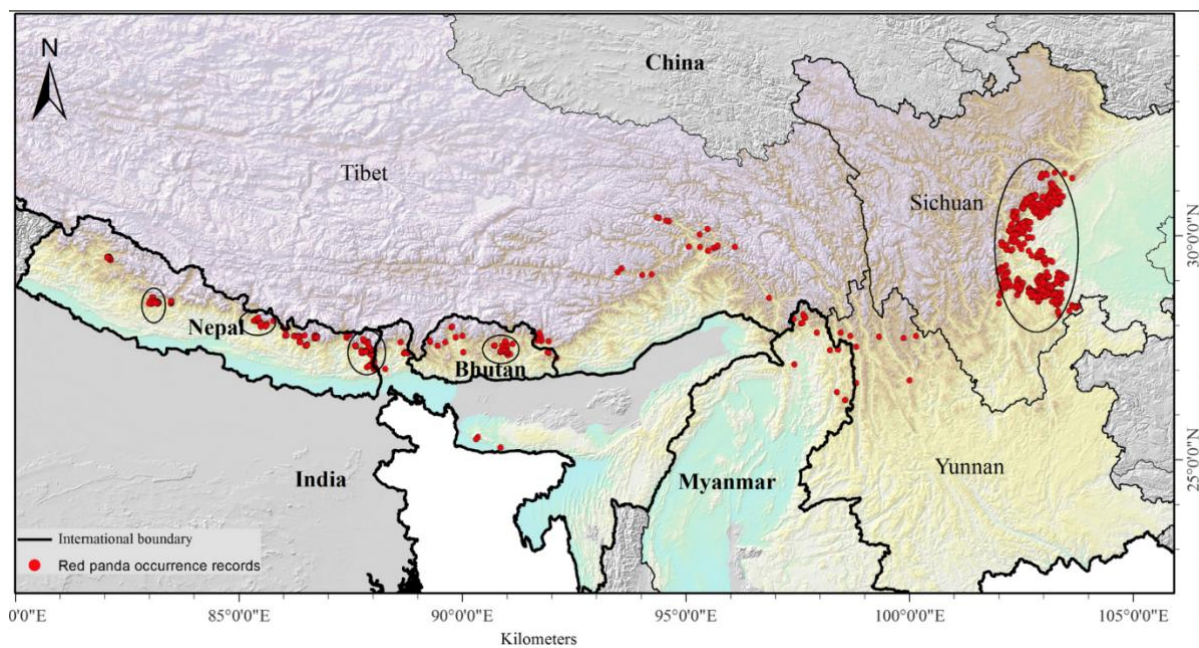
Appendix 5. All known occurrence records of red pandas. Figure from Thapa *et al* 2018b.

Appendix 6. GEE script for RQ1. A link to the code:
https://code.earthengine.google.com/9b3def6e9ca4568bc3516a751147af63

```
////////////////////////////////////////////////////////////
///////// This script is for calcuating forest ////////
///////// loss in red panda habitat classes /////////
///////// per country from 2000-2018.      /////////
///////// Cameron Cosgrove;                /////////
///////// last edited 9-4-19               ////////
////////////////////////////////////////////////////////////


//////// LOAD FILES ///////////////////////////////////////////

//load habitat classes polygons from Cameron's Assets
Map.addLayer(core_habitat, {}, "core habitat");
Map.addLayer(low_habitat, {}, "low habitat");
Map.addLayer(moderate_habitat, {}, "moderate habitat");

// Make a collection of red panda geoms.
var all_habitat = ee.FeatureCollection([
  ee.Feature(core_habitat, {name: 'Core Habitat'}),
  ee.Feature(moderate_habitat, {name: 'Moderate Habitat'}),
  ee.Feature(low_habitat, {name: 'Low Suitability Habitat'})
]).flatten();

// Load country boundaries from LSIB.
var countries = ee.FeatureCollection('USDOS/LSIB_SIMPLE/2017');

        // Define Country(s) of interest here \/

//// Get a feature collection with just the wanted country feature.
var country = countries.filter(ee.Filter.or(
  ee.Filter.eq('country_na', 'China'),
  ee.Filter.eq('country_na', 'India'),
  ee.Filter.eq('country_na', 'Bhutan'),
  ee.Filter.eq('country_na', 'Burma'),
  ee.Filter.eq('country_na', 'Nepal')));  // <- Here insert Country Name
 var china_sub = china_sub; // or define your on area of interest. national
//parks for example

        // Define Country(s) of interest here /\


// Get the loss image from the latest hansen dataset.
var gfc= gfc;
//set the scale defined by hansen import
var scale = gfc.projection().nominalScale();
// pick the forest loss band
var lossnomask = gfc.select('loss').eq(1);
var noloss = gfc.select('loss').eq(0);
// create gain band too
var gain = gfc.select('gain').eq(1);
// Get the loss year images
var lossYear = gfc.select(['lossyear']);
//Get tree cover 2000 layer
var treecover = gfc.select(['treecover2000']);
```

```
// Denine a new layer as forest (canopy 20% - 100%) and make it it either forest (1)
//or no forest (0)
var treecover2000 = treecover.gte(20).eq(1);
var treecover2000mask = treecover.gte(20).eq(1);
// print(treecover);
// Map.addLayer(treecover2000,{}, "Forest layer");

var loss = lossnomask.updateMask(treecover2000mask);
Map.addLayer(loss, {}, 'loss');




/////////////////////////////////////////////////////////////////
/////////// Forest Loss ////////////////////////////
/////////////////////////////////////////////////////////////////


//Filter the habitat class by the country of interest
var intersection_country = all_habitat.filterBounds(country).filterBounds(country);
Map.addLayer(intersection_country, {}, 'int');


//clip the loss image by the defined habitat class in the defined country
var lossintest_country = loss.clip(intersection_country);


//calculate pixel area (nominal scale) and convert m2 -> km2
var areaImage_country =lossintest_country.multiply(ee.Image.pixelArea());
var areaImage_country_km = areaImage_country.divide(1000 * 1000);



/// Gain to loss ratio ///

//GAIN: only shows total cumulative gain from 2000 to 2013
//clip the gain image by the defined habitat class in the defined country
var gainintest_country = gain.clip(intersection_country);

//calculate pixel area (nominal scale) and convert m2 -> km2
var areaImage_country_gain = gainintest_country.multiply(ee.Image.pixelArea());
var areaImage_country_km_gain = areaImage_country_gain.divide(1000 * 1000);
// Sum the values of loss pixels within panda habitat in the selected country.
var stats_gain = areaImage_country_km_gain.reduceRegion({
  reducer: ee.Reducer.sum(),
  geometry: all_habitat,
  scale: 30,
  maxPixels: 1e9
});
print('area of forest gain in km2: ', stats_gain.get('gain'));

/// NOW divide output by the cumulative area of loss up to 2013.




///// % Forest Loss Calcualtion ///////
//There are areas within polygons that are not forested and are not panda habitat.
//I want the area of forest in 2000 within each habitat class to compare %loss.
```

```
// clip my forest cover by the class in the defined country
var treecover_in_habitat = treecover2000.clip(intersection_country);

Map.addLayer(treecover_in_habitat, {}, 'treecover'); // Check it works
// Get area in km2
var cover_area = treecover_in_habitat.multiply(ee.Image.pixelArea());
var cover_area_km = cover_area.divide(1000 * 1000);
// Reduce to sum in geometry
var cover_stats = cover_area_km.reduceRegion({
  reducer: ee.Reducer.sum(),
  geometry: all_habitat,
  scale: 30,
  maxPixels: 1e9
});
print('Treecover area in all Suitability Habitat: ', cover_stats.get('treecover2000'));




//////// Low LOSS per year /////////////

//Reduce with lossYear as a group
var lossByYear = areaImage_country_km.addBands(lossYear).reduceRegion({
  reducer: ee.Reducer.sum().group({
    groupField: 1
    }),
  geometry: all_habitat,
  scale: 30,
  maxPixels: 1e9
});

// Format and print as list (code from hansen tutorial)//
var statsFormatted = ee.List(lossByYear.get('groups'))
  .map(function(el) {
    var d = ee.Dictionary(el);
    return [ee.Number(d.get('group')).format("20%02d"), d.get('sum')];
  });
var statsDictionary = ee.Dictionary(statsFormatted.flatten());
print(statsDictionary);



// Make Loss Chart to make sure things are working. Does this look reasonable
var chart = ui.Chart.array.values({
  array: statsDictionary.values(),
  axis: 0,
  xLabels: statsDictionary.keys()
}).setChartType('ScatterChart')
  .setOptions({
    title: 'Yearly Forest Loss in All habitat',
    hAxis: {title: 'Year', format: '####'},
    vAxis: {title: 'Area (square km)'},
    legend: { position: "none" },
    lineWidth: 1,
    pointSize: 3
  });
print(chart);
```

```
//Export yearly loss of habitat class
var year_fc = ee.FeatureCollection(ee.Feature(null, statsDictionary))
Export.table.toDrive({
  collection: year_fc,
  description: 'yearly_forest_loss_in_india'}); // <------ Change Name Here
```

Appendix 7: GEE script for RQ2.
A link to the code: https://code.earthengine.google.com/871e96c7c6488d6a10b4dfc3d6800250

```
///////////////////////////////////////////////////////////////////////////////////////////
///////// This script maps the % forest loss in 1km across      /////////
///////// red panda habitat from 2000-2018. Sample data is  /////////
///////// also gathered in this script                          /////////
///////// by Cameron Cosgrove; last edited 24-4-19              /////////
///////////////////////////////////////////////////////////////////////////////////////////

//Land mask
var land =gfc.select('datamask').gte(1);


//Add a buffer area around broad panda habitat area for visualisation
// Map a function over the collection to buffer each feature.
var buffered = habitat_outline.map(function(f) {
  return f.buffer(5000); // Note that the errorMargin is set to 100.
});


//////Make a geom representing all habitat //////
var all_habitat = ee.FeatureCollection([
  ee.Feature(core, {name: 'Core Habitat'}),
  ee.Feature(moderate, {name: 'Moderate Habitat'}),
  ee.Feature(low, {name: 'Low Suitability Habitat'})
]).flatten();
// Load country boundaries from LSIB.
var countries = ee.FeatureCollection('USDOS/LSIB_SIMPLE/2017');

         // Define Country(s) of interest here \/

//// Get a feature collection with just the wanted country feature.
var country = countries.filter(ee.Filter.or(
  ee.Filter.eq('country_na', 'Bhutan'),
  ee.Filter.eq('country_na', 'India'),
  ee.Filter.eq('country_na', 'Nepal'),
  ee.Filter.eq('country_na', 'Burma'),
  ee.Filter.eq('country_na', 'China'))); // <- Here insert Country Name
//var country = meghalaya_test_area; // or define your on area of interest. national
//parks for example
```

```
//Make it a geometry
var country2 = ee.Geometry(country);

var habitat_feature = ee.FeatureCollection(habitat_outline);

////// LOAD GFC DATA
var treecover = gfc.select(['treecover2000']);
// Denine a new layer as forest (canopy 1% - 100%) and make it it either forest (1)
//or no forest (0)
var loss = gfc.select(['loss']).eq(1).clipToBoundsAndScale({
  geometry: buffered,
  scale: 100
});
var treecover2000 = treecover.gte(20).eq(1).rename("over_20_pc_canopy_cover");
print(treecover2000);
//Map.addLayer(treecover2000,{}, "Forest layer");
// make the loss image show loss in canopy cover >20 %
var loss20percentcover = loss.updateMask(treecover2000);
//Map.addLayer(loss20percentcover,{}, "loss20percentcover");

//Load elevation data
var elevation = DEM.select('elevation');




/// Define a 1km2 Kernal around each pixel for resampling

var circle = ee.Kernel.circle({ radius: 564,
                    units: 'meters',
                    normalize: true});

/// Make a map that reduces the forest loss data to show % cover for 1km2
var map = loss20percentcover.reduceNeighborhood(ee.Reducer.mean(), circle);

// Clip to aoi and define scale to stop EE from reducing pixels differently
// at differnet zoom levels of the scale pyrimid
var map_sample = map.clipToBoundsAndScale({
  geometry: buffered,
  scale: 30  //Scale of 30 to reflect gfc dataset native scale
});



// ////// Set a colour style to show low disturance and high disturbance


// Define an SLD style of discrete intervals to apply to the image.
var sld_intervals =
  '<RasterSymbolizer>' +
   '<ColorMap  type="intervals" extended="false" >' +
    '<ColorMapEntry color="#BFEFFF" quantity="0" label="0.01"/>' +
    '<ColorMapEntry color="#8470FF" quantity="0.001" label="0.001" />' +
    '<ColorMapEntry color="#FFFF00" quantity="0.1" label="0.1" />' +
    '<ColorMapEntry color="#FFD700" quantity="0.3" label="0.3" />' +
    '<ColorMapEntry color="#EE6AA7" quantity="0.6" label="0.6" />' +
    '<ColorMapEntry color="#EE0000" quantity="1" label="1" />' +
   '</ColorMap>' + '</RasterSymbolizer>';
```

```
// apply the custom palette to the map and fix scale again (important!)
var custom_map = map_sample.sldStyle(sld_intervals).clipToBoundsAndScale({
  geometry: buffered,
  scale: 30
});
var vis_map = custom_map.clip(buffered);
Map.addLayer(vis_map, {}, "figure");
Map.addLayer(custom_map, {}, 'map_vis'); // It will exceed EE capacity if you view this at too
large a scale.
// Zoom in to see data

//print to check the script is working properly
print(custom_map);


////////////// SAMPLING FOREST LOSS /////////////////////////////////

/////////// Add random points in habitat ///////////

var rand_points = ee.FeatureCollection.randomPoints(all_habitat, 5000, 42);
//Seed is 42 incase someone wants to exactly recreate my resutls
//Remove points that fall into no forest in R

//////// Here I am adding in my explanatory variable as an image band so they canbe easily
extracted.
// Countries
var india_image = land.clipToCollection(countries.filter(ee.Filter.or(
  ee.Filter.eq('country_na', 'India')))).rename("India");
var burma_image = land.clipToCollection(countries.filter(ee.Filter.or(
  ee.Filter.eq('country_na', 'Burma')))).rename("Burma");
var bhutan_image = land.clipToCollection(countries.filter(ee.Filter.or(
  ee.Filter.eq('country_na', 'Bhutan')))).rename("Bhutan");
var nepal_image = land.clipToCollection(countries.filter(ee.Filter.or(
  ee.Filter.eq('country_na', 'Nepal')))).rename("Nepal");
var China_main_pop_image = land.clipToCollection(countries.filter(ee.Filter.or(
  ee.Filter.eq('country_na',
'China')))).clipToCollection(china_main_pop).rename("China_main_pop");


// Habitat class
var core_image = land.clipToCollection(core).rename('Core');
var mod_image = land.clipToCollection(moderate).rename('Moderate');
var low_image = land.clipToCollection(low).rename("Low");
var sub_pop_image = land.clipToCollection(sub_pop).rename("sub_species_china");

// protected areas
//load and filter
//Map.addLayer(PA, {}, 'PA');
var IUCN_Ia = PA.filter(ee.Filter.eq('IUCN_CAT', 'Ia'));
var IUCN_Ib = PA.filter(ee.Filter.eq('IUCN_CAT', 'Ib'));
var IUCN_II = PA.filter(ee.Filter.eq('IUCN_CAT', 'II'));
var IUCN_III = PA.filter(ee.Filter.eq('IUCN_CAT', 'III'));
var IUCN_IV = PA.filter(ee.Filter.eq('IUCN_CAT', 'IV'));
var IUCN_V = PA.filter(ee.Filter.eq('IUCN_CAT', 'V'));
var IUCN_VI = PA.filter(ee.Filter.eq('IUCN_CAT', 'VI'));
```

```
//make iamges
var IUCN_Ia_image = land.clipToCollection(IUCN_Ia).rename("IUCN_Ia");
var IUCN_Ib_image = land.clipToCollection(IUCN_Ib).rename("IUCN_Ib");
var IUCN_II_image = land.clipToCollection(IUCN_II).rename("lUCN_II");
var IUCN_III_image = land.clipToCollection(IUCN_III).rename("IUCN_III");
var IUCN_IV_image = land.clipToCollection(IUCN_IV).rename("IUCN_IV");
var IUCN_V_image = land.clipToCollection(IUCN_V).rename("IUCN_V");
var IUCN_VI_image = land.clipToCollection(IUCN_VI).rename("IUCN_VI");


var coords = ee.Image.pixelLonLat();
var myIC = map_sample.addBands(elevation)
  .addBands(coords)
  .addBands(sub_pop_image)
  .addBands(low_image)
  .addBands(mod_image)
  .addBands(core_image)
  .addBands(nepal_image)
  .addBands(india_image)
  .addBands(bhutan_image)
  .addBands(burma_image)
  .addBands(China_main_pop_image)
  .addBands(treecover2000)
  .addBands(IUCN_Ia_image)
  .addBands(IUCN_Ib_image)
  .addBands(IUCN_II_image)
  .addBands(IUCN_III_image)
  .addBands(IUCN_IV_image)
  .addBands(IUCN_V_image)
  .addBands(IUCN_VI_image);


print(myIC);

var points = myIC.select('loss_mean',
                'elevation',
                'longitude',
                'Core',
                'Moderate',
                'Low',
                'India',
                'Burma',
                'Bhutan',
                'Nepal',
                'China_main_pop',
                'sub_species_china',
                'over_20_pc_canopy_cover',
                'IUCN_Ia',
                'IUCN_Ib',
                'IUCN_II',
                'IUCN_III',
                'IUCN_IV',
                'IUCN_V',
                'lUCN_VI')
  .reduceRegions({
  collection: rand_points,
  reducer:ee.Reducer.first()
```

```
  });


Export.table.toDrive({
  collection: points,
  description: 'sample_data',
  fileNamePrefix: 'random_points',
  fileFormat: 'csv'
});


// Define a custom base map for map visulisation

var cams_simple_map_style = [
  {   // Dial down the map saturation.
    stylers: [ { saturation: -100 } ]
  },{ // Dial down the label darkness.
    elementType: 'labels',
    stylers: [ { lightness: 20 } ]
  },{ // Simplify the road geometries.
    featureType: 'road',
    elementType: 'all',
    stylers: [ { visibility: 'off' } ]
  },{ // Turn off road labels.
    featureType: 'administrative.country',
    elementType: 'geometry',
    stylers: [ { visibility: 'on' } ]
  },{ // Turn off road labels.
    featureType: 'landscape',
    elementType: 'all',
    stylers: [ { color: '#FFFFFF' } ]
  },{ // Turn off road labels.
    featureType: 'water',
    elementType: 'all',
    stylers: [ { color: '#FFFFFF' } ]
  },
  { // Turn off all icons.
    elementType: 'labels.icon',
    stylers: [ { visibility: 'off' } ]
  },{ // Turn off all POIs.
    featureType: 'poi',
    elementType: 'all',
    stylers: [ { visibility: 'off' }]
  }
];

Map.setOptions('cams_simple_map_style', {'cams_simple_map_style':
cams_simple_map_style});
```

Appendix 8: R Script for RQ1. Lm_data can be accessed at my Github:
https://github.com/CameronCosgrove/Red-Panda-Hub

```
is_loss_increasing_lm <- lm(measurement ~ Year, data = lm_data)
summary(is_loss_increasing_lm)
```

Appendix 9: R script for RQ2: final_data_2.csv can be accessed at my Github:
https://github.com/CameronCosgrove/Red-Panda-Hub

```
#### Packages ####
library(tidyverse)
library(ggExtra)
library(lme4)
library(ggeffects)
library(stargazer)
library(nlme)
library(multcompView)
library(pgirmess)
library(effects)

#### Filter data ####
modeling_data <- read_csv('R/final_data_2.csv')

tidy_data <- modeling_data %>%
  filter(over_20_pc_canopy_cover == 1) %>%
  filter(habitat_class == "Core" | habitat_class == "Moderate" | habitat_class == "Low") %>%
  filter(country == "China_fulgens" |
        country == "India" |
        country == "Bhutan"|
        country == "Burma" |
        country == "china_styani" |
        country == "Nepal") %>%
  mutate(percent_loss = loss_mean*100) %>%
  mutate(area = percent_loss*1000)


tidy_data[is.na(tidy_data)] <- "none"
tidy_data$habitat_class <- as.factor(tidy_data$habitat_class)
tidy_data$country <- as.factor(tidy_data$country)
tidy_data$longtitude<- as.factor(tidy_data$longtitude)
tidy_data$iucn<- as.factor(tidy_data$iucn)
str(tidy_data)

#### Elevation ####
# Make 0/1 binary dataset with forest loss no forest loss logistic regression

tidy_data$percent_loss[tidy_data$percent_loss>=0.00001] <- "1"
ltidy_data$elevation <- as.numeric(log_tidy_data$elevation)
tidy_data$percent_loss <- as.numeric(log_tidy_data$percent_loss)
logistic_regression <- lm(percent_loss ~ elevation, data = tidy_data, family = binomial)
summary(logistic_regression)

#### IUCN ####
#make a balanced sample
iucn_filter <- tidy_data %>%
```

```
  select(iucn, percent_loss)%>%
  filter(iucn == "IUCN IV" | iucn == "IUCN II" | iucn == "IUCN VI")

write.table(iucn_filter, file="protected.csv",sep=",",row.names=F)

iucn_filter_small <- iucn_fiter[samplwe(1:nrow(iucn_fiter), 170,
                          replace=FALSE),]

write.table(iucn_filter_small, file="170_none.csv",sep=",",row.names=F)

# Import new balanced data set
iucn_data <-  read_csv("data_for_IUCN_areas.csv")
View(iucn_data)
iucn_data$iucn <- as.factor(iucn_data$iucn)

kruskal.test(percent_loss ~ iucn, data = iucn_data)
kruskalmc(percent_loss ~ iucn, data = iucn_data)

#### Country ####
kruskalmc(percent_loss ~ country, data = tidy_data)
kruskal.test(percent_loss ~ country, data = tidy_data)

#### Habitat Class ####
kruskalmc(percent_loss ~ habitat_class, data = tidy_data)
kruskal.test(percent_loss ~ habitat_class, data = tidy_data)
```