Journal of Environmental Management 231 (2019) 397–404

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Mapping and predicting forest loss in a Sumatran tiger landscape from 2002 to 2050

Erin E. Poor[a,*], Yang Shao[b], Marcella J. Kelly[a]

[a] Virginia Tech, Department of Fish and Wildlife Conservation, 100 Cheatham Hall, 310 W. Campus Drive, Blacksburg, VA 24060, USA
[b] Virginia Tech, Department of Geography, 115 Major Williams Hall, 220 Stanger Street, Blacksburg, VA 24060, USA

ARTICLE INFO

Keywords:
Deforestation
Land cover map
Palm oil
Connectivity
Land cover prediction

ABSTRACT

Riau Province in central Sumatra, with its peatland, lowland, and montane forest habitats, was once a stronghold for Sumatran tiger (*Panthera tigris sumatrae)* populations. Today, Riau may have one of the highest deforestation rates in the world and wildlife populations are dwindling, with natural forest now comprising approximately only 18% of the province, mostly contained within protected areas. Agriculture (acacia, rubber, and oil palm) makes up the majority of Riau's land cover and deforestation for the creation of new plantations is rampant. Natural forest and tigers still remain in Bukit Tigapuluh National Park and Rimbang Baling Wildlife Reserve, which remain connected to tiger populations in montane forest on the western edge of Sumatra. In this study, using freely available Landsat imagery and a maximum likelihood classification algorithm, we create land cover maps for central Sumatra from 2002 to 2016. We then use current land cover, elevation, and slope variables to predict changes from forest to plantation from 2016 to 2050 at five year intervals using a multilayer perceptron neural network. Finally, we compare connectivity based on a 100 km distance threshold (based on potential tiger dispersal) across the landscape and across years. Land cover maps had 80–90% accuracy, and we predict forest in Tesso Nilo and the western edge of the study area to be lost by 2050 given current rates of deforestation. Our connectivity analysis shows that Tesso Nilo and the area between Rimbang Baling and Bukit Tigapuluh are important components for maintaining connectivity throughout the study area. Focusing conservation and rehabilitation efforts on forests close to plantations in flat areas, including Tesso Nilo, is necessary to maintain forests and increase connectivity in Riau to ensure future habitat connectivity for survival of tigers and Sumatra's other diverse endemic species.

1. Introduction

Deforestation and modification of natural habitat by human development is one of the main factors driving small isolated global wildlife populations to extinction (Ferreras et al., 2001). Because mammals may be more sensitive to forest disturbance than other taxa worldwide, (Sodhi et al., 2009), they are likely be the most affected by an increase in development, with losses now at unprecedented rates (Pimm et al., 2014). In Southeast Asia alone, estimated losses of 21–48% of mammals are predicted by 2100 (Brooks et al., 1999). Species that are wide-ranging and that exist in low density like many carnivores are often the first to go extinct when habitat is fragmented by development (Beier, 1993; Pimm and Clark, 1996; MacNally and Bennett, 1997).

Carnivore guilds found in Southeast Asia are higher in diversity than on other continents, yet many Asian carnivore species now occur at population sizes too small to fulfill their past ecological functions (Dalerum et al., 2009). As roads and railroads continue to bisect habitat, dams flood habitat, and mines and towns fragment habitats, the overall decrease in habitat and the increased distance among habitat patches will lead to reduced carnivore presence (Crooks, 2002; Mortelliti and Boitani, 2007). Although carnivore presence often correlates with prey abundance, below a certain patch size threshold, use of habitat may completely stop regardless of prey abundance (Mortelliti and Boitani, 2007). In a comparison of a protected area with many small (< 100 ha) patches to one with fewer large (> 400 ha) habitat patches in Thailand, Pattanavibool and Dearden (2002) found the protected area with large patches still contained large mammals that had been extirpated from the more fragmented protected area. Preserving connectivity among isolated patches of habitat during the early stages of degradation is one of the most important factors in conserving endangered carnivore species such as the tiger (*Panthera tigris)* (Carroll et al., 2004).

* Corresponding author.
E-mail address: erinpoor@vt.edu (E.E. Poor).

https://doi.org/10.1016/j.jenvman.2018.10.065
Received 13 March 2018; Received in revised form 17 September 2018; Accepted 18 October 2018

Sumatra holds all of Indonesia's remaining tigers in approximately 88,000 km^2 (Sanderson et al., 2006) but agricultural conversion of tiger habitat has been a growing threat to Sumatran tigers (*P. t. sumatrae*) over the past few decades. In comparison with other tiger habitats across South East Asia, tiger habitat in central Sumatra experienced one of the greatest deforestation rates since 2000 (Joshi et al., 2016). Oil palm was first planted in Sumatra in 1911 (Corley and Tinker, 2003) and there are now approximately 6.1 million ha of oil palm in Indonesia (FAO, 2006). From 1990 to 2005, at least 56% of oil palm expansion replaced forest (Koh and Wilcove, 2008). While tigers have been seen in oil palm, overall, oil palm plantations support fewer than 50% of vertebrate species as primary forests (Danielsen et al., 2009), have lower species richness than disturbed forests, and support fewer species than other types of agriculture (Fitzherbert et al., 2008). Loss of species diversity in oil palm plantations may be due to a loss in structural complexity and plant species richness that occurs when plantations are productive (Chung et al., 2000; Glor et al., 2001; Aratrakorn et al., 2006).

In Indonesia, like many developing countries, funds for habitat protection and enforcement are lacking, and anecdotal evidence and regional national land cover data show a decrease in forest. Tigers have been observed in oil palm plantations, but Sunarto et al. (2012) found that tigers were more likely to use forest than any other land cover type, followed by acacia, oil palm, rubber, and mixed agriculture. Furthermore, Yaap et al. (2016) showed that a wide diversity of mammals use forest remnants outside of national parks or core forest areas, but species richness increased when in larger patches or closer to larger forest blocks. In addition, when compared to forest remnants > 2 km away from core forest, tiger, clouded leopard (*Neofelis diardi*), and leopard cat (*Prionailurus bengalensis*) were all only found in remnant patches within 1 km of core forest, underscoring the importance of accessible natural habitat (Yaap et al., 2016).

While land cover maps have been created for Sumatra and the greater South East Asia region (Gaveau et al., 2009; Miettinen et al. 2012), these maps have been relatively low in resolution (e.g., 800 m and 250 m). In order to more accurately assess loss of tiger habitat in Riau province, we created finer scale land cover maps using Landsat 5, 7, and 8 imagery for 2002, 2010, 2013/14, and 2016, to build on Gaveau et al. (2009) and track changes in potential tiger habitat since the rise of oil palm plantations in the early 2000's. In order to completely assess habitat connectivity, both structural and functional connectivity should be quantified. Structural connectivity may be described as the structure of the habitat with respect to, but independent of, species, while functional connectivity describes the behavioral response of the species or animal to the habitat (Tischendorf and Fahrig, 2000). Although equally or perhaps more important than structural connectivity, we were unable to assess functional connectivity in the current study. As a first step to identifying habitat connectivity for tigers as a whole, here we quantify structural connectivity and predict future habitat connectivity in Riau, using natural forest as a proxy for habitat.

2. Methods

2.1. Study area

Riau Province is in central Sumatra (Fig. 1), bordered on the west by the Barisan mountain range and West Sumatra province, and on the east by peatlands and the South China Sea. Riau's climate is classified in the Koppen-Geiger system as Af, tropical. Average temperature is 27 °C while average rainfall is 2696 mm per year. The network of protected areas in Riau is centered by Tesso Nilo National Park, lowland tropical rainforest. Bukit Tigapuluh National Park is to the southeast of Tesso Nilo and Rimbang Baling Wildlife Reserve is southwest of Tesso Nilo. Both Bukit Tigapuluh and Rimbang Baling are primarily comprised of montane rainforest and may provide connections from the mountainous forests of the Barisan range along western Sumatra to Tesso Nilo and Kerumutan Wildlife Reserve, mostly peast swamp forest, on the eastern side of Riau. Within the Sundaland biodiversity hotspot (Myers et al., 2000), this area still contains endangered and endemic species such as Sumatra tiger, Malayan tapir (*Tapirus indicus*), Sumatran elephant (*Elephas maximus sumatranus*), Sunda clouded leopard (*Neofelis diardi*), and Sunda pangolin (*Manis javanica*).

2.2. Data

We searched for cloud-free Landsat imagery of our study area in the USGS GLOVIS website. Three Landsat scenes were needed to cover our study site. For 2002, we used one image per scene, all from the 2002 dry season. Due to frequent cloud cover in the tropics and smoke cover from slash and burn agricultural practices in Sumatra during the end of the dry season (May–October), images from 2010 were used for the Rimbang Baling and Tesso Nilo scenes, while 2009 and 2011 images were used for the Bukit Tigapuluh scene for the second time step. Similarly, for the third time step, 2013/2014, we used images from 2014 for Tesso Nilo and from 2013 for Bukit Tigapuluh and Rimbang Baling. For the last time step, we used multiple 2016 images to form the Rimbang Baling and Bukit Tigapuluh datasets (Table 1). Therefore, we created land cover maps for four times steps, which varied depending on availability of cloud-free data: 2002, 2009/2010/2011, 2013/2014 and 2016. Land cover was created at 30 m resolution. We created distance to open land and distance to plantation variables using these land cover maps at 30 m resolution. Elevation and slope were derived from ASTER GDEM V2 2011 data (METI and NASA, 2011) at 30 m resolution.

2.3. Land cover mapping

For image preparation, we atmospherically corrected to top of atmosphere reflectance using the Radiometric Calibration tool in ENVI software package. These reflectance bands were then put into the ENVI Fmask tool (Zhu et al., 2015) to identify cloud and shadow. We classified each image separately using a maximum likelihood algorithm. To improve classification accuracy we incorporated a DEM as additional input to classify the 2016 Bukit Tigapuluh scene.

We conducted accuracy assessments for 2013/2014 and 2016 image classifications obtained from ground surveys in March 2015–July 2016. Because teams were surveying for felid scat and signs in forested areas, ground truth points were biased for forest land cover. Although we were able to collect more plantation ground truth points when surveying roads on motorbike, field teams did not feel confident they could safely enter plantations away from roads without being questioned or instigating conflict from plantation workers. After observing low accuracy within the oil palm and bare classes, we shifted the oil palm points 90 m to the west, accounting for collecting ground truth data along roads in plantations and for the low/open ground cover often found along roads in plantations. Since field work began in 2015, field ground truth data were unavailable for 2002, 2009/2010/2011 and 2013/2014. We digitized ground truth points using ArcMap 10.4 for forest, plantations, and open/bare land using visual interpretation of the 2014 image and field knowledge. Using 380–970 points (Table 1) as a reference for all 2013/2014 and 2016 images, we generated error matrices (Supplementary Material). We were unable to assess accuracy for our 2002 and 2009/2010 images due to lack of ground truth data and lack of familiarity with the landscape at this time. Our image classification methods were the same across years, and hence we assume similar accuracy levels from the 2002 and 2009/2010 imagery.

2.4. Land cover prediction

We used IDRISI's TerrSet Land Change Modeler (LCM) (Eastman, 2012) to model land cover change. LCM allows modeling of non-linear relationships between predictor and response variables through its

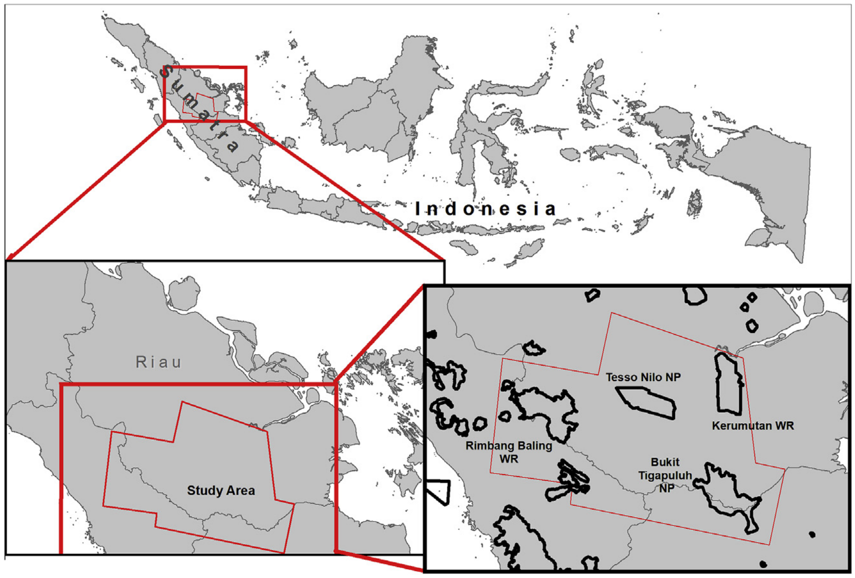

Fig. 1. Location of study area. Study area, which encompasses Tesso Nilo National Park, Rimbang Baling Wildlife Reserve and Bukit Tigapuluh National Park and protected areas of interest within central Sumatra, Indonesia.

multi-layer perceptron neural network algorithm. Additional advantages of LCM include its easy user interface and its multiple accuracy assessment and validation tools (Pontius et al., 2008; Mas et al., 2014). The LCM has also been used to describe changes in tiger habitat elsewhere (Areendran et al., 2017), and has performed well in the tropics (Koi and Murayama, 2010; Fuller et al., 2011; Perez-Vega et al., 2012).

To calibrate the land cover change model, we used the 2002 and 2013 land cover maps. Land cover classes included forest, water, plantation or non-forest vegetation, and open/bare land. We created a deforestation sub-model, to model the transitions of forest to plantation. Predictors were included based on Cramer's V (Table 2) and their potential to impact change on the landscape. Cramer's V is a measure of correlation between two variables, ranging from 0 (no correlation) to 1 (identical variables). Our chosen variables included distance to open areas, distance to plantation, elevation, slope, distance to major roads, and distance to forest. Distance variables were natural log transformed. The land cover variables were selected as dynamic variables that change with changing land cover. Due to the lack of enforcement of protected areas, the high human habitation within the parks and the high human activity in and around parks, we do not include protection status as a variable and we assume that the rate of change inside parks is similar to that outside of officially protected areas. We modeled roads as static variables. Given past trends in Indonesia, and the length of time new infrastructure projects take to complete or even initiate due to bureaucracy, land tenure conflicts, and funding issues, we assume that no new major infrastructure (save for the possibility of the Trans-Sumatra Toll Road, which will largely overlap current roads) will be built within the near future.

Table 2
Overall Cramer's V values for all variables in the transition potential land cover change prediction model, used to predict forest to plantation transitions from 2016 to 2050 in central Sumatra.

Variable	Overall Cramer's V
Distance to 2002 open/bare land (ln)	0.2196
Elevation	0.2095
Distance to 2002 plantations (ln)	0.2056
Distance to major roads (ln)	0.1895
Slope	0.1847
Distance to forest (ln)	0.2039

We used a multi-layer perceptron neural network (MLPNN) to model transition potentials (the simulation portion of our model) with 10,000 cells (50% training and 50% testing) per land cover class and 10,000 iterations. An MLPNN is an assumption-free, machine-learning algorithm used to model non-linear relationships through multiple non-linear algorithms and generalize these relationships with novel data (Gardner and Dorling, 1998). The MLPNN input layer included 6 nodes representing distance to open areas, distance to plantation, elevation, slope, distance to major roads, and distance to forest. The output layer consisted of two output nodes representing two classes of forest to plantation change and persistence forest. Different numbers of nodes (3, 5, and 10) in the hidden layer were tested. The default sigmoid function was used as the activation function. MLPNN weights were automatically updated in the model through the backpropagation training. We modeled forest change from 2013 to 2016 using the modeled transition potentials from 2002 to 2013. To validate the model, we

Table 1
Year of Landsat image used for land cover mapping for each of the three study areas, as well as the accuracy and kappa statistics for 2014 (we were unable to accuracy assess the two earliest time periods). The number of ground truth (GT) points and the percent of ground truth points collected from field work are also reported. If points were not collected from field work, they were digitized using Landsat imagery.

Protected Area	Accuracy 2014	Kappa 2014	% True GT (Total)	Accuracy 2016	Kappa 2016	% True GT (Total)
Tesso Nilo *(2002, 2010, 2014, 2016)*	92.06	0.8986	0% (380)	81.05	0.6992	25% (970)
Rimbang Baling *(2002, 2010, 2013, 2016(2))*	81.59	0.7696	0% (668)	84.38; 82.34	0.8113; 0.7844	19% (576); 23% (467)
Bukit Tigapuluh *(2002, 2009/2011, 2013, 2016(3))*	84.04	0.7809	0% (589)	81.07; 81.24; 86.07	0.7647; 0.7603; 0.8113	34% (693); 35% (673); 47% (499)

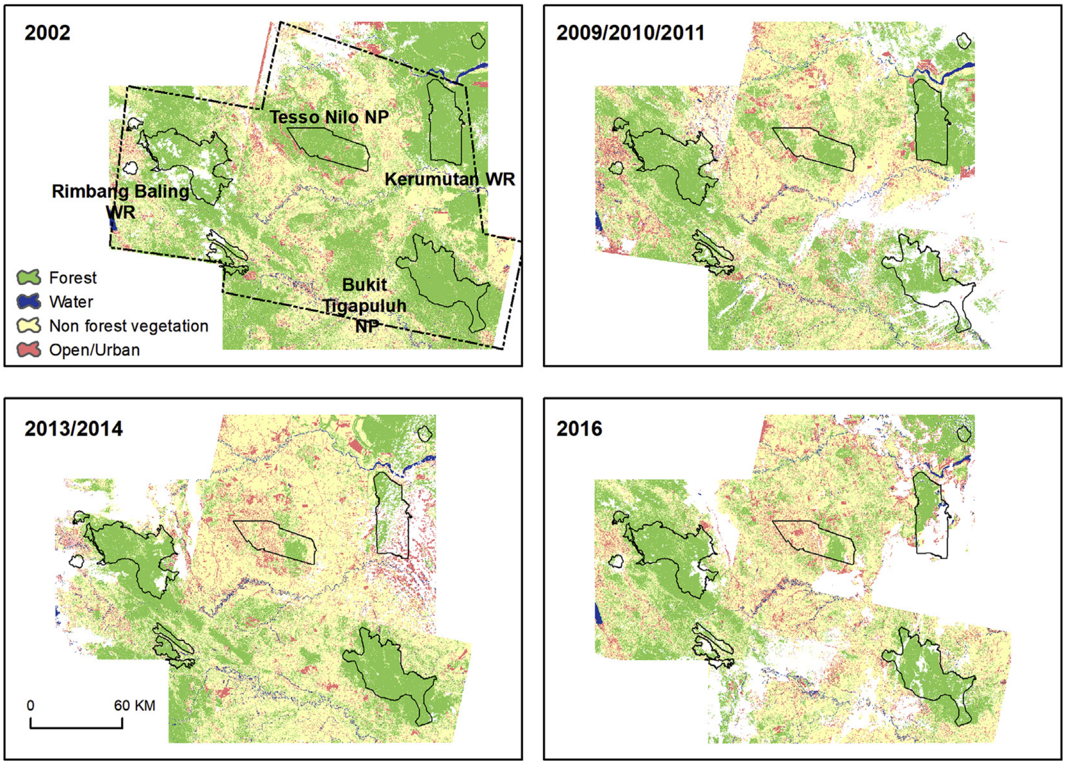

Fig. 2. Land cover maps. Land cover for the larger central Sumatra study area (dotted black line, top left) and focal protected areas, Tesso Nilo National Park, Kerumutan Wildlife Reserve, Bukit Tigapuluh National Park and Rimbang Baling Wildlife Reserve from 2002 to 2016, created using three Landsat scenes, all of which have > 80% accuracy. White areas within the study area indicate cloud cover.

compared the 2016 predicted land cover to the 2016 land cover created using Landsat imagery (for full model information see Supplementary Material). We validated the model using the receiver operating characteristic (ROC) curve, comparing actual 2013–2016 forest to plantation change with the predicted map of 2016 plantations within the previously forested area (Pontius and Schneider, 2001). We then created land cover maps for every five-year interval from 2020 to 2050, with one recalculation stage for each interval. Although the rate of deforestation may not remain constant over time, our model assumes that the rate of change does remain constant. We recognize the rate of change is likely to vary, and as with any predictive modeling, our model uncertainty will be higher for the predictions into the more distant future than it will be for the predictions of the near future. These assumptions are drawbacks of land change modeling and prediction, and we emphasize here that we are predicting land cover under a business-as-usual scenario. See Mas et al. (2014) for a visual depiction of this complete process.

2.5. Habitat connectivity

The simplest method to measure connectivity among habitat patches is to use a Euclidean distance measure (Moilanen and Hanski, 2001), and that is what we use here to describe structural connectivity in this landscape, in the absence of species data. Due to the resolution of our land cover data, we assume ‘habitat’ is forested area. Habitat connectivity measures may be calculated by treating the landscape as a graph of nodes (habitat patches) and links (paths, or distances between habitat patches) (Urban and Keitt, 2001). In identifying specific patches important for maintaining habitat connectivity, we first identified forest patches greater than 0.5 km^2 to increase processing speeds. We then used Conefor Sensinode 2.6 (Saura and Torne, 2009) to calculate the betweenness index (BC) (Bodin and Saura, 2010) and the integral index of connectivity (IIC) (Pascual-Hortal and Saura, 2006) for the actual 2016 landscape and the 2050 predicted landscape to measure the predicted change in structural connectivity of this landscape over time. The improved betweenness index (BC(IIC)) is a measure of node connectivity, and measures the number links in a path passing through a respective patch while taking the patch's area into account (Bodin and Saura, 2010). Shorter paths indicate higher connectivity and are given a higher weight. A patch with a high BC(IIC) can be considered better connected than a patch with a low BC(IIC) measurement. While many habitat connectivity metrics are not sensitive to important changes that impact connectivity negatively, the IIC takes patch area, landscape area, and path distances into account, making it sensitive to fragmentation (Pascual-Hortal and Saura, 2006). This metric can also be used as a general measure of habitat connectivity; an increase in IIC indicates an increase in connectivity, whereas a decrease indicates a connectivity decline landscape-wide (Pascual-Hortal and Saura, 2006). Because our aim is to determine whether forest is still connected in this landscape despite human modification with respect to tigers, we used a 100 km distance threshold, assuming this is the approximate maximum distance tigers can disperse in this landscape (Smith, 1993; Wang et al., 2015). With this assumption, forest patches within 100 km of each other are considered connected for tigers, and more distant patches may be connected to each other through a network of intermediate patches if these intermediate patches are located within the 100 km potential dispersal distance with respect to one another, i.e. a single link between two patches can be 100 km, maximum.

3. Results

3.1. Land cover mapping

Our land cover classification accuracies gathered from ground truth and digitized validation points ranged from 81.05% to 92.06%. Land cover mapping in 2016 for Bukit Tigapuluh proved challenging, requiring the use of three Landsat images and elevation data to achieve accuracies in the 80%'s (Table 1). From 2002 to 2016, 34.55% of forest

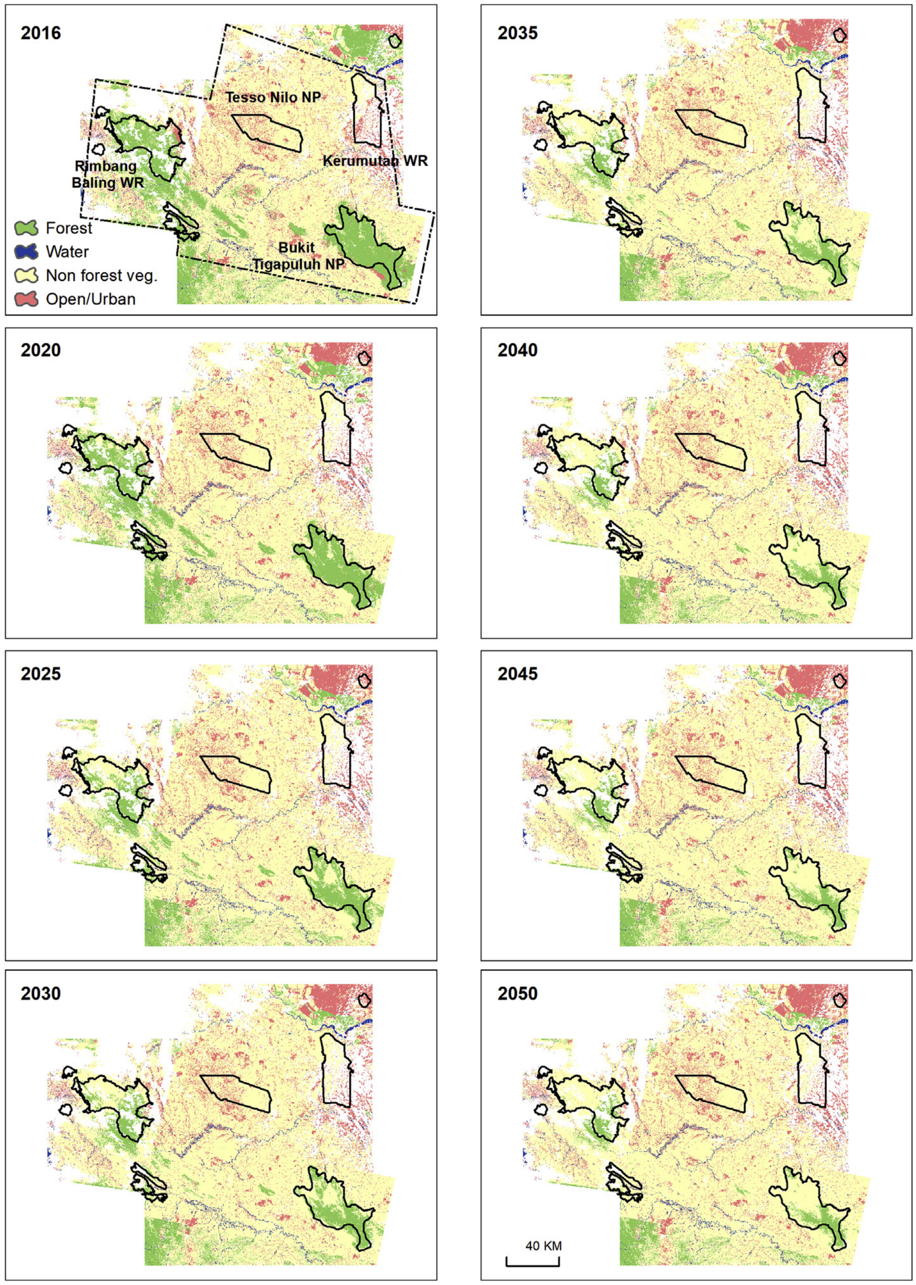

Fig. 3. Land cover predictions. Predictions created using a multilayer perceptron neural network for Tesso Nilo National Park, Kerumutan Wildlife Reserve, Bukit Tigapuluh National Park and Rimbang Baling Wildlife Reserve in Riau, Sumatra, with 2013–2016 used as a validation time period. White areas within the study area (top left; dotted line) are clouds.

has been lost in our study area (Fig. 2).

3.2. Land cover prediction

The MLPNN transition potential model final accuracy rate gathered from validation procedures was 71.75%. Slope was the most influential variable in the model, while distance to forest was least influential. The area under the curve (AUC) for predicted new plantation from forested areas was 68%. The model over-predicted forest loss within Tesso Nilo in comparison with our Landsat-based land cover maps (Fig. 3), with 58.19% of forest predicted to be lost from 2016 to 2050. Small remnant patches of forest seem to remain in Tesso Nilo through 2040, and a small fragment remains through 2050. Our model also under-predicts the amount of forest in Kerumutan, which, despite being surrounded by acacia plantations, does still contain natural peat forests. The most significant losses in forest are predicted to be in the northeast corner of the study area, near Kerumutan, an area rich in peat, and in the forest remnants between Bukit Tigapuluh and Rimbang Baling. In 2050, the models predict forest will remain in Rimbang Baling and Bukit Tigapuluh, presumably due to higher elevation and steeper slopes (Fig. 3).

3.3. Habitat connectivity

Overall, habitat connectivity decreased from 2016 to 2050. In both time periods, all habitat was connected given the 100 km threshold distance (Fig. 4). However, the IIC, a relative measure of habitat connectivity, decreased by nearly 92% (Fig. 4). In 2016, the remaining forest of Tesso Nilo and the forest corridor between Rimbang Baling and Bukit Tigapuluh had the highest BC(IIC), indicating their importance for maintaining connectivity between forest across the landscape.

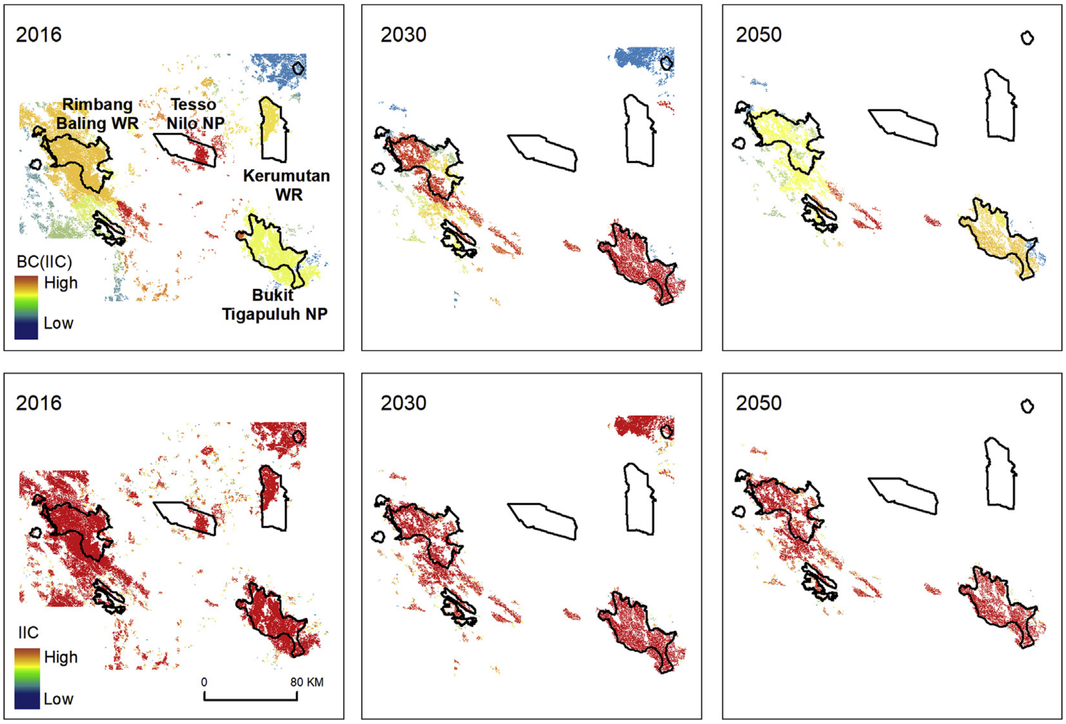

Fig. 4. Landscape connectivity. Two measures of connectivity, betweenness connectivity index (BC(IIC)) (top row) and the integral index of connectivity (IIC), where high values indicate high connectivity, for forest patches $< 0.5\,km^2$ across central Sumatra and a study area including focal protected areas Tesso Nilo National Park, Kerumutan Wildlife Reserve, Bukit Tigapuluh National Park and Rimbang Baling Wildlife Reserve, from 2016 (actual land cover) through 2050 (predicted).

However, in 2050, the forest of Tesso Nilo is lost along with the forest northeast of it, and the remaining patches between Rimbang Baling and Bukit Tigapuluh have the highest BC(IIC) within the landscape.

4. Discussion

The land cover maps that we created as part of this study provide a novel, fine-scale analysis of central Riau's changing land cover since the expansion in palm oil plantations. While we believe that the land cover maps we created from ground truth data are the first accuracy assessed set of maps dating from 2002 to 2016, there is also room for improvement. Validation procedures for land cover change predictions are still debated (Pontius et al., 2004), and typical statistical validation procedures such as k-fold cross validation are insufficient due to the possibility of spatial and land cover class quantity errors (Pontius et al., 2004; Pontius et al., 2008). Improved validation techniques could alter our results. Additionally, distinguishing between natural forest, oil palm plantation, and acacia plantation proves challenging, but was improved with the use of all Landsat bands and in some cases, elevation data. Budgetary restrictions forced us to use freely available, lower resolution Landsat imagery, but our methods are easily repeatable for use in other parts of Sumatra, free of imagery costs, by those wishing to replicate this study. The other challenge we faced when creating the land cover maps included extensive cloud or smoke cover. We attempted to use scenes from the dry season, where cloud cover was less significant, but in some years (2013/2014, 2016), smoke from slash-and-burn land clearing covered significant areas of Landsat scenes. To remedy this, future modelers may incorporate radar data, which can be used regardless of cloud cover.

Our models predict less forest in 2016 than our mapped forest, and they predict a rapid decrease in forest of Kerumutan, to the northeast of Tesso Nilo. This may be due to the inaccuracies of the input land cover map. Distinguishing between acacia and natural forest proved difficult, and we believe our maps may have slightly overestimated the amount of acacia near Kerumutan. While there is a substantial amount of acacia forest in this area, future transitions of additional forest may be slow due to the alteration and draining of the land in this particular area that is required before a first planting. The over-prediction of forest loss may also be attributed to a possibly higher deforestation rate from 2002 to 2013 (used for model calibration) than observed from 2013 to 2016 (model validation). Future work could focus on incorporating socio-economic drivers of land cover change such as the price of palm oil and land tenure regulation enforcement efforts, and could include a sensitivity analysis by adjusting deforestation rates during calibration to compare potential changes to model outputs.

Although all patches are connected under the 100 km distance threshold, (used as a 'best-case' maximum movement distance for tigers), this assumes that wildlife moves from one habitat patch in a straight line to the next closest as they move about the landscape. However, in reality, this may not be true and wildlife may not move directly from one patch to the next closest patch, thus making the distance or effort to travel between forest patches greater. In these cases, the entire landscape may not be 'connected', as our connectivity indices show, under the 100 km distance threshold chosen for this landscape, and wildlife may struggle to move from forest patch to forest patch. While identifying changes in forest structural connectivity is an important first step, identifying functional connectivity of endangered species in this landscape is possibly even more important in informing conservation decisions. Our future work will focus on combining species data with this spatial data analysis to better inform conservation and management by identifying current, and creating future, corridors to enhance Sumatran tiger and other endangered and endemic felid populations.

Despite some minor inaccuracies in our model, it is still clear that if current land clearing practices continue in Riau, we stand to lose a significant amount of forest cover, which could negatively impact critically endangered and endemic wildlife that still exists in this highly modified landscape. This straightforward analysis highlights the need for immediate conservation interventions. Tesso Nilo has already lost > 50% of its natural forest since 2002, and our results could be used as a worst-case scenario of forest loss, assuming the current deforestation laws in Indonesia become better enforced and deforestation slows in the future.

Generally, our model accuracies are relatively high, and, since these are the first accuracy-assessed land cover maps and the first land cover prediction maps created for Riau, we believe they can provide useful guidance to land cover management and valuable insights for areas most vulnerable to forest loss. Our models indicate that clearing for plantations is most likely to happen in flat, lowland areas near areas that are already plantations. The remaining forest within Tesso Nilo meets these prerequisites, which, when combined with its importance in maintaining landscape-wide connectivity, as a potential stepping-stone for wildlife moving from the western edge of Riau to the peatlands of the northeast, makes it a critically important patch of forest to protect. We also recommend focusing efforts on the remaining forest patches between Rimbang Baling and Bukit Tigapuluh to maintain north-south connectivity between these two mountainous protected areas that are likely to persist into the future.

Given the amount of deforestation that has already occurred within this landscape, we stress the potential role that reforestation and restoration could play in this landscape. Average forest patch size in 2016 of patches > 0.5 km^2 was just above 11 km^2. With a home range requirement of around 100 km^2 (Sunarto et al., 2012), tigers in our study area are likely already facing a habitat deficit, further supported by an observed increase in wildlife conflict in this and neighboring provinces. Tesso Nilo has already lost more than half of its forested area, and it currently is not large enough by itself to maintain one tiger, let alone a tiger population. Tigers occasionally are reported by villagers in this area and continued human population growth could lead to conflict echoing that plaguing the resident Sumatran elephant population. Restoring some areas to a forested state would provide additional habitat and potentially could mitigate or decrease future conflicts. We recommend restoring Tesso Nilo to forest, though we also recognize the social and political challenges that would accompany any restoration efforts.

Tracking deforestation and identifying areas for mitigation is extremely important throughout the tiger range, but this is just one piece of the puzzle in achieving the ‘Tx2’ goal of doubling the wild tiger population by 2022, put forth by the St. Petersburg Declaration in 2010. Many tiger landscapes are also experiencing high and/or increased poaching and hunting levels or pressure from more organized poaching syndicates targeting tigers or prey (Risdianto et al., 2016). If these large international, social, and legal issues are not addressed, conservation of habitat is futile. While there are countless scientists and non-governmental organizations working towards tiger conservation and Tx2, sustaining and increasing tiger populations by acting on conservation recommendations remains the responsibility of local and national governments. We hope this work highlights the urgency of the situation of forest loss in Riau and that it better informs those working on the ground as to where best to focus conservation efforts.

Declarations of interest

None.

Funding

This work was supported by the National Science Foundation [Grant Number 1536323], the Philadelphia Zoo, the Cleveland Zoo, and the Fulbright U.S. Student Program.

Acknowledgements

This work was supported by the Cleveland Zoo, the National Science Foundation, the Philadelphia Zoo, the Riverbanks Zoo, US Student Fulbright Program, Virginia Tech, the World Wildlife Fund, the Indonesian Ministry of Research, Technology and Higher Education, and the Ministry of Forestry and Environment. We would like to thank MA Imron, FA Widodo and Sunarto for their support and advice, E Frimpong on comments to improve this manuscript, and A Fardhila, Ata, Awir, Ben, D Susanto, Erizal, E Pajaitan, Gebo, R Wibowo, Tugio and Zulfahmi for their tireless dedication to conservation and hard work in the field.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2018.10.065.

References

Aratrakorn, S., Thunhikorn, S., Donald, P.F., 2006. Changes in bird communities following conversion of lowland forest to oil palm and rubber plantations in southern Thailand. Bird. Conserv. Int. 16 (1), 71–82.
Areendran, G., Raj, K., Mazumdar, S., Sharma, A., 2017. Land use and land cover change analysis for Kosi River wildlife corridor in Terai Arc Landscape of Northern India: implications for future management. Trop. Ecol. 58 (1), 139–149.
Beier, P., 1993. Determining minimum habitat areas and habitat corridors for cougars. Conserv. Biol. 7, 94–108.
Bodin, O., Saura, S., 2010. Ranking individual habitat patches as connectivity providers: integrating network analysis and patch removal experiments. Ecol. Model. 221, 2393–2405.
Brooks, T.M., Pimm, S.L., Kapos, V., Ravilious, C.A., 1999. Threat from deforestation to montane and lowland birds and mammals in insular south-east Asia. J. Anim. Ecol. 68, 1061–1078.
Carroll, C., Noss, R.F., Pacquet, P.C., Schumaker, N.H., 2004. Extinction debt of protected areas in developing landscapes. Conserv. Biol. 18, 1110–1120.
Chung, A.Y.C., Eggleton, P., Speight, M.R., Hammond, P.M., Chey, V.K., 2000. The diversity of beetle assemblages in different habitat types in Sabah, Malaysia. Bull. Entomol. Res. 90 (6), 475–496.
Corley, R.H.V., Tinker, P.B., 2003. The Oil Palm. Wiley-Blackwell.
Crooks, K.R., 2002. Relative sensitivities of mammalian carnivores to habitat fragmentation. Conserv. Biol. 16, 488–502.
Dalerum, F., Cameron, E.Z., Kunkel, K., Somers, M.J., 2009. Diversity and depletions in continental carnivore guilds. Implications for prioritizing global carnivore research. Biol. Lett. 5, 35–38.
Danielsen, F., Beukema, H., Burgess, N.D., Parish, F., Bruhl, C.A., Donald, P.F., Murdiyarso, D., Phalan, B., Reijnders, L., Struebig, M., et al., 2009. Biofuel plantations on forested lands: double jeopardy for biodiversity. Conserv. Biol. 23 (2), 348–358.
Eastman, J.R., 2012. IDRISI Selva. Clark University, Worcester, MA.
Ferreras, P., Gaona, P., Palomares, F., Delibes, M., 2001. Restore habitat or reduce mortality? Implications from a population viability analysis of the Iberian lynx. Anim. Conserv. 4, 65–274.
Fitzherbert, E.B., Struebig, M.J., Morel, A., Danielsen, F., Bruhl, C.A., Donald, P.F., Phalen, B., 2008. How will oil palm expansion affect biodiversity? Trends Ecol. Evol. 23, 538–545.
Food and Agriculture Organization of the United Nations, 2006. Global Forest Resources Assessment 2005. FAO.
Fuller, D.O., Hardiono, M., Meijaard, E., 2011. Deforestation projections for carbon-rich peat swamp forest of Central Kalimantan, Indonesia. Environ. Manag. 48, 436–447.
Gardner, M.W., Dorling, S.R., 1998. Artificial neural networks (the multilayer perceptron) – a review of applications in the atmospheric sciences. Atmos. Environ. 32, 2627–2636.
Gaveau, D.L.A., Epting, J., Lyne, O., Linkie, M., Kumara, I., Kanninen, M., 2009. Evaluating whether protected areas reduce tropical deforestation in Sumatra. J. Biogeogr. 26, 2165–2175.
Glor, R.E., Flecker, A.S., Benard, M.F., Power, A.G., 2001. Lizard diversity and agricultural disturbance in a Caribbean forest landscape. Biodivers. Conserv. 10 (5), 711–723.
Joshi, A.R., Dinerstein, E., Wikramanayake, E., Anderson, M.L., Olson, D., Jones, B.S., Seidensticker, J., Lumpkin, S., Hansen, M.C., Sizer, N.C., et al., 2016. Tracking changes and preventing loss in critical tiger habitat. Sci. Adv. 2 (e1501675), 1–8.
Koh, L.P., Wilcove, D.S., 2008. Is oil palm agriculture really destroying tropical biodiversity? Conserv. Lett. 1 (2), 60–64.
Koi, D.D., Murayama, Y., 2010. Forecasting areas vulnerable to forest conversion in the Tam Dao national park region, Vietnam. Rem. Sens. 2 (5), 1249–1272.
MacNally, R., Bennett, A.F., 1997. Species-specific prediction of the impact of habitat fragmentation: local extinction of birds in the box-ironbark forests of central Victoria, Australia. Biol. Conserv. 82, 147–155.
Mas, J., Kolb, M., Paegelow, M., Teresa, M., Olmedo, C., Houet, T., 2014. Inductive pattern-based land use/cover change models : a comparison of four software packages. Environ. Model. Software 51, 94–111.
Miettinen, J., Shi, C., Tan, W.J., Liew, S.C., 2012. 2010 land cover map of insular Southeast Asia in 250m spatial resolution. Remote Sens. Lett. 3, 11–20.
Ministry of Economy, Trade, and Industry (METI) of Japan, United States National Aeronautics and Space Administration (NASA), 2011. ASTER GDEM v2. NASA

EOSDIS Land Processes DAAC, USGS Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota. accessed [10 15, 2016], at. https://lpdaac.usgs.gov https://asterweb.jpl.nasa.gov/gdem.asp.
Moilanen, A., Hanski, I., 2001. On the use of connectivity measures in spatial ecology. Oikos 95, 147–151.
Mortelliti, A., Boitani, L., 2007. Interaction of food resources and landscape structure in determining the probability of patch use by carnivores in fragmented landscapes. Landsc. Ecol. 23 (3), 285–298.
Myers, N., Mittermeier, R.A., Mittermeier, C.G., da Fonseca, G.A.B., Kent, J., 2000. Biodiversity hotspots for conservation priorities. Nature 403, 853–858.
Pascual-Hortal, L., Saura, S., 2006. Comparison and development of new graph-based landscape connectivity indices: towards the prioritization of habitat patches and corridors. Landsc. Ecol. 21, 959–967.
Pattanavibool, A., Dearden, P., 2002. Fragmentation and wildlife in montane evergreen forests, northern Thailand. Biol. Conserv. 107, 155–164.
Perez-Vega, A., Mas, J.-F., Ligmann-Zielinska, A., 2012. Comparing two approaches to land use/cover change modelling and their implications for the assessment of biodiversity loss in a deciduous tropical forest. Environ. Model. Softw. 29 (1), 11–23.
Pimm, S.A., Clark, T.W., 1996. Marking sense of the policy process for carnivore conservation. Conserv. Biol. 10, 1036–1045.
Pimm, S.L., Jenkins, C.N., Abell, R., Brooks, T.M., Gittleman, J.L., Joppa, L.N., Raven, P.H., Roberts, C.M., Sexton, J.O., 2014. The biodiversity of species and their rates of extinction, distribution, and protection. Science 344, 1246752.
Pontius Jr., R.G., Huffaker, D., Denman, K., 2004. Useful techniques of validation for spatially explicit land-change models. Ecol. Model. 179, 445–461.
Pontius Jr., R.G., Boersma, W., Castella, J.C., Clarke, K., de Nijs, R., Dietzel, C., Duan, Z., Fotsing, E., Goldstein, N., Kok, K., et al., 2008. Comparing the input, output, and validation maps for several models of land change. Ann. Reg. Sci. 42 (1), 11–37.
Pontius Jr., R.C., Schneider, L.C., 2001. Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. Agric. Ecosyst. Environ. 85, 239–248.
Risdianto, D., Martyr, D.J., Nugraha, R.T., Harihar, A., Wibisono, H.T., Haidir, I.A., Macdonald, D.W., D'Cruze, N., Linkie, M., 2016. Examining the shifting patterns of poaching from a long-term law enforcement intervention in Sumatra. Biol. Conserv. 204, 306–312.
Sanderson, E.J., Forrest, J., Loucks, C., Ginsberg, J., Dinerstein, E., Seidensticker, J., Leimgruber, P., Songer, M., Heydlauff, A., O'Brien, T., et al., 2006. Setting Priorities for the Conservation and Recovery of Wild Tigers: 2005-2015. WCS, WWF, Smithsonian and NFWF-STF.
Saura, S., Torne, J., 2009. Conefor Sensinode 2.2 : a software package for quantifying the importance of habitat patches for landscape connectivity. Environ. Model. Software 24, 135–139.
Smith, J.L.D., 1993. The role of dispersal in structuring the Chitwan tiger population. Beyond Behav. 124 (3/4), 165–195.
Sodhi, N.S., Lee, T.M., Koh, L.P., Brook, B.W., 2009. A meta-analysis of the impact of anthropogenic forest disturbance on Southeast Asia's biotas. Biotropica 41, 103–109.
Sunarto, Kelly, M., Parakkasi, K., Klenzendorf, S., Septayuda, E., Kurniawan, H., 2012. Tigers need cover: multi-scale occupancy study of the big cat in Sumatran forest and plantation landscapes. PloS One 7 (1), e30859.
Tischendorf, L., Fahrig, L., 2000. How should we measure landscape connectivity? Landsc. Connectivity 15, 633–641.
Urban, D.L., Keitt, T., 2001. Landscape connectivity: a graph-theoretic perspective. Ecology 82, 1205–1218.
Wang, T., Feng, L., Mou, P., Wu, J., Smith, J.L.D., Xiau, W., Yang, H., Dou, H., Zhao, X., Cheng, Y., et al., 2015. Amur tigers and leopards returning to China: direct evidence and a landscape conservation plan. Landsc. Ecol. 31 (3), 491–503.
Yaap, B., Magrach, A., Clements, G.R., Mcclure, C.J.W., Paoli, G.D., Laurance, W.F., 2016. Large mammal use of linear remnant forests in an industrial Pulpwood plantation in Sumatra, Indonesia. Trop. Conserv. Sci. 9 (4), 1–13.
Zhu, Z., Wang, S., Woodcock, C.E., 2015. Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsats 4-7, 8, and Sentinel 2 images. Remote Sens. Environ. 159, 269–277.