Deforestation and its impact on land surface temperature: a case study in Wilpattu National Park in Sri Lanka

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Abstract

Deforestation, i.e. the process of conversion from forest to any other land use, represents a threat to biodiversity conservation and climate change mitigation. However, in countries such as Sri Lanka, uncontrolled urbanization is leading to losses in forest cover. Our objectives were to assess the magnitude of deforestation in the west border of the Wilpattu National park (Sri Lanka) using remote sensing methods, and to measure the impact of deforestation on land surface temperature. We used Landsat 5 and 8 images from 2001 and 2018 and performed visual interpretation, NDVI-based, and supervised classification-based analyses to identify the deforested area within this period. We identified a deforested area of 15.3 km2 along a North-South road crossing the studied forest. Moreover, we estimated a mean increase in temperature of 1.3ºC (95% CI 0.6, 2) in the areas in which deforestation occurred, whereas no change in temperature was observed in the rest of the study area. Although our analysis was limited to only two different time points because of image availability, our results are aligned with previous research in the study area and add to the literature by providing evidence on surface temperature changes in a heat-prone country. Efforts to avoid further deforestation in the country are urgent, and remote sensing proves to be a cost-effective way to monitor them.

Keywords: Deforestation; Land Surface Temperature; remote sensing; Sri Lanka.

1. Introduction

Deforestation and forest degradation are the biggest threats to forests worldwide (IUCN). By deforestation we mean the conversion of a forest into a non-forest use, independently on the final land-use, while forest degradation happens when services and goods usually provided by a forest are lost. The 15th United Nations' Sustainable Development Goal mentions that at the current time, 13 million hectares of forests are being lost every year and even though up to 15% of land is currently under protection, biodiversity is still at risk. The reasons behind this phenomenon are various, from timber trade to providing new lands for agriculture and farming, as well as for the exploitation of natural resources by the opening of new mines. Moreover, natural disasters such as fire forests, floods, pathogens and parasites, as well as climate change and wars, have an impact on the current situation of forests worldwide.

The strength and importance of forests lies in the services and goods they provide to both humans and nature. Over 80% of the world's terrestrial biodiversity can be found in forests; the degradation and loss of forests threatens the survival of many species and reduce their ability to provide essential services such as clean air and water, healthy soils for agriculture, and climate regulation (FAO). Other than its role on biodiversity, healthy forests take part to sustainable livelihoods of the world's poorest communities and have a crucial role in climate change adaptation efforts

(IUCN). UN 15^{th} Sustainable Development Goal states that by protecting forests, we will also be able to strengthen natural resource management and increase land productivity. Moreover, the United Nations are not the only ones setting goals in terms of forest protection: the SDGs, together with Aichi Biodiversity Targets, Paris Climate Change Agreement, Land Degradation Neutrality (LDN) and many others, are all aimed to lead the planet towards a sustainable development.

Remote sensing is the use of sensors installed on aircraft or satellites to detect electromagnetic energy scattered from or emitted by the Earth's surface (Vyjayanthi N.,Jha C.S.,2008). It provides a unique opportunity to assess and monitor deforestation with good spatial and temporal coverage and thus provide robust, continuous data with synoptic coverage and multi-temporal data acquisitions. Namely, medium and high resolution optical satellite images such as the Landsat series have been widely used in literature because they provide one of the longest and most consistent satellite records of the land surface, with spatial resolution suitable for monitoring many types of anthropogenic land cover changes.

Sri Lanka is one of 25 biodiversity hotspots in the world and it has the highest biodiversity density in Asia (Mittermeier, 2000). However, the growing population and urbanization developments caused forest cover lost in the country (K.U.H.P.T. Senadeera, D.R. Welikanna, 2017), resulting in loss of biodiversity. It is therefore essential to investigate and identify deforestation to improve forest cover conservation and management. In order to fill the knowledge gap regarding deforestation in Sri Lanka, we investigated 1) the magnitude of deforestation in the west border of Wilpattu National park, Sri Lanka using remote sensing methods, and 2) assessed the impact of deforestation on land surface temperatures.

2. Methods

2.1 Study area (limits of study area)

The Democratic Socialist Republic of Sri Lanka is an island nation with a total land area of 65,610 km2 located in the Indian Ocean just off the southeastern tip of India (Lindström, 2011).

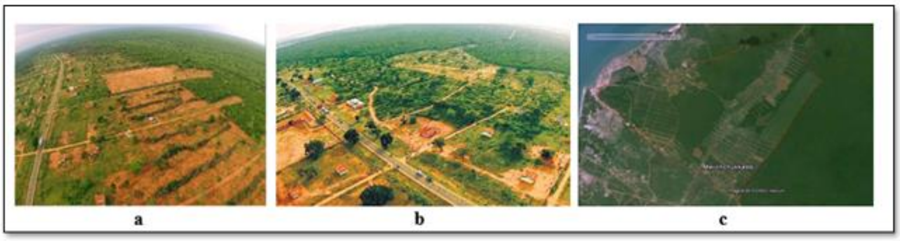

Figure 1: Aerial photos of deforested areas in the study area. Source: News1st (media organization).

As the study area of research, we selected an 18*12 km rectangular area located at the western border of Wilpattu National Park (8.4106° N, 80.0511° E) of Sri Lanka. The selected area covers roughly 220 km2 and is bounded by latitude of 8°31'27"N to 8°41'5"N and longitude of 79°53'42"E to 80°0'26"E.

2.2 Data acquisition and pre-processing

We identified Landsat images from the US Geological Survey EarthExplorer covering the study area with little to no cloud cover over the area of interest. Out of the three possible candidates (2001, 2009, and 2018), we selected the images from 2001-02-09 (Landsat 5 - TM) and 2018-01-07 (Landsat 8 - OLI) corresponding to the period before and after the deforestation event took place. We ordered and downloaded level-2 surface reflectance products. The bands and wavelengths of the two satellites and sensors can be found in the Landsat mission website.

According to the sensors' characteristics, we defined our Minimum Mapping Unit as a pixel of size 30m. Since thermal bands are not processed to level-2, we downloaded Land Surface Temperature (LST) bands corresponding to our selected images from the Remote Sensing Lab of the Foundation for Research and Technology Hellas. Briefly, the research group produced LST products for all Landsat 5, 7, and 8 archive images by applying atmospheric correction to the thermal bands and converting the results to LST using a single channel algorithm, which uses MODIS or ASTER emissivity data in addition to the Landsat data (Parastatidis el al, 2017).

The pre-processing steps we performed included band stacking and cropping to our previously described study area. All products were in WGS 1984 UTM Zone 44N (EPSG: 32644), which we kept as it was suitable for our study area. We produced real and false colour composites to perform visual exploratory analysis of the data and identify potential issues. The results of this step were deemed to be satisfactory and we proceeded to analysis. For LST products, we further processed them to exclude pixels belonging to water (according to classification explained below) as temperature could not be estimated on water surfaces (Parastatidis el al, 2017).

2.3 Analyses

2.3.1 Deforestation assessment based on NDVI

We derived the Normalized Difference Vegetation Index (NDVI) as NDVI=(NIR-Red)/(NIR+Red) for the images in 2001 and 2018, and derived a new raster as the difference as $NDVI_{diff} = NDVI_{2018} - NDVI_{2001}$. We assessed the areas with extreme values in change in NDVI using a statistical approach. Briefly, we classified each pixel based on the number of standard deviations from the mean. This method has the advantage of taking into account the mean differences between time periods occurring in different points in time or vegetation conditions, which a simple visualization of the index difference could mask.

2.3.2 Deforestation assessment based on classification

We used a pixel-based supervised classification to classify each of the two images (2001 and 2018) into 4 land covers (LC) prevalent in our study area: water, forest, bare and built-up, and agriculture. We collected training samples for each of the classes using very-high resolution historic imagery for each of the years available in Google Earth by polygon aerial tracing. We used all available bands available at 30m resolution (six for Landsat 5, seven for Landsat 8). In order to have a glimpse of the spectral signatures of the classes in our training data, we extracted 20 random samples per class and plotted their NIR and Red band values as follows:

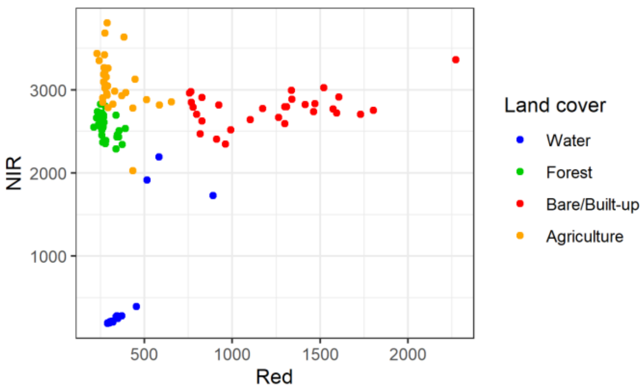

Figure 2: Spectral signatures of random 20 training data pixels per land cover class (2018)

We used Random Forest (RF) models to perform classification based on previous literature indicating the suitability of the RF algorithm for LULC classification problems (Gislason, 2007), as well as based on the fact that our training data did not present a normal distribution. Briefly, the RF algorithm is an ensemble of tree-based CART models that is able to accommodate non-linearities and correlated predictors while generally offering better accuracy that single tree-based models (Gislason, 2007).

With the two models (2001, 2018) we produced LC maps, which were generalised using an 8-pixel majority filter. After, we produced a LC change product by reclassifying the two maps according to the following rules:

1) If LC_{2001} == "Forest" and LC_{2018} == "Forest" ; then "Forest to forest"; otherwise
2) If LC_{2001} == "Forest" and LC_{2018} != "Forest"; then "Forest to other"; otherwise
3) "Other combinations"

We validated our LC change map by applying the following methodology. First, we generated 30 random points per class (90 in total). Second, we assessed the LC types in 2001 and 2018 using visual interpretation of Google Earth historical imagery. Third, we derived the referenced values of land cover change by applying the rule above. Finally, we compared our classified LC change map with the referenced values via a confusion matrix, general accuracy, and producer and user accuracies.

2.3.3 Land surface temperature change according to land cover change

We derived a LST difference layer by subtracting the LST of 2018 and 2001. The resulting raster was centered (i.e. the mean temperature was subtracted) to account for seasonal differences in the two images. In order to assess the change in temperature by LC change type, we generated 30 random points per LC change type and extracted the value from the LST difference band. We plotted the resulting temperatures using boxplots and tested, for each of the LC change types, whether the change in temperature was different than 0 using a two-sided statistical t-test (null hypothesis: mean temperature equal to 0, alternative hypothesis: mean temperature different than 0) with a confidence level of 95%.

2.3.4 Software

All analyses and maps were done in ArcGIS pro 2.4.0, except for the Random Forest modelling (done in R3.6.1 with the "caret" and "RandomForest" packages), non-geographic visualizations and t-tests (done in R3.6.1 with the "ggplot2" package), and the training sample selection and accuracy assessment (done in Google Earth Pro 7.3.2.5776).

3. Results

3.1 Visual interpretation

A first comparison, the true color images for the area in 2001 and 2018 (Figure 3) show that an area of the Wilpattu National Park has been deforested and cleared for the construction of houses (around the center of the image). The event occurred along a dirt road that stretches from a dried up river that crosses from East to West the lands in the Northern part of the image, all the way down to a Southern area with area dedicated to agriculture. The false color composite of figure 3 shows that the deforested area still contains some vegetation. Indeed, when inspected with very-high resolution imagery, it can be seen that much of the deforested area has been replaced by mixed terrain containing houses, bare soil, and sparse vegetation elements such as grass, shrubberies, and small trees.

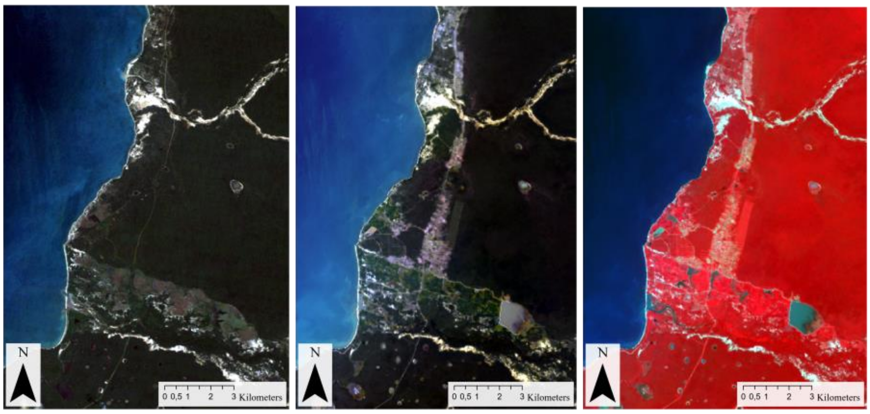

Figure 3: True colour composite of the study area in 2001 (left), 2018 (centre), and false colour composite (R: NIR, G: red, B: green) for 2018 (right).

3.2 NDVI analysis

Figure 4 shows NDVI change results, displaying in red tones areas in which the NDVI decreased from 2001 to 2018, while increases in NDVI are represented in green tones and areas where NDVI has remained fairly stable are represented in yellow. The changes in NDVI are measured in standard deviations (σ) from the mean (μ) of the index.

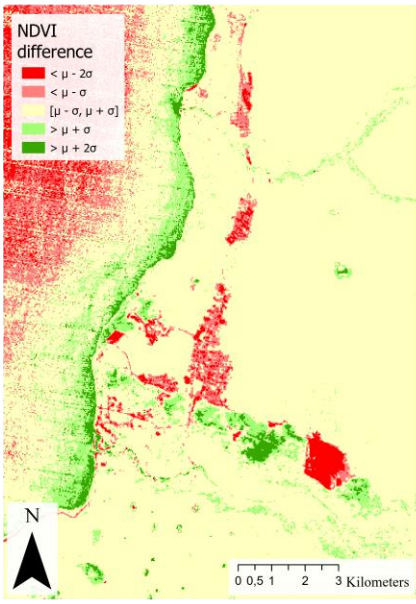

Figure 4: Difference in NDVI between 2018 and 2001.

Figure 4 shows the deforested area in the center and north of the image. We also identified greener patches in a stretch of land in the lower part of the image crossing the land from east to west, representing changes in the agricultural production cycle of that land. It is important to notice that changes in NDVI in areas covered by water can be quite erratic and do not actually reflect changes in vegetation. In our study area these corresponded to the sea (left) and a large red spot on the lower right part of the image that represents a lake area that was dry in the second image in 2018.

3.3 Classification and accuracy assessment

Figure 5 shows the results of the classification and displays the reduction of forested areas in the center of the image in favour of bare/constructed land and agriculture.

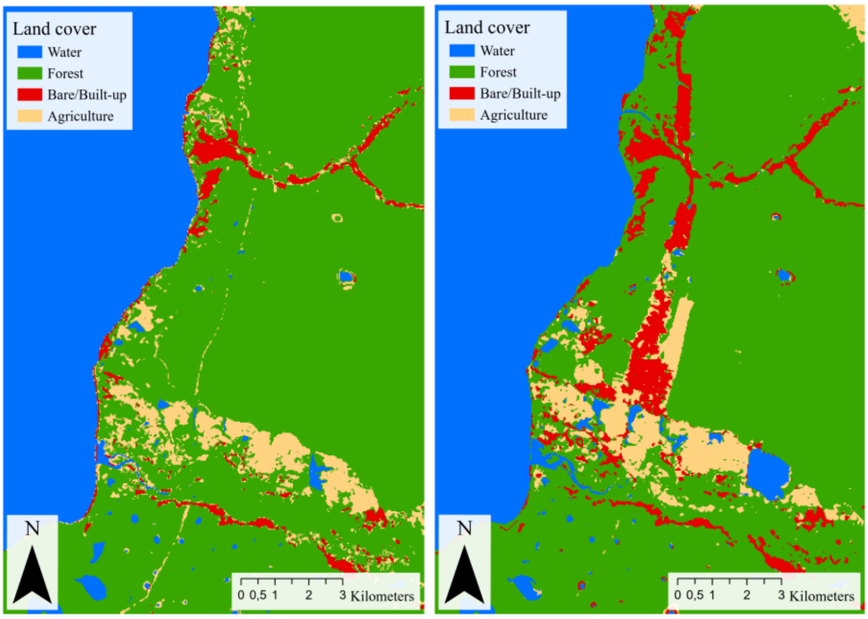

Figure 5: Classification results after generalization for 2001 (left) and 2018 (right).

As table 1 shows, the water and agriculture coverage remained roughly stable. However, figure 5 reveals that the agricultural land slightly changed its location along the study area despite maintaining its rough proportional land cover. It is noticeable that the forested area reduced from 61.2% of the covered area in 2001 to 56.8% in 2018, while bare and built-up lands increased from 2.4% of the study area in 2001 to 5.8% in 2018.

	2001		2018	
	Area (Km²)	**Percentage**	**Area (Km²)**	**Percentage**
Water	68.50	31.1%	70.64	32.1%
Forest	134.86	61.2%	125.03	56.8%
Bare	5.33	2.4%	12.70	5.8%
Agriculture	11.50	5.2%	11.84	5.4%
TOTAL	220.21	100.00%	220.21	100.00%

Table 1: Land cover uses for the year of 2001 and 2018

The confusion matrix with the results of accuracy assessment show an overall accuracy of 85% for the 2018 land cover map (table 2). In general, there is a high user accuracy of around 95% for water, forest and bare soil (of all areas that were covered by water, forest or bare soil, around 95% has been correctly classified). However, the user's accuracy (*U_Accuracy*) of agriculture was quite low: only 56.7%. Forested areas and bare soil were often misclassified as being agricultural land, overestimating the extent of land used for agriculture, which, in turn, reduced the producer's accuracy (*P_Accuracy*) of forest and bare soil areas to 73.7% and 80.6%.

	True Class:					
Classified:	**Water**	**Forest**	**Bare Soil**	**Agriculture**	**Total**	U_Accuracy
Water	29	1	0	0	30	96.7%
Forest	0	28	2	0	30	93.3%
Bare/Built Up	0	1	29	0	30	96.7%
Agriculture	0	8	5	17	30	56.7%
Total	**29**	**38**	**36**	**17**	**120**	
P_Accuracy	100.0%	73.7%	80.6%	100.0%		85.8%

Table 2: Confusion matrix of the accuracy assessment (2018 land cover map)

The change in forest cover according to our reclassification is described in table 3 and figure 6. A 7% of the study area has been deforested, corresponding to an area of 15.3 km2. The largest extent of the study area consists of preserved forest areas, while nearly 39% of the study area was classified as “Other combinations”, a category that predominantly represents areas covered by water, but consists also of bare soil and agriculture.

	Area (Km²)	Percentage
Forest to forest	119.56	54.3%
Forest to not forest	15.31	7.0%
Other combinations	85.34	38.8%
TOTAL	220.21	100.0%

Table 3: Change of landuse between 2001 and 2018

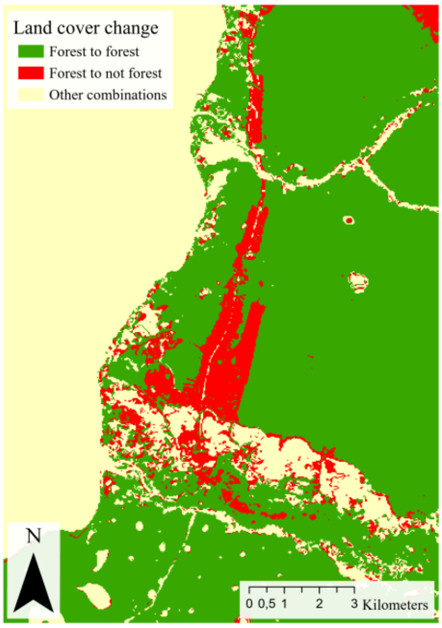

Figure 6: Spatial distribution of change of landuse between 2001 and 2018.

Although the overall accuracy of our change of land cover map (table 4) is high (81%), the user accuracy of deforested areas is quite low with only 50% accuracy, with most of the error coming from misclassifying mostly forested areas as deforested areas. Consequently there is an overestimation of the deforested area, while preserved forests are underestimated. For all other measures, the classification method is very accurate.

Classified:	Forest	Deforested	Other	Total	U_Accuracy
	True Class:				
Forest	30	0	0	30	100.0%
Deforested	12	15	3	30	50.0%
Other	1	1	28	30	93.3%
Total	**43**	**16**	**31**	**90**	
P_Accuracy	69.8%	93.8%	90.3%		81.1%

Table 4: Confusion matrix of the accuracy assessment (land cover change map)

3.4 Land surface temperature analyses

Visual inspection of the change in temperature map (Figure 7) suggests a correlation between positive change in temperatures and deforestation as described in Figure 6. Further statistical analysis of the temperature change by land cover change type reveal an increase in mean temperature of 1.3ºC (95% CI 0.6, 0.2) in deforested areas while the changes in the other categories were not statistically significant different from 0 (p-value > 0.05).

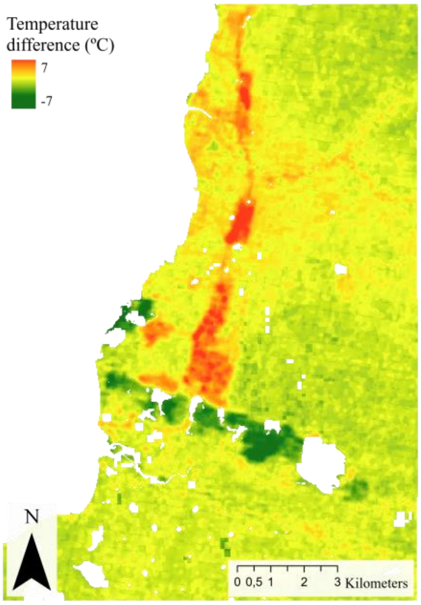

Figure 7: Change in temperature (centered) between 2001 and 2018.

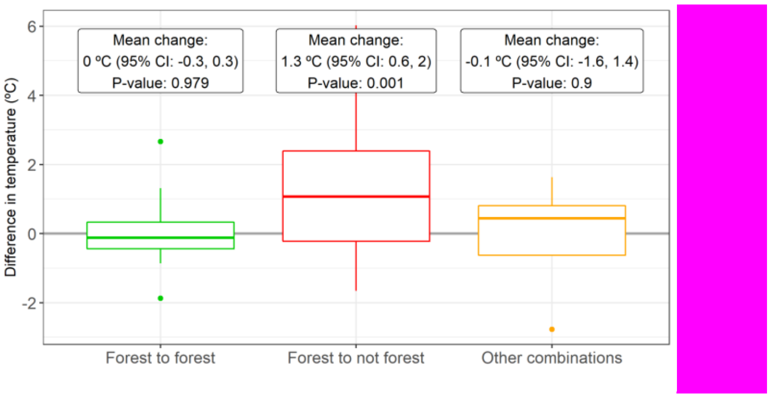

Figure 8: Difference in temperature according to land cover change between 2001 and 2018.

4. Discussion

4.1 Main findings

In accordance to our previously described objectives, during this work we assessed the changes in land cover before and after deforestation as well as the changes in temperature driven by deforestation. We found that the area affected by deforestation from 2001 to 2018 was of 15.3 km2 (7% of the study area). Moreover, areas in which deforestation had mean increase in temperature of 1.3ºC (95% CI 0.6, 2).

4.2 Results from other studies vs. our results

There are two papers investigating deforestation of Wilpattu National Park in Sri Lanka. This subsection will compare the results of those studies with the results produced in this analysis.

Study 1: Deforestation or Reforestation, A Time Series Remote Sensing Perspective of Wilpattu National Park, Sri Lanka, K.U.J. Sandamali, D.R. Welikanna. In this study, a series of Landsat images from 1975 to 2015 were used for analysis. Support vector machine classification and four vegetation indices were applied to the images to detect deforestation. Result of the research showed that there is an intense deforestation with an annual deforestation rate of -0.29% outside the park along the western border. The results of this research are in complete agreement with our findings. This is because the deforested areas delineated in our study were concurrent with the 2015 classification results. However, this study has dealt with a wider study area than ours, so it shows more generalized results.

Study 2: Estimates the Forest Canopy Loss by using Space borne C Band SAR Images, A case study for Wilpattu national park of Sri Lanka, K.U.H.P.T. Senadeera, D.R. Welikanna. The focus of this experiment was to assess the deforestation at Wilpattu National park using Synthetic aperture RADAR data. Methods were based on coherence, correlation coefficient and texture analysis (Gray level co-occurrence matrix- GLCM). Results of the experiment contribute clear support for our research since both studies identify the same area as our study.

4.3 Strengths and limitations

Among the main strengths of our work it is noticeable the analysis of temperature changes, which gains even more importance when considering the lack of such analysis within the already heat-stressed Sri Lanka. Comprehensive accuracy assessment ensures the trustworthiness of our work and we were transparent regarding a few misclassification issues as explained previously. Our study also has limitations. A more thorough and comprehensive study would have been possible by analyzing the changes assessing multiple years creating a time series. Unfortunately, this was not possible given to limitations such as clouds and temperature sensors. We found only 3 images with characteristics necessary for our objectives between 2000 and 2018, which limited us to work only on the chosen dates.

4.4 Conclusions

Our study adds to the current literature by adding new evidence on the deforestation occurring in the western border of Wilpattu National Park in Sri Lanka. Among the consequences of deforestation, we proved that the land use temperatures in deforested areas increase mean surface temperatures. This may have negative impacts to human health in a heat-prone country which are likely to worsen with climate change, as well as to biodiversity in the area. Urgent efforts should be directed to the monitoring and protection of those areas to avoid further uncontrolled deforestation from happening.

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