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Research Paper

Quantifying forest cover changes in response to climate change using a machine learning model

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ABSTRACT: *Anthropogenic factors highly contribute to climate change which affects different forest dynamics devastatingly. A random forest (RF)-based machine-learning model was trained with historical data, including land cover, slope, elevation and aspect, and future data for temperature and precipitation to determine the effect of climate change on Amazon rainforest in Brazil and the Boreal forest in Canada. During the training phase, a coefficient of determination (R^2) scored 0.901 and 0.797 for the Amazonian and Boreal site, respectively. The RF classification model revealed almost the same fate for both zones. According to this study, the representative concentration pathway (RCP) 8.5 model would be more distressing than RCP 4.5 model for both study sites at both 2041–2060 and 2061–2080 periods. According to RCP 8.5, 88% and 42% deciduous species of Amazon and Boreal site will be lost, respectively; more intense and long droughts, followed by lower succession rates and pest attacks, would possibly affect the Boreal region but heavy rainfall in dry areas, prolonged droughts in wetlands and forest fires will destroy tropical Amazonian tree species. Shallow-rooted crops might be more affected by long droughts, but short, heavy rainstorms might facilitate some woody and shrub species in the Canadian Boreal zone.*

KEYWORDS: *Amazon; boreal forest; climate change; machine learning; random forest*

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I. INTRODUCTION

Climate change causes alteration of forest dynamics across the globe. Abiotic (e.g. fire, wind, drought) and biotic (e.g. insects, pathogens) disturbances have increased by more than 28% due to longer warm and dry conditions, which are affecting forest formation (Seidl et al. 2017; Teshome et al. 2020). Based on several general circulation models (GCM) runs, it can be predicted that future high temperatures are likely to bring moderate to severe reductions in precipitation to the Amazon rainforest, followed by significant drying of the forest regionally, which could make it highly prone to fire incidences (Cochrane and Barber 2009; Haghtalab et al. 2020). Furthermore, a model-based study on tropical cloud forests has suggested that less cloud is formed at lower atmospheric levels due to increased air temperatures, which will lead them to suffer drier conditions (Ellison et al. 2017).

Since the early 20th century, primary forests have decreased by 6 million ha annually, 10,000 times faster than in the last glacial period, 21,000 years ago (Kirilenko and Sedjo 2007; Sandel et al. 2011). Moreover, the decrease rate has been the most rapid in the tropical rainforests (Thom et al. 2017; Tang 2019), while the boreal forests face high-velocity biome shifts to avoid higher temperatures and more frequent fire incidences (Beck et al. 2011; Grimm et al. 2013). Nonetheless, it has been found from earlier studies that global vegetation dynamics mainly depend on local climatic conditions; for example, higher temperatures and changes in precipitation patterns are crucial factors in forest cover change in the Amazon Basin.

Tropical forests in the world are rich with diversified tree species. According to Wright et al. (2009) and Colwell et al. (2008), the plant species of tropical forests are more vulnerable to high temperatures because of their lower adaptability to temperature variations (Wright et al. 2009). Associated with temperature, change of precipitation, and soil structure or texture are crucially driving tropical forests to a mono species land (Deb et al. 2014). Meanwhile, research on boreal forests has revealed that high temperatures, followed by droughts, cause higher fire incidences and insect outbreaks (Venalainen et al. 2020). Previous studies have identified fire as the leading cause of damage in boreal forests (Jactel et al. 2012; Hansen, M.C. et al. 2013). Being sensitive to temperature and unprecedented climate warming, the world's boreal forests face a shifting biome problem. Several studies have suggested that the boreal biome's margins will shift northwards towards the current tundra area, and grasslands will replace their southern regions to avoid extreme temperatures (Keret et al. 2020; Pecl et al. 2017; Pautasso et al. 2015; Hansen et al. 2013; Sturrock 2012).

Apart from these studies, most prediction-based research uses machine learning modelling approaches to predict future forest cover, forest ecosystems or species distributions (Pearson and Dawson 2003; Pretzsch et al. 2007). In machine learning studies, selective models are trialled to predict target variables using known predictor variables (Mathew et al. 2017). For example, Pacheco et al. (2010) used a species distribution model to predict the spatial distribution changes of six distinctive tree species in response to climate change in the premontane subtropical forests in South America (Pacheco et al. 2010). Rogan et al. (2008) used three different machine-learning models to predict land cover changes at two sites in California, USA. They found that the neural-networks-based model was the most accurate (Rogan et al. 2008). Other studies have also used machine learning to predict future changes in forest areas over the next decade at national to global scales (d'Annunzio et al. 2015; Reddy et al. 2017).

Machine learning models are used individually or collectively in different studies but verifying the predictions from model-based studies is necessary to demonstrate their validity. For example, Soja et al. (2007) cross-checked the results of a prediction model for landscape change in the boreal zones of Canada, Alaska and Russia using current field observations (Soja et al. 2007). Their field studies supported the predictions from the model.

Another approach using machine learning models is the random forest (RF) classification; this method is usually used to monitor and map large areas to estimate land cover categories or biodiversity changes caused by climate change (Bala et al. 2007). The advantages of the RF classification over other machine-learning models have caused this model to be prioritized for prediction-based studies. Among the benefits of RF, determining important variables, multiple data analysis performances and high classification accuracy is noteworthy (Chan and Paelinckx 2008; Ghimire et al. 2010; Rodriguez-Galiano et al. 2012). In a study on predictive models and modelling techniques, the RF has been proven to have the superior predictive capability in mapping current distributions and future suitable territories for biodiversity (Prasad et al. 2006). One recent machine learning model-based study used a RF model to predict future land cover using spectral-band information from New Mexico and Washington sites (Patil et al. 2017). Their model was able to predict a future land-cover scenario using historical and climate-change data.

Despite the increasing acceptability of model-based studies on future forest distributions, there is a lack of appropriate, rationalized global forest imagery or specific forest area images, hindering forest prediction modelling (Anderegg et al. 2013; Hansen, M. et al. 2013). Few field studies have been undertaken to forecast the future compositional shift of tree species that will result from climate change. Notwithstanding, different model-based studies have been done to quantify the climate change effect on forest productivity. There is a lack of potential explanatory model studies with clear interpretations to inform how far forests will be affected on a large scale due to severe climatic changes. Research on the forest cover of different climatic zones is also necessary for predicting which forest zones will face climate-change effects faster (Bhattacharya 2013; Exbrayat et al. 2017; Pukkala 2017; Albert et al. 2018).

To address this problem, forests had to be selected from different climatic zones where historical, high-resolution land-cover classification data and future climate data was available. Notably, the forests were significantly affected by current climate change rather than direct human interference. The study aimed to assess the relative climate change effects on selected areas of the Amazon and boreal forests by predicting, documenting and comparing the future conditions of these forest areas using an RF classification model for use in future modelling studies and in analyzing the possible eco-physiological processes that would result in the predicted forest cover changes.

II. MATERIALS AND METHODS

2.1 Site description

The Brazilian Amazon rainforest and the other in the Canadian boreal forests were two study sites (Figure 6) considered for this study. These two sites were selected to test our modelling approach against contrasting bioclimatic conditions. Both the sites have multiple types of vegetation cover (Table 2) and almost zero human interference.

The Amazon site is in the East-central region of Para, Brazil, and covers an area of 9551 km2. The Xingu River flows in a North-South direction in the Western part of the site, and the Tapirapé-Aquiri National

Forest is situated in its South Eastern section. The elevation ranges from 18 to 46 m above sea level; the annual mean temperature and precipitation range from 21℃ to 25℃ and 1690 mm to 2400 mm, respectively. The selected site of Amazon is a junction between the rainforest and savannah ecosystems, resulting in a highly diverse landscape that includes evergreen broadleaf forest, woodland, deciduous broadleaf forest and wooded grassland. In addition, a few grassland and cropland areas are also present on the site. The tree species of this area are a mixture of evergreen, seasonal deciduous, palm and rubber. Other prominent families represented across the area include the Chrysobalanaceae, Fabaceae, Annonaceae, Melastomataceae, Moraceae, Sapotaceae, Apocynaceae and Myrtaceae (Morandi et al. 2016). The soil type in this region varies between xanthic and orthic Ferralsols and ferralic Arenosols (FAO 1988; Sombroek 2000).

Our boreal forest site (Figure 6) is situated in the south western part of Canada. It is surrounded by Jasper National Park and Banff National Park, from the east to northeast. The total area covered by the site is 34,708 km2. The elevation ranges from 25 to 194 m from sea level, temperature from 1.4℃ to13.8℃ and precipitation 530 mm to 1730 mm. Evergreen needle leaf forest and mixed forest are the dominant land-cover types (Table 2). Also, woodland, wooded grassland and open shrubland occupy a significant percentage of the area. Among the various evergreen needle leaf and deciduous broadleaf species, black spruce, white spruce, balsam fir, larch (tamarack), lodgepole pine, jack pine, large-toothed aspen, cotton wood, white birch, balsam poplar, trembling aspen and paper birch are significant (Larsen 1980). The soils are mainly Brunisols, enriched in calcium carbonate (Earle 2015).

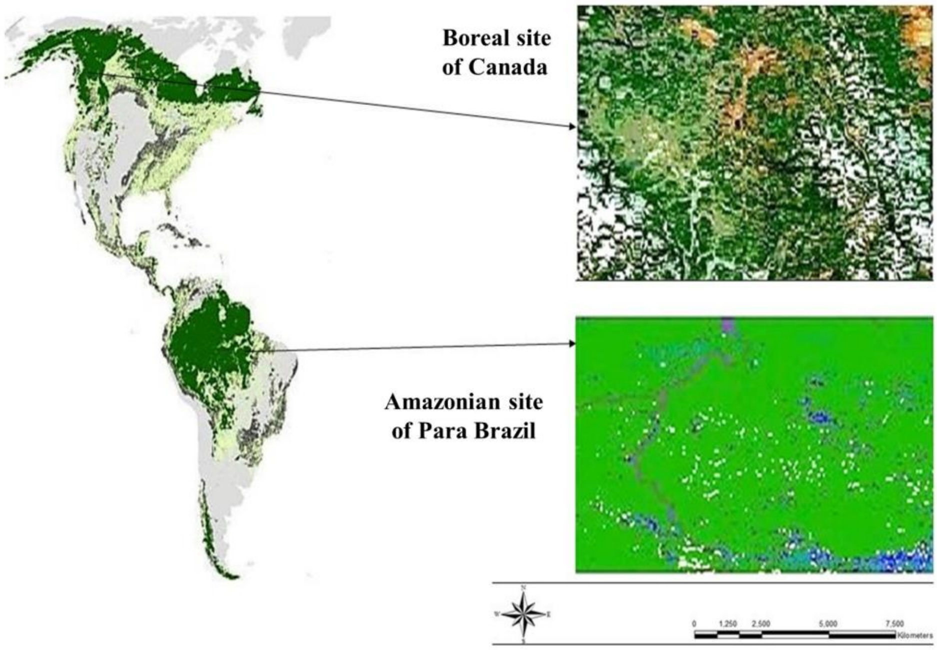


Figure6: location map of study sites (Boreal site of Canada, Amazonian site of Para Brazil)

FIG. 6. Location map of study sites (Boreal site of Canada, Amazonian site of Para Brazil) selected for testing modelling approach against bioclimatic conditions. The Boreal site is in the elevation of 25 to 194 m from sea level with 34,708 km2. The Amazonian site is at an elevation of 18-36 m above sea level with 9551 km2.

2.2 Data

Land cover classification data were obtained from the Global Land Cover Facility, which uses the radiation-detection imager Advanced Very High-Resolution Radiometer (AVHRR) to capture the images. The images of both sites were at a spatial resolution of 1 km. The pixels were used in a hierarchical tree structure to classify the AVHRR data. Following this data from the hierarchical tree were classified into12 land cover types based on multi-temporal AVHRR metrics. Here, the minimum annual red reflectance metric was used to delineate woody areas, while the peak annual greenness was used to describe leaf types. Temperature metrics were used to differentiate among the tropical, temperate, and boreal zones. Temperature metrics were also used to separate the deciduous broadleaf forest from evergreen broadleaf forest, tropical woodland from the general forest, and shrubland from grassland and agriculture. Near-infrared metrics were used to separate cropland from grassland and shrubland, and tropical flooded grassland from woodland (Hansen et al. 2000).

A future-climate dataset for maximum and minimum air temperature and precipitation was collected from WorldClim (Hijmans et al. 2005) based on the CMIP5 climate projections from the HadGEM2-ES ES general circulation models (GCM). All the previous GCMs had limitations, while HadGEM2 has been improved to address the systematic errors present in the previous models and versions (Martin et al. 2010). The HadGEM2-ES model incorporates the terrestrial, tropospheric chemical and ocean carbon cycles. Associated with this, the TRIFFID DGVM model represents the terrestrial vegetation, simulating the carbon balance of five vegetation types (broadleaf trees, needle leaf trees, C3 and C4 grasses, shrubs and bare soil) (Cox 2001; Jones et al. 2011). HadGEM2-ES also includes realistic stratospheric processes and variability, making the model better able to predict future climate (Hijmans et al. 2005). We used the future climate data for two RCPs –4.5and 8.5. The time scales used were 2050 (average of 2041–2060) and 2070 (average of 2061–2080). RCP 4.5 is a scenario that includes long-term, global greenhouse gas emissions, short-lived species and land-cover changes, and has been upgraded from previous GCM scenarios through the incorporation of historical land-cover and emission information, which also stabilizes the radiative force at 4.5W/m2 (≈650 ppm CO_2 equivalent). Another significant feature of RCP 4.5 is that it considers the influence of sulphur aerosols and organic carbon emissions on climate change (Moss et al. 2010; Thomson et al. 2011). RCP 8.5 is the pathway with the highest greenhouse gas emissions, where no specific climate mitigation target is included. In this pathway, the radiative forcing is 8.5 W/m2. As an extreme scenario, RCP 8.5 helps in obtaining a prediction about how land biodiversity will be affected as a result of extreme climate change (Fischer et al. 2007; Martin et al. 2011; Riahi et al. 2011; Betts et al. 2015; Sakschewski et al. 2016). Historical climate data, topographic data, mean annual temperature and annual precipitation data were collected (Table 3).

All the primary data about land-cover, slope, elevation, aspect, and past and future climate images were resampled onto a standard, 150-m-resolution grid for all the images of either site to ensure rapid computation.

2.3 Machine-learning model

For predictive machine-learning modelling, decision trees (DTs) are an important type of algorithm, with RFs being among the most potent DT techniques. As with other computer models, DTs have drawbacks, such as tending to over-fit the training data set, which can lead to poor model performance (Bramer 2007; Patil et al. 2017). Among the DT models, only RFs can limit the risk of over-fitting the dataset; the RFsuse many ensemble members and a bootstrap aggregating method during the training session. In this study, we used the RF DT technique to simulate the future land-cover distribution in response to climate change. The RF model worked via two types of inverted binary tree methods – classification tree (CT) and regression tree (RT) (Breiman et al. 1984). The CT model was used for the categorical variables, while the RT model was used for the numerical variables. We used an RF CT method to predict the future land diversity class (Breiman 2001; Abdollahnejad et al. 2017). Historical, classified AVHRR image data associated with spatial data, such as elevation, aspect, slope, mean annual precipitation and temperature, were used as the predictor variables to training the model. The coefficient of determination (R^2) was used to measure the model's OOB (out-of-bagging / prediction error) score. We found no improvement in the OOB score during preliminary tests of the RF model with our data sets, where we used 50 and 100 ensemble members, respectively. Therefore, during the training phase of the model, we used 50 ensemble members (i.e. a combination of 50 individual CT models), and historical climate data (Table 2) and topographic variables (elevation, slope and aspect). The spectral-band information from the land cover classification images was used to compare the model outputs to calibrate the RF model. The RF model was used in the scikit-learn machine-learning package implemented in the Python® programming language (Pedregosa et al. 2011). Finally, the data collected from the machine-learning model were processed in ArcGIS and analysed using Excel. A comparative analysis was performed following three categories – tropical vs boreal, within tropical vs boreal, and 2050 vs 2070 period.

Table 1 Percent (%) change in forest cover for two averaged periods (2050 and 2070) for both Amazon and Boreal sites

Forest cover	Timeline (present)	Amazon 7216.245 (km^2)	Boreal 12019.365 (km^2)
Evergreen forest	2050 (RCP 4.5)	18%	8%
	2070 (RCP 4.5)	17%	9%
	2050 (RCP 8.5)	19%	11%
	2070 (RCP 8.5)	23%	14%
Deciduous broadleaf forest	Present	680.67 (km^2)	513.607 (km^2)
	2050 (RCP 4.5)	-71%	-36%
	2070 (RCP 4.5)	-75%	-35%
	2050 (RCP 8.5)	-75%	-37%
	2070 (RCP 8.5)	-88%	-42%
Woodland	Present	916.312 (km^2)	4781.925 (km^2)
	2050 (RCP 4.5)	-46%	-9%
	2070 (RCP 4.5)	-41%	-9%
	2050 (RCP 8.5)	-49%	-9%
	2070 (RCP 8.5)	-56%	-10%
Wooded grassland	Present	578.992 (km^2)	1946.902 (km^2)
	2050 (RCP 4.5)	-53%	-21%
	2070 (RCP 4.5)	-50%	-23%
	2050 (RCP 8.5)	-63%	-23%
	2070 (RCP 8.5)	-71%	-27%
Grassland	Present	92.632 (km^2)	1482.907 (km^2)
	2050 (RCP 4.5)	-29%	-7%
	2070 (RCP 4.5)	-34%	-8%
	2050 (RCP 8.5)	-29%	-7%
	2070 (RCP 8.5)	-67%	-11%
Cropland	Present	22.095 (km^2)	280. 643 (km^2)
	2050 (RCP 4.5)	-75%	-24%
	2070 (RCP 4.5)	-73%	-28%
	2050 (RCP 8.5)	-62%	-32%
	2070 (RCP 8.5)	-86%	-35%

Table 2 Present percentage (% of total area) land cover occupied by different tree species

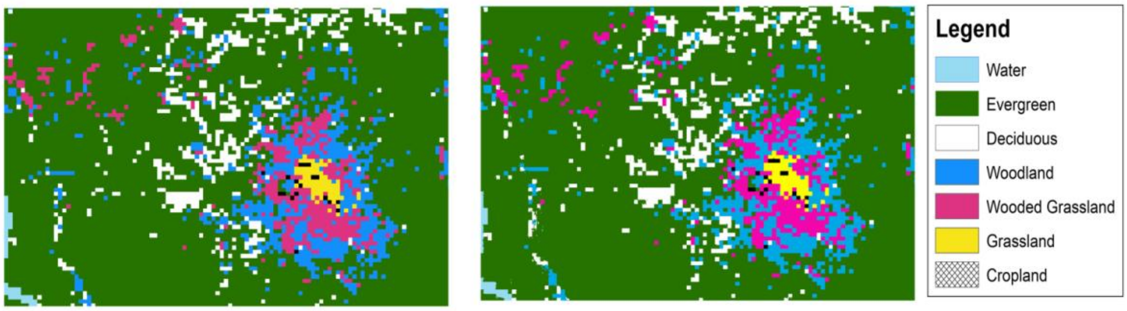
	Amazon site	Boreal site
Evergreen forest	75%	34%
Deciduous broadleaf forest	7%	1.3%
Woodland	9%	13%
Wooded grassland	6%	5%
Grassland	0.9%	4%
Cropland	0.2%	0.8%
Open shrubland	N/A	5.1%
Closed shrubland	N/A	1.3%
Bare land	1.9%	5%

Table 3 Summary of all the input data used for training the machine-learning model

Attribute	Source	Resolution	Importance
Elevation	US Geological Survey elevation data set	30m	Climate condition, vegetation, solar, energy
Aspect	Calculated from elevation data set	30m	Evapotranspiration, species distribution, solar energy
Slope	Calculated from elevation data set	30m	Precipitation, vegetation, flow rate and velocity
Historical mean annual temperature and precipitation	Worldclim-Normal 1950–2000 period (Hijmans et al. 2005)	1000m	
Future mean annual temperature and precipitation	Worldclim, HadGEM2-ES2041–2060 and 2061–2080 (Hijmans et al. 2005)	1000m	
AVHRRI and Classification imagery	Imagery acquired between 1981 and1994; 14 land classes distinguished (Hansen et al. 2000)	30m	

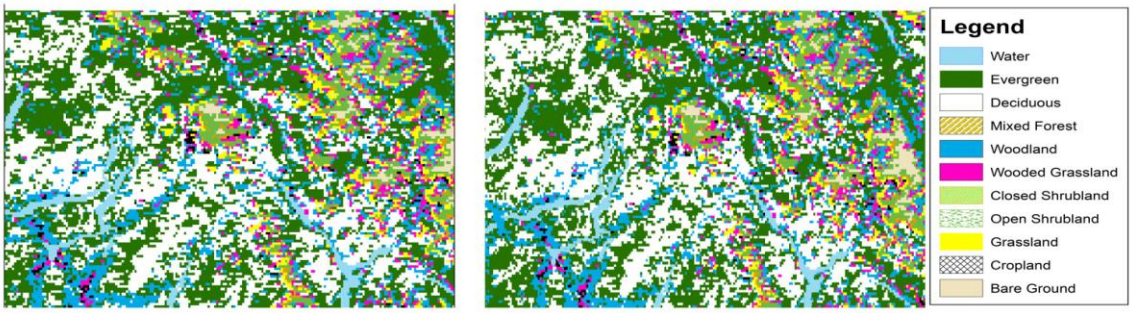
III. FINDING

We focused on the training phase of the RF models, using topographic and historical climate data to train the model to produce predicted images for selected study sites. The Out-of-Bag (OOB) (R^2) value for the Amazonian site was 0.901, whereas the OOB (R^2) score for the Canadian Boreal site was 0.797 (Figure 1). The RF model produced and captured approximately all of the major forest cover at both sites.



Spatial image of Amazonian site of Para, Brazil

Machine-trained image of Amazonian site of Para, Brazil



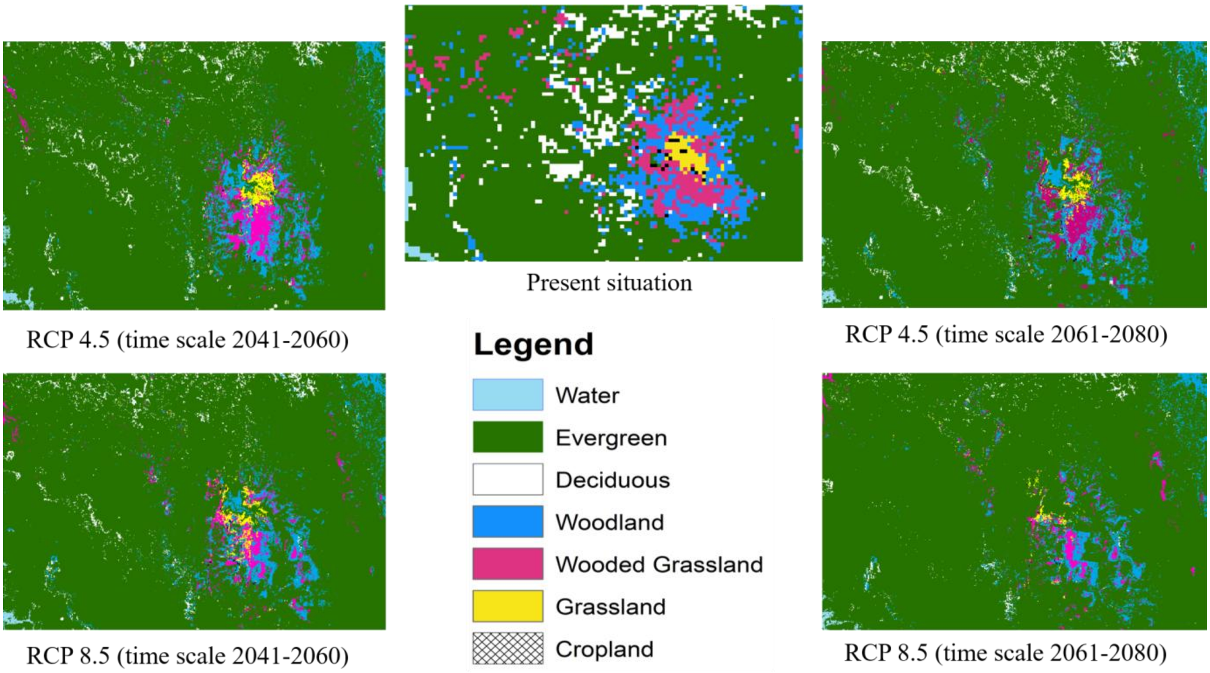
Spatial image of Boreal site of Canada

Machine-trained image of Boreal site of Canada

Figure1: comparison between original (spatial image: left) and random forest (RF: right)

FIG. 1. Comparison between original (spatial image: left) and random forest (RF: right)-trained images for the Amazon site of Para, Brazil (top) and Boreal site of Canada (bottom). Land cover classification data was collected from Global Land Cover Facility. The images were captured by a radiation-detection imager Advanced Very High Resolution Radiometer (AVHRR). Spatial resolution of both images was 1 km.

Figures 2 and 3 show the comparative predicted forest-cover changes during different timelines and RCPs. In comparing satellite images with the modelled future image of the Amazon site, it was clear that the Amazon site will be severely affected under the RCP 4.5 and 8.5 scenarios over the long term. However, the effect is barely visible in the short time (2041–2060). In contrast, the machine learning model revealed comparatively less change in forest cover at the Boreal site (Figures 2 and 3).


Present situation

RCP 4.5 (time scale 2041-2060)

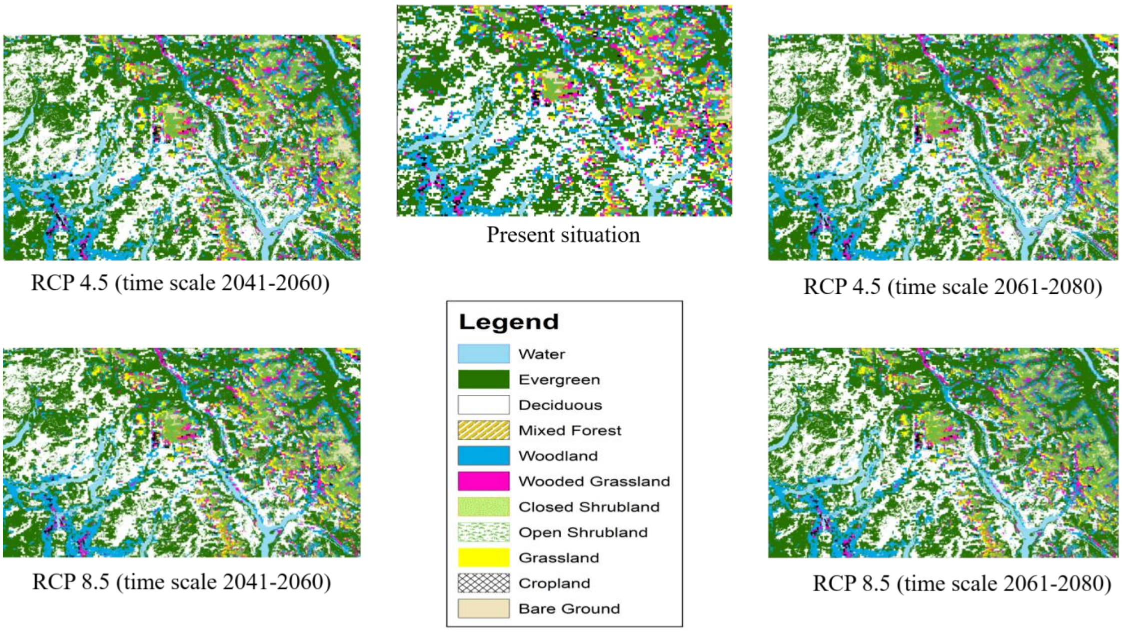
RCP 4.5 (time scale 2061-2080)

RCP 8.5 (time scale 2041-2060)

RCP 8.5 (time scale 2061-2080)

Figure2: predicted forest-cover change

FIG. 2. Predicted forest-cover change for Amazonian forest site of Para, Brazil (evergreen, deciduous, woodland, wooded grassland, grassland, cropland with area 9551 km^2); maximum and minimum air temperature and precipitation was collected from WorldClim (Hijmans et al. 2005) using HadGEM2-ES general circulation models (GCM) model. Representative concentration pathway (RCP) 4.5 is a long-term, global greenhouse gas emissions, short-lived species, and land-cover changes, and has been upgraded from previous GCM scenarios through the incorporation of historical land-cover and emission information, which also stabilizes the radiative force at 4.5W/m2 (≈650 ppm CO_2 equivalent). RCP 8.5 is the pathway with the highest greenhouse gas emissions, where no specific climate mitigation target is included. In this pathway, the radiative forcing is 8.5 W/m^2.


Present situation

RCP 4.5 (time scale 2041-2060)

RCP 4.5 (time scale 2061-2080)

RCP 8.5 (time scale 2041-2060)

RCP 8.5 (time scale 2061-2080)

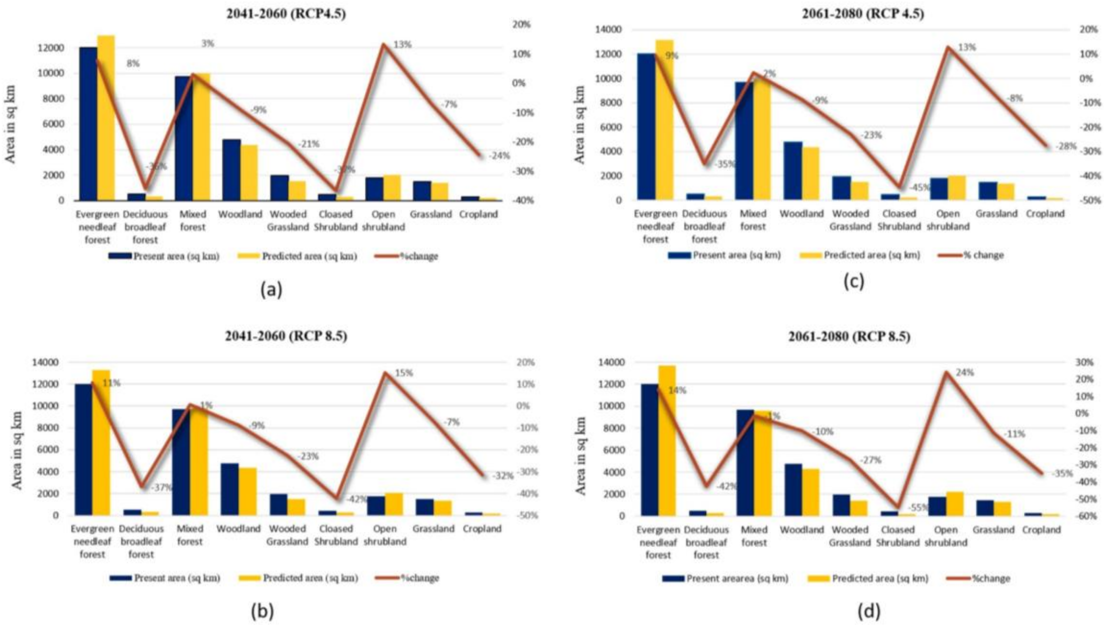
Figure3: predicted forest-cover change

FIG. 3. Predicted forest-cover change for Boreal site of Canada (water, evergreen, deciduous, mixed forest, woodland, wooded grassland, closed shrubland, open shrubland, grassland, cropland, bare ground with area 34,708km^2; maximum and minimum air temperature and precipitation was collected from

WorldClim (Hijmans et al. 2005) using HadGEM2-ES general circulation models (GCM) model. Representative concentration pathway (RCP) 4.5 is a long-term, global greenhouse gas emissions, short-lived species, and land-cover changes, and has been upgraded from previous GCM scenarios through the incorporation of historical land-cover and emission information, which also stabilizes the radiative force at 4.5W/m2 (≈650 ppm CO_2 equivalent). RCP 8.5 is the pathway with the highest greenhouse gas emissions with the radiative forcing 8.5 W/m^2, where no specific climate mitigation target is included.

Among the various land-cover types, there are six that are common to both study sites. These are evergreen forest, deciduous broadleaf forest, woodland, wooded grassland, grassland, and cropland. A comparison of the RF model results between the two sites revealed that the highest rate of decrease occurs in the deciduous forest (-88%), followed by cropland (-86%), with RCP 8.5 in 2070 at the Amazon site. At the boreal site, the climate change effect was also severe for deciduous forest and cropland. According to the model, the deciduous forest would reduce by 35%, and cropland would also reduce by 35% by 2070, relative to the present. The most significant change was found in the evergreen forest for both sites (Table 1).

Studying all types of land covers of both study sites separately, the highest increasing trend was found by the model (13% and 15%, RCP 4.5 and 8.5, respectively) to be for open shrubland at the boreal site by 2050 (Figures 4a and b). Conversely, the highest decreasing trend was for closed shrubland (37% and 42%, under RCP 4.5 and RCP 8.5, respectively). On the other hand, by 2070, the highest increasing trend was also for open shrubland (13% and 24%, under RCP 4.5 and RCP 8.5, respectively) (Figures 4c and 4d). The highest decreasing trend was for closed shrubland (45% and 55%), followed by deciduous broadleaf forest (35% and 42%) under RCP 4.5 and RCP 8.5, respectively.



(a) (c)

(b) (d)

Figure4: comparative land-cover area (square km)

FIG. 4. Comparative land-cover area (square km) changes for the Boreal site of Canada for different periods and representative concentration pathways: a) RCP 4.5 during 2041-2060 time periods, b) RCP 8.5 during 2041-2060 time periods, c) RCP 4.5 during 2061-2080 time periods, d) RCP 8.5 during 2061-2080 time periods. Representative concentration pathway (RCP) 4.5 is a long-term, global greenhouse gas emissions, short-lived species, and land-cover changes, and has been upgraded from previous GCM scenarios through the incorporation of historical land-cover and emission information, which also stabilizes the radiative force at 4.5W/m2 (≈650 ppm CO_2 equivalent). RCP 8.5 is the pathway with the highest greenhouse gas emissions with the radiative forcing 8.5 W/m2, where no specific climate mitigation target is included. *** minus (-) sign indicates decreasing rate

By 2050, if climate change continues according to the RCP 4.5 scenario, the Amazon will lose a large portion of its deciduous forest (71%) and cropland (75%) (Figure 5a), with deciduous forest, decreasing really by 75% and wooded grassland by 63% under RCP8.5 (Figure 5b). By 2070, the highest loss will be to a deciduous forest (75%), followed by cropland (73%) under RCP 4.5 (Figure 5c). The machine learning model also revealed a shocking loss of deciduous forest (88%) and cropland (86%) under RCP 8.5 (Figure 5d).

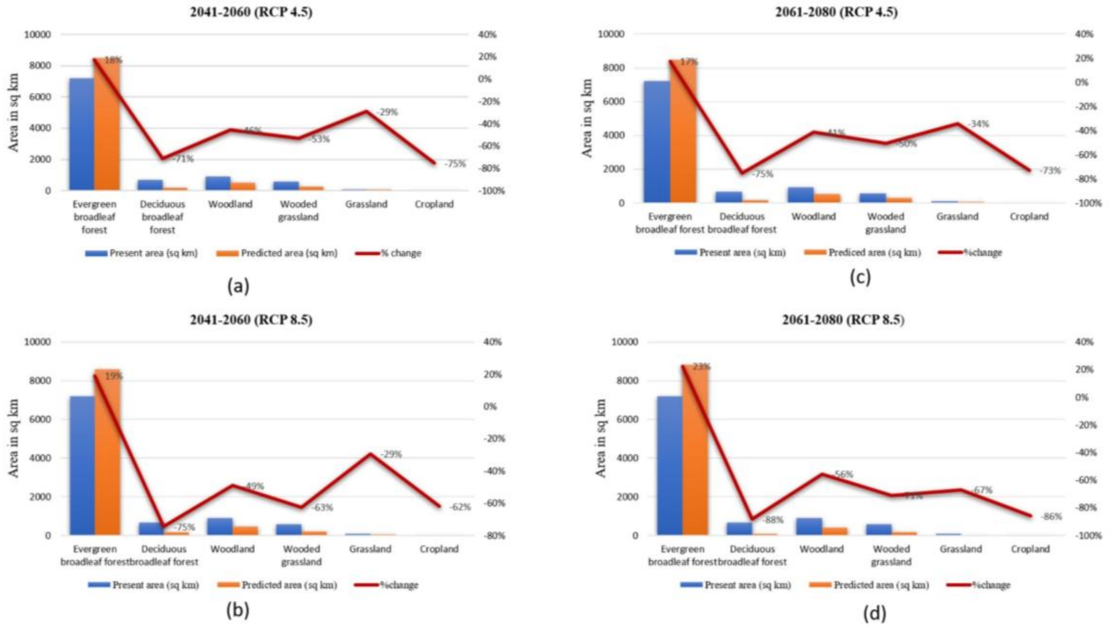


Figure5: comparative land-cover

FIG. 5. Comparative land-cover change for the Amazon site of Para, Brazil for different periods and representative concentration pathway a) RCP 4.5 during 2041-2060 time periods, b) RCP 8.5 during 2041-2060 time periods, c) RCP 4.5 during 2061-2080 time periods, d) RCP 8.5 during 2061-2080 time periods. Representative concentration pathway (RCP) 4.5 is a long-term, global greenhouse gas emissions, short-lived species, and land-cover changes, and has been upgraded from previous GCM scenarios through the incorporation of historical land-cover and emission information, which also stabilizes the radiative force at 4.5W/m2 (≈650 ppm CO_2 equivalent). RCP 8.5 is the pathway with the highest greenhouse gas emissions, where no specific climate mitigation target is included. In this pathway, the radiative forcing is 8.5 W/m2. *** minus (-) sign indicates a decreasing rate.
In all cases, evergreen forests showed an increasing trend at a high percentage.

IV. DISCUSSION

The change of forest-cover losses for wooded grasslands and croplands and an increasing trend of the evergreen forest of Amazon and boreal deciduous forests were identified using a random forest (RF)-based machine learning model. However, the reason for the changes was different between the sites. Field-based research on the Amazon was shown that tropical forest species are highly sensitive to climate change. The productivity of tropical forests increases when water is sufficiently available. Moderate changes in climate can destroy the majority of this forest cover. According to previous climate research, droughts will become more intense, prolonged, and frequent in tropical region. While tropical forests can face a two-to three-month dry season, in expectation of a rainy spell to allow them to flourish, prolonged droughts could kill their habit. Another possible reason for forest cover loss is heavy rainfall. Continuous rainfall is favorable for evergreen broadleaf trees but can quickly kill off the deciduous forest. Heavy rain or prolonged drought are both fatal for cropland and grassland because of their shallow root systems. Heavy rain creates flooding, and intense drought causes severe water shortage. Therefore, nutrients become unavailable to shallow-rooted species (Feeley et al. 2007; Doughty and Goulden 2008; Kang et al. 2009; Sankaran 2019; Matos et al. 2021). Our boreal site belongs to the pacific maritime-ecozone, the most productive boreal site in Canada (Johnston et al. 2009). Research has forecasted that deciduous forests will be benefitted from future warmer climates for a while but will then likely be destroyed by two possible indirect effects of drought– insects and gap re-generation. Generally, drought affects evergreen species faster, creating space that becomes occupied by deciduous species. Prolonged drought and less rainfall will lower the water table and reduce the amounts of nutrients in the soil.

Consequently, the sap inside the deciduous species will decrease, making this valuable species more prone to insect attack. Boreal forest sites store the highest amount of carbon in their soils. This soil organic carbon (SOC) is related to fire combustion. Therefore, prolonged drought and soil-bound carbon will increase the incidence of forest fires that will lead to the problem of succession.

Deciduous species are naturally short-lived. With prolonged and frequent droughts, their offspring will fail to grow, and drought-tolerant evergreen species will take over their niche (Reich and Frelich 2002; Allen et al. 2010; Schindlbacher et al. 2012; Alexander and Mack 2017). Loss of species diversity will make the forests mono-species dominant, and these will then become vulnerable and less resilient to further climate change (Way and Oren 2010; Morandi et al. 2016; Sakschewski et al. 2016; Sung et al. 2016).

Deciduous species will face difficulties flourishing because of prolonged and intense drought anywhere in the world. Meanwhile, with unfavourable conditions, the cell sap within trees will decrease and make the trees more susceptible to pest attack (Givnish 2002; Way and Oren 2010). According to studies, even without higher temperatures or elevated CO_2, a 15% drop in precipitation alone in summer can destroy the diversity of deciduous species in temperate forests if the water output becomes higher than the input. It was also found that the deciduous forest will be heavily impacted by tornadoes, thunderstorms and wind disturbances (Peguero-Pina et al. 2020). According to Reich and Frelich (2002), deciduous forests of the temperate zone among the biomes will be heavily impacted by global change factors, whereas, in the tropics, deciduous forests will be affected by severe extra-tropical low-pressure(Reich and Frelich 2002). These might be the reasons that our RF model-based study showed a severe loss of deciduous forest in the future for both sites while also indicated the flourishing of evergreen forests for the long term.

According to this study, Amazonian deciduous broadleaf forest and cropland will be highly affected. Only evergreen forests will be able to occupy most of the area in the future. Previous research was shown that evergreen species have traits that allow them to be active at low soil water potentials, to reduce xylem cavitations to minimize water loss by producing small leaves, and to have small leaf areas and lower transpiration rates (Medlyn et al. 2001; Ackerly 2004; Kursar et al. 2009; Markesteijn et al. 2011; Carminati et al. 2020). Therefore, our study indicates that under elevated CO_2 or higher temperature, or even during droughts, evergreens can pass less water vapor from their leaves which is vital to maintaining turgor pressure within the cells. Balanced turgor pressure makes species less susceptible to insects and helps them to withstand drought. Deep root structures are another physiological feature for the survival of the plant. Evergreens can increase their water uptake from deeper layers in the soil, allowing them to tap into more reliable water sources, such as that held in parent material or rocks, during dry seasons. This might explain why evergreen species would flourish under future extreme climatic conditions (Nelson et al. 2002; Hasselquist et al. 2010; Tomlinson et al. 2013; Bayala and Prieto 2020).

Elevated temperatures can enhance shoot height, stem diameter and biomass in deciduous species more than evergreen trees. As a drought-avoidant group, deciduous trees can stop water use and loss by shedding leaves and almost halting their physiological activities in drought season (Parry 2000; Chaturvedi and Raghubanshi 2018). In the monsoon season, they use more water and nutrients than evergreen tree species to sustain their high photosynthetic rates and meet their requirements before the next drought. Using the BIOME3 model, Parry (2000) suggested that European temperate deciduous forests could increase their productivity over the next 80 years because Europe will get more rainfall. Previous research has found boosted levels of foliar 18O (Δ18Ol¬) and 13C values in deciduous species, which indicate reduced stomatal conductance and, subsequently, greater water-use-efficiency (WUE) during the rainy season (Hasselquist et al. 2010). Nonetheless, it is known that future higher temperatures will promote drought conditions as well as extreme rainfall in boreal and tropical zones. Our model results showed unexpected increments of open shrubland at the Boreal site. However, rising temperatures, more rain, fewer nutrients, and increased evaporation will combine to promote shrubland to occupy deciduous forest areas (Arnell 2008; Allen et al. 2010; Chadwick et al. 2015). Even under elevated CO_2 conditions, shrubby plants showed less acclimation of stomatal conductance than other species present in the Boreal zone, which gives them the key for survival under drier conditions (Ainsworth and Rogers 2007). Earlier, boreal regions will experience temperature increases from 4˚C to 11˚C with increased precipitation (Scheffer et al. 2012). With this extreme scenario, a large area of boreal forest will be replaced by shrubland (Boisvert-Marsh et al. 2014). Also, habitat shifts will expand evergreen species into the current habitat of the deciduous forests of the boreal zone (McKenney et al. 2007). Regularly updated satellite imagery of forest cover is also needed for more accurate prediction (Wang et al. 2016; Midekisa et al. 2017).

V. CONCLUSIONS

This study predicted that both of our study sites were susceptible to losing a considerable percentage of their forest cover if the climate shifted according to RCP 4.5 and RCP 8.5. In brief, the tropical zone might lose its virgin forest cover due to extreme drought, tornado and fire in future. In contrast, the boreal site may lose its existing healthy forest to a lower succession rate, pest attack, drought, fire and low nutrient availability. According to our model, there is a chance that evergreen mono-species will dominate both highly valuable forests in the future, which could make these forests more prone to further climate shift effects. The dying of these forests will release approximately 5 billion metric tons of carbon into the atmosphere, which would further fuel the process of climate change (Grudgings 2011; Kelly et al. 2013).

To better understanding the future of earth's forest cover and processes, it is essential to quantify and monitor the spatial forest dynamics. Machine-learning studies can provide predictive results but not real-life scenarios. Therefore, the results of this study should validate the data collected at the field level to match the consistency of the machine-learning model.

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Conflicts of interest

The authors declare that they have no conflict of interest.

Author contributions

All authors contributed to the study conception and design. Material preparation, data collection, analysis and interpretation were performed by Joity Hossain. The first draft of the manuscript was written by Joity Hossain. Tanushree Halder and Zakaria Solaiman read and revised the manuscript. All authors approved the final manuscript.

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