



*Original Article*

## Assessing the Impact of Climate Change on the Distribution of Endemic Subalpine and Alpine Plants of New Guinea

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### Abstract

Plant species of alpine and subalpine ecosystems in tropical mountains are prone to habitat loss due to future climate change. In the present study, the impact of climate change on the distribution of five endemic plant species of subalpine and alpine regions in New Guinea is assessed using Maxent. Models developed for all species had an AUC > 0.9, TSS > 0.7 and sensitivity, specificity and overall accuracy better than 0.8, indicating high model performance. Current suitable habitats of the species were predicted to occur mainly along the mountain ranges in the middle of the New Guinea Island, with elevation and extreme temperature related variables being the most influential factors. Future predictions for these species showed significant loss of suitable habitats, especially in Papua New Guinea. These results may serve as a basis for planning the conservation actions needed to conserve the species, especially in addressing potential future climate change.

**Keywords:** alpine, climate change, endemic plants, New Guinea, Subalpine

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### 1. Introduction

One of the biggest issues facing the global community is climate change. The current level of atmospheric CO<sub>2</sub> (402.26 ppm), an important heat-trapping gas, is the highest in the human history and global surface temperature has increased 0.87°C since 1884. This temperature increase is likely to continue up to 2.6-4.8°C by the end of 2100, if the human CO<sub>2</sub> emissions are not strongly reduced. In order to survive, organisms and populations on earth are currently responding to the changing climate through phenotypic plasticity, genotypic evolution and shifts in distribution (Peñuelas *et al.*, 2013).

For mountain plant species, shifts in distributions in response to climate change are well documented (Brusca *et al.*, 2013; Jump *et al.*, 2012). The combination of high elevation and cold environment makes the potential effects climate change on mountain plant species more dramatic.

While most of these species tend to shift to cooler areas (uphill), some species shift in the opposite direction, and a small portion of them show no change (Lenoir *et al.*, 2010). Developing the ability to predict the responses of these species to ongoing climate change is very important for assessing vulnerabilities and avoiding potentially severe biodiversity loss (Dawson *et al.*, 2011).

Species distribution models (SDMs) are widely used tools in ecology and conservation biology that help assess factors affecting species distribution and predicting responses of species to climate change (Guillera-Aroita *et al.*, 2015; Guisan *et al.*, 2013). In addition, SDMs are also used for the management of threatened species, controlling threatening processes, managing landscape, understanding phylogeographic patterns, and managing biological invasions (Guillera-Aroita *et al.*, 2015). To estimate the species distribution, these models correlate species occurrence data and environmental variables using statistical- or machine-learning procedures (Phillips *et al.*, 2006; Roberts & Hamann, 2012). For presence-only data, Maximum Entropy (Maxent) (Phillips *et al.*, 2006) is one of the best and most popular types of SDMs due to its user-friendliness and high predictive accuracy compared to other SDMs (Merow *et al.*, 2013).

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In the present study, the impact of climate change on the distribution of five endemic plant species of subalpine and alpine regions in New Guinea is assessed using Maxent. These species are *Deschampsiaklossii* Ridl. (Poaceae), *Epilobiumhooglandii* Raven (Onagraceae), *Rhododendron culminicolum* F. Muell. (Ericaceae), *Tasmanniapiperita* (Hook. fil.) Miers (Winteraceae), and *Tetramolopiumklossii* (Moore) Mattf. (Asteraceae). The objectives of this study were to: (1) estimate the current distributions of all studied plant species in the Island of New Guinea, (2) identify the environmental factors affecting distributions of the species, and (3) assess potential impacts of future climate on the future distributions of the species. Alpine ecosystems in tropical mountains are often considered as “islands” of cold climate in the warm tropics (Vuilleumier, 1970). Plant species in these regions are prone to habitat loss as it is predicted that climate change will extensively reduce the extent of these ecosystems (McCarthy, 2001). Furthermore, invasions from native and non-native plants as well as expansion of tourism and resource extraction increase the risk of plant species extinction in these environments (Pauchard *et al.*, 2015).

## 2. Materials and Methods

### 2.1 Species occurrence data

The tropical Island of New Guinea is one of the least explored regions on the globe. The island politically was divided into two almost equal parts: Papua New Guinea on the east and Indonesian provinces of Papua and Papua Barat on the west. Extensive central mountain ranges divide the island into north and south. Several peaks of these mountains were covered by glaciers until recently. The Island is home for around 15,000 endemic plant species (Myers *et al.*, 2000). Among them, *D. klossii*, *E. hooglandii*, *R. culminicolum*, *T. piperita*, and *T. klossii* are only found in subalpine and alpine habitats. The conservation status of these plants is unknown as they have not been assessed for the IUCN Red List. Utteridge and Edwards (2009), however, argued that the conservation status of *T. piperita* is critically endangered based on their study in Mt. Jaya. In the present study, the occurrence data of these five plant species were obtained from the Global Biodiversity Information Facility (GBIF), an open access data portal that provides rich information about the known presence of organisms. The initial data were filtered for duplicate records and then used to create model predictions. Total counts of occurrence data used in modeling were 203, 45, 105, 168 and 7 records for *D. klossii*, *E. hooglandii*, *R. culminicolum*, *T. piperita*, and *T. klossii*, respectively.

### 2.2 Environmental variable selection

In total 19 current bioclimatic and 3 topographic variables were used for model building. The bioclimatic variables were obtained from WorldClim 1.4 database (Hijmans *et al.*, 2005) and are derived from monthly rainfalls and temperatures from weather stations across the globe, within the period 1950-2000. For topographic variables, the elevation data set was obtained from the Shuttle Radar

Topography Mission (SRTM) global elevation data, from which slope and aspect data were derived using surface analysis extension in ArcMap 10.1 (ESRI, 2012). Initially, a model was produced using Maxent that included all 22 environmental variables. Based on jackknife analysis provided by Maxent, variables contributing <1% to the full model were excluded and another spatial model was created. The resulting model was then tested for variable correlations. This test is important as a model with correlated variables removed can mislead interpretation. Pearson’s correlation coefficient was calculated using SDMtoolbox (Brown, 2014) and  $r \leq \pm 0.8$  was used as a cut-off threshold to determine the exclusion of highly correlated variables. In the final model, correlated variables were excluded by retaining the variables with the highest model contribution, as determined by Maxent. All the environmental layers used in the model had 30 arc-seconds or  $\approx 1$  km resolution. These layers were clipped to the Papua New Guinea and Indonesian provinces of Papua and Papua Barat political boundaries, and then converted to ASCII raster files using ArcMap 10.1 (ESRI, 2012).

### 2.3 Projection of future climate

To predict the impacts of future climate on the distributions of *D. klossii*, *E. hooglandii*, *R. culminicolum*, *T. piperita*, and *T. klossii*, global circulation models (GCM) of HadGEM2-ES (Hadley Centre Global Environment Model, version 2-Earth System), MIROC-ESM (Model for Interdisciplinary Research on Climate-Earth System Models) and MRI-CGCM3 (Meteorological Research Institute-Coupled General Circulation Model v3.0) for 2050 (average for 2041-2060) and 2070 (average for 2061-2080) were used (Hijmans *et al.*, 2005). These three GCMs are among the most recent climate projections used in the Fifth Assessment IPCC Report. With each GCM, two representative concentration pathway (RCP) emission scenarios, namely RCP4.5 and RCP8.5, were used. While RCP4.5 represents a low emission scenario, RCP8.5 is a scenario with high greenhouse gas emissions and represents the worst case in climate model simulations in the Fifth Assessment IPCC report (Riahi *et al.*, 2011). The final model used for each plant species was obtained by averaging the results from HadGEM2-ES, MIROC-ESM and MRI-CGCM3.

### 2.4 Model performance

In the present study, the Maxent software was set to the “auto feature”, logistic output format and ASCII output file type following the suggestions of Phillips and Dudík (2008). To minimize the level of uncertainty and increase model accuracy, 10-fold cross-validation was used. Model performance was assessed from area under the curve (AUC) of the receiver operating characteristic, true skill statistic (TSS), sensitivity, specificity and overall accuracy (Allouche *et al.*, 2006). Furthermore, a maximum training sensitivity plus specificity (MTSS) logistic threshold was used to convert the continuous suitability index into suitable and unsuitable areas for the plant species. This MTSS thresholding is the best method for threshold selection when only presence data are available (Liu *et al.*, 2013).

### 3. Results and Discussion

#### 3.1 Model performance

The Maxent models developed for *D. klossii*, *E. hooglandii*, *R. culminicolum*, *T. klossii*, and *T. piperita* predicted the distributions significantly better than random expectation. All models had an AUC >0.9, TSS >0.7 and sensitivity, specificity and overall accuracy better than 0.8, indicating high model performance (Table 1). Compared to other model types, Maxent is known to be robust against small sample sizes (Kumar & Stohlgren, 2009). This was the case for *T. klossii* with only 7 occurrence records in the present study; the model was similar in terms of accuracy, sensitivity and specificity to models for the other species that had more records.

#### 3.2 Current distribution of the species

Using MTSS logistic threshold, model estimates of the current distributions identified a total area of 95,577.55 km<sup>2</sup> (10.96% of total land area) as suitable habitat for *D. klossii*, 108,555.31 km<sup>2</sup> (12.45%) for *E. hooglandii*, 112,823.47 km<sup>2</sup> (12.94%) for *R. culminicolum*, 114,203.4 km<sup>2</sup> (13.01%) for *T. klossii*, and 83,626.88 km<sup>2</sup> (9.59%) for *T. piperita* (Table 2). As can be seen in Figure 1, most of the

suitable habitats for the studied species were found along the mountain ranges in the middle of New Guinea Island. They extended from Jayawijaya Mountains in Indonesian provinces of Papua in the west to Easter Highland in Papua New Guinea in the east. The habitat estimates for all species excepting *T. klossii* extended to Owen Stanley Range in the Bird's Tail Peninsula of Papua New Guinea. In addition, except for *D. klossii*, suitable habitats for all studied species were also predicted in Tambrauw Mountains located in the north central region of the Bird's Head Peninsula.

Since all of the species are endemic to alpine and subalpine habitats, it is understandable that habitats considered suitable were found along the mountain ranges with high elevation for all the studied species. In New Guinea, alpine and subalpine zones are generally found above 3000m (Johns *et al.*, 2007; Utteridge & Edwards, 2009). Subalpine areas, however, can also occur in valleys below the 3000m rule of thumb, as a consequence of various factors, including wet soil (Ashton & Hargreaves, 1983), periodic droughts and fire (Johns, 1986), cold air drainage (Paton, 1988), and exposure to strong winds (Ashton & Williams, 1989). In the present study, this kind of areas were found in Tambrauw Mountains located in the north central region of the Bird's Head Peninsula, and these were estimated to be suitable habitats for *E. hooglandii*, *R. culminicolum*, *T. klossii*, and *T. piperita* (Figure 1).

Table 1. Model performances for *D. klossii*, *E. hooglandii*, *R. culminicolum*, *T. klossii*, and *T. piperita* in terms of area under the curve (AUC), true skill statistic (TSS), sensitivity, specificity and overall accuracy. Values given are mean ± standard deviation from 10-fold cross-validation.

Species	AUC	TSS	Sensitivity	Specificity	Overall accuracy
<i>D. klossii</i>	0.95 ± 0.022	0.79 ± 0.075	0.9 ± 0.079	0.89 ± 0.005	0.89 ± 0.005
<i>E. hooglandii</i>	0.95 ± 0.063	0.73 ± 0.14	0.86 ± 0.15	0.88 ± 0.013	0.88 ± 0.13
<i>R. culminicolum</i>	0.94 ± 0.036	0.77 ± 0.078	0.9 ± 0.082	0.87 ± 0.007	0.87 ± 0.007
<i>T. klossii</i>	0.94 ± 0.116	0.73 ± 0.34	0.86 ± 0.38	0.87 ± 0.049	0.87 ± 0.048
<i>T. piperita</i>	0.93 ± 0.045	0.72 ± 0.14	0.82 ± 0.15	0.90 ± 0.007	0.90 ± 0.006

Table 2. Prediction of current and future distribution area of *D. klossii*, *E. hooglandii*, *R. culminicolum*, *T. klossii*, and *T. piperita*. Future habitat predictions are given for the years 2050 and 2070 under the representative concentration pathway scenarios RCP4.5 and RCP8.5, for the average of results from HadGEM2-ES, MIROC-ESM and MRI-CGCM3 climate models. Values are given in km<sup>2</sup> and as percentages of total land area.

Species	Current	RCP4.5		RCP8.5	
		2050	2070	2050	2070
<i>D. klossii</i>	95,577.55 (10.96 %)	70,069.13 (8.04 %)	63,216.19 (7.25 %)	62,443.18 (7.16 %)	47,016.21 (5.39 %)
<i>E. hooglandii</i>	108,555.31 (12.45 %)	92,612.10 (10.62 %)	84,662.04 (9.71 %)	85,500.59 (9.81 %)	69,886.88 (8.02 %)
<i>R. culminicolum</i>	112,823.47 (12.94 %)	84,989.74 (9.75 %)	78,058.69 (8.95 %)	75,471.22 (8.66 %)	59,389.75 (6.81 %)
<i>T. klossii</i>	114,203.40 (13.01 %)	64,892.39 (7.44 %)	53,281.09 (6.11 %)	50,486.23 (5.79 %)	42,981.48 (4.93 %)
<i>T. piperita</i>	83,626.88 (9.59 %)	74,055.38 (8.49 %)	66,941.18 (7.68 %)	64,334.86 (7.38 %)	47,279.27 (5.42 %)

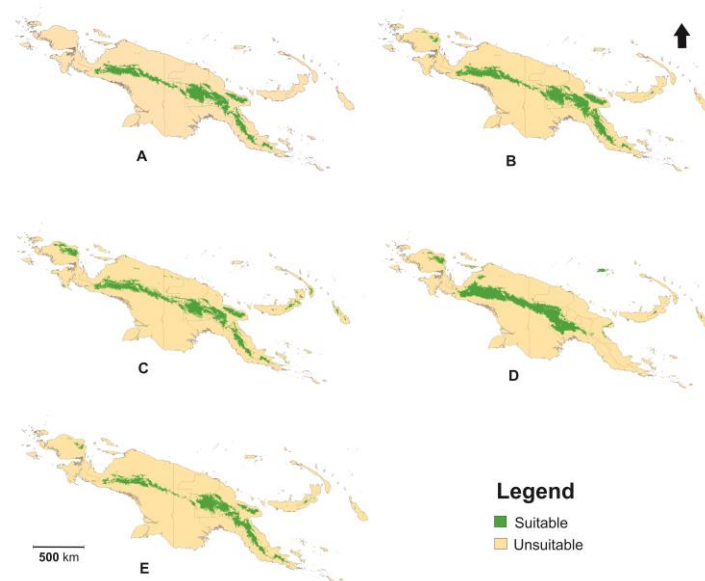


Figure 1. Estimate of the current distribution of *D. klossii* (A), *E. hooglandii* (B), *R. culminicolum* (C), *T. klossii* (D), and *T. piperita* (E).

### 3.3 Contributions of environmental variables in the models

In total, five to nine environmental variables contributed in the predictive models developed for the studied species (Table 3). *D. klossii*, *E. hooglandii*, *R. culminicolum* were affected by four environmental variables, whereas *T. klossii* and *T. piperita* were influenced by five and nine variables, respectively. The environmental variable with the highest contribution to the model was minimum temperature of coldest month for *D. klossii* (65.4%), elevation for *E. hooglandii* (61.1%) and *T. klossii* (34.3%), maximum temperature of the warmest month (70%) for *R. culminicolum*, and mean temperature of driest quarter (38.3%) for *T. piperita*. In general, elevation and extreme temperature related variables (Bio 5, Bio 6, Bio 8, Bio 9, Bio 11) had stronger effects on distributions of the species than other variables. The probability of presence increased for all the studied species with elevation (Figure 2).

The results of the present study are in line with previous studies showing the importance of elevation as dominant factor affecting plants species distribution in mountain habitats (Körner, 2004, 2007). Small changes in elevation relate to changes in microclimate and is often associated with local precipitation and temperature features (Austin, 2002; Körner, 2007). In terms of predictive modeling, Oke and Thompson (2015) have shown that inclusion of elevation as a predictor variable can improve the quality of SDMs for high-elevation plant species. In the present study, elevation was included in all final models as a significant factor retained by the variable selection procedures. This may be the reason why the models achieved high values of AUC, TSS, sensitivity, specificity and overall accuracy. Furthermore, all the models were able to predict suitable elevation ranges for all the studied species, at 3000-5000m, as shown in Figure 2, which matches the elevation range of alpine and subalpine habitats in New Guinea.

Table 3. Relative contributions of the environmental variables (%) in the Maxent models for *D. klossii*, *E. hooglandii*, *R. culminicolum*, *T. klossii*, and *T. piperita*.

Variables	<i>D. klossii</i>	<i>E. hooglandii</i>	<i>R. culminicolum</i>	<i>T. klossii</i>	<i>T. piperita</i>
Aspect	-	1.8	4.6	-	1.3
Elevation	17.4	61.1	11.6	34.3	32.5
Isothermality (Bio 3)	-	-	-	-	2.4
Max Temperature of Warmest Month (Bio 5)	-	-	70	-	-
Mean Diurnal Range (Bio 2)	3	-	-	-	2.5
Mean Temperature of Coldest Quarter (Bio 11)	-	30.8	-	-	-
Mean Temperature of Driest Quarter (Bio 9)	-	-	-	-	38.3
Mean Temperature of Wettest Quarter (Bio 8)	-	-	-	34.1	-
Min Temperature of Coldest Month (Bio 6)	65.4	-	-	-	-
Precipitation of Coldest Quarter (Bio 19)	-	2	-	-	-
Precipitation of Driest Quarter (Bio 17)	-	-	-	-	1.8
Precipitation Seasonality (Bio 15)	3.6	4.3	6.7	30.4	3.9
Slope	-	-	-	-	1
Temperature Annual Range (Bio 7)	10.5	-	7.1	1.2	16.2

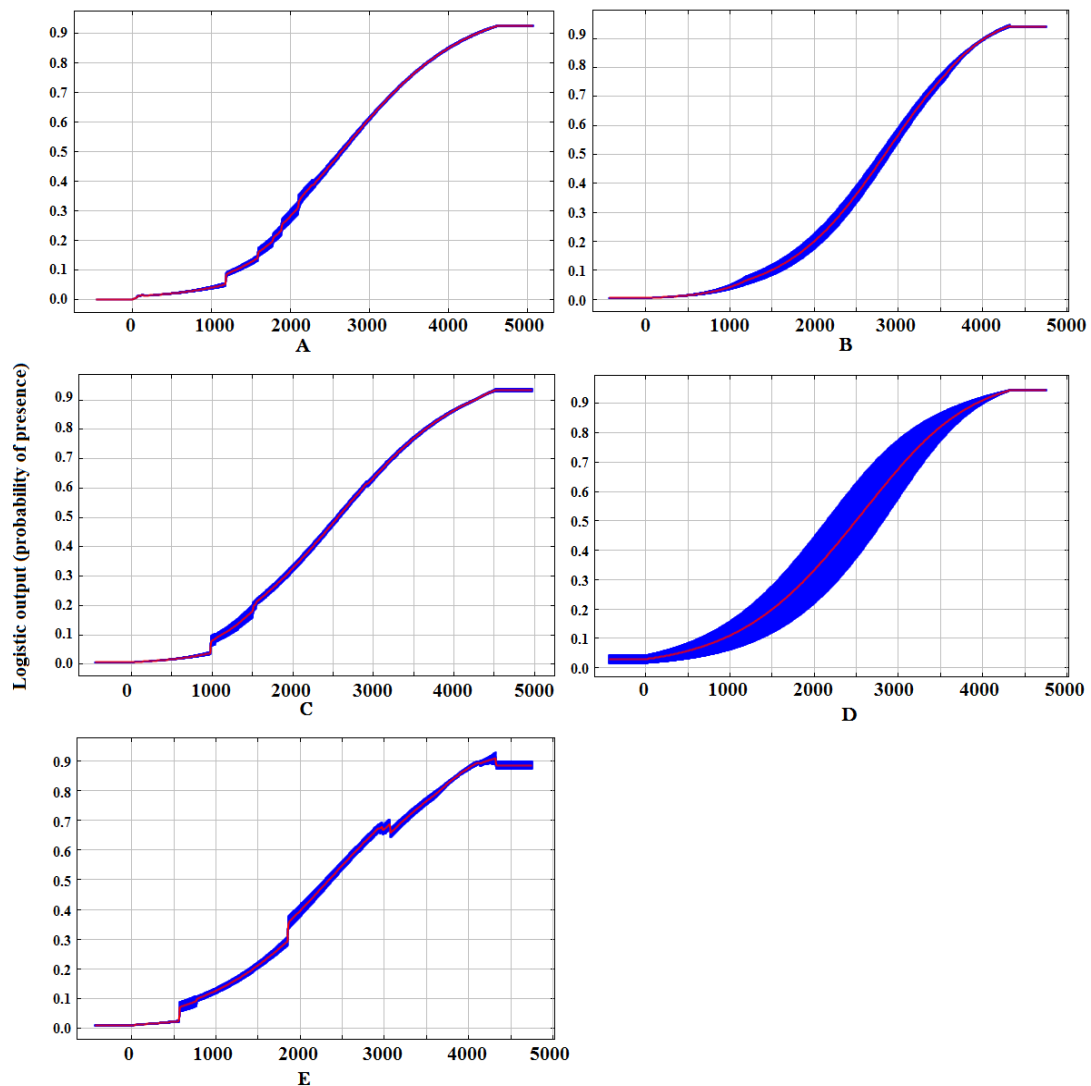


Figure 2. Response curves showing the relationships between elevation (m above sea level) and the probability of presence of *D. klossii* (A), *E. hooglandii* (B), *R. culminicolum* (C), *T. klossii* (D), and *T. piperita* (E). Values shown are averages over 10 replicate runs; blue margins show  $\pm 1$  SD calculated over 10 replicates.

Among the various environmental factors in high mountain habitats, temperatures are a main factor limiting plant species distribution. The present study found that the probability of presence for all the studied species decreased with increasing the temperature related variables. This negative effect of warming temperature on alpine and subalpine plant species is caused by several factors, including 1) reduction of growth period due to winter dormancy period extension (Heide, 2003; Myking & Heide, 1995), 2) damage of buds released from dormancy under warmer temperature caused by late-season frost, 3) damage caused by wintertime and frozen soil (Sevanto *et al.*, 2006), and 4) increased high temperature-induced photo inhibition during summer (Dumais & Prévost, 2007; Mooney & Billings, 1961).

### 3.4 Impact of climate change on species distributions

Climate change is predicted to increase the temperature over New Guinea in the range of 0.2-0.3°C per decade (Boer & Faqih, 2004). Under this temperature increase, suitable habitats for all the studied species are predicted to decline by 2050, with both RCP4.5 and RCP8.5 scenarios (Table 2). Decline of the suitable habitats would then worsen by 2070, especially for *T. klossii* that had the smallest suitable habitats with both RCP4.5 and RCP8.5. As RCP8.5 is the worst case scenario among climate model simulations, it gave more detrimental effects on the species distributions than RCP4.5.

In 2050 under RCP4.5, the suitable habitats would be decreased by 2.92% for *D. klossii*, 1.83% for *E. hooglandii*, 3.19% for *R. culminicolum*, 5.57% for *T. klossii*, and 1.1% for *T. piperita* (Table 2). These species are unable to cope with increased temperature especially at the outer areas of their suitable habitats or in the suitable areas with low elevation (Figure 3). These estimated reductions would mostly occur in Papua New Guinea. Although generally all the species would suffer from habitat loss by 2050 under RCP4.5, the model for *T. piperita* indicates that some populations of this species could deal with future climate, and some of them even could

expand their ranges to higher altitude.

Under RCP8.5, the suitable habitat reduction for all the species would be higher by 2050 than under RCP4.5. The suitable habitats would decrease by 3.8% for *D. klossii*, 2.64% for *E. hooglandii*, 4.28 % for *R. culminicolum*, 7.22% for *T. klossii*, and 2.21% for *T. piperita* (Table 2). Similar to RCP4.5, the reduction of suitable habitats occurred mainly in Papua New Guinea. Furthermore, some habitat gains for *T. piperita* were also observed under this emission scenario, although they were smaller than under RCP4.5 (Figure 4).

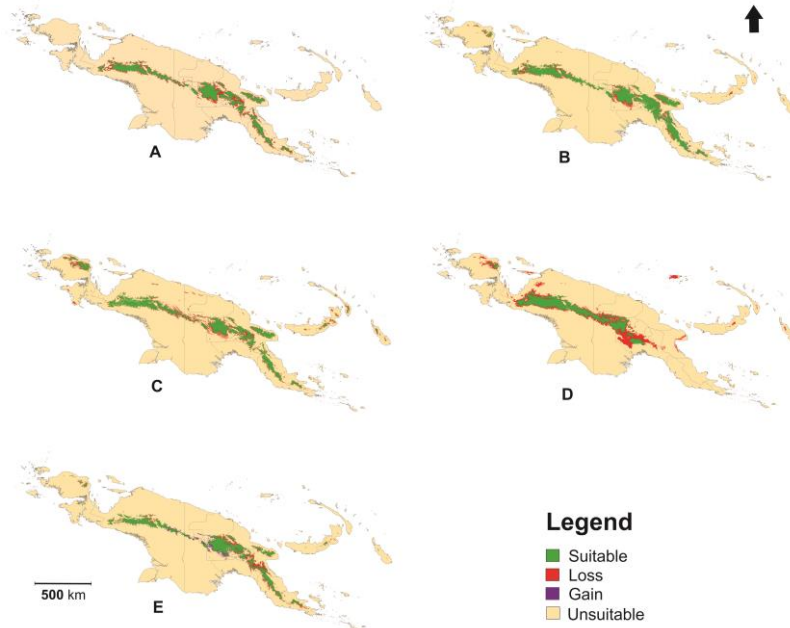


Figure 3. Predicted distribution in 2050 for *D. klossii* (A), *E. hooglandii* (B), *R. culminicolum* (C), *T. klossii* (D), and *T. piperita* (E) under RCP4.5 emission scenario.

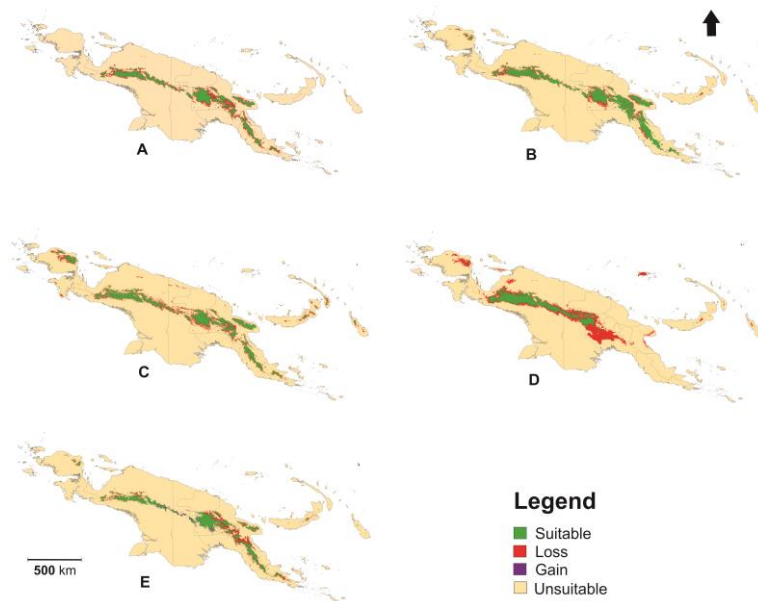


Figure 4. Predicted distribution in 2050 for *D. klossii* (A), *E. hooglandii* (B), *R. culminicolum* (C), *T. klossii* (D), and *T. piperita* (E) under RCP8.5 emission scenario.



By 2070, further decline in suitable habitats for all the species would happen as the temperatures continue to increase. Under RCP4.5, the suitable habitats would decrease by 3.71% for *D. klossii*, 2.74% for *E. hooglandii*, 3.99% for *R. culmicolum*, 6.9 % for *T. klossii*, and 1.73% for *T. piperita*. Under RCP8.5, significantly larger reductions of the habitats are predicted, due to higher carbon emissions. The suitable habitats would decrease by 5.57% for *D. klossii*, 4.43% for *E. hooglandii*, 6.13% for *R. culmicolum*, 8.08 % for *T. klossii*, and 4.17% for *T. piperita* (Table 2). These losses were predicted to occur evenly throughout all suitable habitats of the species in New Guinea. In addition, new suitable habitats of *T. piperita* in Papua New Guinea gained by 2050 would significantly decrease by 2070 under RCP4.5 and would totally disappeared under RCP8.5 (Figure 5, 6).

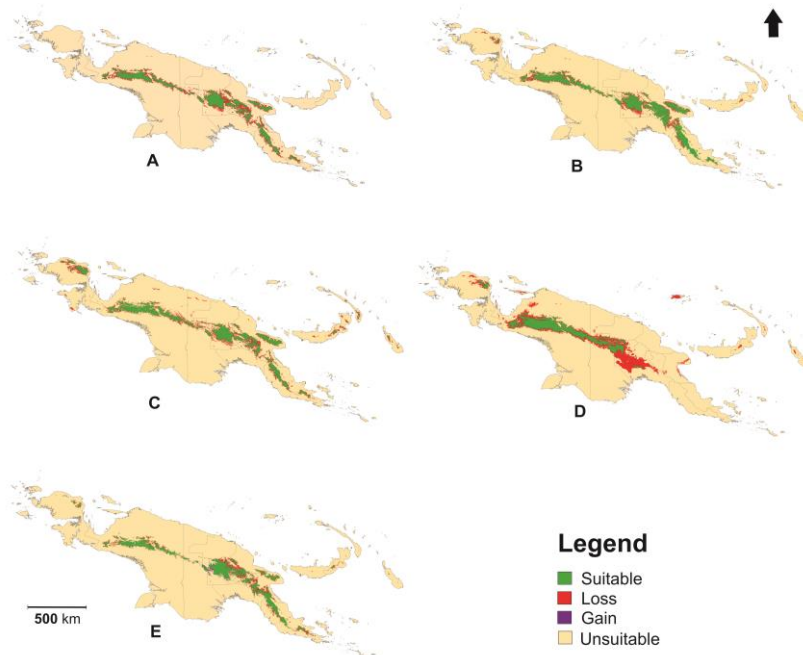


Figure 5. Predicted distribution in 2070 for *D. klossii* (A), *E. hooglandii* (B), *R. culmicolum* (C), *T. klossii* (D), and *T. piperita* (E) under RCP4.5 emission scenario.

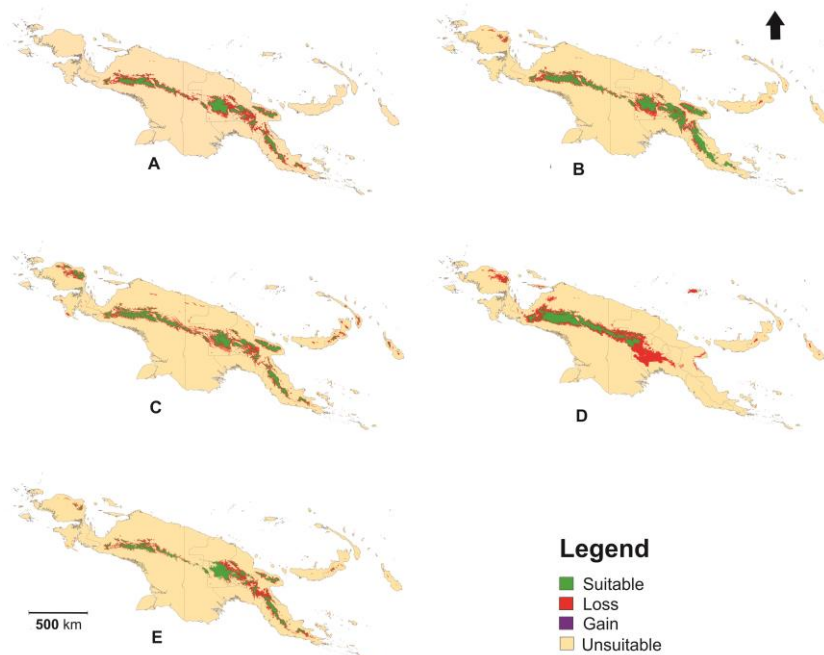


Figure 6. Predicted distribution in 2070 for *D. klossii* (A), *E. hooglandii* (B), *R. culmicolum* (C), *T. klossii* (D), and *T. piperita* (E) under RCP8.5 emission scenario.

Plant species in alpine and subalpine habitats exhibit morphological and physiological adaptations, which allow them to live in a stress-limiting environment. Many of these adaptations heavily depend on air temperature (Buytaert *et al.*, 2011). Climate change is likely to disrupt and alter all of these processes, forcing species to track their new climatic niche or to die out. In the present study, *D. klossii*, *E. hooglandii*, *R. culminicolum*, *T. klossii*, and *T. piperita* seemed unable to keep up with the increasing temperature, leading to significant habitat loss in the future. The last of these was able to track its climatic niche and gain suitable habitats by 2050, although they will significantly decrease or even totally disappear by 2070.

#### 4. Conclusions

Using Maxent and published occurrence data, the present study was able to match the current and predict the future distributions of five endemic alpine and subalpine plants in New Guinea with high sensitivity, specificity and accuracy. Most of the suitable habitats for the studied species were found along the mountain ranges in the middle of New Guinea Island. Concerning future distributions, the present modeling study suggests that there will be significant losses of suitable habitats of the species due to climate change. This habitat loss may already be happening, or is likely to happen sooner as human exploitations and land use transformation are very massive in these areas. For this reason, immediate conservation actions are needed to protect these species from extinction. The results of this study may serve as a basis for conservation actions concerning alpine and subalpine plant species in New Guinea. However, further modeling studies using other methods and direct field studies are required to validate the present modeling results.

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