

Predicting potential impacts of climate change on the geographical distribution of mountainous selaginellas in Java, Indonesia

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Abstract. Setyawan AD, Supriatna J, Nisyawati, Nursamsi I, Sutarno, Sugiyarto, Sunarto, Pradan P, Budiharta S, Pitoyo A, Suhardono S, Setyono P, Indrawan M. 2020. Predicting potential impacts of climate change on the geographical distribution of mountainous selaginellas in Java, Indonesia. *Biodiversitas* 21: 4866-4877. *Selaginella* is a genus of non-flowering plant that requires water as a medium for fertilization, as such, it prefers mountainous areas with high level of humidity. Such unique ecosystem of *Selaginella* is available in some parts of Java Island, Indonesia, especially in highland areas with altitude of more than 1,000 meters above sea level. However, most mountainous areas in Java are likely to be affected by climate change due to global warming, threatening the habitat and sustainability of *Selaginella*. This study aimed to investigate the impacts of climate change on the geographical distribution of *Selaginella opaca* Warb. and *Selaginella remotifolia* Spring. In doing so, we predicted the suitable habitats of both species using Species Distribution Model (SDM) tool of MaxEnt under present climate conditions and future conditions under four climate change scenarios. Species occurrence data were obtained from fieldworks conducted in 2007-2014 across Java Island (283 points: 144 and 139 points for *S. opaca* and *S. remotifolia*, respectively) and combined with secondary data from Global Biodiversity Information Facility (GBIF) (52 points: 35 and 17 points for *S. opaca* and *S. remotifolia*, respectively), and this dataset was used to model present geographical distribution using environmental and bioclimatic variables. Then, future distribution was predicted under four climate change scenarios: i.e. RCP (Representative Carbon Pathways) 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 in three different time periods (2030, 2050, and 2080). The results of the models showed that the extent of suitable habitats of *S. opaca* and *S. remotifolia* will be reduced between 1.8-11.4% due to changes in climatic condition, and in the areas with high level of habitat suitability, including Mount Sumbing, Mount Sindoro and Mount Dieng (Dieng Plateau), the reduction can reach up to 60%. This study adds another context of evidence to understand the potential impacts of climate change on biodiversity, especially on climate-sensitive species, such as *Selaginella*, in climate-risk regions like mountainous areas of Java Island.

Keywords: Java, mountainous areas, climate change, *Selaginella ornata*, *S. remotifolia*

INTRODUCTION

Selaginella Pal. is a single genus of ferns belong to Selaginellaceae family that lives in moist areas and is often found in highlands (Wijayanto 2014). Some species of *Selaginella* have a wide distribution and tend to be invasive, but the others are endemics, or even endangered according to IUCN criteria (Setyawan et al. 2015). Studies on the diversity of this genus recorded a global distribution across several continents. Within the scope Asian continent, *Selaginella* has been found in India (e.g. Singh et al. 2014), Taiwan (e.g. Ebihara et al. 2012), Philippines (e.g. Zamora 2012), China (e.g. Banks 2008), Thailand (e.g. Rupa and Bhavani 2014), Japan (e.g. Ebihara et al. 2012), and Papua New Guinea (e.g. Jorim et al. 2012). In Indonesia alone, from 1998 until 2014, as many 39 species

of *Selaginella* had been found with 22 species were found in Java Island (Wijayanto 2014).

Java Island, like other areas in equatorial zone, has two seasons, i.e. dry season (during May-September) and wet season (during October-April). Java Island has a wide range of precipitation which is divided into three categories of area. The western region of Java (Banten and West Java Province) and central region of Java (Central Java and Special Region of Yogyakarta) have the same average rainfall at about 2,000 mm per year, but in some mountainous areas in western Java the precipitation could reach 3,000 to 5,000 mm per year. On the other hand, the eastern area of Java has a lower precipitation with about 1900 mm per year (Qian et al. 2010). Likewise, average temperature in Java has a broad range according to altitude feature. The coastal areas have an average temperature

ranges between 22 °C to 32 °C, while in higher areas with an altitude of between 400-1350 m a.s.l (above sea level) the average temperature ranges between 18 °C-29 °C. Higher altitude generally means a lower range of temperature, in this case, the lowest temperature in Java island can reach minus 4°C which was recorded in Ranu Pani area in the slope of Mount Semeru (Hariyati et al. 2013).

The broad range of temperature and precipitation in Java makes suitable for *Selaginella* to have a wide horizontal and vertical geographical distribution. Altitudinally, *Selaginella* grows in lowlands, highlands and the ecotone (the transitional zones between the two areas), each with its own preference (Setyawan 2008). For example, the vast extent of mountainous areas in Java with varying climatic features supports the growth of *Selaginella opaca* Warb. and *Selaginella remotifolia* Spring., two of the most dominant and prominent species of mountainous *Selaginella* in Java. Traditionally, *S. opaca* and *S. remotifolia* are used as medicinal plants to treat wounds, menstruation disorders, and even as enhance body fitness (Setyawan 2009).

Due to its potential uses as mentioned earlier, there is an increasing interest to study *Selaginella*. However, current trend on the research and conservation of *Selaginella* has been more focused on the studies of the aspect of taxonomy (e.g. Christian 2013; Weststrand and Korall 2016), morphology (e.g. Schulz et al. 2010, 2013; Singh 2014), utilization (e.g. Setyawan 2009), molecular biology (e.g. Korall and Kenrick 2004; Li et al. 2007) and ethnobotany (e.g. Setyawan and Darusman 2008; Setyawan 2009). Meanwhile, studies on the habitat ecology and geographical distribution of *Selaginella* remain limited. Since most *Selaginella* in Indonesia naturally grows in humid and cool areas, which are currently threatened by natural degradation and global warming, there is an urgent need for conservation efforts to ensure the sustainable use of this biological resource (Setyawan 2011). The detailed knowledge of *Selaginella*'s habitat preferences and distribution is a prime priority for any decision making and action plans in the wildlife management and conservation, in order to guarantee long term survival of this genus.

Since the early 20th century, scientific community has recognized the impacts of climate changes, induced by greenhouse gases (GHG), on biodiversity. Climate change has been proved as a perverse outcome of human activities (Karl and Trenberth 2003; IPCC 2007). Climate, since long time ago, has been identified as a primary control of the geographic distribution of plants (e.g. Forman 1964; Box 1981). Therefore, the distribution of a plant should be expected to exhibit as its response to climate change. In this context, the current and potential future distribution of species in regard to global climate change has been widely investigated (e.g. Thuiller 2007; Kudela 2009). The methodological foundations for such theoretical concepts have been developed in the framework of species distribution modeling (SDM), also called niche modeling or bioclimatic envelopes modeling (Elith and Leathwick 2009).

Species distribution models (SDMs) are numerical tools that combine observation data on species occurrence or abundance with environmental estimates. They are used to gain ecological and evolutionary insights and to predict distributions across landscapes, sometimes requiring extrapolation in space and time (Elith and Leathwick 2009). Species distribution models are useful tools for, among other things, informing the conservation management of wildlife and their habitats under a rapidly changing climate (Porfirio et al. 2014), modeling the potential impacts of climate change on extinction risk (Garavito 2015), and predicting spatial patterns of species biodiversity (Dubuis et al. 2013).

Developing species distribution models can be performed using a variety of algorithms, including combinatorial optimization (e.g. GARP—Fitzpatrick et al. 2007), statistical models (e.g. GAMs—Jensen et al. 2008), heuristic models (e.g. BIOCLIM—Beaumont and Hughes 2002), and machine learning (e.g. ANN— Ostendorf et al. 2001, Berry et al. 2002, Harrison et al. 2013; MaxEnt—Phillips et al. 2006) (Sinclair et al. 2010). Maximum Entropy (MaxEnt) modeling has a great potential for identifying distributions and habitat selection of wildlife given its reliance on presence-only data (Baldwin 2009). MaxEnt is a general-purpose machine learning method with a simple and precise mathematical formulation, and it has a number of aspects that make it well-suited for species distribution modeling (Phillips et al. 2013). The approach presented by MaxEnt appears to be quite promising in predicting suitable habitat for threatened and endangered species with small sample records and can be an effective tool for biodiversity conservation planning, monitoring, and management (Kumar and Stohlgren 2009). MaxEnt has the ability to utilize different climatic scenarios to estimate the extent of occurrence of species (Beaumont et al. 2007), allowing the evaluation of the impact of climate changes on geographical distribution of species (e.g. Rondini et al. 2006; Botkin et al. 2007; Randin et al. 2008; Engler and Guisan 2009; Garavito 2015).

The purposes of this study are to model the geographical distribution of *Selaginella opaca* Warb. and *Selaginella remotifolia* Spring. under present climate conditions, and model its future distribution under the influence of climate change. By using MaxEnt software, we built the models based on localities data and bioclimatic features, in combination with climate change scenarios across predetermined time intervals until 2080. We assume that as a response to climate change, there will be a change in geographical distribution of *S. opaca* and *S. remotifolia*.

MATERIALS AND METHODS

Study area

This study covered Java Island (Indonesia), one of the main habitats of the *Selaginella*. Java Island has been known as one of the 25 identified biodiversity hotspots by Myers et al. (2000) and it is closely located with the four biologically richest hotspots, such as Indo-Burma, Peninsular Malaysia, Wallacea, and The Philippines.

Tropical lowland rain forest in these regions, the richest ecosystems in the world, is being cleared for commercial uses, settlement expansion, and logging. Such problems are massively occurring in Java Island, thus responsible for the increasing level of greenhouse gasses which is expected to negatively affect the condition of *Selaginella*'s habitat.

Java Island has approximately 133,930 km² of land area and altitudinal ranges from 0-3,676 m a.s.l. All of the locality points were collected in the mountainous area of Java. Records points were selected carefully to represent the geographical distribution of both *S. opaca* and *S. remotifolia* in Java Island (Figure 1).

Procedures

Locality data

Geo-referenced occurrence records of *Selaginella opaca* Warb. and *Selaginella remotifolia* Spring. across Java Island were obtained from field survey data collected between 2007 and 2014 with a high confidence level of taxonomic identification. A total of 283 species occurrence points (consisted of 144 points of *S. opaca* and 139 points of *S. remotifolia*) were collected in highland areas of Java Island using a GPS (Garmin eTrex Series). The accuracy of the GPS is normally between 0.01 km to 0.05 km. According to a study conducted by Montgomery et al. (2011) this level of telemetry error, which is much smaller than the resolution of predictors, is expected to have a little effect on the accuracy of predicted models. Thus, an error-correction for these data was not performed. In addition,

several geo-referenced occurrence records of both species (35 points of *S. opaca* and 17 points of *S. remotifolia*) were acquired from the Global Biodiversity Information Facility (GBIF) website (<http://www.gbif.org>). So, 335 points used in this study, include 151 points of *S. opaca* and 156 points of *S. remotifolia*.

Sampling bias has been argued to have a strong influence on SDM prediction ability (Fourcade et al. 2013; Fourcade et al. 2014). Therefore, we initially accounted for spatial sampling bias by performing a spatial filtering (Leitao et al. 2011; Syfert et al. 2013; Boria et al. 2014; Yoan et al. 2014). Automatically, MaxEnt will perform spatial filtering by removing duplicate points that fall into a single environmental cell (Merrow et al. 2013). To enhance the spatial filtering, we reduced the locality points by only one point per 2 km radius within each point. The 2 km radius was chosen based on the modification of a 10-km-radius used by Pearson et al. (2007); Anderson and Raza (2010) in their study which was conducted in mountainous areas with high spatial heterogeneity. Considering the level of spatial heterogeneity of climate variability over Java Island (Qian et al. 2010), we decided to reduce the radius used in those studies from 10 km to 3 km. Moreover, this distance was chosen to reduce the geographic biases associated with collection data, rather than to approximate the species' dispersal capabilities. Geographic Distance Matrix Generator ver 1.2.3 was used to calculate the geographic distance between each pair of occurrence records (Erst 2012).

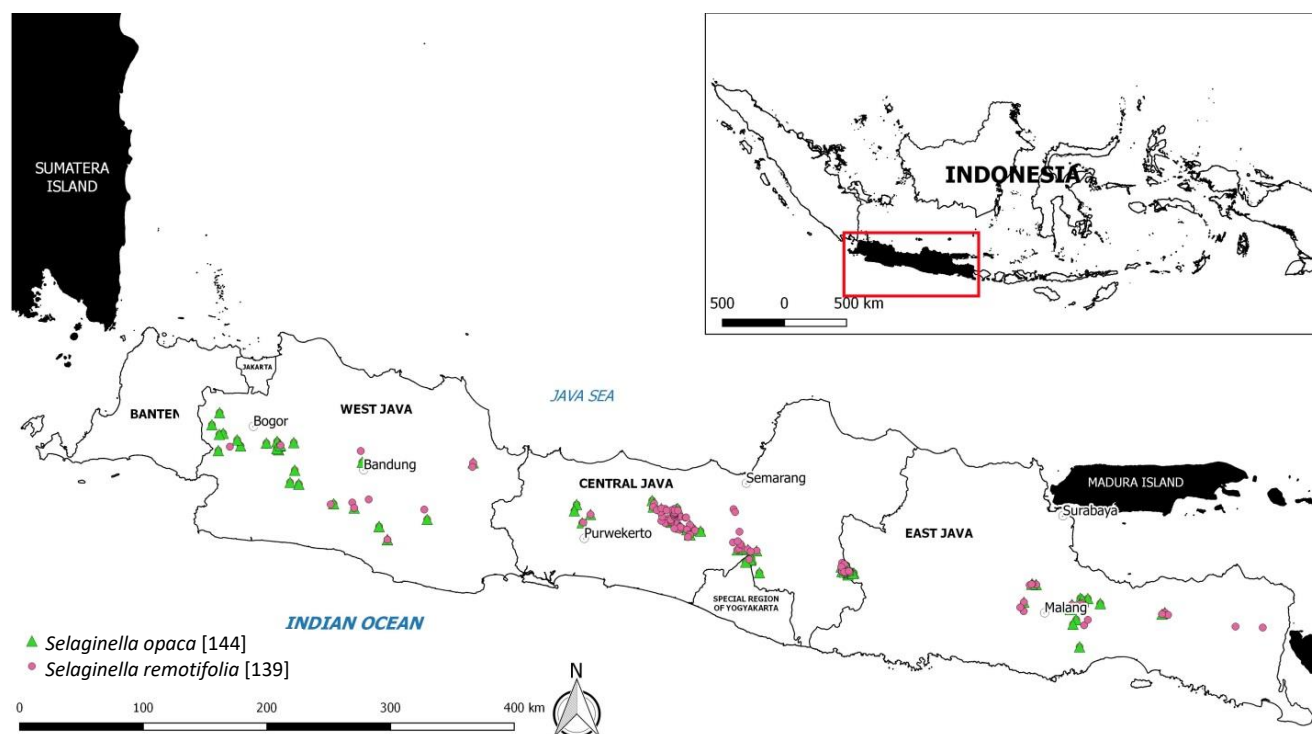


Figure 1. Localities data of *Selaginella opaca* and *S. remotifolia* across Java Island, Indonesia

Predictor variables

Modeling the *S. opaca* and *S. remotifolia* habitat suitability and potential distribution across Java Island under current and future climate conditions were conducted using a set of environmental and bioclimatological variables. In total, we used 22 datasets, consisted of geological features of Java Island, soil type, elevation data, and 19 bioclimatic data layers (11 temperature and 8 precipitation variables). Bioclimatic data were extracted from WorldClim Bioclimatic datasets (<http://www.worldclim.org>). This website provides 19 bioclimatic variables that are interpolated and modeled from observations and averaged over the period 1970 until 2000 at 1 km² spatial resolution. Elevation data were also extracted from the WorldClim database with the same spatial resolution. Geological features and soil types of Java Island were collected from freely available Indonesian Geospatial Information Agency's (Indonesian: Badan Informasi Geospasial, abbreviation: BIG) website. Those data were not ready to use yet, and then, were processed in advance by using geographic information systems method. The process was image cutting, resampling of data in a geographic coordinate system of WGS48 at a resolution of 1 km² (0.008333 decimal degree), and file format converting into ASCII format. All of these processes were performed using QuantumGIS software ver 2.8.10. Since future prediction of land use/land cover changes, human disturbances, and changes in biotic interaction is limited, we did not take these factors into account.

To predict the effect of climate change on the potential distribution of the two mountainous *Selaginella* species under several climate change trajectories, future climate datasets freely provided by CGIAR Research Program on Climate Change, Agriculture, and Food Security (www.ccafs-climate.org) were used. The future climate datasets were downscaled to a 1-km² spatial resolution from its original resolution at scale 100 to 200 km² using the delta method. The delta method interpolates the General Circulation model generally used in climate modeling using a thin plate spline spatial interpolation method to achieve the 30 arc seconds resolution (1 km²) (Ramirez and Jarvis 2008). We selected four RCP (Representative Carbon Pathways), which represents the future greenhouse gas (GHG) trajectories, namely RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 in three different time periods (2030, 2050, and 2080). In this study, we selected the HadGEM2-CC (Hadley Global Environment Model-2 Carbon Cycle) Global Circulation Model, which was developed by the Hadley Center, United Kingdom (Collins et al. 2011). HadGEM2-CC model has been used to perform all the CMIP5 (Coupled Model Inter-comparison Project Phase 5) centennial experiments including ensembles of simulations of the RCPs (Shrestha et al. 2014). RCP 2.6 assumes that global GHG will increase slowly to reach its peak at 3.1 W/m² between 2010-2020, with emissions declining substantially thereafter at 2.6 W/m² by the year 2100 (Van Vuuren et al. 2007; Moss et al. 2009). Emissions in RCP 4.5 is assumed to be stabilized at 4.5 W/m² by the year 2100 due to the employment of a

range of technology and strategies to reduce GHG emissions (Clarke et al. 2007). Likewise, the emissions in RCP 6.0 is projected to reach its peak around 2080 and stabilizes by the year 2100 at 6.0 W/m². In RCP 8.5 emissions continue to rise throughout the 21st century, reaching around 8.5 W/m² as the highest value (Riahi et al. 2011).

The Global Climate Models have been widely used to assess the climate change impact at local to global scales and used as basic information to construct climate change scenarios. However, these models exhibit systematic error (biases) due to the limited spatial resolution, numerical schemes, simplified physics, and thermodynamic processes, or incomplete knowledge of climate system processes (Ramirez-Villegas et al. 2013). Thus, we performed a bias-correction procedure to produce climate projections that fit better for modeling. The Change Factor (CF) and Quantile Mapping (QM) methods were selected in this bias-correction procedure. In the Change Factor (CF) approach, the raw GCM outputs current values are subtracted from the future simulated values, resulting in “climate anomalies” which are then added to the present-day observational dataset (Tabor and Williams 2010). The Quantile Mapping (QM) method was selected to complement the CF method, since the CF method works well for only more non-stochastic variables (i.e. temperature). Thus, a more sophisticated approach for bias-correcting stochastic variables (e.g. precipitation and solar radiation) was needed.

Modeling

Predictive maps of occurrence under current and future climate conditions were modeled by using MaxEnt software ver. 3.3.3a (Computer Science Department-Princeton University 2004) on the basis of occurrence data and environmental variables (Philips and Dudik 2008; Summers et al. 2012). MaxEnt software was selected since it has been proved suitable to be used with presence-only (PO) data, and provides robust and reliable results (Warren and Seifert 2011). Since 2005, more than 1000 published distribution modeling has been conducted using MaxEnt software (Merow et al. 2013; Fourcade et al. 2014). The popular utilization of MaxEnt is due to higher predictive accuracy than any other method (Elith et al. 2006; Summers et al. 2012). MaxEnt also performs well to estimate the effect of climate change on the potential shifting range of species (Kou et al. 2011; Johnston et al. 2012; Duan et al. 2016).

To minimize the impact of multi-collinearity and over-fitting, we calculated pairwise correlation of the predictor variables using R program ver. 3.4.1 and then removed highly correlated variables ($r^2 \leq 0.80$) (Baldwin 2009; Merow et al. 2013). Out of nineteen variables, nine bioclimatic variables (bio_1, bio_2, bio_3, bio_4, bio_12, bio_13, bio_15, bio_18, and bio_19) and three environmental variables (altitude, geological feature, and soil type) were then used to model the potential distribution of both species under current and future climate condition. Despite the fact that MaxEnt has been shown to give robust

and reliable results by just using default settings (Phillips et al. 2008), we modify several parameter values to adjust the calculation with our present data and predictor variables. The adjusted parameter values were: five replicated runs (the averaged value is the one used as the result) with "cross validate" as the replicated run type, maximum iterations = 5,000, and convergence threshold = 10,000. We also created background points data to be included as a bias file to represent sampling effort to reduce sampling bias (Fourcade et al. 2014). Bias file, ideally, represents the actual sampling effort across the study area or could be estimated by the aggregation of occurrences from closely related species (Phillips et al. 2009). Nevertheless, in most real modeling situations, this information is limited. In consequence, following Elith et al. (2010), authors produced a Gaussian kernel density map of the occurrence locations, rescaled from 1 to 20 to be derived as bias file.

Data analysis

The main output of MaxEnt program is continuous data showing the potential suitable habitat distribution which linearly scaled between 0 (lowest) to 1 (highest) probability (Phillips and Dudík 2008). Furthermore, MaxEnt created calculation of the bioclimatic relative contribution to the model and how these variables affect the MaxEnt prediction. Alternate estimation of variable importance was also collected by running the jackknife test. The results of jackknife test show which variable has the most useful information by itself and which variable appears to have the most information that is not present in the other variables.

MaxEnt will calculate an area under the receiver operating characteristic (ROC) curve (AUC) to evaluate model performance. AUC values can range between 0.5 and 1.0, with 0.5 indicating that the model is no better than random prediction; values below 0.7 are low, values between 0.7 and 0.8 are good, and values >0.9 indicate high discrimination or it means that the model is far better than random prediction. Even though the AUC was written as the established method for assessing the fitness of the model in some papers (e.g. Townsend Peterson et al. 2007; Rodder et al. 2010; Donald et al. 2012; and Setiadi 2012), unfortunately, it is also proved wrong by Lobo J.M et al. (2008); Bahn and McGill (2012); and Aguirre-Gutiérrez et al. (2013). These studies also demonstrated that AUC does not provide useful information for assessing SDM performance. Therefore, in this study, the additional evaluation of the model was conducted using True Skill Statistic (TSS) as it has been proved theoretically and empirically better than AUC and also better than Kappa Statistic in measuring the performance of species distribution models (Allouche et al. 2006).

We imported the ASCII file containing the probability of habitat suitability into QuantumGIS software ver. 2.18.10 and reclassified it into three classes: low suitability (25-50 % probability of occurrence), medium suitability, (50-75% probability of occurrence), and high suitability (>75 % probability of occurrence). The reclassification allowed us to compare the change in every class over time and space. Another analysis was conducted to observe the potential change of altitudinal distribution of *S. opaca* and

S. remotifolia by compared the mean values of the predicted areas under current and future climate scenarios condition using independent sample T-test. We then compared the total area of predicted habitat under current and projected future climate conditions by counting the number of "presence" grid cells and multiplied it by their spatial resolution.

RESULTS AND DISCUSSION

Identifying important environmental variables

Twelve predictor variables (environmental and bioclimatic) were utilized to build the ecological niche model of *S. opaca* and *S. remotifolia*. It is important to note that when a single run of MaxEnt software involves two different species in the same genus, MaxEnt, in its settings option, is able to calculate and give separate results for each species. Therefore, the important variables that contribute to build the model for each species can be compiled and explained separately. The four most important variables that contributed a combined total of 83.8% to the model were altitude, annual mean temperature (bio_1), geology feature, and mean diurnal range (bio_2), accounting for 58.8%, 15.3%, 9%, and 6%, respectively (Table 1). These four variables are representative of all four major aspects of environmental variables (temperature, land factor, altitude, and precipitation) included in the model.

MaxEnt produces response curves to illustrate how each variable affects the prediction. The curves show how the logistic prediction changes as each variable are varied, keeping all other variables at their average sample value (Phillips et al. 2006). Altitude, by far, was the most important determinant in the model, with the response curve indicating positive correlation between the increase in altitude level and increase in probability of occurrence which started its significant value at around 1,000 m a.s.l and reached its peak at about 2,100 m a.s.l before decreased gradually at higher altitude to a level below 0.5 (Figure 2.A). The second most important predictor was annual mean temperature, suggested high probability of occurrence in a narrow range of temperatures between 13 and 18°C, then the probability dropped lower and even reach zero at temperature higher than 24°C (Figure 2.B). The next important variable was geology feature, represented with a code number for each category of geological feature. According to Figure 2.C, the highest probability of presence was on Qlv (code number 295) type of rocks which has been approximately existed since the Holocene epoch (1.26 ma) (Hudson 2013). The next notable geological feature was Qtp (code number 281) type of rocks, which has approximately been dated back to the Pleistocene epoch (2.6 ma) (Bhat et al. 2012). These types of rock are classified as volcanic rock which is often found in Java since this island contains numerous volcanoes. Therefore, since these types of geological feature are abundance in highland region in Java, both mountainous *Selaginella* is often found in these types of rock. The fourth important variable was precipitation of wettest month

(bio_13), which represents the mean precipitation during wet season. Figure 2.D illustrates a high probability at precipitation above 600 mm, and increasing along with higher precipitation rate.

Model of geographical distribution under current climate condition

The model of potential distribution of mountainous *Selaginella* under current climate condition is shown in Figure 3. The figure illustrates their wide distribution, with numerous patches of varying sizes and levels of suitability across mountainous areas in Java Island. According to our model, only about 5.07% (6,436 km²) of the areas in Java Island is suitable for *S. opaca* and *S. remotifolia* habitat. The number consists of 4,266 km² (3.35%), 1,751 km² (1.37%), and 417 km² (0.32%) of low, medium, and high probability area respectively. The greatest concentration of suitable habitat is observed covering three mountains in Central Java Province, Indonesia, i.e. Mt. Sumbi, Mt. Sundoro, and Mt. Dieng. This area is expected to have the best climatic and environmental conditions to support the habitat of mountainous *Selaginella*. Another noticeable area with a wide medium probability is in Mt. Merapi. Mount Merapi is a volcanic mountain located in Central Java province and has several steep slopes with dense vegetation on its lower flanks.

There is a clear division of predicted distribution between the central region and both the western and eastern regions of Java, even though these sites have been recorded

carefully with respectable number of locality points. Low probability area in western Java is dominant and distributed widely in small patches. Likewise, low probability area is also dominant in eastern part of Java but with larger patch. The pattern could be due to the difference of unique climatic features between these regions. Another explanation may relate to model sensitivity or data inaccuracies, for example, the scale of bioclimatic data which is larger than many small suitable bioclimatic spaces.

Table 1. Percentages of variables contribute to the final model in MaxEnt

Environmental variables	Contribution (%)
Altitude (Alt)	53.1
Annual Mean Temperature (°C *10) (bio_1)	21.2
Geology feature	10
Precipitation of Wettest Month (bio_13)	5.6
Mean Diurnal Range (Mean of monthly (max temp - min temp)) (bio_2)	3.6
Temperature Seasonality (standard deviation *100) (bio_4)	1.4
Soil type	1.1
Isothermality (bio_3)	1.1
Annual Precipitation (bio_12)	1
Precipitation of Coldest Quarter (bio_19)	0.7
Precipitation of Warmest Quarter (bio_18)	0.6
Precipitation Seasonality (bio_15)	0.6

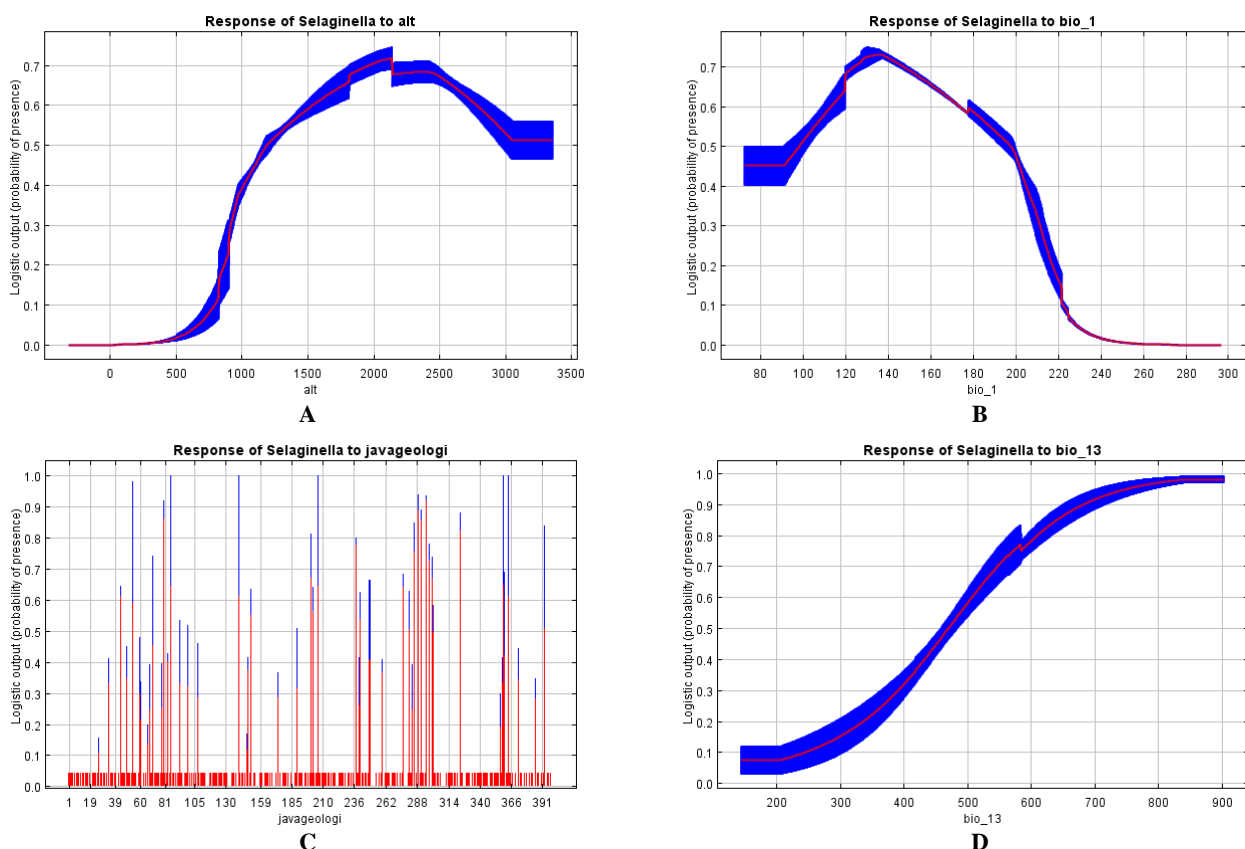


Figure 2. Response curves from MaxEnt to the most important variables for the species distribution model of *S. opaca* and *S. remotifolia*: A. Altitude; B. Annual mean temperature (in °C*10); C. Geology feature; D. Precipitation of Wettest Month (in mm/month)

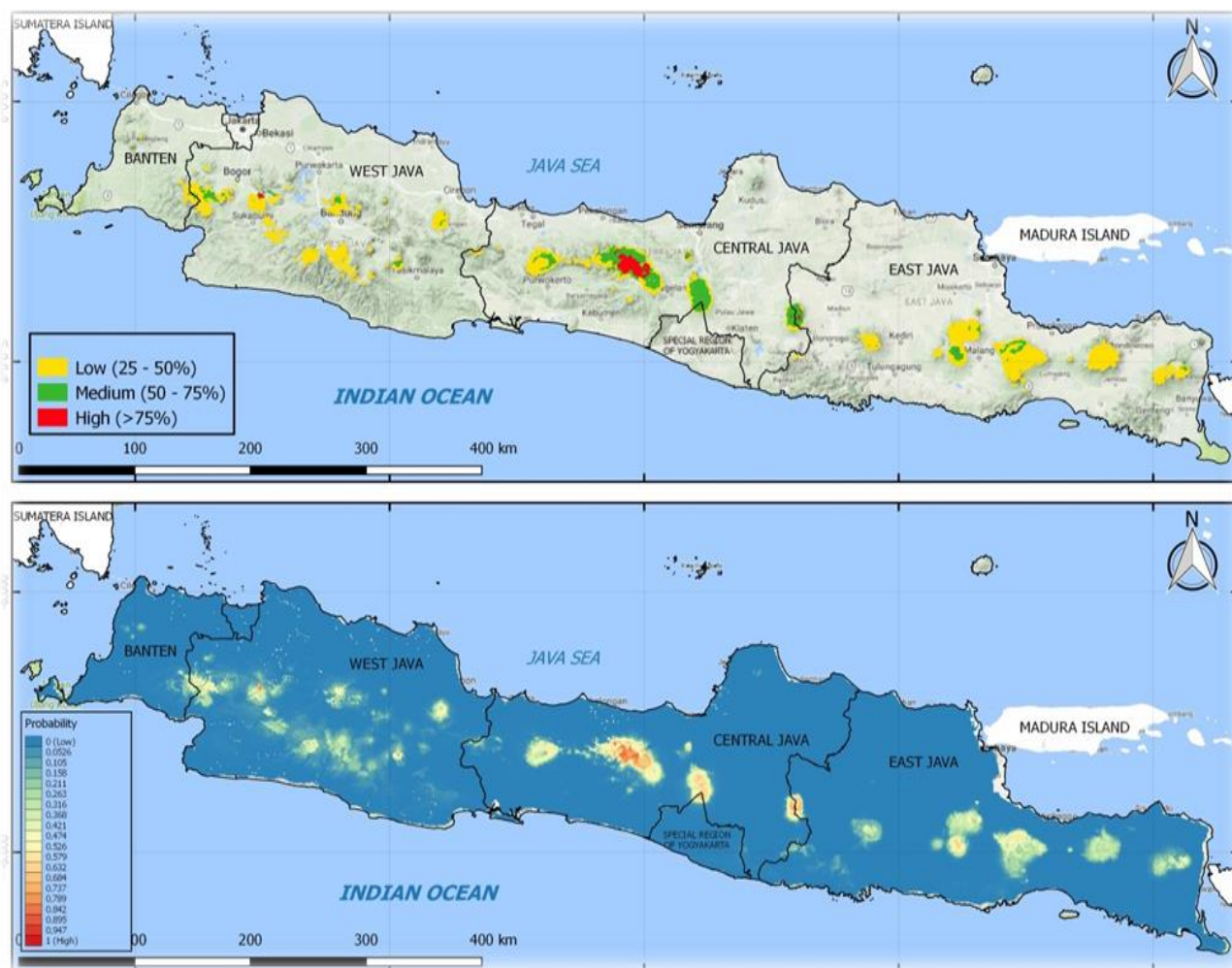


Figure 3. Predicted potential distribution of *Selaginella opaca* and *S. remotifolia* under current bioclimatic condition.

Prediction of future geographical distribution

Prediction of the potential impact of climate change on the distribution of *S. opaca* and *S. remotifolia* is shown in Figure 4. The future modeled scenarios shows a significant decrease in predicted climatically suitable habitat for both species across all scenarios in the given periods of time (Figure 5). The area which has been predicted as mostly affected by climate change is the western part of Java. Model predicted that the suitable habitat in this area will decrease by 15-38 % in all climate scenarios. In the RCP 2.6 scenario (lower emission by the end of century, but with significant increase in the first quarter of century) the highest suitability area will likely decrease by almost 40% in 2080, while the medium and low suitability area in this scenario will fall marginally.

Likewise, in RCP 4.5 and RCP 6.0 (GHG emission will increase dramatically but managed to be stabilized by the end of century), the downward trend of the high suitability area is predicted to be greater than the trend in RCP 2.6. Of the 417 km² of high suitability area in the current condition, more than half (287 km²) will be lost by the end of 2080 under RCP 4.5 climate scenario, and about 295 km² of that area will be lost under RCP 6.0 climate scenario by the same period of time. RCP 8.5 is predicted to have the most

impact on the distribution of suitable habitat of *S. opaca* and *S. remotifolia*. Under this climate projection, both low and medium suitability areas will be gradually decreased while becoming centralized as the higher level of suitability areas are concentrated in the central part of Java. Furthermore, in this scenario, Java Island will only have 98 km² left of high suitability area for both mountainous *Selaginella* in 2080.

The projected climate change also observed to affect the altitudinal distribution of mountainous *Selaginella* (Figure 6, Table 2). The average elevation of the distribution of mountainous *Selaginella* under three climate change pathways: RCP 6.0 (2050), RCP 2.6 (2080), and CP 6.0 (2080) are marginally lower than the average elevation under current climate condition. In contrast, higher average elevation of the distribution is shown under RCP 2.6 (2030) climate pathway. Based on the independent t-test between the altitude means of potential distribution range under current climate conditions and that of future climate conditions, all of these changes are statistically significant ($p = 0.01$). On the other hand, other climate change scenarios show a decrease in average elevation of the distribution. However, none of these changes were statistically significant.

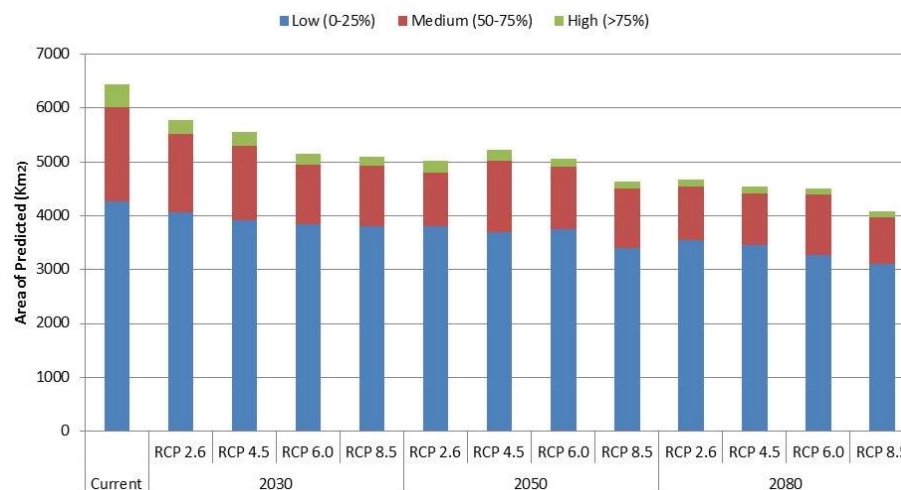


Figure 4. Estimated areas of the predicted distribution of *Selaginella opaca* and *S. remotifolia* habitat under future bioclimatic conditions

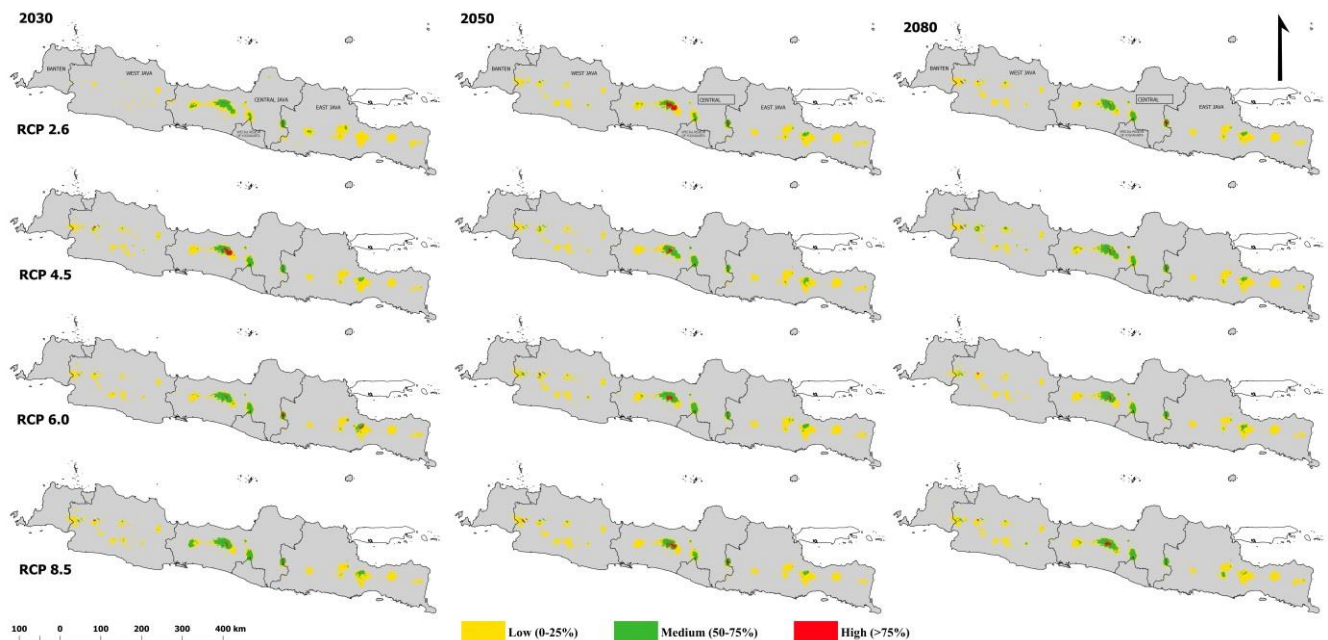


Figure 5. Prediction of future geographical distribution of *Selaginella opaca* and *S. remotifolia* under four climate change scenarios.

Table 2. Independent T-test between average elevation of current and future distributed predictions

Climate scenarios	Year	Mean	SD	P-value
Current condition	-	1668.66	585.21	-
RCP 2.6	2030	1745.5	544.06	1.82E-07
RCP 4.5	2030	1666.06	585.45	0.85
RCP 6.0	2030	1652.22	587.75	0.24
RCP 8.5	2030	1651.17	586.21	0.21
RCP 2.6	2050	1643.26	585.21	0.06
RCP 4.5	2050	1667.09	575.59	0.9
RCP 6.0	2050	1624.48	570.53	0.001
RCP 8.5	2050	1644.24	584.13	0.07
RCP 2.6	2080	1602.35	574.06	0.0001
RCP 4.5	2080	1639.12	578.25	0.03
RCP 6.0	2080	1626.28	556.87	0.001
RCP 8.5	2080	1658.06	586.7	0.44

Discussion

Java as the most densely populated island in Indonesia, home to about 57% of Indonesia's population, will likely suffer more from the worsening human-induced climate change. The fact that this island has a high level of biodiversity (Myers et al. 2000), urges many efforts to study the response of biodiversity to the impacts of climate change. Projection of climate change in Java Island by Measey (2010) predicted a rise in the mean temperature by 0.40 to 0.41 °C in 2020, and has been predicted to increase by 2.0 to 2.5 °C at the end of 21st century by Gosling et al. (2011). This study illustrates the first attempt to model the distribution of mountainous *Selaginella* under current and future climate conditions. Since the change in climate condition has already impacted *Selaginella*'s habitat in the past time in several places (e.g. Boettger 2009; Cao et al.

2010; Bezrukova et al. 2012), it will likely affect the distribution of this genera under future climate condition in Java Island as well. Therefore, this study provides a model

that could predict the impact of climate change on mountainous *Selaginella*'s distribution driven by several representative greenhouse gas concentration pathways.

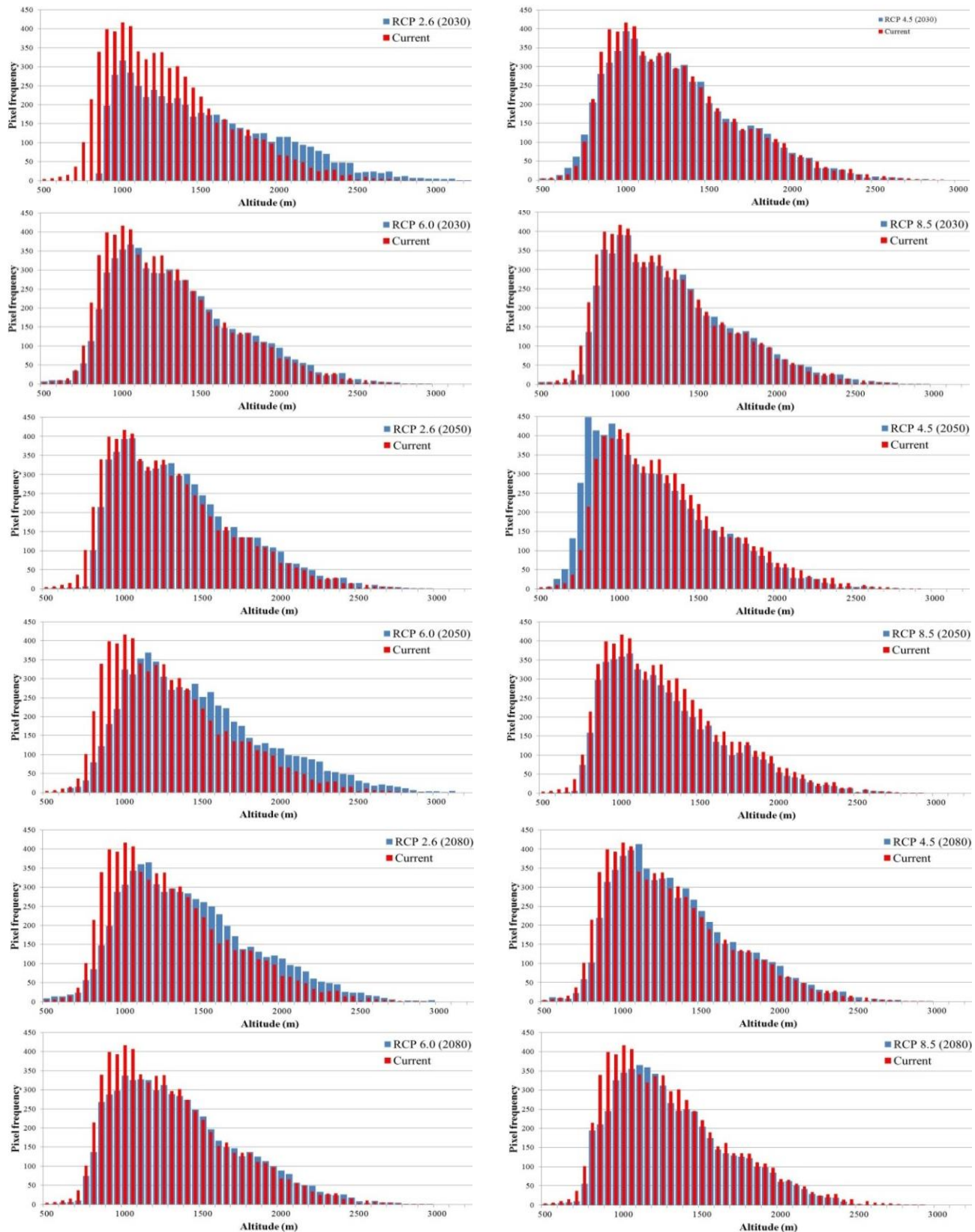


Figure 6. Change in average altitudinal distribution of *Selaginella opaca* and *S. remotifolia* under four future climate scenarios

Our study represents a robust result of a modeling attempt driven by carefully selected locality data and bioclimatic variables. Despite the fundamental problem when using AUC (Area Under the Curve) to validate species distribution modeling, we retrieved the AUC value of 0.957, indicating that the prediction in this study was far better than random prediction and that the selected variables have described the distribution of mountainous *Selaginella* acceptably. Furthermore, additional evaluation of the model was conducted using True Skill Statistic (TSS) to give further confidence in the output of this model. The TSS value of 0.81 gives the impression that the model built in this study has a very good degree of agreement (Li and Guo 2013). Regarding the AUC, its value is highly correlated to prevalence of the locality points and the size of the study area (Lobo et al. 2008). Consequently, this would generate some sort of bias or misunderstanding, for example, if one uses a small study region or if the locality points are localized in small area and the prevalence is small, one would get a high AUC value. Moreover, AUC, just like Kappa, is reliable only if we use PA (Presence-Absence) model due to the fact that both AUC and Kappa are weighting omission and commission errors equally. Thus, in case of this study where presence-only data was used, AUC and Kappa are not necessarily reliable. According to Setyawan et al. 2015, *Selaginella* is a herbaceous plant that will likely grow in the moist or rather wet region. Thus, since Java Island is a tropical island, elevation, which has a strong relationship with the level of humidity, plays another important role in the growth and the distribution of mountainous *Selaginella*. Then, temperature, as a regulator of evapotranspiration level, will become highly important factor as well in order to maintain the level of humidity in the region. Our study that illustrates the importance of altitude, temperature, and precipitation (see results) is in line with the knowledge about the habitat needs of mountainous *Selaginella*. Geological feature, on the other hand, may not represent the preference growth region of mountainous *Selaginella*, but rather to represent the geological feature in the highland region of Java. In this regard, the result of our study shows only the geological feature that predominantly will be found in the volcanoes region. The fact that Java island is part of circum-Pacific belt region (USGS 2012) adds confidence to the former allegation that this result represents only the dominant feature in the mountainous region of Java, rather than the actual preferred geological feature of the growth and distribution of *S. opaca* and *S. remotifolia*.

Despite the limitation to inspect the current distribution predicted by this study across Java Island, there are several conformities with the distribution of *S. opaca* and *S. remotifolia* found by Setyawan et al. (2015) and Setyawan (2016) in Mt. Merapi and in the Dieng plateau, respectively. These areas, by our model, represent a wide area of medium to high level of habitat suitability. However, the model might be slightly underestimating the potential distribution in the western region of Java since several mountainous areas in this region have the same altitudinal and geological feature with the one in the central

and eastern regions. Although the TSS value suggests a very good degree of agreement of this model, further exploration is needed to confirm whether there are several factors that distinguish the western region from the rest of region or whether mainly because of the limitation of the model.

Based on our model, the negative impacts of future climate condition is illustrated by major decrease in the level of habitat suitability and the total area of habitat distribution. The total area of habitat is expected to decrease by 1.8 % to 11.4 % under all climate change trajectories. The most favorable climate scenario is RCP 2.6 (in all periods of time) which predicts no more than 5% of suitable habitat losses. Lower altitude regions under 900 m a.s.l across the island are predicted by this scenario to lost its capability to support the sustainability of mountainous *Selaginella*. Likewise, the worst scenario in this study (RCP 8.5) is predicted not only the lost capability of lower altitude but also lowering the level of habitat suitability in the higher region. The highest level of habitat suitability which concentrated in the region between Mt. Sumbing, Mt. Sundoro, and Mt. Dieng is likely to decrease by almost 60% (Figure 4).

Mean temperature in Indonesia under future climate conditions is projected to increase by 0.72 to 3.92 °C (Crus et al. 2007) depending on different scenarios. Theoretically, since climate in Indonesia is strongly influenced by El Nino Southern Oscillation (ENSO) events, rising in temperature may lead to an excessive drought which in the end will drop the humidity level. Consequently, the increasing level of evaporation in some areas of Indonesia (induced by high-level temperature) would intensify the earth's water cycle, resulting in higher risk of storm and flooding in another Indonesian area during La Nina events. However, annual precipitation in Indonesia is projected to have an opposite path of change. Boer and Faqih (2004) stated that there is significant spatial variability in annual precipitation across all of Indonesia over the last century. They stated that there has been a significant decline in annual rainfall of southern regions of Indonesia (e.g. Java Island, Lampung, South Sumatera, South Sulawesi, and Nusa Tenggara) and an increase of precipitation level in the northern regions of Indonesia (e.g., most of Kalimantan, North Sulawesi, etc). Furthermore, Cruz et al. (2007) gave an estimation number of two percent of the declining precipitation and up to four percent of the increasing level of precipitation by the end of the century.

Since Java Island has been predicted to have a higher level of temperature and lower level of annual precipitation, the average elevation of the suitable habitat for mountainous *Selaginella* may change. Despite the statistically insignificant value (with the exception in RCP 2.6 in 2030), the average altitude of suitable habitat will mostly be shifted to a higher elevation. Hypothetically, the shift may be triggered by the ability of the higher altitude area to maintain the high humidity level in spite of the anomaly of temperature and precipitation level in Java Island. In contrast, our model also predicted a lower average of altitudinal distribution under several climate trajectories. It is unclear to explain what factors may induce

a decrease in altitudinal range under these climate trajectories. The most possible approach is to monitor the impact of past climate change on the distribution of mountainous *Selaginella*. Nevertheless, this approach is impossible to be conducted due to unavailability of historical data on the distribution of mountainous *Selaginella*.

The model built in this study, certainly, has some limitations. Single-species approach via bioclimatic modeling and the absence of more detailed ecological and physiological data are some of the major limitations in the assessment of climate change impact (Hampe 2004; Morin and Thriller 2009; Sinclair et al. 2010; Ellis 2011). Other limitations are related to the spatial resolution of bioclimatic variables. The 30 arcs second resolution used in this study may greater than the range size distribution of mountainous *Selaginella*. However, since new climate models are currently developed while the existing are refined, future research may have the opportunity to re-analyze this existing data under finer temporal and spatial resolution. Further precise modeling of the distribution trends of mountainous *Selaginella* in the future, shall incorporate future model of land use/land cover change and biotic interactions between species in the regional ecosystems. Moreover, sophisticated models to be developed in the future shall include microclimatic variables and landscape heterogeneity of Java Island.

REFERENCES

- Allouche O, Tsoar A, Kadmon R. 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *J Appl Ecol* 43 (6): 223-232.
- Anderson RP, Lew D, Peterson AT. 2003. Evaluating predictive models of species' distributions: criteria for selecting optimal models. *Ecol Model* 162: 211-232.
- Anderson RP, Raza A. 2010. The effect of the extent of the study region on GIS models of species geographic distributions and estimates of niche evolution: preliminary tests with montane rodents (genus *Nephelomys*) in Venezuela. *J Biogeogr* 37: 1378-1393.
- Bahn V, Brian JM. 2006. Testing the predictive performance of distribution models. *Synth Ecol* 43 (6): 1223-1232.
- Baldwin, Roger A. 2009. Use of maximum entropy modeling in wildlife research. *Entropy* 11 (4): 854-866.
- Banks JA. 2009. *Selaginella* and 400 Million Years of Separation. *Ann Rev Plant Biol* 60: 223-238.
- Berry PM. 2002. Modelling potential impacts of climate change on the bioclimatic envelope of species in Britain and Ireland. *Glob Ecol Biogeogr* 11: 453-462.
- Bezrukova EV, Anderson, Vinkovskaya, Kharinsky, Kulagina NV. 2012. Paleoenvironment: The stone age. *Archae Ethno Anthropol Eurasia* 40 (3) (2012): 2-11.
- Bhat GM, Craig J, Thurow J, Thusu B. 2012. Geology and Hydrocarbon Potential of Neoproterozoic-Cambrian Basins in Asia. The Geological Society. London.
- Boettger T, Hiller A, Frank W, Junge, Mania D, Kremenetski K. 2009. Late Glacial/Early Holocene environmental changes in Thuringia, Germany: Stable isotope record and vegetation history. *Quarter Int* 203: 105-112.
- Botkin DB, Saxe H, Miguel B, et al. 2007. Forecasting the Effects of Global Warming on Biodiversity. *Biosci* 57 (3): 227-238.
- Box EO. 1981. Predicting physiognomic vegetation types with climate variables. *Veg* 45: 127-139.
- Cao X, Xu Q, Jing Z, Tang J, Li Y, Tian F. 2010. Holocene climate change and human impacts implied from the pollen records in Anyang, central China. *Quater Int* 227: 13-26.
- Chan LM, Brown JL, Yoder AD. 2011. Integrating statistical genetic and geospatial methods brings new power to phylogeography. *Mol Phy Evol* 59: 523-537.
- Clarke L, Edmonds J, Jacoby H, Pitcher H, Reilly J, Richels R. 2007. Scenarios of Greenhouse Gas Emissions and Atmospheric Concentrations. Sub-report 2.1A of Synthesis and Assessment Product 2.1 by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research. Department of Energy, Office of Biological & Environmental Research, Washington DC.
- Collins WJ, Bellouin N, Doutriaux-Boucher M, Gedney N, Halloran P, et al. 2011. Development and evaluation of an Earth-System model—HadGEM2. *Geosci Model Dev Discuss* 4: 997-1062.
- Cruz RV, Harasawa H, Lal M, et al. 2007. Asia. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. In: Parry ML, Canziani OF, Palutikof JP, van der Linden, Hanson CE (eds). Cambridge University Press, Cambridge.
- Duan RY, Xiao-Quan K, Min-Yi H, Sara V, Xiang J. 2016. The potential effects of climate change on amphibian distribution, range fragmentation and turnover in China. *PeerJ* 4: 165-174.
- Dubuis A, Rossier L, Pottier J, Pellissier L, Pascal V, Guisan A. 2013. Predicting current and future spatial community patterns of plant functional traits. *Ecography* 36: 001-011.
- Ebihara A, Fraser-Jenkins CR, Parriss BS, Zhang XC. 2012. Rare and threatened pteridophytes of Asia 1. An enumeration of narrowly distributed taxa. *Bull Natl Mus Nat Sci* 38 (3): 93-119.
- Elith J, Graham CH, Anderson P, Dudik M, Ferrier S, et al. 2006. Novel methods improve prediction of species distributions from occurrence data. *Ecography* 29: 129-151.
- Elith J, Kearney M, Phillips SJ. 2010. The art of modelling range-shifting species. *Methods Ecol Evol* 1: 330-342.
- Elith J, Leathwick JR. 2009. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annu Rev Ecol Syst* 40:677-97.
- Ellis CJ (2011) Predicting the biodiversity response to climate change: challenges and advances. *Syst Biodivers* 9: 307-317.
- Ellis CJ. 2011. Predicting the biodiversity response to climate change: challenges and advances. *Syst Biodivers* 9: 307-317.
- Engler R, Guisan A. 2009. MigClim: Predicting plant distribution and dispersal in a changing climate. *Divers Distrib* 15 (4): 590-601.
- Ersts PJ. 2012. Geographic Distance Matrix Generator (version 1.2.3). American Museum of Natural History. Center for Biodiversity and Conservation. www.biodiversityinformatics.amnh.org/open_source/gdmg.
- Fitzpatrick MC, Weltzin JF, Sanders NJ, Dunn RR. 2007. The biogeography of prediction error: why does the introduced range of the fire ant over-predict its native range. *Glob Ecol Biogeogr* 16 (1): 24-33.
- Forman TT. 1964. Growth under controlled conditions to explain the hierarchical distributions of a moss, *Tetraphis pellucida*. *Ecol Monogr* 34: 1-25.
- Fourcade Y, Engler JO, Rodder D, Secondi J. 2014. Mapping species distributions with MAXENT using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. *PLoS ONE* 9 (5): e97122. DOI: 10.1371/journal.pone.0097122.
- Fox J. 2010. Polycor: polychoric and polyserial correlations, R package version 0.7-8. www.CRAN.R-project.org/package=polycor. [12 June 2017].
- Fujino J, Nair R, Kainuma M, Masui T, Matsuoka Y. 2006. Multi-gas mitigation analysis on stabilization scenarios using AIM global model. *En J Mitig Climat* 3: 343-354.
- Garavito TN, Golicher D, Oldfield S. 2015. The Relative Impact of Climate Change on the Extinction Risk of Tree Species in the Montane Tropical Andes. *PLoS ONE* 10 (7): e0131388. DOI: 10.1371/journal.pone.0131388.
- Gosling SN, Dunn R, Carrol F, et al. 2011. Climate: Observations, projections and impacts: Indonesia. Met Office Publisher. Devon.
- Graham CH, Elith J, Hijmans R, Peterson AT, Loiselle B. 2009. The influence of spatial errors in species occurrence data used in distribution models. *J App Ecol* 45 (1): 239-247.
- Hampe A (2004) Bioclimate envelope models: what they detect and what they hide. *Global Ecol Biogeogr* 13: 469-476.

- Hariyati JH, Arisoesilarningsih E, Hakim L. 2013. Seedling growth of some native trees in Ranu Pani- Ranu Regulo restoration area, Bromo Tengger Semeru National Park. *J Biodiv Environ Sci* 3 (6): 47-55.
- Harrison D, Prabhu G, Grieve R, et al. 2013. Risk adjustment in neurocritical care (rain)-prospective validation of risk prediction models for adult patients with acute traumatic brain injury to use to evaluate the optimum location and comparative costs of neurocritical care: a cohort study. *Health Technol Assess* 17 (23): 313-350.
- Hudson MR. 2013. New Perspectives on Rio Grande Rift Basins: From Tectonics to Groundwater. The Geological Society of America. Colorado.
- Intergovernmental Panel on Climate Change [IPCC]. 2007. Climate change 2007: the physical science basis, summary for policy makers. www.ipcc.ch. [13 June 2013].
- Johnston KM, Freund KA, Schmitz OJ. 2012. Projected range shifting by montane mammals under climate change: implications for Cascadian National Parks. *Ecosphere* 3 (11): 97-116.
- Jorim RY, Korape S, Legu W, et al. 2012. An ethnobotanical survey of medicinal plants used in the eastern highlands of Papua New Guinea. *J Ethnobiol Ethnomed*. DOI: 10.1186/1746-4269-8-47
- Korall P, Kenrick P. 2004. The phylogenetic history of Selaginellaceae based on DNA sequences from the plastid and nucleus: extreme substitution rates and rate heterogeneity. *Mol Phylo Evol* 31: 852-864.
- Kou X, Li Q, Liu S. 2011. Quantifying Species' Range Shifts in Relation to Climate Change: A Case Study of *Abies* spp. in China. *PLoS ONE* 6 (8): e23115. DOI: 10.1371/journal.pone.0023115.
- Kumar S, Stohlgren TJ. 2009. Maxent modeling for predicting suitable habitat for threatened and endangered tree *Canacomyrica monticola* in New Caledonia. *J Ecol Nat Environ* 1 (4): 94-98.
- Linda JB, Lesley H. 2002. Potential changes in the distributions of latitudinally restricted Australian butterfly species in response to climate change. *Glob Ch Bio* 8 (10): 954-971.
- Lobo JM, Jimenez-Valverde A, Real R. 2008. AUC: a misleading measure of the performance of predictive distribution models. *Global Ecol Biogeogr* 17 (2): 145-151.
- Lobo JM, Jiménez-Valverde A, Real R. 2008. AUC: a misleading measure of the performance of predictive distribution models. *Glob Ecol Biogeogr* 17: 145-151.
- Mariah Measey. 2010. Indonesia: A vulnerable country in the face of climate change. *Glob Major J* 1 (1): 31-45.
- Merow C, Smith MJ, Silander JA. 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecograph* 36 (10): 1058-1069.
- Montgomery R, Roloff GJ, Hoef JMV. 2011. Implications of ignoring telemetry error on inference in wildlife resource use models. *J Wildl Manag* 75: 702-708.
- Montgomery R, Roloff GJ, Hoef M. 2011. Implications of ignoring telemetry error on inference in wildlife resource use models. *J Wildl Manag* 75: 702-708.
- Morin X, Thuiller W (2009) Comparing niche- and process-based models to reduce prediction uncertainty in species range shifts under climate change. *Ecol Lett* 90: 1301-1313.
- Myers, Norman, Russell MA, Cristina GM, et al. 2000. Biodiversity hotspots for conservation priorities. *Nat* 403 (6772): 853-858.
- Pearson RG, Dawson TP. 2003. Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful?. *Glob Ecol Biogeogr* 12: 361-371.
- Pearson RG, Raxworthy C, Nakamura M, Peterson AT. 2007. Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *J Biogeogr* 34: 102-117.
- Phillips SJ, Anderson RP, Schapire RE. 2013. Maximum entropy modeling of species geographic distribution. *Ecol Model* 19: 231-259.
- Phillips SJ, Dudík M, Elith J, Graham CH, Lehmann A, et al. 2009. Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. *Ecol Appl* 19: 181-197.
- Porfirio LL, Harris RM, Lefroy EC, Hugh S, Gould SF, Lee G, et al. (2014) Improving the use of species distribution models in conservation planning and management under climate change. *PLoS ONE* 9 (11): e113749. DOI: 10.1371/journal.pone.0113749.
- Qian JH, Robertson JW, Moron V. 2010. Interactions among ENSO, the Monsoon, and Diurnal Cycle in Rainfall Variability over Java, Indonesia. *J Atm Sci* 67: 3509-3524.
- Ramirez J, Jarvis A. 2008. High resolution statistically downscaled future climate surfaces. International Center for Tropical Agriculture (CIAT); CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) Cali, Colombia. www.ccafs-climate.org/statistical_downscaling_delta [1 June 2017].
- Randin CF, Dirnbock T, Dullinger S, et al. 2006. Are niche-based species distribution models transferable in space?. *J Biogeogr* 33: 1689-1703.
- Randin CF, Engler R, Normand S, et al. 2008. Climate change and plant distribution: local models predict high-elevation persistence. *Glob Ch Biol* 15 (6): 1557-1569.
- Riahi K, Rao S, Krey V, et al. 2011. RCP 8.5—A scenario of comparatively high greenhouse gas emissions. *Climatic Change* 109 (33): 364-379.
- Rondini C, Wilson KA, Boitani L, et al. 2006. Tradeoffs of different types of species occurrence data for use in systematic conservation planning. *Ecol Lett* 9: 1136-1145.
- Rondinini C, Wilson KA, Boitani L, Grantham H, Possingham HP. 2006. Tradeoffs of different types of species occurrence data for use in systematic conservation planning. *Ecol Lett* 9 (10): 1136-1145.
- Rupa P, Bhavani NL. 2014. Diversity, conservation status and medicinal importance of *Selaginella* spp. In: Madhav V, Murthy N (eds.). Recent Trends in Plant Sciences. National Seminar on Recent Trends in Plant Science. Satavahana University, Telangana. 22-23 August 2014.
- Schulz C, Homberg J, Stützel T. 2013. Taxonomic revision of *Selaginella* Subg. *Ericetorum*. *Sys Bot* 38 (1): 5-14.
- Schulz C, Little DP, Stevenson DW, Bauer D, Moloney C, Stützel T. 2010. An overview of the morphology, anatomy, and life cycle of a new model species: The lycophyte *Selaginella apoda* (L.) Spring. *Int J Plant Sci* 171 (7): 693-712.
- Setyawan AD, Darusman LK. 2008. Review: biflavonoid compounds of *Selaginella* Pal. Beauv. and its benefit. *Biodiv* 9 (1): 64-81.
- Setyawan AD, Sugiyarto, Susilowati A, Widodo. 2015. Diversity and distribution of *Selaginella* in the province of Yogyakarta Special Region. *Pros Sem Nas Masy Biodiv Indon* 1 (5): 987-992.
- Setyawan AD. 2009. Traditionally utilization of *Selaginella*; field research and literature review. *Nusantara Biosci* 1: 146-158.
- Setyawan AD. 2011. Review: Recent status of *Selaginella* (Selaginellaceae) research in Nusantara. *Biodiversitas* 12 (2): 112-124.
- Shrestha UB, Bawa KS. 2014. Impact of climate change on potential distribution of Chinese caterpillar fungus (*Ophiocordyceps sinensis*) in Nepal Himalaya. *PLoS ONE* 9 (9): e106405. DOI: 10.1371/journal.pone.0106405.
- Sinclair SJ, White MD, Newell GR. 2010. How useful are species distribution models for managing biodiversity under future climates?. *Ecol Soc* 15: 8-16.
- Singh SK, Dubey NK, Srivastava GK. 2016. The microspore morphology of some species of *Selaginella* (Selaginellaceae) from India. *Palynol* 40 (2): 216-229.
- Singh SK, Yadav BB, Srivastava M, Shukla PK, Srivastava GK. 2014. Comparative morphological studies on spikes of Indian *Selaginella* Beauv. *Plant Syst Evol* 300:1235-1245.
- Summers DM, Bryan BA, Crossman ND, Meyer WS. 2012. Species vulnerability to climate change: impacts on spatial conservation priorities and species representation. *Glob Change Biol* 18 (7): 2335-2348.
- Summers DM, Bryan BA, Crossman ND, Meyer WS. 2012. Species vulnerability to climate change: impacts on spatial conservation priorities and species representation. *Glob Change Biol* 18 (7): 2335-2348.
- Thomas R, Karl, Kevin E, Trenberth. 2003. Modern global climate change. *Science* 302: 1719-1723.
- Thuiller W, Albert C, Araujo MB, et al. 2008. Predicting global change impacts on plant species distributions: future challenges. *Percept Plant Ecol Evol Sys* 9: 137-152.
- van Vuuren D, den Elzen M, Lucas P, Eickhout B, Strengers B, et al. 2007. Stabilizing greenhouse gas concentrations at low levels: an assessment of reduction strategies and costs. *Climat Chang* 81: 119-159.
- Warren DL, Seifert SN. 2011. Ecological niche modeling in MAXENT: the importance of model complexity and the performance of model selection criteria. *Ecol Appl* 21: 335-342.
- Weststrand S, Korall P. 2016. A subgeneric classification of *Selaginella* (Selaginellaceae). *Am J Bot* 103 (12): 2160-2169.
- Wijaya A. 2014. Diversity and distribution of *Selaginella* spp. In Indonesia from 1998 to 2014. *El-Hayah* 5 (1): 31-42.
- Zamora P. 2012. Strobilar Organization in Philippine Species of *Selaginella*. *J Pure Appl Sci* 4 (2): 223-238.

