

Predicting impacts of future climate change on the distribution of the widespread selaginellas (*Selaginella ciliaris* and *S. plana*) in Southeast Asia

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Manuscript received: 6 January 2018. Revision accepted: 30 September 2018.

Abstract. Setyawan AD, Supriatna J, Nisyawati, Sutarno, Sugiyarto, Nursamsi I. 2018. Predicting impacts of future climate change on the distribution of the widespread selaginellas (*Selaginella ciliaris* and *S. plana*) in Southeast Asia. *Biodiversitas* 19: 1960-1977. The current global climate is moving towards dangerous and unprecedented conditions that have been seen as a potentially devastating threat to the environment and all living things. *Selaginella* is a fern-allies that needs water as a medium for fertilization, hence its distribution is presumed to be affected by climate change. In Southeast Asia (SEA), there are two widely distributed selaginellas, namely *Selaginella ciliaris* and *S. plana*. *S. ciliaris* is a small herb (up to 4 cm), annual, abundant during the rainy season, and found in the middle-high plains, whereas *S. plana* is a stout large herb (up to 80 cm), perennial, and mainly found in the lowlands. The purpose of this study was to determine the potential niche distribution of *S. ciliaris* and *S. plana* under current climatic conditions, and to predict its future distribution under the impacts of climate change. We used Maxent software along with bioclimatic, edaphic, and UV radiation variables to model the potential niche distribution of those two selaginellas under current and future predictions climate conditions. We generated future predictions under four detailed bioclimatic scenarios (i.e., RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) over three times intervals (2030, 2050, 2080). The results showed that future climatic conditions in the SEA had been predicted to significantly disrupt the distribution of suitable habitat of *S. ciliaris* and *S. plana*, and alter their geographic distribution patterns. Although some areas were predicted to become suitable habitat in the early period of future climate change, the overall projections show adverse effects of future climate conditions on the suitable habitat distribution of *S. ciliaris* and *S. plana*, as estimated losses of suitable habitat will be higher than the gains.

Keywords: Climate change, distribution, *Selaginella ciliaris*, *Selaginella plana*, Southeast Asia, widespread selaginellas

INTRODUCTION

Global climate is currently moving toward dangerous and unprecedented condition which has been viewed as a potentially devastating threat to the environment and all life within it (Beckage et al. 2008; Fitzpatrick et al. 2008; Hasanuzzaman et al. 2013). The Intergovernmental Panel on Climate Change (IPCC) in the Fifth Assessment Report (AR5) developed predictive scenarios on the future of global climate condition. In this report, IPCC projecting a further increase in global mean surface temperature by 2.6-4.8°C above pre-industrial levels, spatial and temporal changes in precipitation patterns, and increased incidence of floods and droughts in the year 2100 (IPCC 2014). These predictions presenting scientists with serious challenges in forecasting the impact of future climate projection on the sustainability of biodiversity (Fitzpatrick and Hargrove 2009). In the last decade, many scientists have been trying to measure the ecological impact of an ongoing climate change combined with continuous destructive human activities and to predict the response of biodiversity to different drivers of change (e.g. Dillon et al.

2010; Gilman et al. 2010; Pereira et al. 2010; Salamin et al. 2010; Beaumont et al. 2011; Dawson et al. 2011; McMahon et al. 2011; Alice et al. 2012; Bellard et al. 2012; Belgacem and Louhaichi 2013). In order to gain a deeper understanding of biodiversity responses to climate change, it may be more convenient to conduct the assessment on the regional scale, which is spatially heterogeneous, rather than assessing on the global scale (Walther et al. 2002; Bonebrake and Mastrandrea 2010). Currently, among all of the five global climate domains (i.e., tropical, subtropical, temperate, boreal, and polar regions), the tropical biome has been expected to become more vulnerable to the impact of climate change. □

Myers (1988, 1990, 2000) initially defined 14 hotspots in the tropical biome and four in Mediterranean bioclimates. One of the defined hotspots of diversity and endemism in tropical biome is Southeast Asia (SEA) (Sodhi et al. 2010). Climatically, Southeast Asia is monsoonal region with summer-dominant rainfall and a large-scale seasonal reversal of the wind regimes (Loo et al. 2015). However, SEA region has been experiencing a change on its climate condition. Average annual surface

temperature has increased by 0.5-1.1°C during the period 1901-2005 (NIC 2009). Furthermore, climate model projection shows the average temperature will increase by approximately 1°C until 2030 and will keep increasing through the rest of the 21st century (IPCC 2014). Although there is no clear projection in precipitation patterns in this region, climate model suggests that net precipitation rates will increase across the region, but there will likely be a local decrease of precipitation rates in some areas that will vary geographically and temporally (NIC 2009). An acceleration of annual rainfall, a significant increase of mean temperature, and extreme climate events such as floods, drought, and cyclones are several projected negative impacts of climate change in SEA region (IPCC 2014; Loo et al. 2015). The increase of mean temperature also has several impacts on the future climate condition, such as frequent changes and shifts in monsoon precipitation up to 70% below normal level and the delayed of monsoon by up to 15 days (Schewe and Levermann 2012). Along with the human-induced environmental degradation, climate change is believed to negatively affects the current plant diversity patterns (Belgacem et al. 2008). These threats are expected to lead to low emergence of annual species, change the life cycle of plants, changes in phenology and the timing of reproduction and finally reduced plants biodiversity (Thuiller et al. 2008; Belgacem et al. 2008; Hilbish et al. 2010; Hill and Preston 2015). □

A number of plants species have been reported affected by recent climatic change (e.g. Bertin 2008; Skelly et al. 2010; Chen et al 2011; Agnihorti 2017; Evans and Brown 2017). However, this substantial development of assessing the ecological impact of climate change have been conducted almost exclusively on vascular plants, while only a few studies addressed the presumptive impact of future climate on cryptogams (Cornelissen 2007; Ellis et al. 2007). Autotrophic non-vascular cryptogams, such as spike-mosses, are also expected to be one of the earliest groups to be highly affected by the climate change (Cornelissen 2007; Bellard et al. 2012). Examining the impact of future climate condition on this group of species, which has been previously neglected, may be beneficial in acquiring a wider understanding of potential future risks of climate change, and serves as a crucial step in the development of effective management and conservation of biodiversity.

Selaginella Pal. Beauv. is the single remaining genus of vascular plants from the order Selaginellales (family Selaginellaceae), which can be found widely distributed in SEA region. This genus contains about 750 known species with a wide range of characters (Christenhusz and Byng 2016) and about 200 species found in SEA (Camus 1997; Hassler dan Swale 2002). *Selaginella* can be found in both very dry and very humid environments; and in open and shaded habitats (Setyawan et al. 2017). Therefore, the high humidity and tropical-hot characteristics of SEA's climate condition are highly suitable for the wide distribution of *Selaginella*. *Selaginella ciliaris* (Ritz.) Spring. and *Selaginella plana* (Desv. ex Poir.) Hieron are two examples of widespread selaginellas in the SEA region. The capability of these species to spread widely in the vast

variety of microclimatic, physiographic, topographic, and edaphic conditions of SEA region, represent their presumed broad eco-physiological niche. Therefore, it is important to predict how the projected future climate affects the survival and the geographical distribution of these species. □

Selaginella is relicts from ancient times and has survived almost unchanged in appearance for hundreds of millions of years (Banks 2009). To avoid extinction, *Selaginella*, like any other plant groups, may develop micro-evolutionary mechanisms as a response to climate change condition by reducing photosynthetic rates, growth rates, mineral absorption, tissue regeneration, and by increasing concentrations of secondary metabolites (Jochum et al. 2007; Wiens et al. 2009), or more likely, responding by shifting distribution to follow changing environments (e.g., Philips et al. 2006; Wiens et al. 2009; Minter and Collins 2010; Chen et al. 2011; Morueta-Holme et al. 2015). Recently, attention has been shifted toward understanding more about the redistribution mechanism of species to cope with the change in climate condition. To project how the climate change affects the species distribution, Ecological Niche Modeling (ENM), which frequently called as Species Distribution Models (SDM) has become especially popular (Lawler et al. 2009; Merow et al. 2013; Fourcade et al. 2014). Peterson and Soberon (2012) have cautiously overviewed the conceptual considerations in terminology related to ENM and SDM. The authors found that there are a variety of differences in biogeographic and ecological basis of the two terms wherein each term has its own conceptual framework and its basis application. Following this overview, subsequent to reviewing our conceptual framework, we deliberately use the term ENM in this study. Such models were built by using information on the environmental features that define the current ecological niche of species (Wiens et al. 2009). One of the most developed approaches of ENM/SDM is through the use of Maximum Entropy or Maxent algorithms (Belgacem and Louhaichi 2013). Maxent is a general-purpose machine learning method with a simple and precise mathematical formulation, for characterizing probability distribution from presence-only data, as well as a set of environmental predictors across a user-defined landscape (Phillips et al. 2006; Merow et al. 2013). Maxent has the ability to utilize different climatic scenarios to estimate the extent of occurrence of species (Beaumont et al. 2015). Therefore, allowing the evaluation of the impact of climate changes on geographical distribution of species' suitable habitat (e.g. Rondini et al. 2006; Botkin et al. 2007; Randin et al. 2008; Engler and Guisan 2009; Garavito 2015). □

Here in this study, by utilized Maxent software along with bioclimatic, edaphic, and UV radiation variables, we tried to model the potential geographic distribution of *S. ciliaris* and *S. plana*'s suitable habitat under present climate condition, and predict the impacts of projected climate change on their potential distribution. We generate future predictions under four detailed bioclimatic scenarios (i.e., RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) over three-time intervals (2030, 2050, 2080). Quantifying the potential impacts of various climatic scenarios offers opportunities

to develop understanding the plant response to climate change and develop mitigation strategies under all projected scenarios of climate change to effectively conserve biodiversity. □

MATERIALS AND METHODS

Study area

The study was conducted in an attempt to predict the impacts of future climate change on the distribution of *Selaginella ciliaris* and *Selaginella plana* in Southeast Asia (SEA). SEA is a sub-region of Asia, consist of countries that are geographically located in south of China, east of India, west of New Guinea and north of Australia (Kastle 2013). This region consists of eleven political countries that can be categorized into Mainland SEA (i.e., Cambodia, Laos, Myanmar/Burma, Peninsular Malaysia, Thailand, and Vietnam) and Maritime SEA (i.e., Indonesia, Philippines, Malaysian Borneo, Brunei, Singapore, and East Timor) (United Nations 2012). The geographic scope of this study includes the region of approximately 23.5 °N to 10 °S latitude and 97 °E to 141 °E longitude (Figure 1), covers approximately 4,687,481 km² of lands. The highest peak of Southeast Asia is Mount Hkakabo at roughly 5,881 m asl. (meters above sea level), situated in Northern Myanmar (Burma) and on the border with China and Tibet (Leinbach and Frederick 2015). The wide areas and vast altitudinal range of SEA create a wide variation in physiographic, topographic, edaphic, and climatic conditions resulting in rich biodiversity in this region. □

The climate condition in Southeast Asia is mainly humid and tropical-hot all year round with high degree of rainfall variability and its climate generally can be characterized as monsoonal (i.e., marked by wet and dry periods) (Leinbach and Frederick 2015), hence, SEA region has only two seasons (i.e. wet and dry season). The only areas that feature a subtropical climate are in Northern Vietnam and the Myanmar Himalayas, featuring a cold winter with snow. These areas are in high altitudes which lead to milder temperatures and drier landscape (NIC 2009).

Materials

Selaginella ciliaris (Retz.) Spring. (Figure 2.A)

Annual herb, small, creeping, ascending, or sometimes fan-shaped, 4-15 cm. *Stems* recumbent, without significant main stem, 4-5 mm wide (incl. leaves). *Rhizophores* present at intervals, mostly near the base, from the lateral side of branching stem, ca. 0.3 mm in diam. *Leaves* dimorphic, composed in 4 lanes (2 lateral, 2 median), vein single; *lateral leaves* ovate-lanceolate, more or less symmetrical, 1.5-2 mm long, 0.6-1 mm wide, base subcordate or rounded, apex acute or acuminate, margin ciliate or serrulate, single vein reaching the apex, keeled, pointing outwards; *median leaves* ovate to falcate, asymmetrical, 2-2.5 mm long, 0.6-1.5 mm wide, base rounded, apex acute, cuspidate or attenuate, margin serrulate but lacinate at basal part, pointing upwards, minutely toothed, ciliate, midrib prominent, single vein

reaching or nearly reaching the apex; *axillary leaves* lanceolate to ovate, bisymmetrically, 1.8-2.5 mm long, 1-1.5 mm wide, single vein reaching or nearly reaching the apex, base subcordate to rounded, ciliate, apex acute, margin toothed, lacinate at basal and serrulate at apical. *Strobilus* terminal, solitary or twin, complanate, flattened, up to ca. 1.5-2 cm long (Setyawan et al. 2013).

Habitat: Steep cliff, banks of irrigation water, ditches, small tributaries, and waterfalls, cliff edge of road, only abundant in the rainy season (Setyawan et al. 2013).

Distribution: Java, Sulawesi, Maluku (e.g. Ternate), Myanmar, Thailand, Vietnam, Philippines, New Guinea, Solomons, Northern Australia, Marianas, Palau, Micronesia, India, Sri Lanka, Southern China (Guangdong), Taiwan, (Hassler and Swale 2002).

Selaginella plana (Desv. ex Poir.) Hieron. (Figure 2.B)

Perennial herb, stout. *Stems* sub-erect with stoloniferous rhizome, without branches on the lower part, ascending from subterranean trailing base, up to 80-100 cm long, 3-10 cm wide (incl. leaves); rhizome (subterranean stems) shallowly radiating. *Rhizophores* sometimes at the branching stem, from the dorsal side of stem at the branch site, ca. 1-1.5 mm in diam. *Leaves* on the lower part and main stem monomorphic, well spaced, upper part slightly spreading, appressed, 1.5-3 mm long, 1-2 mm wide, ovate, apex acute or acuminate, but rounded tip, asymmetrical, margin translucent, entire. Leaves on the branches dimorphic, arranged in 4 lanes (2 dorsal, 2 ventral), loosely arranged at lower stem, closely arranged at branches; *lateral leaves* ovate to oblong, asymmetrical, 2-4.5 mm long, 2-3 mm wide, apex acute to acuminate, rounded tip, sessile, vein single, obscure, not reaching the apex, base truncate and rounded, upper base with spur-like lobe which overlaps the stem, margin entire, transparent; *median leaves* ovate to oblong, asymmetrical, 1.5-3 mm long, 1-2 mm wide, apex acuminate to acute, rounded tip, sessile, vein single, obscure not reaching the apex, base rounded and truncate, margin entire, transparent; *axillary leaves* ovate, asymmetrical, 2.5-3.5 mm long, 1.5-2.5 mm wide, apex acute, minutely ciliate, base rounded, margin entire. *Strobilus* terminal, solitary, tetragonal, up to more than 3 cm long (Setyawan et al. 2013).

Habitat: Steep cliffs above small irrigation channel, tributary, and waterfall, remaining abundant in the dry season (Setyawan et al. 2013).

Distribution: Sumatra, Java, Bali, Flores, Sumbawa, Solor, Timor, Sulawesi, Maluku (Ambon, Banda, Buru, Ceram, Kei, Ternate), Malay Peninsula (Hassler and Swale 2002).

Procedures

The occurrence data of Selaginella ciliaris and Selaginella plana

General information relating to the occurrence of *S. ciliaris* and *S. plana* across its whole range in SEA region was obtained from several literatures (Spring 1843; Mishra et al. 2001; Rachata and Boonkerd 2001; Beukema and

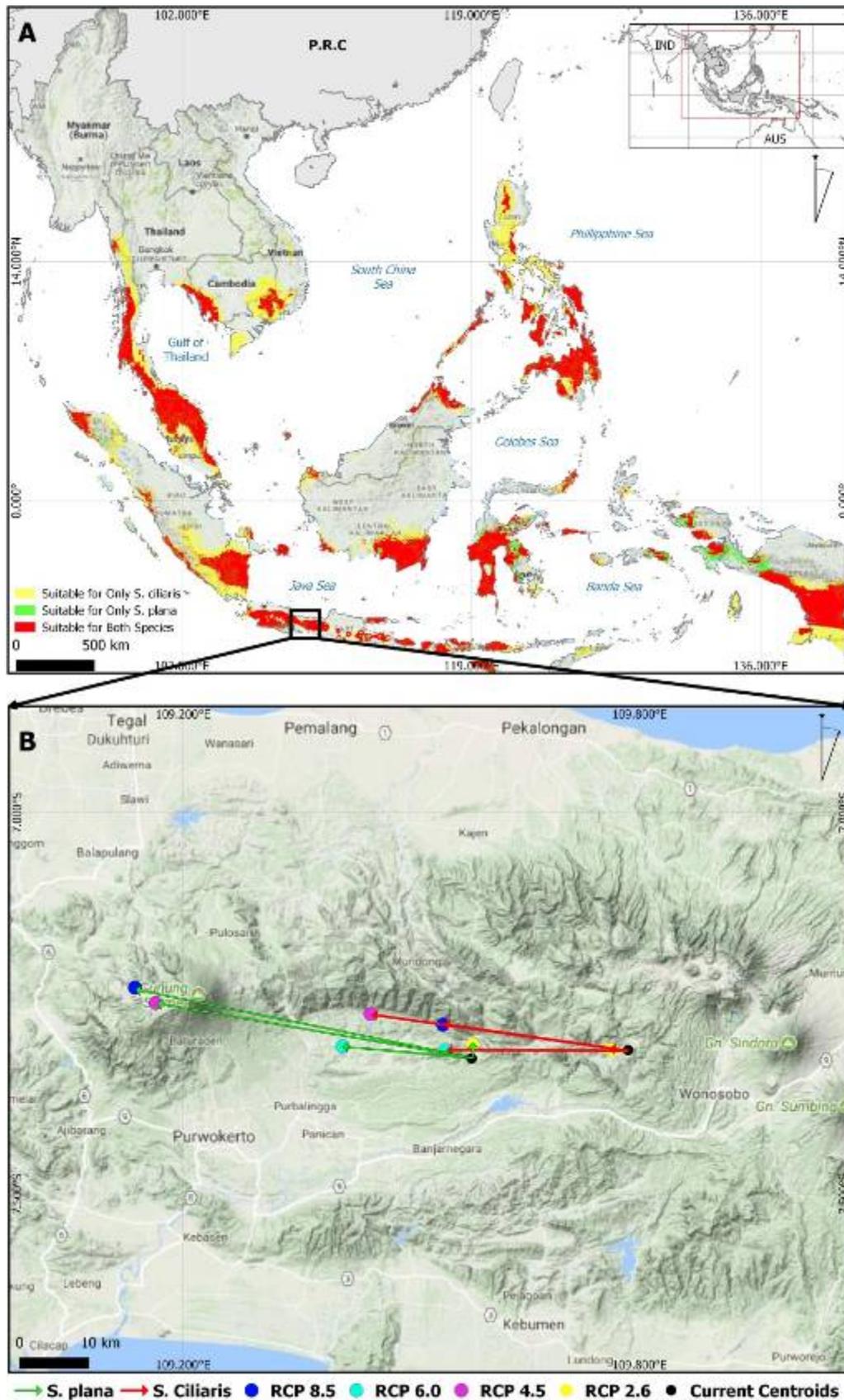


Figure 1. A. Predicted distribution of potential habitat for *Selaginella ciliaris* and *Selaginella plana* under current climate condition. B. Core distributional shifts under different climate scenarios in the year 2080. Black dot indicates the geometric center of suitable area under current climate condition. Colored dots indicate the new geometric centers. The arrows depicting magnitude and direction of predicted change (Basemap source: Google Physical Maps 2014)



Figure 2. Selaginella species used in research. A. *Selaginella ciliaris*, B. *Selaginella plana*

Noordwijk 2004; Ali et al. 2006; Setyawan et al. 2015a,b,c; Setyawan and Sugiyarto 2015), as well as Global Biodiversity Information Facility (<http://www.gbif.org>). Authors collected the occurrence data for *S. ciliaris* and *S. plana* from two main sources, i.e., field survey and GBIF database. Field survey aiming to collect the locality data for both species was conducted in all province across Java island between July 2007 and January 2014. The island of Java was chosen because of its diverse habitat and easy access; as well as both species are distributed widely and evenly throughout Java. All specimens founded were identified using several references on *Selaginella* of the Malay Archipelago and adjacent regions (Alston 1934, 1935a,b, 1937, 1940; Wong 1982, 2010; Tsai and Shieh 1994; Li and Tan 2005; Chang et al. 2012; Zhang et al. 2013) to ensure the high-confidence level of species identification.

During the occurrence data collection, we tried to cover as wide area as possible while attempted to cover the possible climatic variability of Java island as an attempt to minimize bias in sampling intensity (Elith et al. 2006; Yackulic et al. 2013). Using Garmin eTrax GPS series, we collected 379 occurrence points of *S. ciliaris* and 384 occurrence points of *S. plana* which were found distributed in Java island. We conducted none of error-correction method for the data as we ensuring the level of telemetry error on modern GPS (normally between 0.01 km and 0.05 km), which is smaller than the resolution of predictor variables, has a little effect on the accuracy of models (Montgomery et al. 2011). Global Biodiversity Information Facility (GBIF 2016) database, which provides freely accessible occurrence points in its website (<http://www.gbif.org>), was the second source of locality points for both species. All of the occurrence record acquired from GBIF were carefully verified and errors that may occur were corrected using Google Earth software (Google Earth Pro 2017). Biogeomancer Workbench (<http://www.biogeomancer.org>) was used as a tool to geo-

reference data record which lacks latitudinal and longitudinal value, guided by locality descriptions on each datum (Guralnick et al. 2006), and then data record that does not have specific locality description and cannot be geo-referenced were removed. The remaining 369 locality points of *S. ciliaris* and 214 points of *S. plana* were compiled with the occurrence points collected from the field survey.

The increasing number of regional to continent-wide ENM/SDM study was mainly induced by the availability of biodiversity and environmental datasets globally (Hijmans et al. 2005; Kozak et al. 2008). Nevertheless, a strong geographic bias often contained in such datasets derived from opportunistic observation and/or collection of records (Stolar and Nielsen 2015). Sampling bias correction is highly important and strongly advised to be conducted to minimize the strong influence of sampling bias on modeling prediction ability and later interpretation (Kramer-Schadt et al. 2013; Fourcade et al. 2014). Fourcade et al. (2014) proposed five option methods of sampling bias correction which carefully designed to overcome or minimize the effect of four types of bias that might occur when collecting observation. Subsequently, after we identified the type of sampling data bias contained in the sampling data used for this study, we conducted two out of five sampling bias correction methods, i.e., (i) We conducted spatial filtering by creating a grid of 2 km x 2 km cell size and randomly select only one point of occurrence per grid cell. Nevertheless, it should be noted that the size of this grid is not the representation of approximate species' dispersal capabilities, but rather as a result of modifying the 10-km radius rule of spatial filtering proposed by Kramer-Schadt et al. (2013) and Boria et al. (2014). The grid creation and points selection were conducted using QuantumGIS software ver. 2.18.14 (QGIS Development Team 2017). (ii) Bias file was created and included it into Maxent modeling process through setting options (Dudik et al. 2005; Elith et al. 2010; Phillips

et al. 2017). Bias file is a probability surface represented by cell value that reflects the intensity of sampling effort across the area of study and provides a gradual weight to random background data used for modeling (Fourcade et al. 2014). Bias file can be artificially estimated using the aggregation of occurrences from closely related species (Phillips et al. 2009). Nevertheless, in real modeling situation, this information is limited. Therefore, by following Elith et al. (2010), we produced a Gaussian kernel density map of the occurrence locations, then rescaled it from 1 to 20 to be derived as bias file instead of using our knowledge to create artificial bias file (Fourcade et al. 2014). As the distribution of both species occurs in different countries (of different areas), we used the political state boundary extracted from Global Administrative Areas website (www.gadm.org/), to limit the background areas for the models. □

Current environmental and bioclimatic variables

Environmental and bioclimatic variables to build the models in this study were selected based on the model-driven selection process. Model-driven selection is a selection process that will use all possible predictors and choose those with greatest importance in the model to be considered as the main factor influencing the distribution of species, rather than expert-driven selection where the expert priority will choose the predictors expected to directly affect the species distribution (Fischer 2011). For this study, on the basis of earlier screenings of related variables (Soria-auza 2009; Hu et al. 2015; Mod et al. 2016; Setyawan et al. 2017; Velazco et al. 2017), we collected 19 bioclimatic, two edaphic variables, and five environmental variables, which are expected to have direct effect on plant growth. We collected 19 bioclimatic layers ver 2.0 plus one altitude layer from WorldClim Bioclimatic datasets website (www.worldclim.org). The bioclimatic datasets were generated through interpolation of average monthly climate data from about 9,000 to 60,000 weather stations on a 30 arc-second resolution grid (often referred to as "1 km²" resolution) (Fick and Hijmans 2017). We collected Global UVB radiation layers (UVB1, UVB2, UVB3, UVB4) from the glUV database (<http://www.ufz.de/gluv/>) (Beckmann et al. 2014). Additionally, we collected global Soil pH (SpH) and soil organic carbon (SOC) datasets from the International Center for Tropical Agriculture (<https://dataverse.harvard.edu>). All of these layers were processed through several steps including resampling data, image cutting, and type file converting by using Qgis Software Ver. 2.18.14 (QGIS 2017). Variables that considered related to the occurrence of species, i.e., land use/land cover changes, human disturbances, and species dispersal or biotic interaction changes were not included as the availability of these data were limited.

Bioclimatic layers are highly correlated with each other, and although including all of the bioclimatic layers into modeling process will not affect the predictive quality of model greatly (Elith et al. 2011), it does, nonetheless, will significantly limit any inference of the contribution of any correlated variables since Maxent often excludes all other highly correlated variables from being incorporated (Van

Gils et al. 2012, 2014). Therefore, we decided to remove highly correlated variables to minimize the effect of autocorrelation of climatic variables. SDM toolbox Ver. 2.0 (Brown 2014) in ArcGIS ver. 10.3 was used to perform the autocorrelation calculation and then we omitted the bioclimatic variables yielding correlation values above 0.95 (Spearman's rho coefficient) in the pairwise cross-correlation matrix of each dataset (intra-dataset correlations) (Bedia et al. 2013). The remaining six bioclimatic variables (i.e., bio_1, bio_2, bio_3, bio_4, bio_12, and bio_19), two edaphic variables (Soil pH and Soil Organic Carbon), plus five environmental variables (i.e., altitude, UVB1, UVB2, UVB3, and UVB4) were then compiled to be used as predictor variables in Maxent (Table 1).

Future climate scenarios

Future climate scenarios used to predict the impact of future climate change on the redistribution of *S. ciliaris* and *S. plana*'s suitable habitat, were acquired from CGIAR Research Program on Climate Change, Agriculture, and Food Security website (www.ccafs-climate.org). For this study, the HadGEM2-CC (Hadley Global Environment Model-2 Carbon Cycle) global circulation model, which was developed by the Hadley Center, United Kingdom was selected to build the models (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 and Bawa 2014). We selected four future greenhouse gas (GHG) trajectories, which were represented by Representative Carbon Pathways (RCP), namely RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 for three different periods of time (2030, 2050, and 2080). RCP 2.6, the most optimistic projection, assumes that global GHG will increase slowly to reach its peak at 3.1 W/m² in between 2010-2020, with the emissions declining substantially thereafter to 2.6 W/m² by the year 2100 (van Vuuren et al. 2007; Moss et al. 2010). Emissions level in RCP 4.5 is assumed to be stabilized at 4.5 W/m² by the year 2100 due to the variety of technology and strategies which predicted will be implemented to reduce GHG emissions level (Clarke et al. 2007). Likewise, the emissions level in RCP 6.0 is projected to reach its peak

Table 1. Environmental parameters used to build the models

Code	Name	Unit
Alt	Altitude	m asl
bio_1	Annual Mean Temperature	°C×10
bio_2	Mean Diurnal Range	°C×10
bio_3	Ishotermality	×100
bio_4	Temperature Seasonality	×100
bio_12	Annual Precipitation	mm
bio_19	Precipitation of Coldest Quarter	mm
soil_carbon	Soil Organic Carbon	
soil_ph	Soil pH	
UVB1	Annual Mean UVB	J m ⁻² day ⁻¹
UVB2	UVB Seasonality	J m ⁻² day ⁻¹
UVB3	Mean UVB of Lightest Month	J m ⁻² day ⁻¹
UVB4	Mean UVB of Lowest Month	J m ⁻² day ⁻¹

around 2080 and stabilizes in 2100 at 6.0 W/m². In RCP 8.5, emissions level continue to increase throughout the 21st century, reaching around 8.5 W/m² as the highest level by the end of the century (Riahi et al. 2011). As the availability of future projection of environmental variables is currently limited, the six environmental variables (Soil pH, Soil Organic Carbon, UVB1, UVB2, UVB3, and UVB4) remained unchanged for the following ENM analysis under future climate projection. Furthermore, the same altitude layer was used since this variable is a static variable that does not change with time. □

Global Climate Models (GCMs) have become the fundamental resource of information for constructing future climate scenarios and for developing impact assessments of climate change from local to global scale. Nonetheless, these climate models exhibit systematic error (biases) due to the simplified physics and thermodynamic processes, limited spatial resolution, and numerical schemes or incomplete knowledge of climate system processes (Ramirez-Villegas et al. 2013). Consequently, we implemented the bias correction data provided by CGIAR-CCAFS under three different calibration approaches: (i) Bias Correction, this approach revise the projected raw GCM output using the differences in the mean and variability between observations and GCM, in a reference period (Hawkins et al. 2013). (ii) Change Factor (CF): in this 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). (iii) Quantile Mapping (QM), this approach removes the systematic bias in the GCM simulations and account the biases in all statistical moments, however, like all statistical downscaling approaches, it is assumed that biases relative to historical observations will be constant in the projection period (Thrasher et al. 2012). □

Model development

Developing the model of potential distribution of climatically suitable habitat for *S. ciliaris* and *S. plana* under current climate condition and assess its redistribution under the impact of projected future climate change scenario was conducted by using MaxEnt software ver. 3.4.1 (Phillips et al. 2017). Certainly, there is no "silver bullets" in correlative ecological niche modeling (Qiao et al. 2015), which means that there is no single algorithm approach that can provide robust, reliable, and acceptable results under all circumstances. Maxent software, however, utilized in this study as it has been proved to give the best results among other modeling algorithms available on the basis of presence-only (PO) data (Philips and Dudik 2008; Summers et al. 2012). Further, consideration to utilize Maxent in this study was the aim of this study which met the capability of Maxent to performs well in estimating the effect of climate change on the potential shifting range of species (Kou et al. 2011; Johnston et al. 2012; Duan et al. 2016), whereas more than 1000 published distribution modeling study has been conducted by using Maxent software since 2005 (Merow et al. 2013; Fourcade et al. 2014). □

ENM/SDM using Maxent software are often confronted with a wide variety of modeling options, from choosing appropriate input datasets to choosing the right multiple settings available in the software package (Merow et al. 2013). As the aim of this study is beyond simple exploratory analysis, we tried to ensure that the modeling setting decisions are adjusted to our specific hypothesis, study aims, and species-specific considerations and reflect our intended a priori assumptions (Peterson et al. 2011; Araujo and Peterson 2012; Merow et al. 2013). The adjusted parameter values were: maximum iterations which were set to 5,000 for each run to allow the model to have adequate time for converging. Convergence threshold was set to 1×10^{-6} . The number of replicated runs was set to ten times (the averaged value is the one used as the result) using "cross-validate" as the replicated run type. Using "cross-validate" means to split the data ten times (10% per partition), train the model ten times on 90% of the data, and test it each time on the 10% partition alternately. To avoid over-fitting and assuming that both selaginellas are responded directly to the predictors (vs to correlated factors), we decided to "smooth" the model by choosing only hinge features to model both *S. ciliaris* and *S. plana*. Considering that we used a large collection of occurrence from diverse regions to be projected to different climate condition, we doubled the default "regularization multiplier" value to accommodate aforementioned type of data and aim of study (Elith et al. 2006; Merow et al. 2013; Radosavljevic and Anderson 2013). We used the "projection" feature to extrapolate the model into different climate projection to predict the impact of projected future climate condition to the redistribution of climatically suitable habitat for both species (van der Wall et al. 2009). □

Core distributional shifts

We tried to further examine the trend of suitable area changes by calculating and comparing the centroids of current and future suitable areas. We utilized a python-based GIS toolkit, SDM tool-box (Brown 2014) to summarize the core distributional shifts of the ranges of suitable habitat for both species in between two binary models (i.e., current and future SDMs). The tool will produce the centroids by calculating the average of latitude and longitude of binary input pixels, then depict their magnitude and direction of change (based on centers of the species ranges-the centroids). Assessment of core distributional shifts was conducted only on Java island for the following reasons: (i). SEA region has very wide areas, consists of several big archipelagic countries separated by seas, hence it is impractical to conduct core distributional shifts assessment in the whole region. (ii). Java island closely represents the vast variations in physiographic, topographic, edaphic, and climatic conditions of SEA region, therefore the results will closely depict the projected core shifts in the whole region. Furthermore, we used only projected future climate condition in the year 2080 to represent maximum shifts of the geometric distribution center. □

Data analysis

The main output of Maxent software is predictive map which represents the distribution of potential ecology niche of species across the study area. The degrees of potential suitable are linearly scaled between 0 (lowest) to 1 (highest) probability (Phillips and Dudik 2008). Additionally, Maxent software will calculate the variables' relative contribution to the model and quantify the degree of these variables affect the prediction. We also retrieve the alternate estimation of variable importance by running the jackknife test. Jackknife test show which variable appears to have the most information that is not present in the other variables and which variable have the most useful information by itself (Phillips et al. 2006). The predictive maps, which by default are in ASCII format, were further analyzed using QuantumGIS software ver. 2.18.14 (QGIS Development Team 2017). To allow us to compare and quantify the geographical distribution of predicted suitable habitat, we applied the binary calculation, categorized the value into two categories (i.e. suitable vs unsuitable) using the selected threshold rule. Selecting the threshold rule is one of the many sources of bias that should be minimized by Maxent user (Phillips and Dudik 2008; Nenzen and Araujo 2011; Bean et al. 2012; Syfert et al. 2013). In the process of selecting threshold rule, one should avoid arbitrariness and should consider the relative importance difference between commission and omission error (Phillips and Dudik 2008; Nenzen and Araujo 2011; Bean et al. 2012). Norris (2014) in his study proposed the "minimum training presence" or "fixed cumulative value 1" to be the most appropriate threshold rule, considering that reducing omission error is more important determinant than reducing commission error. However, Liu et al. (2016) stated that the threshold rule proposed by Norris (2014) may be more convenient for rarer species, but when considering a more common species, commission error should be weighted more than omission error. Accordingly, we selected "maximum training sensitivity plus specificity" threshold rule since this rule will produce lower commission error. □

To evaluate model performance, as used by several studies (e.g., Pearson and Dawson 2003; Pearson et al. 2007; Jiménez-Valverde 2012), Maxent software will calculate an area under the receiver operating characteristic (ROC) Curve (AUC). AUC value is ranged between 0 (lowest value) to 1 (highest value), wherein value between 0-0.5 represents that the model is no better than random prediction, value below 0.7 is low, value between 0.7-0.9 is good, and value above 0.9 is indicating high discrimination or means that the model is far better than random prediction. However, studies conducted by Lobo et al. (2008); Bahn and McGill (2013); and Aguirre-Gutiérrez et al. (2013) proved that AUC value does not provide useful information to assess and/or to evaluate the SDM performance. Therefore, for this study, we conducted True Skill Statistic (TSS) (also known as the Youden index) calculation as an additional measurement to evaluate the performance of the model (Youden 1950; Allouche et al. 2006).

RESULTS AND DISCUSSION

Contribution of the variables and model evaluation

Based on our known occurrences of *S. ciliaris* and *S. plana* combined with climatic, topographic, edaphic, and UVB radiation data, we generated geographic distribution maps predicting areas wherein both species can live in concordance with all the aforementioned variables. Our models demonstrated that the variable which provides the highest relative contribution to explain the predicted geographic distribution of both *S. ciliaris* and *S. plana*'s suitable habitat in SEA region is similar (Table 2). Isothermality (bio_3) was the highest relative contributor to the distribution pattern of the models, with a contribution of 28.5% and 39.4% for *S. ciliaris* and *S. plana* respectively. Combined variables of soil organic carbon, UVB2, and temperature seasonality (bio_4) explained in total of 36.5% of the variation in the distribution pattern of *S. ciliaris*' suitable habitat, whereas the remaining variables, each contributed less than 10% to the model. Another variable significantly contributed to the model of *S. plana* were temperature seasonality (bio_4), UVB2, and soil organic carbon which in total had a relative contribution of 36.9%. Others, appeared to had a little contribution to this model with only less than 25% contribution in total (Table 2).

Additionally, we retrieved the alternate estimation of variable importance through the utilization of jackknife test. The results showed that for both *S. ciliaris* and *S. plana*'s model, the environmental factors with the highest gain when used in isolation is isothermality (bio_3), which therefore appears to have the most information by itself (Phillips et al. 2006). These results confirmed to the previous result that the same bioclimatic factor has the highest relative contribution to the models. Nevertheless, the results of jackknife test showed a different finding of which factor which will reduce the gain the most when it is omitted. Annual precipitation (bio_12) appears to have the most information that is not present in the other variables, thus, omitting this variable will decrease the fitness of *S. ciliaris*' model. For *S. plana*'s model, isothermality (bio_3) variable was both the highest gain when used in isolation and decrease the gain highest when it is omitted from the model, which indicates that bio_3 variable has the most useful information which is not present in the other variables (Figure 3).

To assess predictive performance and statistical significance of the models, a post-hoc evaluation of distribution models is commonly performed (Peterson et al. 2011). Despite the fundamental problems when using AUC (Area Under the Curve) for model evaluation, we retrieved the AUC value of 0.946 for *S. ciliaris* model and AUC value of 0.978 for *S. plana* model to illustrate that the predictions in this study perform better than any model with a set of random predictors (Lobo et al. 2008; Fourcade et al. 2017). Furthermore, we conducted additional evaluation of the models using True Skill Statistic, which has been proposed as an alternative metric of evaluation (e.g., Allouche et al. 2006; Hijmans 2012; Phillips and Elith 2010). The TSS value of 0.83 and 0.86 for *S. ciliaris*

and *S. plana*'s models respectively, give the impression that the models built in this study have a good degree of agreement and also have a good predictive capacity (Li and Guo 2013). Studies had also demonstrated the use of Kappa statistic for Maxent validation (e.g. Duan et al. 2014; Ali and Hossein 2016; Bagheri et al. 2017), but, regarding the use of Kappa value, it is highly correlated to prevalence of the locality points and the size of the study area (Lobo et al. 2008; Fourcade et al. 2017). Therefore, it would generate some sort of bias or misunderstanding. Moreover, due to the fact that both AUC and Kappa are weighting omission and commission errors equally (Allouche et al. 2006; Lobo et al. 2008; Jimenez-Valverde 2012, 2014; Fourcade et al. 2017), Kappa, just like AUC, is more reliable if it is applied in PA (Presence-Absence) model. Consequently, in case of this study where presence only data were used, we assume that the use of TSS is more suitable than Kappa statistic.

Predicted distribution of current potential habitat

We built the models by using 748 unique locality points of *S. ciliaris* and 598 locality points of *S. plana*, which were the remaining points after the implementation of spatial filtering to reduce bias sampling (see method). The potential present-day distribution of suitable habitat for both species, as derived from Maxent (Phillips and Dudik 2008; Elith et al. 2011; Phillips et al. 2017), are shown in Figure 1. Our models predicted roughly 26% (1,361,050.9 km²) of the SEA region is suitable for *S. ciliaris*. In Mainland SEA area, the predicted suitable habitat spread patchily in southern part of Myanmar, Cambodia, and Vietnam, with a wide predicted suitable area in Peninsular Malaysia and Singapore. While in Maritime SEA, the predicted suitable habitat for *S. ciliaris* spread widely in all of big islands of Indonesia (Sumatra, Java, Sulawesi, Borneo, and Papua), and also appears in Lesser Sunda islands. Additionally, the predicted suitable habitat also appears in most of the Philippines archipelago. Moreover, our model predicted there are approximately 18% (871,889.51 km²) of *S. plana*'s suitable habitat in SEA region, spread in mainland SEA almost at the same area as the suitable habitat for *S. ciliaris* (i.e. southern of Myanmar, Cambodia, Vietnam, and in most area of Peninsular Malaysia). In the maritime SEA, the predicted suitable areas spread across big islands of Indonesia (mostly in the southern part of Sumatra, Borneo, Sulawesi, Java, and Papua). Additionally, the predicted suitable habitat of *S. plana* also appears in most of the southern part of the Philippines archipelago. □

Potential future changes in the distribution of suitable habitat

The predicted redistribution of suitable habitat for both species as the impact of climate change is illustrated in Figure 4. Overall, under all RCP scenarios in three different periods of time, the suitable areas were predicted to significantly decreased, even though there is also a significant increase in areas wherein predicted to become suitable for both species as a result of a warming climate condition in the future. Under the influence of RCP 2.6 climate projection (lowest GHG emission) in the year

2030, Maxent predicted roughly 2.6% gains of the currently suitable habitat area for *S. ciliaris*. Expansions in area increased with increasing latitude and elevation, and predicted will occur in the western and northern part of Sumatra, southern part of Peninsular Malaysia and Philippines archipelago, northern and southern part of Sulawesi, and southwestern part of Papua. Furthermore, for the next four decades, until the end of 2080, the predicted losses of suitable habitat area are greater than the gains. Maxent predicted a total of 0.6% and 2.1% reduction of current suitable area in the year 2050 and 2080 respectively. The losses were predicted to occur mostly in the lower altitude area of southern Vietnam and Sumatra. Likewise, the predicted suitable habitat for *S. plana*, under the same RCP 2.6 climate trajectory, will likely to increase at about 2.1% in 2030 before continuously losing its suitable area to reach a decrease of ca. 2.9% of the current suitable area by the end of 2080. The pattern of losses and gains of suitable habitat for *S. plana* is almost the same as the pattern of losses and gains of *S. ciliaris*' suitable habitat (Table 3, Figure 4).

Under the future climate scenario of RCP 4.5, Maxent software also predicted a slight gain in both suitable habitat area for *S. ciliaris* and *S. plana* at almost the same pattern. The areal extent of gains were predicted to appear in southern Peninsular Malaysia, northern part of Sumatra, and in the eastern part of Papua, which amounted to 0.24×10^5 km² (1.7%) and 0.06×10^5 km² (0.7%) for *S. ciliaris* and *S. plana*'s suitable habitat, respectively (Table 3, Figure 4). Furthermore, the predicted suitable habitat areas for *S. ciliaris* and *S. plana* in the year 2050 and 2080 were predicted to be about 1.6-2.7% less than the currently suitable habitat areas (Table 3). The predicted suitable area under RCP 6.0 was projected to be more decreased than under former RCP trajectory. Under this GHG emission trajectory, in all three different time periods (2030, 2050, and 2080), the predicted suitable area for *S. ciliaris* will gradually to decline by about 0.3-4.5% of currently suitable habitat and about 0.2-11.1% of current *S. plana*'s suitable habitat will be lost. □

Table 2. Percentage of variable contribution to the final model

Variables	Description	Contribution (%)	
		<i>S. ciliaris</i>	<i>S. plana</i>
Alt	Altitude	1.5	3.4
bio_1	Annual Mean Temperature	0.5	0.2
bio_2	Mean Diurnal Range	7.2	5.8
bio_3	Ishothermality	28.5	39.4
bio_4	Temperature Seasonality	10.2	13.3
bio_12	Annual Precipitation	8.9	8.1
bio_19	Precipitation of Coldest Quarter	4.3	0.4
soil_carbon	Soil Organic Carbon	15.3	11
soil_ph	Soil pH	6.2	4.8
UVB1	Annual Mean UVB	0.2	0.3
UVB2	UVB Seasonality	11	12.6
UVB3	Mean UVB of Lightest Month	0.5	0.1
UVB4	Mean UVB of Lowest Month	5.4	0.7

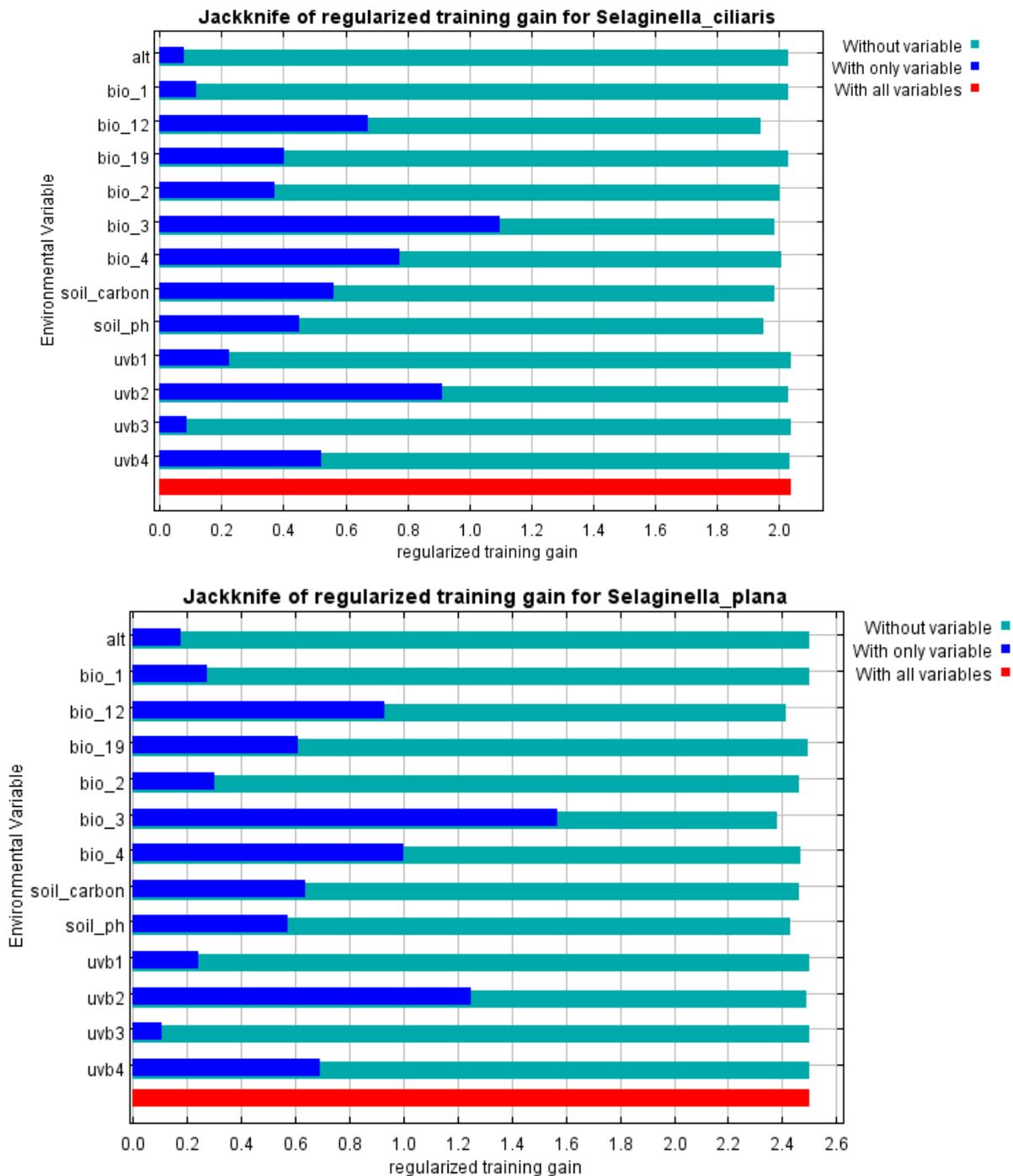


Figure 3. Results of jackknife test of relative importance of predictor variables for *Selaginella ciliaris* and *Selaginella plana*

The biggest reduction of suitable area was predicted to happen under RCP 8.5 trajectory. In 2030, there will be a significant decrease of approx. 1.2% and 0.4% of suitable habitat area for *S. ciliaris* and *S. plana* respectively. Moreover, approximately 1.6% of *S. ciliaris* and 2.3% of *S. plana*'s suitable habitat area will vanish by the end of 2050. For the next three decades, the predicted suitable habitat will continue to decrease, and predicted to affect more on the sustainability of suitable habitat for *S. plana* than for *S.*

ciliaris By the end of 2080, approx. 14.4% of currently suitable habitat for *S. plana* will be lost, whereas only about 6.6% of *S. ciliaris*' suitable habitat area will vanish under the effect of this future climate trajectory. During all of the aforementioned periods of time, indeed there are also gained areas which were predicted to become suitable habitat for both species. However, the predicted losses of suitable area are greater than the gains (Table 3).

Table 3. Dynamics of changes in suitable habitat area for *Selaginella ciliaris* and *Selaginella plana* under four combinations of future climate scenario within three different periods of time

Year	RCP Projection	<i>S. ciliaris</i> (Area × 10 ⁵ km ²)				<i>S. plana</i> (Area × 10 ⁵ km ²)			
		Loss	Gain	Total	Future	Loss	Gain	Total	Future
2030	RCP 2.6	0.92	1.51	0.59	14.2	0.95	1.14	0.19	8.9
	RCP 4.5	0.9	1.6	0.7	14.31	2.25	2.31	0.06	8.77
	RCP 6.0	1.16	1.2	0.04	13.65	1.48	1.49	0.01	8.72
	RCP 8.5	1.56	1.4	-0.16	13.49	1.38	1.35	-0.03	8.68
2050	RCP 2.6	0.4	0.37	-0.03	13.58	1.06	1.02	-0.04	8.67
	RCP 4.5	0.51	0.42	-0.09	13.52	1.7	1.62	-0.08	8.63
	RCP 6.0	0.63	0.52	-0.11	13.5	0.94	0.82	-0.12	8.59
	RCP 8.5	1.06	0.83	-0.23	13.38	1.06	0.87	-0.19	8.52
2080	RCP 2.6	0.8	0.51	-0.29	13.32	1.2	0.94	-0.26	8.45
	RCP 4.5	0.78	0.41	-0.37	13.24	1.46	0.97	-0.49	8.22
	RCP 6.0	1.65	1.03	-0.62	12.99	1.9	0.93	-0.97	7.74
	RCP 8.5	2.69	1.82	-0.87	12.74	2.6	1.34	-1.26	7.45

Note: - = Negative mark indicates suitable habitat area contractions

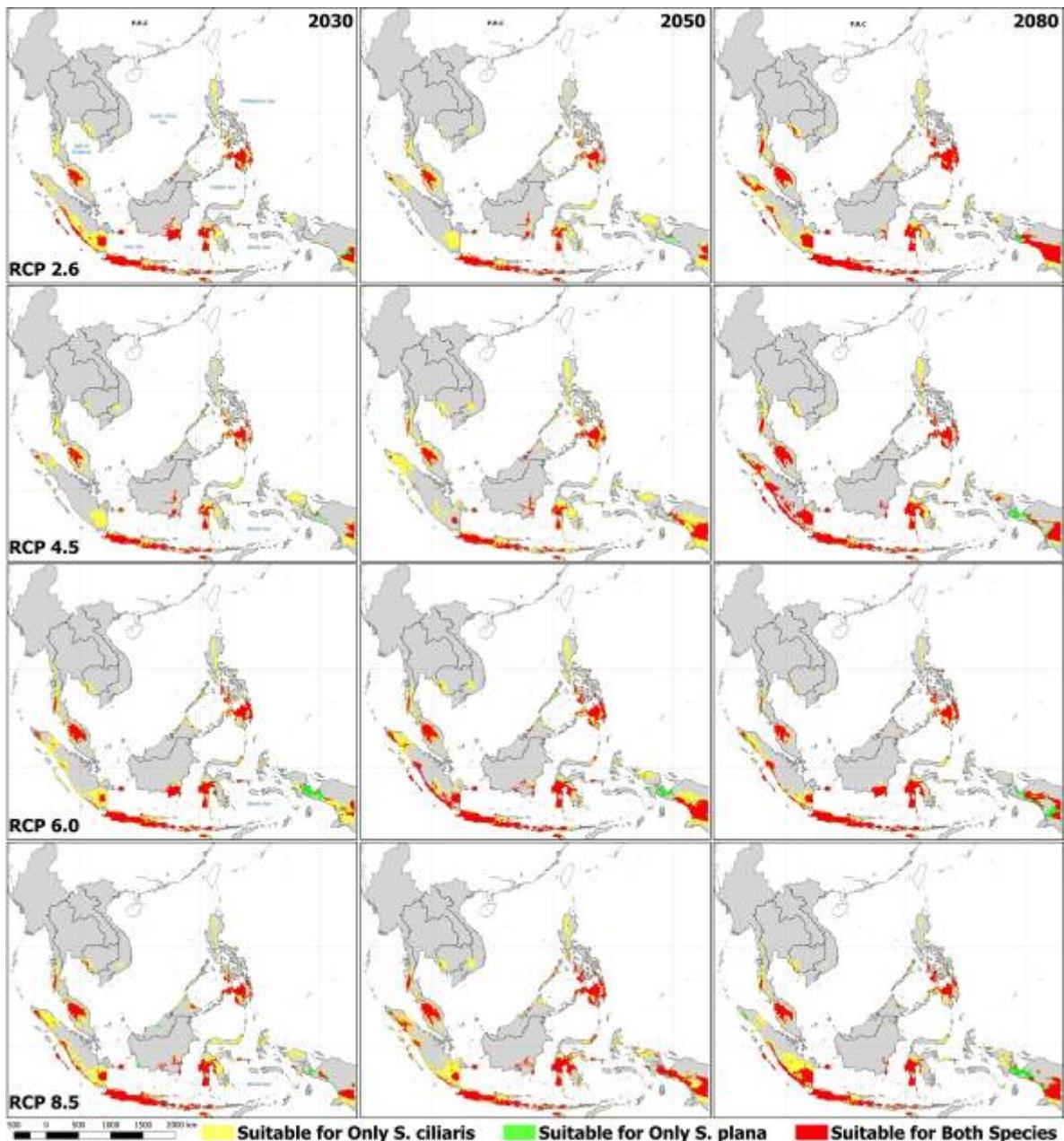


Figure 4. Redistribution of climatically suitable habitat under future climate projections

Core distributional shifts

Given the aforementioned reasons over why core distributional shifts assessment was conducted only on Java, we may look first into the predicted distribution of both species' suitable habitat in this particular island. Under current climate condition, it has been predicted that there are approx. 55,676.4 km² (41.5%) suitable areas for *S. ciliaris* and about 45,500.1 (33%) km² areas are suitable habitat for *S. plana*. These numbers were predicted to gradually decreasing as future climate change altering the habitat capability to support the survival of both *S. ciliaris* and *S. plana*. In the year 2080, under all of the GHG emission trajectories, current suitable habitat area for *S. ciliaris* and *S. plana* will decrease by up to 11% and by up to 19% respectively. Furthermore, redistribution of predicted suitable habitat for both species, under future climate condition, will also alter its geometric distribution core. The centroid of the currently suitable habitat for *S. ciliaris* was located at the position of 109.786E longitude and 7.313S latitude in Central Java (Figure 1.B). The centroid of future suitable area under RCP 2.6 was predicted to shift marginally to west direction to the position of 109.760E, 7.310S. The shift under the RCP 4.5, RCP 6.0, and RCP 8.5, show a greater extent wherein the centroid shift about 26.13 km to 37.32 km to west direction at the position of 109.446E, 7.263S under RCP 4.5, 109.547E, 7.312S under RCP 6.0, and 109.540, 7.277S under RCP 8.5. Likewise, major shift of currently suitable habitat centroid of *S. plana* has been predicted to occur under the RCP 4.5, RCP 6.0, and RCP8.5 whereas under the influence of RCP 2.6, the shift is relatively small. Under the RCP 2.6 the centroid predicted to shift to the north at the position of 109.579E, 7.300S, which is about 2.5 km from its original position at the position of 109.579E, 7.324S. Under the influence of other RCPs, the centroid shift to west direction about 18.76 to 49.78 km from its original position. The farthest shift of suitable habitat centroid is under the RCP 8.5 at the position of 109.139E, 7.231S. The new centroid position under RCP 4.5 and RCP 6.0 are 109.409E, 7.305S, and 109.165E, 7.254S, respectively. Overall, there is tendency of centroid shifting to the western side of the island under all future RCP trajectories, and the weakest shift of suitable habitat core of both species is always under the influence of RCP 2.6 (Figure 1.B). □

Discussion

Recently, only a few studies attempt to model the impact of climate change on the sustainability of autotrophic non-vascular cryptogams (e.g., Cornelissen 2007; Ellis et al. 2007). The number is even less for study which focuses on the particular genus such as *Selaginella* (e.g., Setyawan et al. 2017). Nonetheless, several studies have reported that the sustainability of *Selaginella*, as a member of biotic component of vegetation, is also predicted to be affected by any measured changes in climate both in the past condition and in the projected of future condition (e.g. Muller et al. 2003; An et al. 2005; Trivedi et al. 2008; Cao et al. 2010; Xu et al. 2010). Indeed, discrepancies may occur between different climate

modeling system used in the preceding studies (Cheaib 2012), but the approaches nevertheless can be functioning as an important research tool for assessing and predicting the effect of both current and future climate condition on the distribution of suitable habitat for, especially, genus of *Selaginella*.

Selaginella ciliaris is predicted to has a wide but fragmented distribution in the southern part of mainland SEA region (South Vietnam, Cambodia, Myanmar, Peninsular Malaysia, and Singapore) and in most of the big islands in maritime SEA. The model prediction is in agreement with past and recent years studies reported its occurrences in Vietnam (Thin 1997; Costion and Lorence 2012), Cambodia (Spring 1843; Zhang et al. 2013; Rundel and Middleton 2017), Myanmar (Spring 1843; Winter and Jansen 2003; Chang et al. 2012), Peninsular Malaysia and Singapore (Hanum and Hamzah 1999; Yusuf et al. 2003; Tan et al. 2014), Philippines (Barcelona 2003; Tan 2013), Sumatra (Spring 1843; Iwatsuki 1973; Wardani and Adjie 2017), Borneo (Spring 1843; Iwatsuki and Kato 1981; Said 2005). Sulawesi (Spring 1843), Java (Setyawan 2009; Setyawan 2012), and Papua (Johns et al. 2012; Gartmann 2015). Likewise, the predicted distribution of *Selaginella plana*'s suitable habitat has almost the same pattern as the predicted suitable habitat for *S. ciliaris*. Several documents and studies had also reported the occurrence of *S. plana* in Vietnam (Spring 1843; Chang et al. 2012), Cambodia (Spring 1843; Chang et al. 2012), Myanmar (Chang et al. 2012; Parveen et al. 2017), Peninsular Malaysia and Singapore (Turner et al. 1998; Chua et al. 2005; Bedawi et al. 2009), Philippines (Alston 1935; Zamora et al. 1999; Tan 2013; De Guzman et al. 2014), Sumatra (Sauerborn 2003; Beukema and Noordwijk 2004), Borneo (Said 2005; Ahmad and Holdsworth 2008; Komara et al. 2016), Sulawesi (Mansur 2003; Hidayat 2011), Java (Rahayu et al. 2012; Setyawan et al. 2013; Setyawan et al. 2015a;b; Setyawan et al. 2016; Trimanto and Hapsari 2016), and Papua (Sambas et al. 2003; Ebihara et al. 2012; Johns et al. 2012).

Based on the modeling results, constancy and stability of temperature (isothermality and temperature seasonality) are among the most important factors affecting the distribution of both *S. ciliaris* and *S. plana*. Isothermality (bio_3) is defined as the quantification of how large the diurnal temperature range oscillate with annual temperature oscillations, while temperature seasonality (bio_4) is defined as a measure of temperature change over the course of the year (O'Donnell and Ignizio 2012). Past studies confirmed the importance of stability of temperature in preserving the survival of genus *Selaginella*. Temperature, allegedly affect both the photosynthetic capability and preservation of photosynthetic apparatus of *Selaginella* (Jagels 1970, Eickmeier 1986). Additionally, water availability which was measured in annual precipitation is also among the most important factors affecting the distribution of both species. Water availability is correlated with many environmental factors that influence the biochemical and physiological processes of plants (e.g. Platt et al. 1994; Wang et al. 1998; Rusala et al. 2011). Therefore, these hydrothermal factors may have played

main roles in shaping the ecological adaptation and the distribution pattern of both *S. ciliaris* and *S. plana*. Moreover, these results also indicate that both *S. ciliaris* and *S. plana* appear to grow well in a highly isothermal environment and with low variability of temperature.

The intensity of UV radiation also predicted to have a major role in shaping the distribution range of both *S. ciliaris* and *S. plana*. Generally, UVB radiation has a great effect on the sub-aerial organs of plants (Yang et al. 1994). Plants species subjected to elevated UVB reveal that UVB radiation affects plants morphology by inhibiting leaf area expansion and stem elongation (Caldwell et al. 1998). UVB radiation also influences the protective mechanism of plants (Bellare et al. 1995; Márquez-Escalante et al. 2006) and decreases photosynthetic activity (Jagels 1970; Battaglia et al. 2000). Another environmental factors, such as increased CO₂ concentration, water stress, and availability of nutrients interact with this form of radiation (Wu et al. 2009), which in turn affect the plant response to the changes in environmental parameters (Caldwell et al. 1998; Teklemariam and Blake 2003; Qaderi and Reid 2005). Past studies on several *Selaginella* species also confirmed that net photosynthesis, stress regulation mechanism, and local distribution are closely related to the component of light source (Jagels 1970; Eickmeier 1979; Márquez-Escalante et al. 2006). However, further specific information on effects of UVB radiation on the changes in biochemistry and physiology of *Selaginella* is limited, hence future studies regarding these subjects are recommended.

Future climate condition in SEA region has been predicted will significantly disturb the distribution of suitable habitat of *S. ciliaris* and *S. plana*, and alter its geographical distribution pattern. Despite there are some gained areas which were predicted to become suitable habitat in the early period of future climate change, overall projection shows a negative effect of future climate condition on the distribution of *S. ciliaris* and *S. plana*'s suitable habitat; as the predicted losses of suitable habitat will be greater than the gains. Under the lowest and medium GHG emission projection (RCP 2.6, RCP 4.5 and RCP 6.0); wherein radiative forcing will gradually rise up before it stabilizes at the certain figure by 2100 (Meinshausen et al. 2011; IPCC 2014), annual mean temperature will rise up to about 1.7-5°C in all areas of SEA region. Unlike in the case of temperature changes, the changes in precipitation will not be equivalent in all of SEA region areas. There will be both areas wherein the amount of precipitation shows an increasing tendency by up to 15% of current annual precipitation rate (Northern Philippines, Myanmar, and Laos) and areas wherein the amount of precipitation will tend to decrease by about 10% (e.g., southern Indonesia, Thailand, Laos, and Myanmar) by the end of 21st century (IPCC 2014). This condition predicted leads to a slight increase of *S. ciliaris* and *S. plana*'s suitable habitat area by the end of 2030. The gains are mostly predicted to occur in a higher latitude area, as future climate increases its probability to support the existence of both species. However, for the next five decades, as climate continues to change, these figures will

gradually to decrease. The same negative trend will also predict to occur under the worst GHG emission scenario (RCP 8.5), with no gained area will appear under this scenario in all periods of time. Core distributional shifts assessment indicates that there will be upward shifts to higher elevation area as the atmosphere warms, which is in line with certain studies that predicted a shift of forest ecosystems to a higher altitude (e.g. Walther et al. 2005; Bertrand et al. 2011). Increased temperature and occurrence of severe drought, as indicated by precipitation variability, should increase plant stress in some years (Kelly and Goulden 2008). Thus, expected to decrease the species' ability to survive in the drier, warmer, lower parts of its range (Allen and Breshears 1998; Lenoir et al. 2008a,b) and increase its competitive ability and tolerance in the wetter, cooler, upper parts of its range (Parmesan and Yohe 2003; Parmesan 2006). □

Generally, plant species may migrate to higher elevations and latitude as its mechanism to cope with the changes in climate condition (Lenoir et al. 2008a; Bertrand et al. 2011). However, the trends may differ between narrowly distributed plant species and widely distributed plant species. Plants with narrow distribution usually have a constrained capability of ecological adaptation, and are more vulnerable to the impact of climate change, whereas plants with wider distribution tend to have broader adaptability and have a stronger resistibility to climate change (Hu et al. 2015). This tendency, is what the models have predicted in this study, wherein the distribution of suitable habitat for both species is increased at first, but then began to decrease as climate change intensified. Several studies have also reported the early sign of plants migration into higher altitude areas under the effect of changes in climate condition (e.g., Zhang et al. 2001; Parmesan and Yohe 2003; Root et al. 2003; Leng et al. 2008; Lenoir et al. 2008a). Additionally, an attempt of evaluating the impact of climate change on the distribution of suitable habitat for both species, should also incorporate anthropogenic factors such as deforestation activity which will be resulting in fragmentation and shrinkage of habitat area. The results of this study may suggest that both *S. ciliaris* and *S. plana* have a medium degree of vulnerability to the impact of climate changes, nonetheless, under the influence of human-induced land conversion, the loss of suitable habitat for both species will be greater than expected. Therefore, more studies are needed to quantify and qualify the future anthropogenic impacts on the sustainability of *S. ciliaris* and *S. plana*.

The maps, presented in this study, depict the predicted distribution of suitable habitat for both species, which were built by using climate, topography, edaphic, and UVB radiation variables. Nonetheless, it must be taken into account that, like most of the ENM, the "predicted" distribution of suitable habitat does not represent the "true" prediction of the distribution of species eco-physiologically, but rather the prediction of the distribution of "suitable" habitat based only on the aforementioned predictors. Therefore, in the predicted suitable area, the species may not actually exist. There are also several assumed reasons for the absence of species in the predicted

area, i.e. (i) Micro-climate variation affect the existence of species in the predicted areas, but were not included in the model as a result of limited availability of data. (ii) The weak resolution of the recorded environmental variables has not yet capable of represents the unique environmental condition that greatly drives the probability of the occurrence of species. (iii) Human-induced changes that causing the predicted areas are no longer habitable for the species (e.g. deforestation, construction activity, etc.). Moreover, omission error may also occur as a result of occurrence data which were supplied into the models did not represent all the varieties of environmental condition that can sustain the existence of species. Despite all of bias correction methods which were carefully applied to achieve greater quality of models, these possible mismatches between the models and real-life situation may still occur. Nevertheless, we may acknowledge the result of the model as an appropriate representation of how the current climate condition shapes the distribution of suitable habitat for *S. ciliaris* and *S. plana*, and its predicted redistribution under the effect of future climate change.

Building an ideal model requires the availability of multiple compounding factors which are expected to have either direct or indirect effect on the target species and its associated biota. However, such ideal packages of data are currently limited. This limitation in the availability of more detailed ecological and physiological data prevents the construction of more ideal models (Morin and Thriller 2009; Sinclair et al. 2010; Ellis 2011). Nevertheless, recent development of new climate models and the refining of current models provide opportunity to build more precise and ideal model. Further modeling attempt should also incorporate potential human-induced land use/land cover changes, biotic interactions between species in the regional ecosystems, more detailed ecological data, and better presence data which accurately represent the variability of ecological niche of species. Despite all of these limitations, this study provides the baseline of understanding the potential effect of climate change on the distribution of predicted suitable habitat for *S. ciliaris* and *S. plana*. Using different technique of species distribution modeling, such as profile technique (e.g. DOMAIN, ENFA) and Regression-based technique (e.g. GLM, GAM, and MARS), may present slightly different quantitative results. Nonetheless, we believe that by using currently available resources of data, the overall trend and projection results would be similar. Therefore, it is concluded that the sustainability of *S. ciliaris* and *S. plana* potentially will negatively be influenced by all of the scenarios of future climate condition presented in this study. □

ACKNOWLEDGEMENTS

The authors thank Directorate General of Higher Education of the Republic of Indonesia for financial support through PUPTN grand scheme in 2013 to the first author, as well as Fundamental Research grand scheme in 2007 to Dr. T. Chikmawati; we thank both of them. We

also thank Herbarium Bogoriense (BO) for possibility to observe and identify its sellaginellas collection.

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