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Potential climate change effects on tree distributions in the Korean Peninsula: Understanding model & climate uncertainties

Kyung Ah Koo [a], Seon Uk Park [a], Woo-Seok Kong [b], Seungbum Hong [a], Inyoung Jang [a], Changwan Seo [a,*]

[a] National Institute of Ecology, 1210 Geumgang-ro, Maseo-myeon, Seocheon-gun, Chungnam, 33657, Republic of Korea
[b] Department of Geography, Kyung Hee University, 26 Kyungheedae-ro, Dongdaemun-gun, Seoul, 02447, Republic of Korea

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ABSTRACT

The projections of species distribution models (SDMs) have provided critical knowledge for conservation planning under climate change in the Republic of Korea. However, uncertainty about the SDM projections has been criticized as a major challenge to reliable projections. The present research investigated uncertainty among competing models (Model uncertainty) and uncertainty of future climate conditions (climate uncertainty) driving from different GCMs and CO_2 emission scenarios in predicting the future distributions of plants. For this purpose, using nine single-model algorithms and the pre-evaluation weighted ensemble method, we modeled the geographical distributions of Silver Magnolia (*Machilus thunbergii* Siebold & Zucc.), a warm-adapted evergreen broadleaved tree; furthermore, we predicted its future distributions under 20 climate change scenarios (5 global circulation models (GCMs) × 4 CO_2 emission scenarios (RCPs)). The results showed a great variation in the accuracies of nine single-model projections: the mean AUC values of nine single-models ranged from 0.764 (SER) to 0.970 (RF), and the mean TSS ranged from 0.529 (SRE) to 0.852 (RF). RF (mean AUC = 0.970, mean TSS = 0.852) and the ensemble forecast (AUC = 0.968, TSS = 0.804) showed the highest predictive power, while SRE showed the lowest. The future distributions of Silver Magnolia projected with the ensemble SDM clearly varied according to GCMs and RCPs. The twenty climate scenarios produced twenty different projections of the magnolia prospective distribution. GCMs commonly projected the maximum range expansion under RCP 8.5 in 2050 and 2070, but CO_2 emission scenarios explaining the minimum expansions differed according to GCMs. In conclusion, our results show that GCMs, CO_2 emission scenarios and SDM algorithms produce considerable variations in the SDM projections. Therefore, this research suggests that understanding of model and climate uncertainties is critical for an effective conservation planning in forest management under climate change on the Korean Peninsula.

1. Introduction

Climate change has caused the upward and poleward range shifts of plants (Díaz-Varela et al., 2010; Ernakovich et al., 2014; Feeley et al., 2011; Flagmeier et al., 2014; Pauli et al., 2012; Sproull et al., 2015; Stöckli et al., 2011). Such changes will modify ecosystem structure and processes, resulting in substantial impacts on ecosystem services for human well-being and economic growth (Cheaib et al., 2012). Therefore, providing reliable projection of species distribution under climate change is essential for nature conservation and sustainable ecosystem services (Prato, 2008; Wiens et al., 2009). Species distribution models (SDMs) have been widely used to predict the climate change effects on species distributions (Baker et al., 2016; Guisan and Thuiller, 2005; Kearney et al., 2010). However, uncertainty about the SDM projections has been criticized as a major challenge to reliable projections (Barry and Elith, 2006; Pearson et al., 2006; Wang et al., 2012; Wenger et al., 2013; Wiens et al., 2009).

Such uncertainty derives mainly from three reasons: (1) parameter uncertainty; (2) model uncertainty; and (3) uncertainty in future climate conditions (climate uncertainty) (Barry and Elith, 2006; Wang et al., 2012; Wenger et al., 2013). Multiple resources

* Corresponding author.
E-mail addresses: kyungah.koo@gmail.com, kkoo@nie.re.kr (K.A. Koo), psu1201@nie.re.kr (S.U. Park), wskong@khu.ac.kr (W.-S. Kong), sbhong@nie.re.kr (S. Hong), iyjang@nie.re.kr (I. Jang), dharmascw@nie.re.kr (C. Seo).

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explain parameter uncertainty: imperfect species occurrence data, unknown variables bringing on species occurrence, unavailableness in important predictor variables, and disregard of ecological processes, such as biotic interactions, dispersal limitation, acclimation, and adaptation (Barry and Elith, 2006; Wenger et al., 2013). Model uncertainty consists of within-model and between-model uncertainty. Within-model uncertainty comes from model parameter estimations, *i.e.* standardized error and confidence interval, and has been quantified to reduce misinterpretation of the SDM projection (Hartley et al., 2006; Roura-Pascual et al., 2009; Wenger et al., 2013). Between-model uncertainty lies in that different SDMs produce different predictions and species-environmental relationships (Hartley et al., 2006; Pearson et al., 2006; Thuiller et al., 2009; Wenger et al., 2013). Ensemble approaches, such as multi-model inference and model-averaging, have been employed to reduce between-model uncertainty and improved the predictive power of SDMs under current conditions (Diniz-Filho et al., 2009; Hartley et al., 2006; Thuiller et al., 2009; Wenger et al., 2013). However, due to uncertainties in the future climate conditions, predicting species' future distributions remains a challenge (Bagchi et al., 2013; Thuiller, 2004). Future climate conditions depend on CO_2 emission scenarios and the output of General Circulation Models (GCMs) (Osborne et al., 2013). Therefore, any climate change impact assessment depends on the selection of GCMs and CO_2 emission scenarios (the Representative Concentration Pathways, RCP).

The SDM projections for plants and animals have been important knowledge for conservation practices and policies in the Republic of Korea (http://motive.kei.re.kr/main/main.do) (Ahn et al., 2015; Jeong et al., 2015; Kim et al., 2015; Kwon, 2014; Park et al., 2014; Song and Young, 2012). The projections of SDMs have been applied for prioritizing species and sites for conservation planning under climate change (http://motive.kei.re.kr/main/main.do). However, many projections have not considered uncertainties in modeling species distributions (Jeong et al., 2015; Kim et al., 2015; Park, 2011). Several studies have recently started to consider uncertainties of the SDM projections (Koo et al., 2015; Kwon, 2014; Yun et al., 2014, 2011). While they quantified model uncertainties or uncertainties of future climate conditions, they did not comprehensively account for the two of them together (Ahn et al., 2015; Koo et al., 2015; Song and Young, 2012; Yun et al., 2014, 2011). In addition, even when accounting for climate uncertainty, uncertainty stemming from GCMs has rarely been considered (Ahn et al., 2015; Koo et al., 2015).

This research particularly focused on uncertainty among competing models (model uncertainty) and uncertainty of future climate conditions (climate uncertainty) that derived from different GCMs and CO_2 emission scenarios. Therefore, we did not intend to acquire an optimal projection for the plant distribution or to investigate the full range of uncertainty in this study; rather, we aimed to account for variations in projections introduced by CO_2 emission scenarios, GCMs and SDM algorithms. For this purpose, we modeled the geographical distributions of Silver Magnolia (*Machilus thunbergii* Siebold & Zucc.), a warm-adapted evergreen broadleaved tree (Yun et al., 2011), using nine single-model algorithms and the pre-evaluation weighted ensemble method (Thuiller et al., 2012) and predicted its future distributions under twenty climate change scenarios (5 GCMs $\times$ 4 RCPs). Model uncertainty was examined by comparing predictive accuracies of nine-single-model SDMs. Climate uncertainty was investigated by predicting future distributions of Silver Magnolia under twenty climate change scenarios using an ensemble projection of single-model SDMs. It will improve our understanding of uncertainties in the SDM projections under climate changes, providing fundamental and practical knowledge for conservation planning in forest management on the Korean Peninsula.

2. Methods and materials

2.1. Study area

The study area was the Korean Peninsula (KP), The Republic of Korea (ROK) in the south and The Democratic People's Republic of Korea (DPRK) in the north (see Fig. 1). The following information was summarized from Kong and Watts (1993). The total area of KP is 220,847 km^2, consisting by ca. 70% of mountainous areas and over 3400 islands. Most mountains are located in the eastern and northern parts of the peninsula and plains in the western and southern parts. Summer is hot and humid, while winter is dry and cold. The 30-year mean temperatures are 19.1 °C to 27.1 °C for August and −17.2 °C to 6.8 °C for January. Most rainfall takes place during summer, the East Asian monsoon in midsummer, and little snowfall during winter; there is little snow accumulation outside of the mountainous areas. Such diverse landscapes and a broad range of climate conditions have created three main floristic zones with over 3500 plant species, including more than 500 endemics: warm-temperate, temperate, and cold-temperate (Kong and Watts, 1993). In particular, the southern peninsula with well-developed plains is relatively warm and wet and is occupied by warm-adapted broadleaved evergreen species.

Silver Magnolia (*Machilus thunbergii* Siebold & Zucc.) is a warm-adapted evergreen broadleaved tree (Yun et al., 2011). Silver Magnolia is distributed in the southern parts of KP and prevails on the southern coast and the islands (Lee and Hee, 2010). This species has been considered as a climate change sensitive species by the Ministry of Environment, the Republic of Korea (http://www.nibr.go.kr/species/home/main.jsp). It is also considered as an indicator species to estimate climate change effects on our ecosystem, in particular, the warm-temperate and temperate ecosystem. The expansion of Silver Magnolia may imply increases in warm-temperate forests and decreases in temperate forests (Yun et al., 2011). As other warm-adapted species, Silver Magnolia presents the northern distribution limit and a strong preference to warm and humid climate condition. Therefore, it has been expected that the range of Magnolia will expand or shift to the north in KP under climate change (Yun et al., 2011). Previous studies of the magnolia predicted that it could greatly expand and reach to the northern part of KP under climate changes (Yun et al., 2011).

2.2. Model variables

Presence and absence of Silver Magnolia (*Machilus thunbergii* Siebold & Zucc.) along the Korean Peninsula were obtained from previous studies (Koo, 2000; Lee and Yang-jai, 2002) and Korea National Arboretum (http://www.nature.go.kr/index.jsp). Presence/absence data were collected at 722 sites (ROK: 670 sites, DPRK: 52sites). The data of 52 sites in DPRK were obtained from the literature (Lee and Yang-jai, 2002). As more recent data of DPRK are not currently available due to political reasons, the data of DPRK used in the present study include inquiries from the early 1900s to 1965. 670 sites for ROK and 52 for DPRK were visited by qualified plant taxonomists to generate species lists in each site over the past forty years. Thus, the dataset can be regarded as having reliable absence data, which is a challenge for the SDM modeling.

We first considered 19 bioclimatic variables assumed to be important for determining the distribution of plants (Araújo et al., 2005a). Afterward, we tested correlations on pairs of predictors using Pearson's r, and, finally, six bioclimatic variables showing weak correlations among them ($r < 0.7$) were selected for modeling (Koo et al., 2015). The six bioclimatic variables were BIO1, BIO2, BIO3, BIO12, BIO13 and BIO14 (Table 1a; see Koo et al. (2015) for further detail on the variable selection). The current and future gridded bioclimatic data were obtained from the WorldClim